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Mapping of Skills Intelligence in the EU – Technical Report

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Contents

Abstract

This report maps the data sources and indicators available for measuring skills demand, supply and mismatch across the European Union. It assesses which of them can support regular monitoring by the European Skills Intelligence Observatory (ESIO). Each instrument is profiled on a common template covering description, methodology, published indicators, granularity, coverage, update frequency, microdata access, strengths and limitations. The mapping spans Eurostat surveys and online job advertisement data, the skills intelligence system of Cedefop, shortage and surplus reporting by the European Labour Authority, Eurofound surveys, sectoral partnerships, the OECD adult skills programmes, and private vacancy analytics. Three results follow. First, qualification mismatch, measured through credentials, and skills mismatch, measured through assessed or reported competencies, overlap only modestly. Hence, household, employer and vacancy sources are complementary rather than substitutable. Second, measured incidence depends on the instrument, because wording and thresholds differ even among sources asking about the same concept. Third, many of the instruments are also interdependent, each inheriting the constraints of the sources it draws on. The report converts this mapping into a scoring framework in which candidate indicators are rated on seven criteria. Scoring is comparative rather than threshold based, and records fitness for the ESIO dashboard use rather than quality.

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Executive summary

This report identifies and analyses the relevant data sources and derived indicators on skills intelligence in the EU. It undertakes a rigorous examination, on common terms, of key data sources and instruments, including an assessment of the strengths and limitations. Based on this mapping, it sets out a method for deciding which of them should feature on the data platform and dashboard of the European Skills Intelligence Observatory.

Policy context

A key initiative proposed as part of the Union of Skills is the creation of a European Skills Intelligence Observatory (ESIO), whose mission is to enhance EU-wide skills intelligence through effective aggregation and analysis of relevant data and evidence on skills demand, supply and mismatch in the EU.

ESIO will facilitate EU-wide skills intelligence by means of a data platform and dashboard and through providing insights to the European Skills High-Level Board and the European Semester, including the EU-27 Recommendation for Human Capital.

The Joint Research Centre (JRC) prepared this report for the Directorate-General for Employment, Social Affairs and Inclusion to provide the technical groundwork for the choice of ESIO's data platform architecture.

Key conclusions

No single indicator can monitor skills mismatch in the EU. More education does not automatically translate into better skills, and the empirical overlap between qualification mismatch and skills mismatch is only modest. Household surveys capture mismatch for individuals, employer surveys capture gaps inside firms, and vacancy or administrative data capture market-level signals. Each is partial. Combining them is not a compromise but the only route to a coherent picture.

The report supplies a scoring framework so that it can be recorded and revisited. Five actions follow.

- **The Observatory should adopt the multi-criterion indicator assessment as a standing governance tool**, so that every dashboard configuration can be audited and kept up to date.
- **The Observatory should arrange platform outputs in compatible layers built on the standard classifications** of occupations, education, sectors and skills, allowing users to move from headline indicators down to occupation and skill detail.
- **The Observatory should build unified monitoring on established statistics**, and integrate real-time vacancy data and project outputs over time in a controlled second layer.
- **The Commission should follow EU-funded initiatives systematically**, in particular under Horizon Europe and Erasmus+, reviewing whether their tools, composite measures and analytical models can be made fit for purpose for the Observatory.
- **The Observatory should document limitations next to every published metric**, especially where cross-country comparison is difficult or a conceptual workaround stands in for the concept of interest.

Main findings

On what basis are the instruments compared?

The report maps each source on a common technical template: description, methodology, published indicators and dashboard links, granularity, time coverage, update frequency, microdata accessibility, and a paired assessment of strengths and limitations. This uniform treatment lets otherwise heterogeneous instruments be read against one another, and shows where they are complementary. The purpose is to assess fitness for regular, comparable, EU-wide monitoring, not overall instrument quality.

What does the landscape contain?

Coverage spans Eurostat skills-related data, the Cedefop skills intelligence system, EURES shortage reporting by the European Labour Authority, Eurofound working conditions and company surveys, the Pact for Skills sectoral mechanisms, OECD assessments, private vacancy analytics, national administrative data and EU-funded research projects. Capability is uneven and improving in places: the Cedefop forecast projects to 2035, the 2024 EU Labour Force Survey module introduced direct measures of self-reported mismatch, and EURES reporting now classifies all 436 detailed occupations rather than a selected list.

How do the instruments connect?

The report makes the connecting architecture explicit. Online job advertisement infrastructure feeds the Cedefop vacancy tool, the Skills Forecast draws on EU surveys and in turn powers shortage indices. Cedefop curates Eurostat statistics in its own dashboards, and sectoral alliances feed intelligence back into that system. Each instrument inherits the properties and constraints of the sources it depends on, so a weakness at the base propagates upward.

Related and future Joint Research Centre work

This report is part of the JRC's support to the Skills Observatory. Future steps are providing technical support to the setting up of the data platform architecture and producing tailored policy analysis to assist the High-Level Skills Board in supporting the Commission's work on the European Semester.

Quick guide

— The report maps all major EU instruments measuring skills demand, supply and mismatch, described on common terms.
— No single indicator suffices: a coherent picture requires combining household, employer and vacancy data.
— A transparent seven-criterion scoring framework converts the mapping into the indicator set for the Skills Observatory's platform.
— The core should rest on Eurostat and Cedefop statistics, with real-time vacancy data in a controlled second layer and limitations documented next to every metric.

1. Introduction and Conceptual Framework

"The Union of Skills aims to support the development of quality, inclusive and adaptable education, training and skills systems to increase the EU's competitiveness. Enhanced skills intelligence at EU level will be of key importance in this context, for effective and targeted policies. Through a newly created European Skills Intelligence Observatory, the Commission will provide strategic data and foresight regarding skills (current and future) stocks, use and needs, in concrete sectors and regions, and the performance of education and training systems. The European Skills Intelligence Observatory (ESIO) will allow to centralise granular, real-time and comparable data, providing the necessary inputs to the High-Level Skills Board and feeding the work of the European Semester." (European Commission, 2025)

To support the work of the European Skills High-Level Board, the ESIO should establish a coherent set of tools and indicators to identify, monitor, anticipate and signal critical skills shortages. This requires a structured assessment of available data sources, existing indicators and current methodologies, with a view to strengthening the analytical basis for evidence-based policy making, while ensuring that the framework can be updated regularly.

This is the task of the current report: map and assess the relevance of existing data sources and indicators on skills shortages and skills mismatches in the EU. This includes examining key EU sources, such as the EU Labour Force Survey, Eurobarometer, the European Pilot Graduate Survey, the European Company Survey, the European Training and Learning Survey, the European Skills and Jobs Survey, Skills-OVATE and the European Working Conditions Survey, as well as existing indicators including Cedefop Skills Forecast indicators and the ELA/EURES Demand for Occupations Dashboard, and additional sources that complement this identified evidence base.

Building on this mapping, this report assesses the robustness, relevance and policy usefulness of the identified data and indicators for the Data Platform. Particular attention is paid to consistency across indicators, data quality issues and remaining gaps.

Skills mismatches[1] (shortages or gaps – see box Box 1) represent a critical challenge for labour markets, economic productivity, and individual well-being across the European Union (EU). The consequences of skills mismatches are pervasive: at the individual level, mismatched workers suffer wage penalties, reduced job satisfaction, and, where mismatch persists rather than resolving into a better-matched job, elevated turnover risk; at the firm level, mismatch constrains productivity and innovation; and at the macroeconomic level[2].

[1] Mismatch is the most nuanced inefficiency, i.e. aggregate supply and demand for skills may clear, yet the composition is wrong. Workers hold credentials in declining sectors while vacancies cluster in emerging ones. This is what Beveridge curve outward shifts capture: vacancies and unemployment coexist because the skills on offer aren't the skills being sought.

[2] Garibaldi, Gomes and Sopraseuth (2025) quantify the output costs of education and skills mismatch for 17 OECD economies, using a calibrated model of vertical mismatch. Eliminating the frictions generating mismatch would raise output by 3% to 4% on average, varying between 0.5% to 9% across countries.

Box 1. What we mean by

Skills: what a person knows, understands and can do[3]. Skills are elements of human capital that enhance productivity: they enable staff to apply the newest technologies to produce more goods and services of higher quality, and to innovate. Skills also influence decisions in education, training and labour markets. Solid basic skills[4] provide the essential foundations for lifelong learning, and up- and reskilling where needed. This enables workers to move more easily from declining sectors and companies to more dynamic ones, including in newly emerging economic activities and sectors (Brunello and Wruuck, 2021).

Skills shortages: a lack of skilled workers in the labour market - employers cannot recruit staff with required skills. Shortages operate at the extensive margin. Even if every available worker were perfectly skilled, there simply aren't enough of them to fill demand.

Skills gap: internal, firm-level, mismatch where current employees lack the skills necessary for their roles. According to the OECD *"Skill gaps can therefore be understood as micro-level mismatches, whereas skill shortages are macro-level mismatches"* (OECD, 2024). Gaps sit at the intensive margin. Workers are employed (or employable) but lack specific competencies the role requires, e.g. digital skills deficits within otherwise qualified workforces. The match exists in principle but is incomplete in practice, reducing productivity and often suppressing wages.

1.1. Typology of Skills Mismatch

While the importance and pervasiveness of skills mismatches has led to a large volume of research, **no consensus** has emerged on how mismatch is to be defined, conceptualised, or operationalised. A fundamental fault-line runs through the literature between education-based and skill-based conceptualisations. Education mismatch, or overeducation, treats attained educational qualifications as a proxy for competencies and compares them against the qualifications nominally required for a given occupation. Skill mismatch, or overskilling, moves beyond credentials to assess the direct correspondence between workers' actual cognitive and technical proficiencies and the demands placed upon those abilities in the workplace (Desjardins and Rubenson, 2011; Pellizzari and Fichen, 2013). A further distinction applies within each of these categories: mismatch can be measured through objective, externally validated benchmarks or through subjective self-reports by workers themselves. The choice among these approaches is far from trivial, as different operationalisations produce markedly different estimates of the incidence, distribution, and determinants of mismatch — with direct implications for labour market policy.

The Organisation for Economic Co-operation and Development (OECD) defines skills mismatches as discrepancies between the skills workers possess and those required by their jobs (OECD, 2013). These mismatches can manifest in various forms, including overeducation, undereducation, overskilling, underskilling, field-of-study mismatches, and skill obsolescence, each with distinct implications for workers, employers, and policymakers.

The framework distinguishes two overarching categories. Qualification (or education) mismatches arise when workers' formal educational attainment diverges from the qualifications nominally required for their occupation. Skills mismatches arise when workers' actual cognitive and technical proficiencies diverge from the demands placed upon those proficiencies in the workplace. Crucially, the OECD (2013, p. 31) observes that these two dimensions are not interchangeable: 'more

[3] As defined in the 'A New Skills Agenda for Europe', (2016).

[4] The Action Plan on basic skills has adopted a wider definition of basic skills which includes digital and civic knowledge in addition to literacy, mathematics and science.

education does not automatically translate into better skills', a point confirmed empirically by PIAAC data across all participating economies. Skills can be gained in a wider variety of contexts: education, but also different forms of training or work-based learning and on-the-job[5].

Within each category, the OECD recognises vertical mismatch (surplus or deficit of the educational level relative to job requirements), horizontal mismatch (misalignment of field of study with occupation), and temporal mismatch (skill obsolescence arising from technological change or training inactivity). Table 1 summarises this typology.

Table 1. Typology of Skills Mismatch

Mismatch Type	OECD Category	Direction	Primary Dimension
Overeducation	Qualification mismatch	Upward	Formal credentials
Undereducation	Qualification mismatch	Downward	Formal credentials
Overskilling	Skills mismatch	Upward	Actual competencies
Underskilling	Skills mismatch	Downward	Actual competencies
Field-of-study mismatch	Qualification mismatch	Horizontal	Subject-occupation alignment
Skill obsolescence	Skills mismatch	Dynamic/temporal	Depreciation over time

Source: Authors' elaboration

Effective policy response requires intelligence that can distinguish among these dimensions. Different indicators capture different facets: household surveys measure individual-level mismatch, employer surveys measure firm-level shortages or gaps, and administrative or vacancy data capture market-level signals. No single indicator is sufficient; a coherent framework must combine complementary sources.

1.1.1. Qualification Mismatch

Qualification mismatches take formal credentials as the unit of analysis. They compare a worker's attained level or field of education against the qualification required for their occupation. The credential is treated as an observable, internationally comparable proxy for competence, but leaves open whether the attained credential actually corresponds to the worker's competencies. Three subtypes are conventionally distinguished.

Overqualification (Overeducation): workers whose attained education exceeds the level required for their job. This is the most extensively studied form of mismatch, and three measurement traditions coexist (Hartog, 2000): (i) *job analysis*, which uses expert assessments of occupational requirements mapped to the International Standard Classification of Occupations (ISCO); (ii) *realised matches*, following Verdugo and Verdugo (1989), which compare attainment to the modal or mean education within an occupation cell; and (iii) *self-reported job requirements*, which ask the worker directly about the qualification usually needed to get their job. The latter approach is used by The Programme for the International Assessment of Adult Competencies PIAAC, the European Skills and Jobs Survey, and the REFLEX/EUROGRADUATE graduate surveys. The three methods yield substantially different incidence rates (McGuinness, Pouliakas and Redmond, 2018), and the choice of method has direct implications for cross-country comparison.

Underqualification (Undereducation): the mirror image of overeducation: workers performing jobs whose qualification requirement exceeds their attained education. It is conceptually distinct from overqualification, since it captures substitutability between formal credentials and experience

[5] See explanatory notes from the Labour Force Survey ad hoc module 2024, S-CIRCABC.

or informal learning, and the associated wage premium is generally smaller in absolute value than the overqualification penalty. Underqualification is particularly relevant when interpreting shortage signals: an increase in the share of underqualified incumbents may indicate that employers have lowered hiring standards in response to unfilled vacancies.

Field of Study Mismatch: the horizontal dimension of qualification mismatch: a worker whose field of education does not correspond to the typical field associated with their occupation (Robst, 2007; Wolbers, 2003). For example, a software engineer working in sales. Measurement relies either on normative crosswalks between fields of study (the International Standard Classification of Education (ISCED) and occupations (ISCO), as in PIAAC, or on self-reports of the relatedness of training and current job. A consistent empirical finding is that workers in field of study mismatch earn less than their matched peers (Montt, 2017; Iriondo and Pérez-Amaral, 2016; Robst, 2007). The combination of vertical and horizontal mismatch carries the largest wage penalty. Field mismatch is particularly consequential in occupations with strong occupation-specific human capital (e.g. medicine, law, engineering), where transferable returns to credentials are limited.

The three subtypes share both an analytical virtue and a common limitation. The virtue is comparability: ISCED attainment and ISCO occupation are collected consistently across EU surveys, allowing harmonised indicators to be produced annually. The shared limitation is that a credential certifies education at a point in time, not current proficiency. Therefore, qualification-based indicators measure how credentials are allocated across occupations, not whether skills are well used. Closing that gap requires measuring competence directly, which is the object of skills-based mismatch.

1.1.2. Skills Mismatch

Skills mismatches shift the unit of analysis from credentials to assessed or used competencies. The distinction is not merely terminological: as the OECD (2013, p. 32) emphasises and PIAAC confirms, “more education does not automatically translate into better skills”. A worker can be matched on qualifications but underuse their skills, or be overqualified on paper but appropriately skilled for the job. Empirically, the overlap between qualification mismatch and skills mismatch is modest (Pellizzari and Fichen, 2017), so the two categories are complementary rather than substitutable.

Overskilling: actual competencies exceed those required to perform their job. Two measurement strategies dominate. The first is a self-assessment measure. It asks workers whether they have the skills to cope with more demanding duties. This approach is taken in Cedefop’s European Skills and Jobs Survey and in Eurofound’s European Working Conditions Survey. The second, the OECD/Pellizzari–Fichen approach (Pellizzari and Fichen, 2017; 2013), derives objective skill requirement bands from PIAAC’s assessed proficiency: minimum and maximum requirements for each occupation are defined as the lowest and highest plausible-value scores observed among self-reported well-matched workers in that occupation. Workers whose scores fall above that band are classified as over-skilled. Overskilling is associated with wage and job-satisfaction penalties and is the form of mismatch most directly linked to productivity loss, since it captures unutilised skill capital regardless of how it was acquired.

Underskilling: competencies fall below those needed for a job. Measured incidence is typically lower than for overskilling, but underskilling is operationally more consequential because it corresponds to the firm-level skill gap defined in Box 1 above. It signals either rapid change in task content or recruitment under tight labour market conditions. Measurement parallels overskilling, identifying workers below the well-matched requirement band or who self-report difficulty meeting current task demands.

Skills Obsolescence: the temporal dimension, where previously valuable competencies depreciate. Following de Grip and van Loo (2002), two channels are distinguished. *Technical obsolescence* refers to the physical depreciation of skills through non-use or age-related cognitive change. *Economic obsolescence* refers to declines in the market value of skills caused by technological change, structural reallocation, or shifts in product markets. This is the more policy-salient channel in the context of automation, the green transition, and digitalisation, which continuously reshape demand for specific competencies. Direct measurement is rare since obsolescence is typically inferred from declining returns to previously valuable skills, gaps in training participation among workers in declining occupations, or career-trajectory analyses. Robust quantification requires longitudinal data.

What unifies the three is reliance on a direct measure of competency, whether assessed (PIAAC) or self-reported (ESJS, EWCS), rather than on credentials. That is their strength. They capture utilisation and depreciation that credential-based measures miss and align with the firm-level gap that drives recruitment difficulty. It is also the source of their principal constraint: assessed data are expensive and infrequent, covering only the domains and sporadic waves PIAAC reaches. By contrast, self-reports are more timely but vulnerable to anchoring and cross-country differences in response style. Neither category substitutes for the other, which is why a coherent measurement framework must draw on both. We set out this approach in Section 1.2.

The problem runs deeper than the assessed–self-reported divide: even among self-reported instruments, the same underlying concept is operationalised differently, which is partly why incidence estimates vary. The European Working Conditions Survey asks whether workers need further training (underskilled), have skills matching their duties, or have skills to cope with more demanding tasks (overskilled), whereas the 2024 EU Labour Force Survey ad hoc module records whether skills are matched, higher, or lower than the job requires. Cedefop's European Skills and Jobs Survey uses similar self-assessment wording. Because the question wording and thresholds differ, and also because sampling methods and sample sizes differ across surveys, the resulting over- and under-skilling rates are not directly comparable across sources.

1.2. Basic framework to organise data and indicators

The design of effective skills policies requires **granular, accurate and timely** data on and interpretation of skills needs, stocks and flows, so called **skills intelligence**.According to **EUROSTAT[6], three main data-driven measures** underpin the analysis of supply, demand and use of skills:

1. **Direct measures** of skills **demand or supply** through objective evidence such as job-vacancy data or test scores.
2. **Indirect measures** of skills **demand and supply** capturing skills that are assumed to have been acquired through formal education (supply) or estimates of skills needs by analysing data on occupations (demand).
3. **Self-reported measures** of skills **demand** and **supply** rely on how employers express their needs and on how individuals assess their skill portfolio.

Skills gaps and shortages/surpluses can be detected by comparing the skills workers have with the skills that particular jobs/occupations require based on the chosen measure of skills use, or a combination of them.

[6] https://ec.europa.eu/eurostat/web/skills/information-data

Box 2. Union of Skills (UoS) - Skills intelligence data sources

> Examples of existing relevant data sources to be analysed are mentioned in the Union of Skills Communication and include data from Eurostat, EU agencies (Cedefop, Eurofound, and the European Labour Authority), as well as sectoral partnerships under Pact for Skills and 'Blueprint' skills alliances, the European graduate tracking initiative, the Education and Training Monitor, the European Higher Education Sector Observatory (EHESO), the Research and Innovation Careers Observatory (ReICO), the European Data Space for Skills, and the Eurydice network.
>
> Some of the more specific data sources include the EU Labour Force Survey (by Eurostat), and Adult Education Survey (by Eurostat), European Company Survey (by EUROFOUND and CEDEFOP), European Training and Learning Survey (by CEDEFOP), European Skills and Jobs Survey (by CEDEFOP), Skills-OVATE (by Eurostat/CEDEFOP), European Working Conditions Survey (by EUROFOUND). Further evidence could be taken from Eurobarometer (by European Commission, DG COMM), Survey of Adult Skills (PIAAC by OECD) and PISA (by OECD).

A useful organising distinction is between supply-side indicators (measuring what skills workers bring to the market) and demand-side indicators (measuring what skills employers need).

Supply-side information comes primarily from household surveys such as the EU Labour Force Survey (EU-LFS) and the European Survey on Income and Living Conditions (EU-SILC), which record workers' education, training, occupation, and self-assessed skill use.

Demand-side information comes from employer surveys such as the Job Vacancy Statistics, Continuing Vocational Training Survey (CVTS), or Online Job Ads (OJAs). Matching or imbalance indicators then compare supply and demand. A distinctive feature of matched employer-employee datasets is that both demand and supply aspects could be available from the same source.

A second organising axis is the level of aggregation of the available data source: macro (national), meso (sectoral or regional), and micro (individual or firm). The value of microdata lies in enabling analysis at the most disaggregated level, allowing researchers to study heterogeneity, construct custom aggregates, and implement causal identification strategies that published tables cannot support.

A third axis is the **level of granularity** that indicators can provide, their **timeliness** (permitting up-to-date insights) and the **frequency** of their updates (permitting trend analysis).

The main emphasis of this report is on data sources and indicators mentioned in the UoS (see Box 2), complemented with other relevant indicators and data sources:

- Eurostat
- Cedefop´s Skills Intelligence System
- ELA/EURES
- EUROFOUND
- Pact of Skills and Sectoral Intelligence
- Other data sources:
  - Eurobarometer (DG COMM)
  - European Higher Education Sector Observatory (EHESO)
  - Education and Training Monitor (Toolbox?)
  - Research and Innovation Careers Observatory (ReICO)
  - The European Data Space for Skills

- The Eurydice network
- OECD: PIAAC Survey of Adult Skills and PISA
- European Training Foundation (ETF)
- Lightcast, LinkedIn
- National Administrative Data
- EU funded Skills Projects (Horizon Europe, Erasmus +)

Circumscribing the scope of this report

Sector- and technology-specific skills intelligence: Several of the sources and indicators reviewed in this report are designed, wholly or in part, to address skills questions within specific sectors or for technologies central to EU competitiveness, notably the digital and AI, green, entrepreneurship, and STEM domains. Where such a focus is a defining feature of a source, it is noted in the relevant section. A systematic, domain-by-domain treatment of sectoral and technological skills intelligence is nonetheless beyond the scope of this report, which is organised by data source and indicator rather than by sector or technology. This is a deliberate scoping choice, and an acknowledged limitation: the report does not offer a consolidated view of skills needs within any single strategic domain, nor does it map the specialised instruments — and the gaps between them — that such a view would require.

National and non-EU skills intelligence. This report concentrates on EU-level data sources and indicators, namely those produced by Eurostat or other services of the European Commission, EU agencies, international organisations (such as the OECD) to the extent that they produce comparative data that cover (most) EU Member States. Two adjacent bodies of evidence fall outside its scope. The first is national skills anticipation and forecasting systems, which several Member States operate to project skill needs at the national or regional level. The second is skills intelligence produced outside the EU, including by international organisations and by individual non-EU countries. Both can be valuable. The national anticipation systems in particular often achieve a granularity and institutional specificity that EU-level instruments cannot match. They are nonetheless excluded here for two reasons. First, they are highly heterogeneous in method, definition, and coverage, which makes them difficult to compare or to integrate into a harmonised EU dashboard. Second, a systematic review would require a country-by-country treatment beyond the remit of this report. Their omission is therefore a deliberate scoping choice and an acknowledged limitation of this report.

1.3. Skills Taxonomies

Classification of skills and occupations is fundamental for mismatch measurement. Every mismatch indicator is ultimately a comparison between two coded quantities: what a worker brings and what a job requires. Hence, the classification scheme determines what can be compared and at what resolution. Three statistical classifications currently anchor the EU evidence base[7]: (a) International Standard Classification of Occupations (ISCO-08) codes occupations[8] into a four-level hierarchy mapped to four broad skill levels; (b) International Standard Classification of Education (ISCED 2011) codes educational attainment, with its companion ISCED-F 2013 coding field of study (the pairing that makes qualification and field mismatch measurable); and (c) NACE Rev. 2 codes economic activity for sectoral analysis. All three are hierarchical, so units aggregate cleanly, and

[7] ESCO (see below) is not yet used for such purpose, but it should as it would provide more granular information.

[8] The level of detail per digit, as this is mentioned throughout the report is: 10 major groups (1-digit code), 43 sub-major groups (2-digit code), 130 minor groups (3-digit code), 436 unit groups (4- digit code) (International Labour Organization. Department of Statistics, 2023).

internationally standardised, so indicators built on them are comparable across countries and over time. This is what makes them the backbone of official statistics.

That design is also their limit: they are built for aggregation rather than for describing competence. Occupation codes proxy for skills bundles rather than measuring skills directly. For example, two workers in the same ISCO-08 2-digit group may hold very different competency profiles, and the code itself says nothing about the tasks a job entails. This pervades all occupation-based indicators and is the structural reason credential-based measures cannot capture skills utilisation.

European Skills, Competences, Qualifications and Occupations (ESCO) was built to close this gap. It is a structured[9], multilingual vocabulary linking occupations, skills and competences. Its occupational pillar takes the four levels of ISCO-08 as its upper structure and adds more granular occupations beneath them: ISCO-08 supplies the top four levels of the pillar, while ESCO occupations sit at level 5 and below (ESCO, 2025). Because ISCO is a statistical classification whose groups do not overlap, each ESCO occupation maps to exactly one ISCO unit group, and ESCO occupation concepts can be equal to or narrower than an ISCO unit group but never broader. ESCO therefore extends ISCO downward rather than competing with it, with each unit group subdividing into more specific ESCO occupations, each carrying a profile of essential and optional skills. This skill-level granularity is exactly what the statistical classifications lack, and it is what makes ESCO suited to online vacancy data and other text-based demand signals, where the unit of observation is a skill phrase, not an occupation code.

The trade-off is integration. ESCO's richness comes with a large, periodically revised vocabulary that no existing household or enterprise survey collects, so its use requires either cross walking survey occupation codes or applying natural-language processing to free text. The US O*NET system is the instructive contrast: it attaches quantitative analyst ratings of skills, abilities, and work activities to occupational descriptors, offering measurement depth beyond ESCO's binary essential/optional structure — but it is built on the US SOC classification[10] and does not transfer to the European occupational structure without cross walking. The choice of taxonomy is therefore not neutral:

— ISCO maximises comparability and timeliness at coarse granularity,
— ESCO maximises skill-level detail at the cost of survey integration, and
— O*NET-style instruments offer rich task content but need adaptation to the EU context.

They are best treated as complementary layers, with the appropriate choice set by whether the analytical priority is harmonised aggregation or granular skill content.

1.4. Data gaps: General Remarks

Six cross-cutting gaps constrain how well published indicators can measure skills mismatch.

Timeliness. Most surveys run on annual or multi-annual cycles of data collection. Moreover, there is a time lag between data collection and processing to publication. Hence, demand shocks (such as the pandemic, an AI-adoption shift) register only with a lag, blunting the indicators' value for early warning.

Granularity: published indicators are typically available at coarse ISCO or NACE level, rendering it impossible to detect occupation- or sector- specific shortages. Microdata access can partially address this but are subject to disclosure controls.

[9] ESCO is a hierarchical classification where it organises content based on clear and pre-defined categories: ISCO for occupations, skills clusters for skills; ISCED-f for knowledge etc.

[10] See SOC home: U.S. Bureau of Labor Statistics.

Employer-side coverage. There are fewer surveys among employers covering skills , and the main instruments, have low frequency (every five years or more years). Labour demand is therefore observed less systematically than supply, and firm-level skill gaps are inferred rather than measured.

Task and skill content. European surveys code occupation and qualification well but lack some detail in capturing the underlying tasks and competencies. ESCO's skill profiles and the EU-LFS ad hoc job-skills modules provide valuable task and competency information linked to occupations. Still, they were not designed to deliver the kind of standardized, continuously rated task content that would enable direct, fine-grained measurement across European occupations.

Demand–supply linkage. Even where demand and supply are each measured adequately, they are rarely observed on a common classification or a common unit (person, job, or vacancy levels). Mismatch is therefore typically inferred by comparing two separately measured distributions rather than identified within a matched dataset, which limits causal interpretation and prevents the direct measurement of who is mismatched and why.

Stocks versus flows. Published indicators are in most cases stock measures, i.e. the share of mismatched employees at a point in time and reveal little about transitions. They cannot distinguish transient mismatch, such as early-career overqualification resolved through job mobility, from persistent mismatch that becomes a 'trap' (self-reinforcing over time). The distinction is policy-relevant, since the two call for different instruments, but measuring it requires EU-wide longitudinal microdata that largely does not exist. The same constraint makes skills obsolescence (see Section 1.1.2) hard to quantify.

These gaps compound. Data on skills are fragmented and struggle to capture the multidimensional skills employers actually need. On the demand side, job advertisements and employer surveys tend to be noisy, non-standardised, and prone to reporting bias. On the supply side, qualifications, test scores, and self-reports vary across Member States and do not cover informal, on-the-job learning. The two sides rarely share a classification or unit of observation, so mismatch is generally inferred rather than observed. Limited frequency and small sample sizes at fine occupational levels may yield unreliable estimates, often outdated snapshots. The absence of education–employment–vacancy linkages, jointly with their largely cross-sectional nature, prevents both person-level matching and the analysis of mismatch dynamics over time. **Since skills are multidimensional and shift rapidly, skills intelligence would ideally build on harmonised taxonomies, richer and more frequent data, and improved, longitudinal data linkage.**

2. Eurostat-Based Indicators and Data Sources

Eurostat serves as the central statistical authority of the European Union, responsible for producing and harmonising comparable, high-quality statistics across Member States. In the context of skills intelligence, its role is not merely to collect data but to establish the methodological frameworks, classification systems, and quality standards that make cross-country comparisons meaningful. In specific areas, Eurostat compiles experimental statistics using new data sources and methods to meet emerging needs promptly. Such statistics are not yet fully harmonised or comprehensive, and they are always marked as being experimental and are accompanied by detailed methodological notes that inform users of their limitations[11].

The European Statistical System offers several major survey data instruments that, taken together, provide a picture of skills supply, demand, and mismatch across EU labour markets. Each instrument was designed with a different primary purpose.

1. **EU Labour Force Survey (EU-LFS)** is a continuous household survey covering all EU Member States, it captures employment status, occupation (at ISCO 4-digit level), sector, hours worked, and educational attainment.
2. **Job Vacancy Statistics (JVS)** focuses on the demand side, measuring unfilled positions by sector and size class. It is the primary tool for detecting labour shortages and recruitment difficulties.
3. **Continuing Vocational Training Survey (CVTS)** is an enterprise survey conducted every five years that examines how companies invest in training their workforce: participation rates, training hours, costs, and the types of training offered.
4. **Adult Education Survey (AES)** is a household survey that captures participation in formal, non-formal, and informal learning among adults aged 18–69. It complements CVTS by capturing the individual rather than the firm perspective on learning and skills development.
5. **ICT Usage Survey and Digital Skills Indicators** combines an enterprise survey (ICT usage by firms) and a household/individual component measuring digital skill levels.
6. **EU Statistics on Income and Living Conditions (EU-SILC)** is primarily a welfare and income survey, but it contains rich data on educational attainment, working conditions, health, and subjective assessments of job quality. Its longitudinal dimension (rotating panel) gives it potential for analysing trajectories.
7. **Eurostat´s Web Intelligence Hub (WIH)** provides researchers with capabilities to gather content from the web to produce statistics. In particular, it provides detailed and timely information on job characteristics in demand through data extracted from online job advertisements on the occupation, job location and skills required.

2.1. EU Labour Force Survey (EU-LFS)

2.1.1. Description

The EU-LFS is a large, continuous household survey covering all EU/EFTA countries, with a quarterly sample of approximately 1.5 million individuals aged 15 and over. It is the primary source for labour market statistics in Europe, collecting information on employment status, occupation (ISCO-08, typically at 2- or 3-digit level in microdata), sector (1-digit NACE Rev. 2), educational attainment (ISCED levels, programme orientation, fields), hours worked, contract type, and job tenure.

11 Innovating statistics - Eurostat.

2.1.2. Measurement Methodology

For skills mismatch measurement, the EU-LFS enables construction of several key indicators. Qualification mismatch is computed by comparing a worker's ISCED level with the modal or mean ISCED level of workers in the same ISCO occupation group (the 'realised matches' or statistical approach). Over-qualification rates, i.e. the share of workers with tertiary education employed in occupations that do not typically require it, by NACE Rev. 2 and country of birth are published by Eurostat. Under-qualification is the mirror concept. Field-of-study mismatch can be approximated using the ISCED-F 2013 field codes combined with ISCO in the microdata. Ad hoc modules in specific years (e.g. 2014 on labour market situation of migrants, 2024 on young people on the labour market) have included subjective mismatch questions asking workers whether their skills match their job requirements.

2.1.3. Key Published Indicators

This list includes direct and supplementary indicators to understand mismatch in the LFS. It does not include ad hoc modules.

Table 2. Key indicators derived from EU-LFS data

Description	Further grouping	Time	Time Frequency	Table Code and Link
Over-qualification rates by 1-digit NACE Rev. 2 activity	By gender, age class (15-64, 15+, 20-34, 20-64, 25-34, 25-64, 35-64)	2008-2024	Annual	lfsa_eoqgan2
Over-qualification rates by citizenship	By gender, age class (15-64, 15+, 20-34, 20-64, 25-34, 25-64, 35-64)	1995-2024	Annual	lfsa_eoqgan
Over-qualification rates by country of birth	By gender, age class (15-64, 15+, 20-34, 20-64, 25-34, 25-64, 35-64)	1995-2024	Annual	lfsa_eoqgac
Employed persons by occupation (ISCO) and education level (ISCED)	By gender, age class (15+, 20-64)	1983-2024	Annual	lfsa_egised
Employed persons by professional status and occupation	By gender, age class (15-24, 15-39, 15-59, 15-64, 15-74, 15+, 20-64, 25-49, 25-54, 25-59, 25-64, 25-74, 25+, 40-59, 40-64, 50-59, 50-64, 50-74, 50+, 55-64, 55-74, 65+, 75+)	1983-2024	Annual	lfsa_egais
Employment by sector (NACE Rev. 2) and occupation (ISCO-08)	By gender, age class (15+, 20-64)	2008-2024	Annual	lfsa_eisn2
Unemployment rates by education attainment level	By gender, age class (15-19, 15-24, 15-39, 15-59, 15-64, 15-74,	1983-2024	Annual	lfsa_urgaed

Description	Further grouping	Time	Time Frequency	Table Code and Link
	20-24, 25-29, 25-39, 25-59, 25-64, 25-74, 30-34, 40-44, 40-59, 40-64, 45-49, 50-54, 50-59, 50-64, 50-74, 55-59, 55-64, 60-64, 65-69)			
Participation rate in education and training (last 4 weeks)	By gender, age class (18-24, 18-64, 18-69, 18-74, 20-34, 25-34, 25-49, 25-54, 25-64, 25-69, 25-74, 30-54, 35-44, 35-54, 45-54, 50-74, 55-64, 55-69, 55-74, 65-74)	1992-2024	Annual	trng_lfse_01
Participation rate in education and training (last 12 weeks)	By gender, age class (18-24, 18-64, 18-69, 18-74, 20-34, 25-34, 25-49, 25-54, 25-64, 25-69, 25-74, 30-54, 35-44, 35-54, 45-54, 50-74, 55-64, 55-69, 55-74, 65-74)	2022, 2024	Annual	trng_lfse_18

Source: Authors' elaboration

Relevant LFS *ad hoc* module surveys are:

— **Job skills in 2022 (lfso_22)** including aggregated structure of work tasks (e.g. employed persons by working time spent on cognitive tasks, manual tasks or social tasks, by professional status, employment status, professional status, educational attainment level and economic activity); utilisation of digital technology in social skills and cognitive tasks, manual tasks, and methods of work.

— **2024 LFS Module: Young People on the Labour Market — Match Variables (lfso_24match)** The 2024 EU-LFS 8-yearly module 'Young people on the labour market' (lfso_24) includes, for the first time, three variables that directly measure subjective mismatch between workers' education/skills and their current or last main job. The three match variables are: LEVMATCH (match between educational attainment level and job), FIELDMATCH (match between field of the highest level of education and job), and SKILLMATCH (match between skills and job). Unlike the standard over-qualification indicators (which compare ISCED levels statistically), these capture workers' own assessment of whether their qualifications and skills match their job. The module also collects data on formal education dropout (DROPEDUC, DROPEDUCLEVE, DROPEDUCREAS) and medium educational attainment qualifications (MEDLEVQUAL). Each match variable is cross-tabulated by occupation (ISCO), work experience while studying, years since completion of education, job tenure, field of education, and country of birth[12].

[12] Legal basis: Implementing Regulation (EU) 2022/2312 under the IESS Framework Regulation (EU) 2019/1700; Delegated Regulation (EU) 2020/256 (multiannual rolling planning).

Table 3. Indicators from 2024 LFS ad hoc module

Description	Link
Qualification level match × work experience while studying	lfso_24match01
Qualification level match × occupation (ISCO)	lfso_24match02
Qualification level match × years since completion of education	lfso_24match03
Qualification level match × country of birth	lfso_24match04
Field-of-education match × work experience while studying	lfso_24match05
Field-of-education match × field of education	lfso_24match06
Field-of-education match × occupation (ISCO)	lfso_24match07
Field-of-education match × years since completion of education	lfso_24match08
Field-of-education match × country of birth	lfso_24match09
Skills match × work experience while studying	lfso_24match10
Skills match × occupation (ISCO)	lfso_24match11
Skills match × years since completion of education	lfso_24match12
Skills match × job tenure	lfso_24match13
Skills match × country of birth	lfso_24match14

Note: All variables can be further grouped by gender, age class (15-24, 15-29, 15-34, 20-24, 20-34, 25-29, 25-34, 30-34), work experience during studies, ISCED. These variables are only available for 2024.
Source: Authors' elaboration

2.1.4. Strengths

- The EU-LFS is the largest harmonised household survey in the EU, enabling cross-country comparison of mismatch at scale.
- Quarterly frequency with relatively short publication lags; microdata available with a delay of approximately one year via Eurostat's microdata access system. However, the time horizon is shorter.
- ISCO-08 at 2- or 3-digit level in microdata allows moderately granular occupation-based mismatch analysis, beyond published 1-digit tables.
- Longitudinal component (sub-sample followed for up to 6 quarters in many countries) permits analysis of transitions into and out of mismatch.
- Consistent time series from 1983 (for some countries) and full EU coverage from 2005, enabling long-run trend analysis.
- Supply-side measures can be estimated[13].
- For the demand-side, unemployment rate can be retrieved to use in relation to the Job Vacancy Statistics (JVS) data[14].

2.1.5. Limitations

- Qualification mismatch is an imperfect proxy for actual skills mismatch. ISCED level captures years and type of formal education attainment, not competencies or their relevance to the job.

[13] EU-LFS microdata allow for the estimation of supply-side relevant measures. For example, one can estimate the labour force participation and unemployment rates, the working-age population, and economically inactive.

[14] JVS data will be explored in more detail in the next sub-section of this report.

- The statistical (realised matches) method is circular: the 'required' education level is derived from the distribution of actual workers, so any systematic upgrading of worker education raises the benchmark itself mechanically reducing measured overeducation.
- Occupation coding at 2-digit ISCO is still coarse. For example, ISCO-24 (Business and Administration Professionals) bundles occupations with very different skill requirements. Finer coding (3-digit) is available in some country files but not all, and small cell sizes create noise.
- No direct measurement of tasks performed or skills used on the job. The LFS records what occupation a worker is in, not what tasks she/he actually performs.
- Subjective mismatch questions appear only in ad hoc modules and are not repeated every year.
- Regional detail in microdata is at NUTS-2 level (population 800,000 – 3 million), which is too aggregate for local labour market analysis. Some countries further restrict geographic identifiers for disclosure control.
- The longitudinal component has high attrition in several countries and the panel dimension is short (typically 4–6 quarters), limiting dynamic analysis of mismatch persistence, for whichEU-SILC (see Section 2.6) may be more appropriate.
- Ad hoc module 2024 on skills and education match: the target population is restricted to persons aged 15–34 only, meaning mismatch among prime-age and older workers is not captured by this module.

2.2. Job Vacancy Statistics (JVS)

2.2.1. Description

Job vacancy statistics (JVS) provide information on the level and structure of labour demand. The Job Vacancy Statistics regulation (EC No 453/2008) requires all EU Member States to report the number of job vacancies and occupied posts by NACE Rev. 2 section, quarterly. Some countries also provide breakdowns by occupation (ISCO) and by region (NUTS-2). A job vacancy is defined as a paid post that is newly created, unoccupied, or about to become vacant, for which the employer is taking active steps to fill from outside the enterprise, and which the employer intends to fill immediately or within a specific period.

2.2.2. Methodology

The JVS enables construction of vacancy rate indicators (vacancies as a share of occupied posts plus vacancies) by sector, which signal the intensity of labour demand. Combined with unemployment data from the LFS or SILC, it underpins Beveridge curve analysis, which is the empirical relationship between the vacancy rate and the unemployment rate. This is a standard tool for diagnosing structural mismatch. An outward (or rightward) shift of the Beveridge curve (higher number of vacancies for any given unemployment rate) is interpreted as rising mismatch or decreasing labour market efficiency.

From 2024, Eurostat also publishes annual vacancy data by ISCO 3-digit occupation and NUTS-1 region, expanding the diagnostic potential significantly.

2.2.3. Key Published Indicators

Table 4. Key indicators from JVS data

Description	Further grouping	Time	Frequency	Link
Job vacancy statistics by NACE Rev. 2 activity, quarterly	By employment size (total, 10+)	2001Q1 – 2025Q4	Quarterly	jvs_q_nace2
Annual job vacancy rate by NACE Rev. 2	By employment size (total, 10+)	2008-2025	Annual	jvs_a_rate_r2
Annual job vacancy rate by occupation (ISCO 3-digit) and NUTS-1 region	Indicators: Employees, OJA, vacancies, occupied (posts) jobs, JVR	2019-2024	Annual	jvs_a_isco3_r1
Job vacancies in number and rate – quarterly headline, NACE Rev. 2 B-S	Indicators: vacancies, JVR	2023Q1-2025Q4	Quarterly	tps00172
Job vacancy statistics by occupation, NUTS 2 region and NACE Rev. 1.1 activity	Indicators: vacancies, occupied (posts) jobs, JVR, JVaR of change	2000-2008	Annual	jvs_a_nace1
Job vacancy statistics by NACE Rev. 1.1 activity	Indicators: vacancies, occupied (posts) jobs, JVR, JVaR of change, JVqR of change	2001Q1 – 2009Q4	Quarterly	jvs_q_nace1
Job vacancy statistics by occupation, NUTS 2 region and NACE Rev. 2 activity	Indicators: vacancies, occupied (posts) jobs, JVR, JVaR of change	2008-2015	Annual	jvs_a_nace2

Source: Authors' elaboration

2.2.4. Strengths

— Mandatory EU-wide collection ensures broad country coverage.
— Quarterly frequency provides relatively timely demand-side signals. Data are normally released around 50 and 78 days after the reference quarter
— Sectoral breakdown by NACE section (21 categories) allows identification of sectors with tight labour markets.
— When combined with LFS unemployment by sector or occupation, enables Beveridge curve analysis at moderate levels of disaggregation.
— Vacancy rates are a leading indicator of labour market tightening, useful for early warning systems.
— New annual tables by ISCO 3-digit and NUTS-1 (jvs_a_isco3_r1) substantially improve occupation-level diagnostic capability from 2024 onward.

2.2.5. Limitations

— Occupation-level breakdowns (ISCO) are not mandatory under the regulation and are provided by only a subset of countries, making cross-country comparison of occupation shortages difficult.
— Not all 3-digit ISCO have disaggregated data.
— The vacancy definition captures only 'active recruitment' vacancies. Latent demand (positions employers would create if suitable candidates were available) is not measured.
— Small firms (typically fewer than 10 employees) are excluded in some national implementations, biasing sectoral vacancy rates downward in sectors dominated by small enterprises.

— No information on the skill content of vacancies. A vacancy in NACE J (ICT) could require anything from basic helpdesk skills to advanced AI research capability.
— Regional coverage (NUTS-2) is optional and patchy in the quarterly data, limiting sub-national analysis.
— No microdata are made available to researchers; only pre-aggregated tables are published. This fundamentally limits the scope for custom dis-aggregations or linking to other sources.

2.3. Continuing Vocational Training Survey (CVTS)

2.3.1. Description

The CVTS is an enterprise-level survey conducted every five to six years (waves in 1993, 1999, 2005, 2010, 2015, 2020) covering firms with 10 or more employees across most NACE sections. It collects detailed information on the incidence, intensity, fields, costs, and organisation of employer-provided continuing vocational training (CVT), as well as reasons for not providing training and perceived obstacles. The database folder in Eurostat is `trng_cvt`.

2.3.2. Methodology

Skills indicators from the CVTS include: the share of enterprises providing CVT courses; the participation rate (share of employees participating); training intensity (hours per participant or per employee); training expenditure as a share of labour costs; and fields of training. Skills gap proxies can be derived from questions about reasons for training (e.g. to address skill deficiencies due to new technologies) and obstacles to training (e.g. lack of suitable courses, high cost, difficulty releasing staff). The CVTS thus provides an employer- (or demand-) side perspective on internal skills gaps and the firm's response through training investment.

Table 5. Key indicators from CVTS data

Description	Further grouping	Time	Time frequency	Link
Enterprises providing CVT courses, by size class and NACE	By empl size (10-49, 50-249, 250+)	2005, 2010, 2015, 2020	Annual	trng_cvt_01s
Participants in CVT courses as % of employees, by NACE	By gender	2005 (trng_cvt_12n1; NACE Rev. 1.1), 2010, 2015, 2020	Annual	trng_cvt_05s (discontinued since Jul 2018), trng_cvt_12n2
Hours in CVT courses per 1000 hours worked	By gender, empl sizes (10-49, 50-249, 250+)	2005, 2010, 2015, 2020	Annual	trng_cvt_12s
Cost of CVT courses as % of total labour costs	By empl size (10-49, 50-249, 250+)	2005, 2010, 2015, 2020	Annual	trng_cvt_16s
Enterprises not providing training by reason for non-provision and NACE Rev. 2 activity - % of non-training enterprises		2010, 2015, 2020	Annual	trng_cvt_02n2

Source: Authors' elaboration

2.3.3. Strengths

— Enterprise-level survey capturing the employer perspective on skills and training investment, complementing household-based supply-side data.
— Microdata are available through Eurostat's microdata access system (scientific use files for 2005, 2010, 2015, 2020), enabling analysis of firm-level determinants of training provision.
— Detailed information on training fields, costs, and obstacles can provide insight into the nature of skills gaps, not just their existence.
— Harmonised across EU countries with broadly consistent methodology, enabling cross-country comparisons.

2.3.4. Limitations

— Low frequency of data collection and dissemination (every 5 years).
— Covers only enterprises with 10+ employees, excluding the self-employed and micro-firms that account for a large share of employment in many EU economies.
— Sectoral coverage excludes some NACE sections (e.g. agriculture, parts of public administration in some waves).
— Training incidence and intensity measure the employer response to perceived gaps, not the gaps themselves.
— No information on individual workers' characteristics (education, occupation) within the firm.
— Small sample sizes in some country–sector cells restrict the reliability of disaggregated estimates.

2.4. Adult Education Survey (AES)

2.4.1. Description

The AES is a household-based survey conducted approximately every five to six years (waves in 2007, 2011, 2016, 2022) covering adults aged 18–69 (25–64 before 2022). It collects information on participation in formal education, non-formal education (courses, workshops, seminars, guided on-the-job training), and informal learning activities during the 12 months prior to the interview. It also records motivations for participation, obstacles, and the self-assessed usefulness of learning activities. The database folder in Eurostat is trng_aes.

2.4.2. Methodology

From a skills mismatch perspective, the AES provides individual-level indicators of adult learning engagement, which can be interpreted as a supply-side response to perceived skills gaps. Key indicators include: participation rates in non-formal education by occupation, education level, age, and employment status; reasons for participation (e.g. to do the job better, to acquire new skills for a different job); obstacles to participation (e.g. cost, scheduling conflicts, lack of employer support). Under the 2021 IESS regulation, the AES is integrated into the social statistics framework with a target periodicity of six years.

2.4.3. Key Published Indicators

Table 6. Key indicators from AES data

Description	Further grouping	Time	Time frequency	Link
Participation rate in education and training by sex	By age class (18-24, 18-64, 18-69, 25-64, 25-69) and type of training (formal and non-formal education and training)	2007, 2011, 2016, 2022	Annual	trng_aes_100
Participation rate in education and training by age	By type of training (formal and non-formal education and training)	2007, 2011, 2016, 2022	Annual	trng_aes_101
Participation rate in education and training by educational attainment level	By age class (18-24, 18-64, 18-69, 25-64, 25-69) and type of training (formal and non-formal education and training)	2007, 2011, 2016, 2022	Annual	trng_aes_102
Providers of non-formal education and training activities	By age class (18-24, 18-64, 18-69, 25-64, 25-69)	2007, 2011, 2016, 2022	Annual	trng_aes_170
Obstacles to participation in education and training	By age class (18-24, 18-64, 18-69, 25-64, 25-69) and gender	2007, 2011, 2016, 2022	Annual	trng_aes_176
Reasons for participation in non-formal education	By age class (18-24, 18-64, 18-69, 25-64, 25-69)	2007, 2011, 2016, 2022	Annual	trng_aes_180

Source: Authors' elaboration

2.4.4. Strengths

- Individual-level data allowing analysis of who participates in adult learning and why, enabling profiling of skills gap responses by sociodemographic and labour market characteristics.
- Microdata available via Eurostat (scientific use files for 2007, 2011, 2016, and 2022 from up to 30 countries), with linkage potential to EU-LFS under the IESS framework.
- Captures informal learning and non-formal education, not just formal programmes, providing a broader picture of skills acquisition.
- Information on obstacles to learning participation helps identify structural barriers to addressing skills gaps.

2.4.5. Limitations

- Low frequency limits timeliness and time-series analysis.
- Self-reported participation and motivation data are subject to recall bias and social desirability bias.
- No direct measure of skills acquired or competencies gained. Participation in training as such does not imply skills improvement.
- Sample sizes are moderate (typically 5,000–30,000 per country), restricting disaggregation by detailed occupation or region.
- The 12-month reference period may miss sporadic or very recent learning activities.

— Limited employer-side perspective: the AES captures the individual's view, not the employer's assessment of whether training addressed the gap.

2.5. ICT Usage Survey and Digital Skills Indicators

2.5.1. Description

Eurostat's survey on ICT usage by individuals (part of the Community Survey on ICT Usage in Households and by Individuals) is an annual household survey measuring digital skills and internet activities across the EU. Since 2015, digital skills are measured using a composite indicator based on the Digital Competence Framework (DigComp)[15], assessing five domains: information and data literacy, communication and collaboration, digital content creation, safety, and problem solving. From 2021, a revised DigComp 2.0-based indicator (`isoc_sk_dskl_i21`) replaced the original (`isoc_sk_dskl_i`). The survey also covers internet use frequency, e-commerce, e-government, and online activities. The enterprise ICT usage survey complements this with demand-side information.

2.5.2. Methodology

The digital skills indicator classifies individuals into levels (no skills, low, basic, above basic) based on proxy activities performed online. This serves as a direct measure of the digital competency dimension of skills mismatch. Eurostat publishes breakdowns by age, sex, education, employment status, and urbanisation level.

Complementary indicators from the ICT usage by enterprises survey cover the share of firms reporting hard-to-fill ICT specialist vacancies and ICT training provision. The Digital Decade target is that 80% of EU citizens (aged 16–74) should have at least basic digital skills by 2030.

2.5.3. Key Published Indicators

Table 7. Key indicators from ICT Usage Survey and Digital Skills Indicators data

Description	Further grouping	Time	Time frequency	Link
Individuals' level of digital skills (from 2021 onwards, DigComp 2.0)	By age, gender, nationality, ISCO groups	2021, 2023, 2025	Annual	isoc_sk_dskl_i21
Individuals' level of digital skills (until 2019, DigComp 1.0)	By age, gender, nationality, ISCO groups	2015 – 2017, 2019	Annual	isoc_sk_dskl_i
Share of individuals with at least basic digital skills, by sex (SDG 4)	By gender	2021, 2023, 2025	Annual	sdg_04_70
Enterprises that provided ICT training		2012, 2014-2020, 2022, 2024	Annual	isoc_ske_ittn2

[15] The European Digital Competence Framework (DigComp) describes *"what is needed to be digitally competent in today's society, and supports the development of digital competence among individuals of all ages. It covers a wide range of skills levels, from basic to highly advanced, and offers a stable reference point in a rapidly-evolving digital technological landscape"*. DigComp 3.0 is the fifth and latest version of the framework. The first version was published in 2013 (Ferrari, 2013), with updates published in 2016 (Vuorikari, Punie, Carretero Gomez et al., 2016), 2017 (Carretero Gomez, Vuorikari and Punie, 2017) and 2022 (Vuorikari, Kluzer and Punie, 2022). The framework is developed by the European Commission's Joint Research Centre (JRC), in collaboration with the Directorate-General for Employment, Social Affairs and Inclusion (DG EMPL).

Description	Further grouping	Time	Time frequency	Link
to their employees by NACE Rev. 2				
Employed ICT specialists		2004-2024	Annual	isoc_sks_itspt

Source: Authors' elaboration

2.5.4. Strengths

- Frequency provides timely tracking of digital skills evolution, unlike most other skills-related surveys.
- Directly measures a specific, policy-relevant skills domain rather than relying on qualification proxies.
- Broad country coverage and harmonised methodology across all EU Member States.
- Granular demographic breakdowns enable identification of digital skills gaps by age, education, and labour force status.

2.5.5. Limitations

- The DigComp-based indicator measures only digital skills, not the broader spectrum of skills relevant to mismatch (e.g. cognitive, social, manual).
- The activity-based proxy approach is indirect: performing an activity (e.g. using a spreadsheet) is taken as evidence of the corresponding skill, which may not capture proficiency levels.
- Microdata access is not available and the survey is not designed for linkage with employer-level data.
- Methodological breaks between DigComp 1.0 (`isoc_sk_dskl_i`) and DigComp 2.0 (`isoc_sk_dskl_i21`) complicate trend analysis.
- No regional breakdown below NUTS-1 or NUTS-2 (country-dependent), limiting sub-national digital divide analysis.

2.6. European Survey on Income and Living Conditions (EU-SILC)

2.6.1. Description

EU-SILC is an annual household survey covering all EU/EFTA countries, designed primarily to measure income, poverty, social exclusion, and living conditions. It collects detailed information on individual and household income (including earnings, social transfers, and income from self-employment), employment characteristics, health, housing, education, and material deprivation. The survey has both a cross-sectional component (approximately 130,000 households annually across the EU) and a longitudinal (panel) component following individuals for at least four years. The database folder in Eurostat is `ilc`.

2.6.2. Methodology

While EU-SILC is not designed as a skills mismatch survey, it contributes to important complementary indicators. Earnings data by education and occupation enable analysis of wage returns to education and occupation-specific wage premia, which serve as price signals of skills scarcity: unusually high returns to a particular qualification–occupation combination suggest shortage, while low or negative returns suggest over-supply.

The over-qualification indicator can be computed from ISCED and ISCO variables (similar to the LFS approach) but with the advantage of linked income data, allowing analysis of the wage penalty associated with qualification mismatch. The longitudinal component enables tracking of how mismatch evolves over individual careers. The P-file in the microdata contains personal-level variables including `PL050` (ISCO occupation), `PE040` (ISCED education level), and `PY010` (employee cash income).

Table 8. Key indicators from EU-SILC data

Description	Further grouping	Time	Time frequency	Table code and Link
Mean and median income by age and sex		1995-2025	Annual	ilc_di03
Distribution of income by quantiles – EU-SILC and ECHP surveys		1995-2025	Annual	ilc_di01
Mean and median income by educational attainment	Mean/ median equivalised net income	1995-2025	Annual	ilc_di04

Source: Authors' elaboration

2.6.3. Strengths

— Rich income and earnings data can be linked to education and occupation, enabling wage-based mismatch analysis.
— Longitudinal panel design (4+ years) allows individual-level tracking of mismatch dynamics, wage trajectories, and transitions.
— Microdata are accessible through Eurostat's microdata access system (cross-sectional and longitudinal files).
— Broad EU coverage with harmonised methodology under the IESS regulation.
— Income data enable distributional analysis of mismatch costs: who bears the wage penalty of over-education?

2.6.4. Limitations

— Not designed for skills or mismatch analysis per se; occupation coding is typically at ISCO 1- or 2-digit level only, which is too coarse for detailed occupation-based mismatch measurement.
— Earnings data refer to the previous income reference year, introducing a lag. Combined with ISCO coding in the current survey year, there is a timing mismatch between occupation and income.
— Sample sizes per country are smaller than the LFS (typically 10,000–30,000 individuals), limiting disaggregation possibilities.
— The longitudinal panel has attrition issues that may be non-random with respect to skills mismatch.
— No information on tasks, skills used, or job content—only occupation and education level are available as mismatch inputs.
— Regional identifiers are restricted in microdata (often NUTS-1 only or even country level in small countries), severely limiting spatial mismatch analysis.

2.7. Web Intelligence Hub (WIH) and Experimental Job Statistics

2.7.1. Web Intelligence Hub (WIH)

2.7.1.1. Description and methodology

Eurostat's Web Intelligence Hub (WIH) for Online Job Advertisements (OJA) is a collaborative initiative developed in partnership with Cedefop. The WIH systematically aggregates online job posting data from diverse sources, including private job portals, public employment services, and recruitment agencies across Member States. Unlike traditional labour market statistics, which often rely on periodic surveys with inherent time lags, the WIH provides high-frequency data that can be used to provide near-real-time insights into hiring trends, occupational shifts, and skill requirements.

The WIH's microdata offers a granular breakdown of job advertisements, categorised by occupation, economic sector, geographical region, and-critically-ESCO-coded skills, enabling precise analysis of demand patterns.

While the raw text of job advertisements is not publicly accessible the structured metadata allows for robust quantitative skills analysis.

These data feed directly into Skills-OVATE (Online Vacancy Analysis Tool for Europe, section 3.2.3), a joint Eurostat-Cedefop instrument that applies natural language processing (NLP) and machine learning to classify skills and occupations according to the ESCO framework. By integrating the WIH's OJA dataset with Cedefop's skills forecasting models and labour market projections, the system contributes to a timely view of skill gaps, emerging occupational trends, and regional disparities.

2.7.1.2. Strengths

Real-Time and High-Frequency Data

— The WIH provides quarterly updates (with a one-month lag), offering far more timely insights than traditional labour market surveys (e.g., EU Labour Force Survey, which is annual or biennial).
— Enables early detection of emerging skill demands, such as AI, cybersecurity, or green transition competencies, before they appear in official statistics.

Scalability and Automation

— Uses machine learning and NLP to process millions of job ads efficiently, reducing manual coding errors and enabling large-scale, cross-country comparisons.
— Can be adapted for new skill domains (e.g., AI, sustainability) as labour markets evolve.

Complementarity with Other Data Sources

— Enhances traditional labour market statistics through providing demand-side data (what employers seek) rather than just supply-side data (worker qualifications).

2.7.1.3. Limitations

Coverage and Representativeness Bias

— Not all job vacancies are advertised online (e.g., informal hiring, internal promotions, SMEs relying on word-of-mouth), leading to underrepresentation of certain sectors (e.g., agriculture, small businesses)[16].

[16] See for instance Sostero and Fernandez Macias (2021).

— Variations in job portal usage across countries may skew comparisons.

Data Quality and Standardisation Challenges, Privacy and Commercial Restrictions

— Raw job ad text is inaccessible due to GDPR and commercial agreements with job portals, restricting deeper textual analysis (e.g., sentiment analysis, employer (soft skill) preferences, context of skill requirements).
— Some private job platforms may not share data, leading to gaps in coverage (e.g., LinkedIn, niche industry boards).
— Small sample sizes in some regions/sectors may lead to statistical reliability issues for fine-grained analysis.

Time Lag and Dynamic Labour Markets

— While faster than traditional surveys, the one-month delay in data release means it is not truly real-time (e.g., sudden economic shocks may not be immediately visible).
— Short-term fluctuations (e.g., seasonal hiring) may obscure long-term trends.

Limited Context on Skill Supply and Mismatches

— The WIH only captures demand (job ads), not supply (worker skills), making it difficult to directly measure skill mismatches without additional data (CV data, survey responses).
— No information on hiring outcomes (e.g., whether positions were filled, wage levels, or required experience), limiting insights into labour market tightness.

2.7.2. Experimental Statistics

Eurostat publishes experimental labour-demand statistics[17], built on online job advertisements (OJA): Job vacancy rate by occupation and region — breaks down the official job vacancy rate by detailed occupation and region.

It combines OJA data from Eurostat's Web Intelligence Hub (WIH) with EU Labour Force Survey (EU-LFS) data on the number of employees to break down the total number of job vacancies and occupied posts. The job vacancy rate is then derived at the three-digit level of the ISCO occupation classification and by NUTS-1 region and disseminated as experimental statistics under `jvs_a_isco3_r1`. The totals still come from the official, regulation-based Job Vacancy Statistics (JVS) survey; the OJA data are used only to distribute those totals across occupations and regions, a breakdown the survey itself does not provide. Eurostat notes that covering this gap through dedicated surveys would impose high cost and response burden.

The approach leans on web data for granularity while anchoring magnitudes in regulated survey totals. This distinction matters for interpretation: the totals come from JVS, but OJA coverage varies across occupations and regions. The allocation of those totals across cells inherits the representativeness biases discussed in Section 2.7.1. The method therefore corrects the scale of raw web advertisements without fully correcting their distribution.

The "experimental statistics" by Eurostat reflects that the methodology and quality are still being refined, and should not be read as equivalent to the official JVS series.

[17] Eurostat published several indicators as Experimental Statistics, notably 'Job vacancy statistics by occupation and NUTS 1 region (OJA breakdowns)' – experimental statistics under [jvs_a_isco3_r1].: https://ec.europa.eu/eurostat/databrowser/view/jvs_a_isco3_r1/default/table?lang=en&category=labour.jvs.jvs_oja_.

3. The Cedefop Skills Intelligence System

3.1. Introduction

The European Centre for the Development of Vocational Training (CEDEFOP) serves as the European Union's (EU) reference agency for vocational education and training (VET) and skills intelligence, providing evidence-based insights to inform labour market policies, education reforms, and economic strategies.

Cedefop's skills intelligence system is built on several underlying primary datasets, which are then used to develop many different indicators illustrating several dimensions of skills intelligence. These are presented in thematic dashboards on the CEDEFOP website. Table 9 summarises the main characteristics of the primary datasets.

Table 9. Characteristics of primary datasets used by Cedefop

Dataset	Producer	Time Dimension	Primary Unit	Core Coverage
European Skills & Jobs Survey (ESJS2)[18]	Cedefop	2021 (wave 2)	Individual worker	EU-27 + Norway + Iceland (46,213 obs.)
Skills OVATE / WIH-OJA Database[19]	Cedefop + Eurostat	Quarterly updates	Online job advertisement	32 countries (EU-27 + EFTA + UK)
European Labour Force Survey (EU-LFS)[20]	Eurostat/NSIs	Quarterly	Individual person	EU-27 + EEA + candidate countries
EU-SILC[21]	Eurostat/NSIs	Annual (longitudinal component)	Household/ Individual	EU-27 + EEA
ICT Usage Survey[22]	Eurostat/NSIs	Annual	Individual	EU-27 + EEA + candidate countries

Source: Authors' elaboration

Cedefop defines an 'indicator' as a slice of a dataset that provides a particular piece of information — typically the intersection of a metric (e.g., employment level, training participation rate) with a set of breakdowns (e.g., by country, sector, occupation, age group): As of April 2026, there are 43 published indicators[23].

An architectural distinction is between indicators that originate from Cedefop's own data production (Skills forecast, Skills OVATE and the European Skills and Jobs Survey) and those that originate from Eurostat official statistics (EU-LFS, EU-SILC, ICT Usage Survey) but are curated and contextualised

18 cedefop.europa.eu/en/tools/european-skills-jobs-survey

19 cedefop.europa.eu/en/tools/skills-online-vacancies

20 ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey

21 ec.europa.eu/eurostat/web/income-and-living-conditions

22 ec.europa.eu/eurostat/web/digital-economy-and-society/ictu-usage

23 *"Indicators are the building blocks of skills intelligence visualisations. They are based on datasets (such as Labour Force Survey, or Cedefop Skills Forecast), sourced by various organisations (such as Eurostat or Cedefop). An indicator is a slice of the data, providing a particular piece of information, such as future employment growth, unemployment rate or task importance. This information can usually be broken down even further - most often by occupation, education, age, gender or sector."* The complete and current list of all indicators is available at https://www.cedefop.europa.eu/en/tools/skills-intelligence/indicators.

by Cedefop within the skills intelligence framework. This distinction has material consequences for temporal coverage, methodology governance, and update frequency. For instance, the over-qualification rate of tertiary graduates (Section 3.4.3) is computed from EU-LFS data but presented within Cedefop's Skills and Learning dashboard, while the ESJS-based Education Mismatch indicator (Section 3.4) is Cedefop's own production. Both measure mismatch but using fundamentally different methodologies, i.e. normative (based on comparison of educational attainment and occupation) vs. subjective (self-reported by individual worker).

Cedefop's skills intelligence system is structured around six thematic dashboards, each aggregating multiple indicators:
1. Employment Trends
2. Digitalisation and Technology
3. Future Jobs
4. Skills and Learning
5. Workplace Trends
6. Skills in online job advertisements

Additionally, Skills OVATE offers detailed information on the jobs and skills employers demand based on online job advertisements (OJAs) in 32 European countries. It is powered by Cedefop's and Eurostat's joint work in the context of the Web Intelligence Hub (see Section 2.7.1).

3.2. Cedefop Skills Forecast

The CEDEFOP Skills Forecast is an analytical tool that projects employment and skills demand across EU Member States, sectors, and occupations up to 2035. Unlike static labour market analyses, the Skills Forecast employs a dynamic model – the E3ME (Energy-Environment-Economy Model) by Cambridge Econometrics – to simulate macro-level economic trends (e.g., GDP growth, technological change, demographic shifts) and their impact on occupational demand. The model is sectorally disaggregated, using NACE Rev. 2 classifications at the 2-digit level, and occupationally granular, aligning with ISCO-08 at the 2-digit level.

The Skills Forecast relies on a combination of primary and secondary data sources, including:
- Eurostat's Labour Force Survey (LFS – Section 2.1) and National Accounts for employment and GDP trends.
- OECD's Programme for the International Assessment of Adult Competencies (PIAAC – Section 7.7) for skills proficiency data.
- CEDEFOP's European Skills and Jobs Survey (ESJS – Section 3.4) for skills use and mismatch insights.
- Cambridge Econometrics' E3ME model for macroeconomic simulations.

The skill supply and demand forecasts are used in indicators with an aim to provide an assessment of on the future labour market trends in Europe and to act as an early warning mechanism to help alleviate potential labour market imbalances and support different labour market actors in making informed decisions.

3.2.1. Key Published Indicators

Table 10. Key indicators using the Cedefop Skills Forecast data

Indicator Name	Description	Further grouping	Time and update frequency	Link
Future Employment Growth	Projected changes in skills demand in terms of overall percentage change. The indicator makes use of Cedefop's Skill Projections database.	NACE 1 digit, ISCO 2 digit	2022-2035, Annual Update	Future employment growth
Future Annual Employment Growth	Estimate of the expected annual percentage change in employment demand for each country: that is, how much the demand for jobs is expected to grow or shrink each year.	NACE 1 digit, ISCO 1 digit	2022-2035, Annual Update	Future annual employment growth
Future Job openings	The indicator provides the number of people who will be required to work in an occupation in forthcoming years (expansion demand and replacement demand).	ISCO 2 digit	2022-2035, Annual Update	Future job openings
Future Employment Needs	This indicator extends Future Job Openings by adding the qualification dimension: it distributes the total job openings across ISCED qualification levels.	ISCO 2 digit, ISCED – 3 categories	2022-2035, Annual Update	Future employment needs
Future Job Prospects	Ratio of total future job openings to current employment in the occupation, expressed as index 0-100. Scoring: >60 = high prospects; 40-60 = average; <40 = low prospects.	ISCO 2 digit	2022-2035, Annual Update	Future job prospects

Indicator Name	Description	Further grouping	Time and update frequency	Link
Future Qualification Demand	Percentage change in employment share accounted for by each qualification level (ISCED low/ medium/high). It expresses the relative upskilling or downgrading trend within occupations: is the share of high-qualified workers within a given occupation growing, stable, or declining?	ISCO 2 digit, ISCED – 3 categories	2022-2035, Annual Update	Future qualification demand
Future of VET Occupations	Employment outlook to 2035 for three typologies of VET occupations vs. non-VET occupations. VET typology: (1) Traditional VET (construction, plant operations); (2) Modern Vocational (care, personal services — upskilling to tertiary); (3) New Vocational (ICT technicians, health associates — require higher-level non-traditional VET skills).	VET Typology group	2022-2035	Future of VET occupations
Employment in High-Tech Economy and High-Tech Occupations	Four related indicators (employment share and growth rate, for both 'economy' and 'occupations' dimensions) use the Eurostat/OECD high-tech sector and occupation classification	High-Tech Economy: (i) High-technology manufacturing (Eurostat HTMT definition); (ii) Knowledge-intensive hi-tech services (KIS definition); (iii) Combined hi-tech	2022-2035, Annual Update	Employment in high-tech economy

Indicator Name	Description	Further grouping	Time and update frequency	Link
	applied to the Cedefop Skill Projections database.	economy. High-Tech Occupations: ISCO 21 (Science & engineering professionals), 25 (ICT professionals), 31 (S&E associate professionals), 35 (ICT technicians)		

Source: Authors' elaboration

3.2.2. Strengths

- Integration of macro and micro data: The LFS micro data allows the macro sectoral totals from E3ME to be broken down into occupation-by-sector matrices, bridging the two classification systems. The EU-LFS is used to disaggregate the sectoral employment and labour supply forecast by occupations and qualifications. The occupational matrices built from LFS microdata are applied to the E3ME sectoral employment totals to produce occupation-level projections throughout the forecast period.
- Scenario-based approach: the modelling of alternative scenarios/variants with different assumptions should indicate a plausible range of future developments. The inclusion of alternative scenarios (e.g., optimistic vs. pessimistic future macroeconomic variables) enhances its policy relevance, allowing stakeholders to stress-test different futures.
- Relatively granular occupational and sectoral breakdowns: The use of ISCO-08 (2-digit) and NACE (2-digit) classifications enables some targeting of skills policies (e.g., identifying specific occupations at risk of automation).
- ISCO-08 2 digit: The level of granularity is sufficient to identify broad structural shifts — e.g., growth in ICT professionals vs. decline in craft workers — which is appropriate for medium-to-long-term strategic policy use.
- NACE 2 digit: 41 industries represent a meaningful level of sectoral detail that allows sector-specific policy conclusions — distinguishing, for example, between manufacturing sub-sectors or different service industries.

3.2.3. Limitations

- There is no disaggregation to 3- or 4-digit ISCO occupations, meaning fine-grained distinctions (e.g., between software developers and database administrators) are not captured. This limits usefulness for curriculum design or very targeted labour market interventions. In addition, There is no subnational granularity.
- Dependence on economic assumptions: The model's long-term projections are highly sensitive to assumptions about GDP growth, migration, and technological adoption. For instance, an unexpected recession or accelerated AI adoption could render forecasts obsolete.
- Lag in data updates: The Skills Forecast is updated approximately every two years, aligned with Cedefop's work programme cycles. The main editions have been released in 2012, 2016, 2018, 2020, 2023, and most recently 2026.

3.3. Skills-OVATE (Online Vacancy Analysis Tool for Europe)

3.3.1. Scope and Coverage

Skills OVATE (Online Vacancy Analysis Tool for Europe) is Cedefop's big-data skills intelligence instrument, built on the systematic collection and NLP-based analysis of online job advertisements (OJAs). The technical infrastructure has been developed jointly with Eurostat since 2020 through the Web Intelligence Hub (WIH). As of 2025, Skills OVATE covers 32 countries — all 27 EU Member States, plus Norway, Switzerland, Liechtenstein, Iceland, and the UK.

Data Collection and Processing Mechanism

The collection pipeline involves: (1) web scraping of OJAs from a curated panel of job portals (private boards, public employment service portals, corporate career sites, recruitment agencies) via Eurostat's WIH infrastructure; (2) deduplication to remove duplicate postings of the same vacancy across portals or re-postings over time; (3) language detection and text normalisation; (4) occupation classification using a supervised machine learning classifier (job title + description features → ISCO-08 4-digit codes); (5) sector classification using employer name/description features → NACE Rev.2 codes; (6) skills extraction using a custom NER (Named Entity Recognition) model trained on ESCO skill names, aliases, and related terms; (7) mapping of extracted skill terms to canonical ESCO v1 skill Unique Resource Identifiers (URIs); (8) geographic assignment to NUTS-2 regions based on job location text. The system is updated quarterly, covering the most recent four-quarter window. The skills taxonomy available in Skills OVATE offers a dual classification: ESCO version 1 (European multilingual skills/competences taxonomy) and O*NET (US-origin taxonomy, available for comparison purposes). The ESCO taxonomy includes three hierarchical levels: skill pillar → skill group → individual skill. The most granular level represents individual ESCO skill codes (approximately 13,890 defined skills), though the display in the dashboard uses ESCO level 3 (skill groups) for practical readability.

3.3.2. Variables and Granularity

Skills OVATE's key dimensions are:
— Country: all 32 covered countries
— Region: NUTS-2 level — with systematic sub-national regional disaggregation
— Occupation: ISCO-08 3-digit (demand for occupations - Demand for occupations | CEDEFOP) – 4-digit for digital and green transition + EURES
— Sector: NACE Rev.2 2-digit (88 divisions, aggregated for display)
— Skills: level 3 ESCO and level 3 O*NET - Regions and skills | CEDEFOP
— Time: rolling four-quarter window; quarterly updates; yearly averages via Skills Intelligence platform

3.3.3. Strengths

— ISCO 4-digit resolution — the finest occupational granularity in any EU comparative source for the digital and green transition and the EURES data, enabling differentiation of economically meaningful occupational specialisations within broad ISCO groups. Coarser granularity for other occupations.
— ESCO-level skill granularity — linking employer demand to the EU's official skills taxonomy, enabling direct integration with VET curriculum development processes that use ESCO occupational profiles.

— Near real-time signal — quarterly updates can detect emerging skill requirements months or years before they appear in survey-based sources, providing genuine early warning capability for VET and upskilling policy.
— Regional dimension — NUTS-2 breakdowns provide the only regularly-updated regional skills demand intelligence in the EU, partially compensating for the absence of sub-national household survey data on skill demand.
— Green and digital skills dashboards — dedicated taxonomies (green skills taxonomy, digital skills taxonomy) built on ESCO and applied to OJA text enable monitoring of skill demand changes specifically associated with the twin transition, unavailable in any other EU source.
— Scale — hundreds of millions of OJAs analysed, allowing statistically robust estimates even for rare occupation-skill combinations that would require enormous survey samples.

3.3.4. Limitations

— Coverage bias (see also Section 2.7) — the most widely documented limitation. OJAs systematically over-represent: white-collar occupations; medium-to-high-skill roles; digitally-recruiting sectors; large employers with dedicated HR portals; urban labour markets. They under-represent: agriculture; domestic services; care workers informally recruited; public sector recruitment through closed administrative systems; micro-enterprise hiring through word-of-mouth; informal sector employment. The share of vacancies posted online varies from 15-20% (some Southern/Eastern EU countries) to 70-80% (Nordic countries, Netherlands, Ireland), creating fundamental comparability problems across Member States.
— Deduplication imperfection — the same vacancy may appear on multiple platforms (employer website, LinkedIn, national job board, Cedefop's WIH panel) and be re-posted multiple times. Deduplication algorithms identify likely duplicates through hash matching on job title + employer + date, but multi-platform cross-posting with slight text variation can go undetected by deduplication algorithms, inflating absolute OJA counts. This is documented as 'continuously improving' but without published precision/recall metrics for the deduplication algorithm.
— ESCO mapping accuracy — the NLP-based skill extraction and ESCO mapping introduce systematic errors. Job advertisements use colloquial, abbreviated, context-dependent language that does not always map cleanly to ESCO's formal taxonomic structure. The precision and recall of skill extraction are not publicly reported for the production system, making it difficult to assess the reliability of rare skill frequency estimates. Cutting-edge skills may be extracted from OJAs but may not yet map to any canonical ESCO code until a new version of the classification is released.
— No absolute vacancy count — Skills OVATE reports skill frequencies as shares of OJAs, not as counts of actual vacancies. This means it is impossible to directly translate OJA frequencies into absolute vacancy counts or workforce equivalents. The link to Eurostat's official Job Vacancy Statistics is not automated within the OVATE platform.
— No employer response data — OJAs represent stated preferences, not hiring outcomes. Employers routinely post aspirational requirements knowing they will compromise in practice; advertised skill requirements may not reflect what is actually assessed or used in job selection.
— Limited information on data coverage — the specific web portals included in WIH collection, their relative contribution to the total OJA count by country, and the selection criteria for portal inclusion are not published in a form allowing external reproducibility. Portal coverage changes over time as WIH expands or contracts its scraping targets, which can create spurious trend signals.

The WIH and Skills-OVATE represent a major advancement in labour market and skills intelligence, offering timely, granular, and policy-relevant insights into skill demand. However, their limitations-particularly coverage biases, data gaps, and the lack of supply-side context mean they should be used alongside traditional surveys and administrative data for a comprehensive understanding of EU labour markets. Future improvements could include expanding data sources, refining ESCO mappings, and integrating supply-side datasets (e.g., worker profiles, training records) to better assess skill mismatches and workforce transitions.

3.4. 3.4 European Skills and Jobs Survey (ESJS)

The European Skills and Jobs Survey (ESJS) is Cedefop's own periodic survey collecting information on the job-skill requirements, digitalisation, skill mismatches and workplace learning of representative samples of European adult workers. Wave 1 (ESJS1) was conducted in 2014 across EU-28, collecting approximately 48,676 interviews. Wave 2 (ESJS2) was conducted in 2021 across EU-27, Norway, and Iceland, collecting 46,213 interviews. Both waves used Computer-Assisted Telephone Interviewing (CATI) with nationally representative quota samples of employed adults aged 24–65, stratified by sex, age, and occupation, with a minimum of n=1,500 per country. A cognitive testing phase was carried out in six countries in 2020, followed by a pilot survey in early 2021 to validate the ESJS2 questionnaire.

The ESJS2 aims to inform policy makers on the impact of digitalisation on the future of work and skills, also in the context of the COVID-19 pandemic. It does so by collecting harmonised international data using a common methodological approach, enabling cross-country comparisons across economic sectors, occupations and other key socioeconomic and demographic variables.

ESJS2 marks a significant thematic shift from ESJS1. While the first wave focused on skill mismatch typologies (over/under-qualification, over/under-skilling), ESJS2 expands to cover: the impact of digitalisation on job tasks and skill requirements; the COVID-19 pandemic's labour market effects; Industry 4.0 technology adoption; and digital skills utilisation. New composite indices derived from ESJS2 — the Digital Intensity Index (DTI) and the Task Displacement Index — are used to compute the Automation Risk and Digital Skills Intensity indicators in the skills intelligence system.

3.4.1. Key Published Indicators

Table 11. Key indicators using ESJS data

Indicator Name	Description	Further grouping	Time	Link
Automation Risk	Workers are classified as automation-exposed using ESJS2 questions on task structure. Specifically: respondents whose jobs involve a high share of 'easily automated' tasks (operating specialised equipment, performing routine or non-autonomous tasks)	EU Countries, NACE 1 digit, ISCO 2 digit	2021, 2025, 2030, 2035	Automation risk

Indicator Name	Description	Further grouping	Time	Link
	and low reliance on communication, collaboration, critical thinking, or customer service. The number is then weighted by Skills Forecast employment projections to provide current and future estimates.			
Digital Skills Intensity	Digital intensity measures the extent to which jobs incorporate digital and computerized tasks. The indicator provides current and future estimates of digital activity across sectors and occupations, by displaying the number of individuals who engage in digital activities at work. The level of digital intensity reflects the digital skills applied by workers. Three levels of digital skills are defined based on the complexity of the digital activities: Basic, Intermediate, and Advanced.	EU Countries, NACE 1 digit, ISCO 2 digit	2021, 2025, 2030, 2035	Digital skills intensity
Skills Utilisation	Share of workers reporting they use their skills to a great extent / not at all in their current job. Derived from ESJS2 item: 'To what extent do you use the skills	EU Countries, NACE 1 digit, ISCO 2 digit	2021, 2025, 2030, 2035	Skill utilisation

Indicator Name	Description	Further grouping	Time	Link
	you have in your current job?’			
Education Mismatch	Workers report the level of education needed to perform their job (‘What level of education is needed to perform your job well?’) vs. their own attained education. Overqualified = attained > required; Underqualified = attained < required.	EU Countries, NACE 1 digit, ISCO 2 digit	2021, 2025, 2030, 2035	Education mismatch
Future Training Gap	The Future training gap indicator measures the expected growth in qualification requirements across sectors and occupations and assesses the upskilling challenge it presents for workers. It combines the Skills forecast data with the second wave of the European skills and jobs survey (ESJS2). The indicator includes two key metrics: the Qualification demand growth rate (based on Skills forecast), which estimates the weighted shares of qualification levels, and the Perceived training need/gap (based on ESJS2), which measures the share of workers who feel a	EU Countries, NACE 1 digit, ISCO 2 digit	2021, 2025, 2030, 2035	Future training gap

Indicator Name	Description	Further grouping	Time	Link
	significant or moderate need to improve their skills but did not participate in any training over the past 12 months. The main indicator presents these measures in a comparable format, ranging from −1 to 1 (the closer to 1 the larger the share).			
Skill Demand (ESJS-derived)	Share of workers reporting that a specific skill area is important for performing their job.	For the EU as a whole (not for countries separately), NACE 1 digit, ISCO 2 digit, Skills	2021, 2025, 2030, 2035	Skill demand
Skill Gap (ESJS-derived)	Share of workers reporting they lack specific skills to perform their job well (self-reported skills deficit).	EU Countries, NACE 1 digit, ISCO 2 digit, Skills	2021, 2025, 2030, 2035	Skill gap

Source: Authors' elaboration

3.4.2. Strengths

— Subjective skills mismatch: The ESJS provides an EU-wide, harmonised measure of workers' own assessment of whether they are over-skilled, under-skilled, or well-matched in their current job.
— Skills underutilisation: The survey captures whether workers feel their skills are being used to their full potential — directly measuring the underutilisation dimension absent from other sources.
— Initial vs. continuing mismatch: The ESJS distinguishes between skills mismatch at job entry (reflecting recruitment mismatches) and mismatch that develops over time (reflecting skills obsolescence or inadequate learning).
— Learning behaviour link: The survey links mismatch status to learning participation, enabling analysis of whether mismatched workers are more or less likely to engage in training.

3.4.3. Limitations

— Two published waves so far (2014 and 2021):
  • Gap of seven years between the (only) two waves complicates trend analysis. The labour market of 2014 bears limited resemblance to that of the mid-2020s, particularly regarding digital and green skill dynamics.

- Any future wave will face challenges of maintaining comparability with 2014 and 2021 data, particularly given changes in the labour market and in ESCO's development since then (e.g. generative AI).

— Subjective measurement: workers may assess their 'skills' differently from their 'qualifications', and perceptions of underutilisation vary with job tenure, sector norms, and individual aspirations.
— Relatively small sample sizes, limiting granularity.

3.5. European Training and Learning Survey (ETLS)

3.5.1. Description

The European Training and Learning Survey[24] aims to gain insights into adult learning and development. It specifically wants to examine how the European population of employees obtains training and learning at or outside their workplace to upskill or reskill themselves in face of the ever-evolving work environment and determine the factors influencing these learning activities.

The data of the European Training and Learning Survey were collected between October 2023 and February 2024 among adults aged 16-64 who are in wage and salary employment (i.e. paid employees, excluding those in self-employment and family workers), from each EU Member State, as well as from Iceland and Norway.

A key innovation of the ETLS is its assessment of how workers perceive the development of their job-related capabilities, which approximate the growth of expertise and practical wisdom. The survey employs a scaling method to track the progressive development of expertise among employees. Given the challenges in objectively measuring expertise in unstructured work environments, the scale relies on workers' self-reported improvements in key aspects of their roles over the past year.

Additionally, the ETLS examines workers' participation in learning activities, evaluating the frequency of engagement in 10 distinct professional development activities-excluding mandatory health and safety training, induction programmes (for new employees), and workplace conduct training. The survey distinguishes between:

— Employer-supported learning (training organised and provided by employers)
— Personal learning (employee-initiated activities)

However, the boundary between these two categories is not always clear: employers may arrange training in response to employee requests, while employees may pursue personal learning following encouragement from managers or supervisors.

Given the short-term (one-year) focus of the ETLS, learning activities may not always directly correlate with skills development, and it remains difficult to predict when participation in a specific activity will lead to expertise enhancement. As a cross-sectional survey, the ETLS is subject to standard limitations and hence its findings should be interpreted as associations (correlations) rather than causal relationships.

[24] The survey employed a cross-sectional design, drawing from a representative sample based on probability-based online surveys (where feasible) or probability-based telephone interviews. To enhance sample sizes and improve the reliability of estimates, the probabilistic sample was supplemented with responses from commercial non-probability panels.

3.5.2. Strengths

- Pan-European comparability: Harmonised questionnaire and methodology across 29 countries enables robust cross-national benchmarking - a feature absent from most national adult learning surveys.
- Worker-centric perspective: Unlike employer or administrative data sources, the ETLS captures the subjective experience of learning in the workplace, including informal and incidental learning typically missed by participation statistics.
- Comprehensive learning ecosystem: Covers formal, non-formal and informal learning modalities simultaneously, providing a fuller picture of how skills are actually developed at work.
- Innovation on enablers: Focus on workplace contextual conditions (autonomy, managerial support, culture) that facilitate or hinder learning - a dimension absent from comparators like the AES or LFS.
- Sector and occupation granularity: NACE/ISCO coding enables disaggregated analysis relevant to industrial and VET policy.

3.5.3. Limitations

- Infrequent data collection: As a periodic (rather than annual) survey, the ETLS cannot track year-to-year dynamics..
- As a cross-sectional survey, the ETLS cannot establish causal relationships between workplace conditions, learning participation and skill outcomes at the individual level.
- Self-reported data: All variables rely on worker perceptions and recall, introducing common biases: social desirability, telescoping and variation in how respondents interpret learning concepts across languages and cultures.
- Employed workers only: The survey is restricted to wage and salary employees, excluding the self-employed, unemployed and inactive populations - groups often most in need of upskilling support.
- No employer-side data: The ETLS does not include a matched employer component, not allowing to directly link worker learning experiences to organisational investment, HR practices or firm performance.
- Sub-national limits: National sample sizes may be insufficient for robust NUTS 2 or regional analyses, constraining use by regional governments and employment agencies.

3.6. Eurostat-Sourced Indicators[25]

A significant portion of Cedefop's 43 indicators derive from Eurostat official statistics (EU-LFS, EU-SILC, ICT Usage Survey) rather than from Cedefop's own data production. Cedefop's value-added in these cases is curation, contextualisation, and integration with its own datasets — presenting Eurostat data through the lens of skills intelligence rather than general labour market monitoring. This section covers the primary Eurostat-sourced indicators.

3.6.1. Employment Group (EU-LFS Core Indicators)

Multiple Cedefop indicators are directly computed from EU-LFS microdata or published aggregates:

Table 12. Key indicators from Cedefop computed from the EU-LFS microdata

[25] This subsection has been added for completeness. However, for the purpose of using the indicators described in this section in the ESIO data platform and/or dashboard the primary Eurostat data sources will be used.

Indicator Name	Description	Further grouping	Time	Link
Employed Population	Count and share of employed persons.	EU Countries, NACE 1 digit, ISCO 2 digit	2023	Employed population
Recent Employment Trends	Total employed + % change (6-month update cycle).	EU Countries, NACE 1 digit, ISCO 2 digit	2014-2024	Recent employment trends
Employment by Detailed Occupation	Employment by ISCO sub-major and minor group.	EU Countries, ISCO 3 digit	2015-2023	Employment by detailed occupation
Employment by Field of Study	Shares of people with certain field of study in total employment in an occupation. The fields of study are based on ISCED 2013 classification (all estimations are Skills intelligence Team own calculations based on Eurostat data).	EU Countries, ISCO 1 digit, ISCED: Agriculture and veterinary; Arts and humanities; Business, administration and law; Education; Generic programmes; Health and welfare; ICT; Natural sciences and math; Services; Social sciences; Technical sciences	2016-2023	Employment by field of study
Occupation Employment in Sector	Number and share of occupation within sector. All estimations are Skills intelligence Team own calculations based on Eurostat data.	EU Countries, NACE 1 digit, ISCO 2 digit	2011-2023	Occupation employment in sector
Sector Employment by Occupations	This indicator shows where people with a certain occupation - for example managers - work. "Where" means a sector of economic activity, such as manufacturing or construction.	EU Countries, NACE 1 digit, ISCO 2 digit	2011-2023	Sector employment by occupations

Source: Authors' elaboration

The Recent Employment Trends indicator features a methodological innovation. Standard EU-LFS annual indicators are published with a lag of 12-18 months. By drawing on Eurostat's provisional quarterly LFS releases and updating every 6 months, this indicator provides the most current available view of employment change by occupation and sector, trading off some statistical precision (smaller effective sample for sub-annual periods) for timeliness.

The Employment by Detailed Occupation indicator, at ISCO 3-digit level (minor groups, approximately 130 categories), represents the finest occupational granularity available in any Cedefop indicator based on official statistics. However, even the ISCO 3-digit resolution remains coarse to distinguish many economically significant occupational distinctions (e.g., within ISCO 251 'software and applications developers', there is no separation between 2511-Systems Analysts, 2512-Software Developers, 2513-Web and Multimedia Developers, 2514-Applications Programmers and 2519-Software and applications developers and analysts not elsewhere classified).

3.6.2. Workplace Trends Group (EU-LFS Labour Market Structure Indicators)

Table 13. Labour Market Structure Indicators from Cedefop using the EU-LFS microdata

Indicator Name	Description	Further grouping	Time	Link
Part-time Employment	Share of employed in part-time work.	EU Countries, age group, gender and level of education (low, medium and high), ISCO 2 digit	2011-2023	Part-time employment
Involuntary Part-Time Employment	Part-time workers over total employment reporting inability to find full-time work.	EU Countries, ISCO 2 digit	2011-2023	Involuntary part-time employment
Temporary Employment	The number of people that have a temporary contract as a share of all people in employment.	EU Countries, age group, gender and level of education (low, medium and high), ISCO 2 digit	2011-2023	Temporary employment
Involuntary Temporary Employment	Temp workers who could not find permanent work.	EU Countries, ISCO 2 digit	2011-2023	Involuntary temporary employment
Self-Employment	Share of employed who are self-employed (own-account or employer).	EU Countries, gender and level of education (low, medium and high), ISCO 2 digit	2011-2023	Self-employment
Recently Hired Workers	Share employed for 12 months or fewer in current job — proxy for recruitment rate.	EU Countries, by gender, ISCO 2 digit	2011-2023	Recently hired workers

Source: Authors' elaboration

3.6.3. Over-Qualification Rate of Tertiary Graduates (2011-2023)[26]

This is the most widely cited measure of vertical education-occupation mismatch in the EU and the primary operationalisation used in EU policy monitoring. It uses a concordance table matching ISCO major groups (1-digit) to ISCED required levels, where ISCO 1-3 are assumed to require tertiary education. Workers with tertiary education employed in ISCO 4-9 are classified as overqualified.

[26] Dashboard URL: cedefop.europa.eu/tools/skills-intelligence/over-qualification-rate-tertiary-graduates. Source: EU-LFS.

The indicator is available with a content focus on Skills and Learning in Cedefop's system, where it is presented alongside the ESJS-based Education Mismatch indicator to highlight the different estimates produced by normative vs. subjective approaches.

3.6.3.1. Limitations

— The ISCO 1-digit normative criterion is crude — ISCO group 3 ('technicians and associate professionals') includes roles that in some countries require tertiary education but in others do not.
— The indicator defines over-qualification relative to the ISCO-ISCED concordance table, which does not reflect recent changes in credential requirements.
— It does not include horizontal mismatch (field of study mismatch) and qualitative skill mismatch.
— The absence of occupational or sectoral breakdown in the Cedefop indicator presentation limits its analytical utility compared to using the raw EU-LFS data directly[27].
— It measures qualification mismatch, not skill mismatch — the distinction matters for policy, since the root causes of and solutions to credential over-qualification (graduate overproduction at ISCED 5) differ substantially from genuine skill underutilisation.

3.6.4. Unemployment Indicators (LFS-Based)

Cedefop presents four unemployment-related indicators within its skills intelligence system:
1. Unemployment Rate — standard ILO definition, by age group / country / education / gender (NUTS 0) - https://www.cedefop.europa.eu/tools/skills-intelligence/unemployment-rate
2. Long-term Unemployment Rate — share of labour force unemployed for 12+ months; same breakdowns - https://www.cedefop.europa.eu/tools/skills-intelligence/long-term-unemployment-rate
3. Unemployment by Occupation — unemployment rate for former occupation (ISCO 1-digit); country dimension- https://www.cedefop.europa.eu/tools/skills-intelligence/unemployment-occupation
4. Young persons Neither in Employment nor Education or Training (NEET) Rate — Young persons (15-29) neither in employment nor education or training; country × age × education × gender - https://www.cedefop.europa.eu/tools/skills-intelligence/young-persons-neither-employment-nor-education-or-training-neet

The Unemployment by Occupation indicator is analytically notable as it provides unemployment rates broken down by the former occupation of unemployed workers, enabling identification of which occupational groups face the highest job-finding difficulty. This is more policy-relevant than the overall unemployment rate for understanding structural labour market challenges. Limitation: the occupation variable for unemployed workers in the LFS refers to the 'last job held', which may be significantly out of date for long-term unemployed and thus may not reflect the structural displacement dynamics of current labour market transitions.

The NEET rate indicator aggregates heterogeneous groups — job seekers (actively unemployed youth), discouraged workers (no longer seeking), carers (economically inactive), and genuinely disengaged youth — whose policy needs are different. Presenting the rate without this decomposition in the indicator dashboard, can lead to misleading cross-country comparisons where countries with high NEET rates driven by youth caregiving are compared with countries where NEETs are predominantly job-seekers.

[27] Researchers can compute their own over-qualification rates at ISCO 2-digit x country x year from EU-LFS microdata, which is exactly what the lfso_24match02 indicator from the 2024 module now partially provides (though limited to ages 15-34) – See Section 2.1.

3.6.5. Digital Skills Level

The digital skills level[28] provides an *"indicator (i) for all individuals (essentially a measure of potential digital skills supply); (ii) for individuals aged 25-34 years (a measure of new skills supply); and (iii) all in employment (employed, self-employed and family workers). Data for the digital skills indicator are derived from the European Union Survey on ICT Usage in Households and by Individuals which gauges individual's digital skill capabilities in five domains"*:

1. information
2. communication
3. problem solving
4. software, and
5. safety

In terms of granularity there is no sub-national occupational, sectoral, age or educational breakdown in the indicators presented.

This indicator is distinct from the ESJS-based Digital Skills Intensity indicator (Section 3.4). It measures population-level digital competences (not just employed workers) using Eurostat's annual ICT Usage Survey. The self-assessment methodology asks respondents whether they have performed specified tasks (e.g., 'used a search engine', 'sent email', 'copied files', 'installed software', 'changed privacy settings'), and classifies them as basic or above-basic based on the number and type of tasks reported.

3.6.5.1. Limitations

— Self-reported digital proficiency correlates imperfectly with actual assessed competences. The tasks used to define 'above-basic' digital skills (changing security settings, online file transfer, using job-specific software) may be easy for some people while genuinely challenging for others, creating measurement non-invariance.

— The absence of granularity reduces its analytical value compared to the full Eurostat ICT Usage Survey dataset (e.g cannot tell which segments of the workforce are most digitally underskilled).

3.6.6. Monthly Gross Income and Relative Monthly Gross Income[29]

Wage data within the Cedefop skills intelligence system are sourced from EU-SILC's structural earnings component. These indicators provide the wage signal that enables assessment of whether observed labour market tightness in specific occupations is generating wage premia (as theory predicts in competitive labour markets). The relative income indicator — expressing each occupation's median wage as a ratio of the national median — enables cross-country comparison adjusted for overall wage level differences.

3.6.6.1. Limitations

— The EU-SILC structural earnings data are collected with a substantial publication lag (typically 18-24 months) and the sample size at the country × ISCO 2-digit cell level may be insufficient for reliable point estimates. Cross-country comparability of gross earnings is complicated by differences in social contribution regimes, net-of-tax income, and non-wage compensation.

— The indicators do not include any dimension for non-wage compensation, benefits, or job quality adjustments that affect the true compensation premium for shortage occupations.

[28] Dashboard URL: cedefop.europa.eu/tools/skills-intelligence/digital-skills-level

[29] Monthly Gross Income - cedefop.europa.eu/tools/skills-intelligence/monthly-gross-income Relative Income - cedefop.europa.eu/tools/skills-intelligence/relative-monthly-gross-income

3.7. Labour Skills Shortage Index (LSSI)

3.7.1. Description

The Cedefop Labour and Skills Shortage Index (LSSI)[30] was introduced in 2024 as a new standardised tool for measuring occupational shortages. It computes a quantitative shortage index directly from Skills Forecast projections.

The LSSI evaluates occupational shortages through 2035 across three component factors:

1. Demand pressure — the pressure created by employment growth. High-growth occupations may face skill supply lags as education and training systems respond with delay. Operationalised as the projected employment growth rate (from the Skills Forecast) for each ISCO occupation.
2. Supply pressure — the recruitment challenge arising from replacement needs. Large replacement waves (driven by retirement) create high openings volumes even in stable or declining occupations. Operationalised as the replacement demand rate (from the Skills Forecast) relative to current employment.
3. Skills supply constraint — the gap between projected qualification demand and supply. Operationalised as the projected qualification mismatch rate ((from the Skills Forecast): the degree to which projected employment growth in higher-qualification jobs outpaces the supply of appropriately qualified workers from the education system.

3.7.2. Methodology

Powered by the 2025 Cedefop Skills Forecast, it generates insights into future labour market trends. Users can explore ISCO two-digit occupations grouped by skill level, filter data by country, or compare labour and skill shortages between two countries. Each occupation's shortage is ranked from **1 to 4**, with **1 indicating no shortage or surplus** and **4 indicating an intense shortage**, making it an informative resource for targeted workforce planning and policy development."

The available dimensions are: Country (EU-27) | Occupation (ISCO 2-digit) | Skill level (ISCED 3-level).

3.7.3. Strengths

— The LSSI provides a standardised shortage measure with consistent methodology across Member States, expressed as an ordinal 1-to-4 ranking (from no shortage/surplus to intense shortage).
— The three-component structure distinguishes genuine expansion-driven shortages (high demand growth, adequate supply) from structural supply constraints (adequate demand growth, insufficient skill pipeline) and replacement-driven vacancies — distinctions that have entirely different policy implications.
— The forward-looking dimension (projections to 2035) enables identification of emerging shortages before they become acute labour market crises.

3.7.4. Limitations

— The LSSI is derived entirely from the Skills Forecast's projections, which means it inherits the instrument's limitations — in particular the ISCO 1-2 digit resolution, the absence of confidence intervals, and time lags.
— The three components are equally weighted in the composite without empirical underpinning.

[30] cedefop.europa.eu/en/tools/european-skills-index/labour-skills-shortage-index

— The dashboard presents only country-level comparisons and does not provide the underlying component scores, making it difficult to diagnose whether a high LSSI score for an occupation reflects demand pressure, replacement pressure, or skills supply constraint — information that is essential for designing the appropriate policy response.
— Because the index is ordinal, the categories rank severity but do not quantify it: the intervals between ranks are not equal, so differences cannot be interpreted on a cardinal scale.

3.8. Skills Trends and Anticipation System (STAS)

STAS is a dynamic, data-driven system that combines multiple sources of information to provide a holistic view of the EU labor market - STAS - Short-term anticipation of skills trends and VET demand | CEDEFOP. It leverages:

— Online Job Advertisements (OJAs), which provide real-time insights into emerging skills needs (e.g., AI, cybersecurity, green jobs).
— Eurostat's Labor Force Survey (LFS) and Adult Education Survey (AES), which offer data on employment, skills mismatches, and lifelong learning.

3.8.1. Methodology

The STAS produces projections on employment in the EU **up to two years ahead of from the last period of available data**. Its methodology relies on a three-fold econometric modelling approach: a Vector Autoregression (VAR) and Vector Error Correction Model (VECM) method linking sectoral vacancies and employment; a univariate Autoregressive Integrated Moving Average (ARIMA) to model occupational employment; and a "Naïve" forecast based on past average of quarter-on-quarter growth.

The STAS uses the EU-LFS quarterly and annual data on employment by occupation, sector and Member State as well as vacancy data from the European Job Vacancy Statistics. The STAS baseline is then aligned to the forecasted total employment growth released by DG ECFIN in the Annual Macro-Economic database of the European Commission's Directorate General for Economic and Financial Affairs (AMECO database). The projections are updated with fresh data every six months, following the AMECO spring and autumn releases.

STAS presents timely data on employment in the EU by occupation (ISCO 1-digit and 2-digit) and country. The 6-monthly bulletin summarizes the most recent key trends and dynamics in the EU labour market, reflecting shifting demands across occupations and within countries.

3.8.2. Strengths

— **6-monthly update cycle:** Projections are updated every six months, following the AMECO spring and autumn releases, ensuring forecasts remain reflective of the latest employment trends. This semi-annual cadence makes STAS far more responsive than the biennial Skills Forecast, enabling near-real-time detection of emerging occupational shifts.
— **Job Vacancies as Leading Indicators:** The VAR/VECM approach exploits estimated relationships between past employment and vacancies, which economic theory suggests are early indicators of future employment changes. This gives STAS a genuine predictive edge over purely extrapolative approaches by capturing hiring intentions before they materialise in employment statistics.
— **EU-Wide Coverage with Occupational Granularity:** STAS produces projections at the 1-digit and 2-digit ISCO level for all 27 Member States, updated every six months, nowcasting up to two

years ahead. Harmonised pan-European coverage enables cross-country comparisons that no national system can replicate
— Near-term horizon (2 years) complementing the long-term Skills Forecast.

3.8.3. Limitations

— **Short forecast horizon limits strategic planning**; Time-series models calibrated on historical patterns become unreliable precisely when conditions change most abruptly — the moments early-warning tools are most needed
— **No skills dimension** (only employment by occupation); Unlike the Skills Forecast, it models neither the qualifications being produced by education systems nor skill mismatches.
— **Fixed Occupational Share Assumptions** Occupational results are derived by applying sector-by-occupation shares averaged over the last two years of LFS data, held constant to avoid excessively volatile shares. This means the model cannot detect shifts in the occupational mix within sectors — for instance, a sector becoming more automation-intensive while its total employment remains stable
— **Dependent on JVS vacancy data** which itself has known coverage issues (see Section 2.2).

3.9. CEDEFOP Talent Gap Index[31]

The Cedefop Talent Gap Index is a web tool that estimates how future occupational demand and expected labour market imbalances combine with recruitment difficulty to create shortages. It draws on the same two Cedefop sources discussed above: future demand for occupations (from both newly created jobs and the need to replace existing workers), expected imbalances, and a set of recruitment-difficulty aspects (competencies needed, tasks performed, experience requirements and relative wages, following McGuinness, Staffa, Lee et al. (2025)), based on estimations using the Skills Forecast and the European Skills and Jobs Survey. It is therefore the published indicator that operationalises the forecast-plus-survey combination noted in Section 3.2, blending labour and skill shortage signals into a single measure.

Like the LSSI, the index is ordinal. Each occupation’s Talent Gap is ranked from 1 to 4, where 1 indicates no or very small gap and 4 an intense gap. A high value signals that, when job openings arise, employers are likely to face recruitment difficulty because the occupation requires a higher-than-average skill level, which must be compensated accordingly.

The Talent Gap Index is distinct from the Labour and Skills Shortage Index (Section 3.7). The LSSI focusses on the scale of projected shortages from the demand and replacement side; the Talent Gap Index adds a recruitment-difficulty dimension drawn from ESJS, so a high score reflects not only that workers will be needed but that suitable candidates will be hard to find. As with the LSSI, the 1-to-4 scale is ordinal: it ranks the severity of gaps across occupations but does not quantify the interval between ranks, and the index inherits the limitations of its two underlying sources.

3.10. CEDEFOP Skills Intelligence: Summary Table

The following table summarises the CEDEFOP Skills Intelligence Tools indicators by frequency of update, occupation granularity, time and country coverage and microdata availability.

[31] Source: https://www.cedefop.europa.eu/en/tools/european-skills-index/talentgap-index?#1

Table 14. Summary comparison of Cedefop Skills Intelligence Tools

Instrument	**Mismatch / Inefficiency Measured**	**Update Frequency**	**Occupation Granularity**	**Country Coverage**	**Time Horizon**	**Microdata / Data Access**
Panel A: Cedefop Own Data Production						
Skills Forecast (E3ME model)	Projected employment demand by sector and occupation; projected qualification supply–demand gaps; expansion and replacement demand	Every 2–3 years	ISCO 1-digit (9 groups); some 2-digit detail	EU-27 + selected non-EU	Forward-looking: projections to 2035	No microdata. Published tables and interactive dashboard on Cedefop website
Skills OVATE (Online Vacancy Analysis Tool)	Real-time employer skill demand from online job ads (OJAs); skill frequency profiles by occupation/region; emerging skill detection; green and digital skill demand	Quarterly (rolling 4-quarter window)	ISCO 3-digit (standard); ISCO 4-digit for green/digital occupations; ESCO level 3 for skills	32 countries (EU-27 + NO, CH, LI, IS, UK)	Near real-time: current + recent quarters	No microdata (individual OJAs not accessible). Dashboard + bulk data download via WIH
European Skills and Jobs Survey (ESJS) — Wave 1: 2014; Wave 2: 2021	Self-assessed skill mismatch (over/ under-skilling); qualification mismatch; digital intensity of jobs; automation risk; task displacement; skill obsolescence; workplace learning	Irregular, 7 years between waves	ISCO 1-digit (respondent's occupation); n≈1,500/ country limits finer disaggregation	ESJS1: EU-28; ESJS2: EU-27 + NO + IS	Retrospective/current: snapshot at survey date	Microdata available for research via Cedefop; 46,000 observations (ESJS2)

Instrument	Mismatch / Inefficiency Measured	Update Frequency	Occupation Granularity	Country Coverage	Time Horizon	Microdata / Data Access
Labour and Skills Shortage Index (LSSI) — introduced 2024	Composite shortage index combining: demand pressure (employment growth); supply pressure (replacement demand); skills supply constraint (qualification gap)	Aligned with Skills Forecast cycle (2–3 years)	ISCO 2-digit (sub-major groups)	EU-27	Forward-looking: projections to 2035 (derived from Skills Forecast)	No microdata. Dashboard only; component scores not published
STAS (Short-term Anticipation of Skills Trends)	Short-term employment projections by occupation and sector; near-term labour demand shifts	6-monthly (aligned with AMECO spring/ autumn releases)	ISCO 1-digit and 2-digit; NACE sector level	EU-27	Short-term: 2 years ahead of latest data	No microdata. 6-monthly bulletin + dashboard
Cedefop Talent Gap Index	Web tool that estimates how future occupational demand and expected labour market imbalances combine with recruitment difficulty to create shortages. It draws on the future demand for occupations, expected imbalances, and a set of recruitment-difficulty aspects.		ISCO 2-digit (sub-major groups)	EU-27	Forward-looking: projections to 2035 (derived from Skills Forecast)	No microdata. Dashboard only; component scores not published
Panel B: Eurostat-Sourced (curated by Cedefop)						

Instrument	Mismatch / Inefficiency Measured	Update Frequency	Occupation Granularity	Country Coverage	Time Horizon	Microdata / Data Access
EU-LFS Employment Indicators (via Cedefop dashboards)	Employment trends by occupation/sector; unemployment by former occupation; over-qualification rate of tertiary graduates (normative ISCO–ISCED concordance); NEET rates	Annual (standard); 6-monthly (Recent Employment Trends indicator)	ISCO 1-digit (most indicators); ISCO 3-digit (Employment by Detailed Occupation)	EU-27 + EFTA (per EU-LFS coverage)	Retrospective: latest available year (12–18 month lag)	Not via Cedefop. EU-LFS microdata accessible from Eurostat (see Section 2.1)
Digital Skills Level (ICT Usage Survey)	Population-level digital competences (DigComp framework); proxy for digital skills supply gap	Annual	None; country-level only in Cedefop presentation	EU-27 + EFTA	Retrospective: latest survey year	Not via Cedefop. ICT Usage microdata via Eurostat (see Section 2.5)
Wage Indicators (EU-SILC earnings)	Occupation-specific wage premia as price signals of scarcity; relative monthly gross income by occupation (ratio to national median)	Annual (18–24 month publication lag)	ISCO 2-digit; small cell sizes at country × ISCO-2d level	EU-27 + EFTA	Retrospective: income reference year (t−1 or t−2)	Not via Cedefop. EU-SILC microdata via Eurostat (see Section 2.6)

Note: ISCO = International Standard Classification of Occupations (08); ESCO = European Skills, Competences, Qualifications and Occupations; NACE = Statistical Classification of Economic Activities; E3ME = Energy-Environment-Economy Model (Cambridge Econometrics); WIH = Web Intelligence Hub (Eurostat); OJA = Online Job Advertisement; LSSI = Labour and Skills Shortage Index; STAS = Short-term Anticipation of Skills Trends.
Source: Authors' elaboration

4. European Labour Authority (ELA) / EURES Labour Shortages and Surpluses Reports

4.1. Description

The *EURES Report on Labour Shortages and Surpluses* is an annual publication that compiles national assessments of occupation-level labour shortages and surpluses across Europe. The report is produced in line with Article 30 of EURES Regulation (EU) 2016/589, which mandates Member States to collect and analyse gender-disaggregated information on labour shortages and surpluses on national and sectoral labour markets. EURES National Coordination Offices (NCOs) are responsible for sharing the available information within the EURES network and contributing to the joint analysis.

The report uses the ISCO08 4-digit level occupations and classifies each into shortage, surplus, or neither categories for each participating country. It identifies widespread shortages and surpluses (occupations reported as shortage/surplus in a large number of countries), assigns severity ratings, analyses the characteristics of workers in affected occupations (gender, age, education, country of origin), examines trends over time, maps transnational matching possibilities, and includes a thematic sectoral deep-dive (construction in 2023; transportation and storage in 2024, health and care in 2025).

4.2. Series History and Institutional Evolution

The series has been published almost continuously since 2016. It was originally produced by the European Commission, DG Employment, Social Affairs and Inclusion in cooperation with the European Network of Public Employment Services (PES Network). From the 2021 edition onwards, European Labour Authority (ELA) is responsible for the report. The 2025 report is the eighth edition.

— 2016 (published Feb 2017; European Commission, Directorate-General for Employment, Social Affairs and Inclusion and ICON-INSTITUT (2017)): ISCO 3-digit. First formal edition. First to include surplus occupations alongside shortages. 23 PES submitted data. Introduced LFS cross-check methodology. Explored matching shortages with surpluses across countries.
— 2017 (published Feb 2018; European Commission, Directorate-General for Employment, Social Affairs and Inclusion, ICON-INSTITUT Public Sector GmbH, Behan et al. (2018)). Moved to ISCO 4-digit codes—a major methodological advance enabling identification of specific occupations rather than bundles. 28 PES submitted shortage data, 18 surpluses. Introduced skill vs. labour shortage distinction and ratio of unemployed to new hires as accuracy cross-check. Cap of 20 occupations per country.
— 2019 (European Commission, Directorate-General for Employment, Social Affairs and Inclusion and McGrath, 2019). Continued 4-digit methodology. Shortages dominated by STEM occupations and healthcare; surpluses by clerical and humanities disciplines.
— 2020 (European Commission, Directorate-General for Employment, Social Affairs and Inclusion and McGrath, 2020). 30 countries/regions; reporting cap raised to 30 occupations. First COVID-19 pandemic impact analysis: health care assistant appeared as widespread shortage for the first time; vacancy notifications to PES fell 60pp in Q2 2020. Analysis of travel restriction impacts on shortage intensification.
— 2021 (published Nov 2021, European Labour Authority and McGrath (2021)). First edition under ELA. 30 countries/regions including 25 EU Member States. Continued pandemic analysis. Open list format (no maximum occupation cap).

— 2022 (published Sept 2023, European Labour Authority and Fondazione Giacomo Brodolini (2023)). This report **went beyond previous reports** with more intensive analysis of causes (aggregate demand/supply shifts, occupational dimension, workplace dimension). Introduced Beveridge curve analysis. Comparison of widespread shortages over 2017–2022. Open list; approximately 400 distinct ISCO 4-digit occupations identified as shortage by at least one country.
— 2023 (published May 2024, European Labour Authority and Fondazione Giacomo Brodolini (2024)). Thematic deep-dive on **construction sector**. Five country fiches (Ireland, Italy, Latvia, Netherlands, Poland). Analysis of four vulnerability dimensions (gender, education, age, country of origin).
— 2024: (published June 2025, European Labour Authority, Fischer-Barnicol, Lechtenfeld et al. (2025)). Major methodological change: NCOs now classify all 436 ISCO 4-digit occupations (not just a selected list), enabling a comprehensive country/occupation matrix. 29 EURES countries. Thematic deep-dive on transportation and storage with five standalone sub-sector analyses. Accompanied by a Strategic Foresight Exercise projecting to 2030–2035.
— 2025 (published June 2026, European Labour Authority, Fischer-Barnicol, Lechtenfeld et al. (2026)): 8th edition. 28 reporting EURES countries[32]. NCOs again classified all 436 ISCO-08 4-digit occupations, continuing the exhaustive country × occupation matrix. 2,617 shortage instances and 2,177 surplus instances reported, with almost all four-digit occupations in shortage in at least one country. Thematic deep-dive on the health and care sector. Introduced a pilot quantification of imbalances comparing labour demand against an extended labour supply (including the potentially active, not only the unemployed) by two-digit ISCO occupations, applied to all EURES countries. Accompanied by analysis of AI and green-transition effects on shortage and surplus occupations. Six countries (Spain, Italy, Malta, Portugal, Slovakia, Finland) reported methodological updates, so direct comparison with earlier editions is not possible for them.

Key methodological evolution across editions

— Occupation classification: ISCO 3-digit (2015–2016) → ISCO 4-digit (2017 onward) → full classification of all 436 occupations (2024-2025)
— Occupation cap per country: 20 (2015–2017) → 30 (2019–2020) → open list (2021–2023) → exhaustive (2024-2025)
— Institutional home: EC/DG Employment (2015–2020) → European Labour Authority (2021 onward)
— Quantification: qualitative/threshold-based NCO assessments throughout, with a pilot demand-versus-extended-supply quantification introduced in 2025.

4.3. Methodology

Each EURES National Coordination Office identifies shortage and surplus occupations using nationally determined methods and data sources. The methodology is not centrally harmonised: countries draw on a heterogeneous mix of indicators depending on available infrastructure. Common approaches include the ratio of registered jobseekers to vacancies from Public Employment Service (PES) administrative data, vacancy rates, employer skill shortage surveys, expert assessments, and qualitative views of PES staff. Some countries use composite approaches (e.g. Belgium combines seven indicators including vacancy duration and expert views); others rely on a single ratio (e.g. Austria and Czechia use jobseeker-to-vacancy ratios from PES data). Each NCO sets its own threshold, so classifications are not directly comparable: Bulgaria, for instance, classes

[32] Iceland, Liechtenstein and Switzerland did not submit data

an occupation as in shortage when there are fewer than 20 jobseekers per vacancy, whereas Austria applies a stricter ratio below 1.4. The reference years, in the latest publication of 2026, for the underlying data are 2024 and 2025.

Occupations are classified at the ISCO-08 4-digit level. An occupation is labelled a widespread shortage if it is reported in shortage by more than half of the countries that provided data; in the 2025 edition this corresponds to a threshold of at least 15 countries. The glossary defines widespread surplus occupations as those reported by at least 14 countries. On this basis the 2025 edition identifies 24 widespread shortage occupations (down from 43 in the previous edition), of which an average of 30 percent of the underlying reports are classed as high severity. The report assigns severity on a three-point scale (low, medium, high) based on the intensity of the imbalance.

4.4. Strengths

— Seven (almost)[33] annual editions provide the longest continuous longitudinal record of occupation-level shortage persistence in Europe. Reports consistently show that occupations such as software developers, nursing professionals, welders, plumbers, heavy truck drivers, and building electricians appear as widespread shortages in every edition—indicating structural rather than cyclical imbalances.

— Combines quantitative indicators (PES vacancy/jobseeker ratios, vacancy duration, employer surveys) with qualitative expert assessments, capturing signals that purely statistical indicators may miss.

— The underlying data 2024 file provides a research-ready country x occupation matrix suitable for cross-country analysis of shortage patterns, sectoral concentration, and co-occurrence with surplus.

— The 2024 edition's exhaustive classification of all 436 ISCO occupations represents a major methodological advance over earlier editions' selected-list approach, enabling comprehensive coverage and eliminating selection bias in which occupations are reported.

— The 2017 edition introduced a valuable distinction between skill shortages (insufficient qualified workers) and labour shortages (sufficient qualified workers unwilling to take up the occupation), which was maintained in subsequent editions.

4.5. Limitations

— Methodology is not harmonised across countries. Each NCO uses different indicators, thresholds, data sources, and reference periods, undermining strict cross-country comparability. For example, Austria uses a single jobseeker-to-vacancy ratio from PES data, while Belgium combines seven indicators including qualitative expert views; some countries use employer surveys or immigration data that cannot identify surpluses at all. This heterogeneity has been documented in every edition since 2016.

— Reliance on PES administrative data introduces selection bias: vacancies and jobseekers registered with PES are a non-random subset of total labour market activity. However, the 2017 report found that the concern about bias toward lower-skilled occupations was unfounded; professional occupations were the most frequently reported in both shortage and surplus lists.

— Surplus data has historically been much weaker than shortage data. The 2017 report noted that only 18 of 28 PES could provide surplus data, partly because employer surveys and forecasting models used for shortage identification cannot identify surpluses. Although coverage improved over time (23 countries in 2020; 25 in 2024), four countries still did not report surpluses in 2025 (Ireland, Italy, Poland, Switzerland).

[33] Analysis for 2018 is missing.

— The binary shortage/surplus classification may not account for within-country regional variation. An occupation may be simultaneously in shortage in one region and surplus in another within the same country. Only about one in three PES could provide data at sub-national level (as documented in 2017).
— Methodological break in 2024: The shift from open lists to exhaustive classification of all 436 ISCO occupations represents a major improvement but limits direct comparability with earlier editions. The 2024 report itself notes this constraint.
— The definition of 'widespread' (shortage in ≥15 out of 29 countries in 2024) is somewhat arbitrary. As the report itself notes, *the number of shortage occupations reported by each country varies significantly*, partly reflecting methodological differences rather than true variation in labour market tightness.
— The "widespread" threshold is a raw country count, unweighted. An occupation reported in shortage by 15 countries qualifies as "widespread" regardless of whether those countries are Malta, Cyprus, and Croatia (combined population around 6m) or Germany, France, and Italy (around 210m). This treats each NCO submission equally. An occupation in shortage across many small economies could have different implication than one in shortage in a few large ones.
— Severity is subjective and unstandardised. NCOs are asked to classify magnitude as high/medium/low using "an objective source or criterion" — but the questionnaire also allows "Information not available." The meaning of "high" severity varies across countries.

5. Eurofound Data Sources

Eurofound, the European Foundation for the Improvement of Living and Working Conditions, contributes to skills intelligence primarily through its surveys and research on working conditions, job quality, and workplace organisation. Eurofound's data are distinctive in emphasising the worker and firm perspective on the conditions in which skills are deployed and developed, rather than the skill composition of the workforce per se.

This section reviews Eurofound's principal data sources and analytical tools that contribute to skills intelligence in the EU. It examines their scope, methodology, periodicity, key variables and granularity, and assesses their respective strengths and limitations. The main sources covered are:

— The European Working Conditions Survey (EWCS) — the workers' survey on job quality and working life, covering skills use, learning, autonomy and career development at the individual worker level.
— The European Company Survey (ECS) — an establishment-level survey covering skills strategies, training provision, work organisation and human resource management.
— The European Jobs Monitor (EJM) — an analytical framework tracking structural shifts in employment by occupation, sector and skill level, primarily drawing on EU Labour Force Survey data.
— The European Quality of Life Survey (EQLS) — a broader quality-of-life instrument with relevant dimensions on education, employment and social participation.
— The Living and Working in the EU e-Survey — a rapid online instrument deployed since 2020 to capture emerging trends in working and living conditions.

Together, these instruments provide a multi-layered ecosystem of evidence that supports European skills policy.

5.1. European Working Conditions Survey (EWCS)

5.1.1. Description and methodology

The European Working Conditions Survey (EWCS) is Eurofound's flagship instrument and the longest-running harmonised survey of working conditions in Europe. Launched in 1990, it has now completed eight rounds: 1990, 1995, 2000, 2005, 2010, 2015, 2021 (as a telephone survey, EWCTS) and 2024. The 2024 edition, based on more than 36,000 interviews across all 27 EU Member States, EFTA and EU candidate countries, represents the most recent comprehensive mapping of job quality in the EU.

The EWCS was conceived to fill a gap in European statistics: while Eurostat's EU Labour Force Survey provided data on employment and unemployment, no pan-European instrument existed to examine the quality of working life — the nature of tasks performed, physical and psychosocial risks, working time arrangements, learning opportunities, and worker autonomy. Over three decades, the EWCS has become the authoritative reference for EU-level analysis of working conditions, forming the empirical backbone for reports such as Eurofound's periodic overviews on working conditions and job quality.

Box 3. EWCS - Survey Scope

Population: Workers (employees and self-employed) aged 15+ in employment.

Geographic coverage: All 27 EU Member States; often also EFTA and EU candidate countries.

Sample size: 1,000 per country (up to 1,400 for larger countries); 36,000+ total in 2024.

Mode: Face-to-face interviews (CAPI); telephone in 2021 (EWCTS).

The EWCS targets all workers — both employees and the self-employed — who are in employment at the time of the survey, using the International Labour Organization (ILO) definition of employment (working for pay or profit for at least one hour in the reference week). This inclusive scope is a significant methodological strength, allowing analysis of non-standard workers, the self-employed, and platform workers alongside mainstream employees.

Geographic coverage has expanded over successive rounds in parallel with EU enlargement. From an initial focus on EU Member States, the survey has consistently included EFTA countries (Norway, Switzerland) and often EU candidate countries (Turkey, North Macedonia, Albania, Montenegro, Serbia), making it a genuinely pan-European rather than purely EU instrument. In 2024, the survey was conducted across all 27 EU Member States.

The EWCS uses a multi-stage, stratified, random probability sampling design. In each country, primary sampling units (typically municipalities or census areas) are selected with probability proportional to population size, stratified by region and degree of urbanisation. Within each primary sampling unit, individuals are selected at random. The target sample size per country is typically 1,000, increased to 1,200 in Poland, 1,300 in Spain, and 1,400 in Italy to reflect larger workforce size.

Data are collected through computer-assisted personal interviewing (CAPI), with fieldwork conducted by a specialised contractor. The questionnaire is translated into all relevant national languages using a rigorous forward-backward translation procedure, with cognitive pre-testing and piloting in multiple countries to ensure conceptual equivalence across different cultural contexts. Quality assurance follows the European Statistical System (ESS) quality criteria framework and the Total Survey Error paradigm.

The 2021 edition (EWCTS) was carried out by telephone (CATI) in response to COVID-19 pandemic restrictions, allowing fieldwork to proceed while introducing some methodological differences from the face-to-face design. The 2024 survey returned to face-to-face interviewing as the primary mode, while also piloting an online component to inform future methodological decisions.

The EWCS has historically been conducted every five years, providing a periodic rather than continuous monitoring instrument. The five-year interval was designed to balance the resource demands of a large-scale comparative survey with the need for trend data. In practice, the interval between waves has varied slightly: the 2021 EWCTS was conducted as an emergency supplement during COVID-19, with the full 2024 wave following three years later.

The relatively long periodicity is one of the EWCS's recognised limitations. In a rapidly evolving labour market — particularly with regard to digital technologies, platform work and new forms of work organisation — five years can represent a substantial lag between data collection and policy relevance. Eurofound has partially addressed this through the Living and Working in the EU e-survey (see Section 5.4.2), which provides more frequent data points between EWCS waves.

5.1.2. Key Variables and Skills-Related Indicators

The EWCS questionnaire covers more than 100 items organised around six core dimensions of job quality, each with direct or indirect relevance to skills intelligence:

Skills and Discretion

This dimension is most directly relevant to skills intelligence and includes indicators on:
- Task complexity: whether work involves complex tasks, monotonous tasks, and the level of problem-solving required.
- Learning and training: access to employer-provided training; opportunities to learn new things at work; whether current skills match job requirements (skills match/mismatch indicators).
- Autonomy and discretion: worker control over task order, methods, pace and working time — dimensions associated with higher-skill work and skill utilisation.
- Skills utilisation: the degree to which workers feel their skills are fully used in their current job.
- Career prospects: perceived opportunities for career development, job security, and upward mobility.

Work Organisation and Task Content

The EWCS collects detailed information on task content, including the use of computers and digital tools, the degree of standardisation and repetitiveness of tasks, and the presence of cognitive, physical and social demands. Since 2016, task content indicators have been used by Eurofound (in the European Jobs Monitor context) to construct composite indices of cognitive, physical, social and emotional task demands, enabling analysis of task-biased technological change and automation risk.

Physical and Psychosocial Environment

Indicators on physical exposures (noise, vibrations, heavy loads, chemicals, extreme temperatures) and psychosocial risks (emotional demands, harassment, discrimination, time pressure) relate to health and safety conditions that are strongly linked to occupational skill requirements and working conditions quality.

Other Dimensions

The EWCS also collects information on earnings (subjective income adequacy), working time (hours, schedules, flexibility, work-life balance), employment status and contract type, and — increasingly — the use of digital technologies and algorithmic management. The 2024 wave introduced new questions on the impact of digitalisation and decarbonisation on working life, directly addressing the twin transition agenda.

Granularity

EWCS data are available at the following levels of disaggregation:
- Country: All 27 EU Member States (and additional countries where included).
- Occupation: ISCO-08 classification (typically at 1-digit level for published analysis; micro-data allow deeper disaggregation).
- Sector: NACE Rev. 2 classification (typically at 1-digit or broad sector level).
- Gender, age group, educational attainment: Systematic cross-tabulations published in overview reports.

— Employment status: Employees vs. self-employed; full-time vs. part-time; permanent vs. temporary.
— Establishment size: Small, medium and large enterprises.

Regional (sub-national) disaggregation below the country level is generally not possible with standard EWCS samples, which are designed to be nationally representative. This is a notable limitation for regional policy analysis. The public-use micro-data allow researchers to undertake their own dis-aggregation, though cell sizes become small for finer breakdowns.

5.1.3. Strengths

— Skills utilisation: EU-wide, harmonised measure of whether workers feel they are using their skills to their full potential, capturing the underutilisation dimension not covered in most official statistics.
— Informal and workplace learning: Captures learning from colleagues, supervisors, and through practical experience — the non-formal learning channels that are dominant in many sectors but invisible to survey-based formal training measures.
— Digital work: The EWCS 2024 includes an expanded digital work module capturing how ICT use shapes task content, job autonomy, and skill requirements — providing a micro-level complement to the macro-level digital transformation narrative.
— Skills and job quality interaction: The EWCS enables analysis of how skills mismatch (overqualification, underutilisation) interacts with job satisfaction, health outcomes, and retention — crucial for understanding the full social cost of mismatch.
— Sector and occupation comparisons: Despite sample size constraints, the EWCS provides the ability to compare working conditions across occupational groups, including sectors experiencing structural change.

5.1.4. Limitations

— Five-year periodicity: The primary limitation of the EWCS for skills intelligence is its low frequency. A survey conducted every 5 years provides trend information but cannot track rapid shifts in skill demand or working conditions dynamics. The EWCS 2024 follow-up surveys (planned for November 2025 and February 2026) partially address this for a sub-sample.
— Sample size constraints for granular analysis: While the EWCS covers 35 countries with approximately 800–1,000 respondents per country, subgroup analysis at the occupational or sectoral level (particularly for small occupational categories in small countries) is statistically unreliable.
— Subjective measures: Like the ESJS, the EWCS relies on self-reported perceptions of skill utilisation, task complexity, and training participation. These are systematically shaped by respondents' reference frames, cultural context, and industry norms.
— No employer-side complement: The EWCS is exclusively a worker survey. It captures whether workers feel their skills are used, but not whether employers are making efficient use of their workforce's skills.

5.2. European Company Survey (ECS) (with CEDEFOP)

5.2.1. Description, Scope and Coverage

The European Company Survey (ECS) (European Company Surveys (ECS) | Eurofound) provides an establishment-level perspective on workplace practices, complementing the worker-level data of the EWCS. It was first conducted in 2004–2005 as the European Establishment Survey on Working Time and Work-Life Balance (ESWT). Subsequent rounds — in 2009, 2013 and 2019 — progressively expanded the thematic scope. The 2019 edition, carried out jointly with Cedefop, placed skills use and development strategies at the heart of the questionnaire. A fifth edition is in preparation for 2028[34]. The ECS has been conducted every four to five years since 2004. Like the EWCS, this periodic design reflects the resource constraints of large-scale comparative surveys.

Between editions, Eurofound has published supplementary outputs — for example, a follow-up COVID-19 online survey in 2020 examining the immediate impact of the pandemic on business continuity and remote working — to address emerging policy needs between regular survey rounds.

The ECS has a dual-respondent design: it interviews both managers responsible for human resources (MM respondent) and, where present, employee representatives (ER respondent) in the same establishment. This paired approach allows comparison of management and worker perspectives on issues such as training provision, employee participation and work organisation, providing more nuanced and validated data than a single-respondent approach.

The ECS focusses on establishments with 10 or more employees, excluding agriculture (NACE A), households (NACE T) and extraterritorial organisations (NACE U). This scope excludes micro-enterprises, which represent a significant share of EU employment, particularly in Southern and Eastern European Member States — a recognised limitation. The 2019 survey covered all 27 EU Member States and the United Kingdom. The sample size is about 21,900 establishments in recent rounds[35].

5.2.2. Methodology and Key Variables and Granularity

Sampling is stratified by establishment size (number of employees) and broad sector of activity (industry vs. services), with oversampling of larger establishments to ensure adequate representation across size classes. Country-level sampling frames are drawn from national business registers, though the quality of these registers varies across Member States, introducing some heterogeneity in sampling quality.

The 2019 ECS introduced web-based self-completion (CAWI) as the primary data collection mode, replacing the telephone interviewing used in earlier rounds. This shift to online administration enabled a more complex questionnaire structure, with skip patterns and show cards not easily administered by phone. However, it also required careful management of response rates and potential bias from differential take-up of online modes across firm types and countries.

The ECS questionnaire covers a range of workplace practices, with the 2019 edition particularly rich in skills-related content. Key thematic areas include:

Table 15. Thematic dimensions and key indicators

Thematic dimension	Key indicators
Skills use and development (jointly with Cedefop, core in 2019)	Skills-use strategies (job redesign, task allocation); management-perceived skills gaps; training provision (formal/informal, needs assessments, learning plans); barriers to training (cost, time, relevance, motivation); links between skill development and career progression

34 See Gijs van Houten - Senior research manager | Eurofound

35 *"The survey collected information from 21,869 human resources managers and 3,073 employee representatives in the 27 EU Member States and the United Kingdom."* according to https://www.eurofound.europa.eu/en/publications/all/european-company-survey-2019-workplace-practices-unlocking-employee-potential

Thematic dimension	Key indicators
Work Organisation	Worker autonomy; team-working; task rotation; job enrichment; “learning-rich” environments
Human Resource Management	Recruitment practices; performance appraisal; variable pay; motivation strategies; employee involvement in decision-making (‘high-performance work system’ context)
Digitalisation	Use of advanced digital technologies (cloud, big data, robotics, AI); perceived impact on skill requirements and training
Social Dialogue and Employee Voice	Presence and role of employee representatives; topics covered (incl. training and skills); quality of industrial relations

Source: Authors’ elaboration

Granularity

ECS data are disaggregated along the following dimensions:
— Country: All participating Member States.
— Establishment size: Small (10–49 employees), medium (50–249), large (250+).
— Sector: Broad NACE Rev. 2 groupings (industry vs. services, with further sub-sectoral analysis possible in micro-data).
— Presence of employee representative body: Distinguishing establishments with and without formal worker representation.

The ECS does not allow regional sub-national disaggregation, and sectoral analysis is limited by the need for adequate sample sizes within each cell. The minimum threshold of 10 employees means the data are not representative of micro-enterprises.

5.2.3. Strengths

— Establishment-level perspective: Fills a critical gap in EU skills intelligence by capturing the demand side — what employers do in terms of training, skills strategies and work organisation.
— Dual-respondent design: The management-employee representative pairing provides a more complete and internally validated picture of workplace practices.
— Skills coverage: Joint design with Cedefop in 2019 resulted in an unusually rich skills-specific questionnaire, integrating human capital theory (ability, motivation, opportunity framework) with empirical measurement.
— Linkage to EWCS: The parallel design of ECS and EWCS allows analytical triangulation between employer and worker perspectives.
— Micro-data availability: The public-use data file supports secondary research.

5.2.4. Limitations

— Exclusion of micro-enterprises: Establishments with fewer than 10 employees — accounting for a substantial share of EU employment — are outside scope.
— No longitudinal tracking: Establishments are not followed over time, preventing analysis of how skills strategies evolve.
— Self-reported data: Manager self-reports on training provision and skills strategies may be subject to social desirability bias.

— Low periodicity: The four- to five-year cycle means the data can become outdated quickly in a dynamic context.
— Sectoral depth: Sample sizes within detailed sectors may be insufficient for sector-specific policy analysis without pooling data across rounds

5.3. Labour Market Change Research – The European Jobs Monitor (EJM)

The European Jobs Monitor (EJM)[36] is an analytical framework — rather than a primary data collection instrument — that tracks structural change in European labour markets. It analyses shifts in employment structure in terms of occupation and sector and provides a qualitative assessment of these shifts using proxies of job quality, particularly wages and skill levels. The EJM is published as an annual or biennial series and is updated regularly as new data from the EU Labour Force Survey become available.

The EJM is particularly relevant to skills intelligence in its capacity to identify patterns of job growth and decline across the skill distribution — capturing phenomena such as job polarisation (growth at the top and bottom of the wage distribution, decline in the middle), employment upgrading and sectoral restructuring. These trends have direct implications for workforce skill requirements and training investment priorities.

The EJM does not collect primary data. Instead, it draws primarily on two administrative and statistical data sources:
— European Union Labour Force Survey (EU-LFS): The primary source for employment counts by occupation (ISCO-08, 2-digit level) and sector (NACE Rev. 2, 1-digit level). The EU-LFS provides annual data for all Member States with consistent classifications.
— Structure of Earnings Survey (SES): Used to derive mean hourly wages by occupation-sector cell, enabling the ranking of job types along a wage distribution. SES data are collected every four years by Eurostat.

5.3.1. Strengths

— High frequency: Annual updates allow tracking of labour market structural change in near real time relative to Eurofound's surveys.
— Full EU coverage: Based on EU-LFS data collected by Eurostat for all Member States under a harmonised methodology.
— Multi-dimensional: Integration of wage, task content and educational attainment data provides a richer picture of skill-level shifts than wage data alone.
— Long time series: EU-LFS data extending back to the mid-1990s enable long-run trend analysis.

5.3.2. Limitations

— Wage as skill proxy: Using wages to rank jobs by skill level is an indirect and imperfect measure; it conflates market returns with skill content.
— Occupational classification changes: The shift from ISCO-88 to ISCO-08 in 2011 and from NACE Rev. 1 to NACE Rev. 2 in 2008 introduce breaks in time series that require careful bridging.
— No direct skills measurement: The EJM does not measure the actual skills of workers or the skills required by jobs — these are inferred from wages, educational attainment and task indices.
— Limited regional disaggregation: Sub-national analysis requires significant methodological adaptation due to EU-LFS sample constraints

[36] See: European Jobs Monitor | Eurofound.

5.4. Other Related Data Sources

5.4.1. The European Quality of Life Survey (EQLS)

The European Quality of Life Survey (EQLS)[37] is Eurofound's third major survey instrument. First conducted in 2003, and carried out in 2007, 2011-12 and 2016-17, it examines both the objective circumstances of European citizens' lives and their subjective assessments of those circumstances. While its primary focus is broader than employment — covering housing, health, family, social participation and subjective well-being — it includes dimensions that are directly relevant to skills intelligence, particularly regarding education, employment quality, and the capacity of individuals to participate in learning.

5.4.2. The Living and Working in the EU e-Survey

In April 2020, in response to the COVID-19 pandemic, Eurofound launched the Living, Working and COVID-19 e-Survey[38] — a large-scale online instrument designed to capture rapidly evolving changes in working and living conditions. The e-survey has since been institutionalised as a regular instrument, with further rounds conducted in 2021, 2022 and 2023, and a 2024 round aligned with the EWCS. It complements the EWCS by providing higher-frequency data between the five-year survey waves, and by enabling rapid deployment when new policy-relevant questions arise. By contrast to other surveys, sampling is based on self-selection (including via social media advertisements), which produces a non-representative sample (with weighting applied).

[37] See: European Quality of Life Surveys (EQLS) | Eurofound

[38] See: Living and Working in the EU e-survey | Eurofound

6. Pact for Skills and Sectoral Intelligence

The Pact for Skills, launched by the European Commission in November 2020 as a flagship action of the European Skills Agenda, is a public-private engagement model for workforce upskilling and reskilling. Now embedded within the Union of Skills initiative, the Pact provides an institutional framework through which industry stakeholders, social partners, education providers, and public authorities collaborate to identify and address sectoral skills gaps. As of early 2026, the Pact has grown to more than 4,000 member organisations across all EU Member States, collectively investing over €1 billion in skills development and committing to train over35 million people by 2030.

The Pact does not produce harmonised statistical indicators. Instead, sectoral skills intelligence is generated within the Pact through two principal mechanisms: Large-Scale Skills Partnerships (LSPs) and Blueprint Alliances for Sectoral Cooperation on Skills. This intelligence is **qualitative** and **operational** in nature, grounded in the direct experience of sector actors rather than in survey-based or administrative data.

6.1. Large-Scale Skills Partnerships (LSPs)

Large-Scale Skills Partnerships are collective initiatives operating within 14 industrial ecosystems. As of 2026, 20 LSPs have been established across five categories: 1. clean transition and industrial decarbonisation; 2. health, biotech, agriculture and bioeconomy; 3. digital leadership; 4. resilience and security, defence industry and space; and 5. consumer, social, and service-oriented industries.

Each LSP brings together industry actors, VET providers, higher education institutions, social partners, and public authorities to identify skills gaps within their ecosystem and develop collaborative responses. Their skills intelligence activities include enhancing the ability of members to identify, anticipate and address skills changes, employment trends and skills needs in specific sectors, as well as transversal skills such as networking, entrepreneurship, or research skills, encompassing emerging competencies including digital and green skills along with sector-specific capabilities.

According to the 2025 Pact for Skills Annual Survey (Ecorys, 2026; N=1,534), LSP members reported that the most valuable aspects of partnership were opportunities for collaboration (115 responses), knowledge sharing including peer learning and joint skills intelligence generation (104 responses), and newly developed training programmes (101 responses). In 2025, LSP members trained an average of 26% of their workforce.

The skills intelligence produced by LSPs is primarily operational: identification of which specific occupational profiles face recruitment difficulties, which emerging skills are not yet covered by existing training programmes, and which training courses and qualification pathways need updating. This intelligence is sector-specific and practitioner-driven, offering a granularity of insight into - sector-specific skills dynamics that no survey-based source can match.

6.1.1. Key LSP examples with skills intelligence outputs

— The Shipbuilding and Maritime Technology LSP focusses on attracting 230,000 new workers to the industry within 10 years, requiring detailed occupational profiling of emerging roles in green shipbuilding.
— The Proximity and Social Economy LSP has mapped care economy skills gaps across member countries.

— The Aerospace and Defence LSP has developed sector-specific competence frameworks for emerging roles in autonomous systems and space technologies.

Data access: LSP skills intelligence outputs are not published as structured datasets. They are disseminated through the Pact for Skills online library (pact-for-skills.ec.europa.eu), which serves as a European one-stop shop for tools and resources concerning upskilling and reskilling, including online tools, policy reports and research papers developed by stakeholders at international, EU and national level.

6.2. Blueprint Alliances for Sectoral Cooperation on Skills

Blueprint Alliances[39] are the Pact's primary instrument for structured, project-based sectoral skills intelligence. Funded through Erasmus+ (Key Action 2, Alliances for Innovation, Lot 2), each Blueprint Alliance is a 4-year transnational project covering at least 8 EU Member States, with a minimum consortium of 12 organisations including at least 5 labour market actors and 5 education/training providers (including at least 1 Higher Education Institution (HEI) and 1 Vocational Education and Training (VET) provider). The award criteria for Blueprint proposals favour LSPs and registered members of the Pact for Skills.

Blueprint Alliances produce four mandatory deliverables, each constituting a distinct form of skills intelligence:

1. **Sectoral skills intelligence:** A detailed assessment of current and anticipated skills needs within the ecosystem, identifying skills gaps, skills shortages, and emerging occupational profiles. This is the diagnostic foundation.
2. **Sectoral skills strategy:** A strategic roadmap with clear activities, milestones and objectives to match demand and supply of skills within the ecosystem, designed to support the overall implementation of the corresponding LSP.
3. **Occupational profiles and training programmes:** Revised and newly developed job profiles and related training content at EQF levels 3–8 (vocational and higher education), designed for quick take-up at regional and local level. Programmes must address urgent skills needs resulting from the digital and green transitions within the first project year.
4. **Long-term action plan:** A plan for the progressive roll-out of project deliverables at national and regional level after EU funding ends, ensuring sustainability.

Coverage by industrial ecosystem: Under the Erasmus+ programme 2021–2027, Blueprint Alliances have been selected in annual waves. Seven alliances started in 2022, seven more in 2023, five in 2023, eight in 2024–2025, and seven in 2025–2026 — covering 14 industrial ecosystems. These include: aerospace and defence; agri-food; construction; cultural and creative industries; digital; energy-intensive industries; energy-renewables; health; microelectronics; mobility–transport–automotive; proximity and social economy; retail; textile/ clothing/ leather/ footwear; and tourism.

6.2.1. Strengths

— **Sectoral depth:** The skills intelligence produced by Large Scale Partnerships and Blueprint Alliances within the Pact for Skills is sector-specific and practitioner-driven, offering a granularity of insight into within-sector skill dynamics that no survey-based source can match.

[39] Source: European Commission, DG Employment — Blueprint for Sectoral Cooperation on Skills (employment-social-affairs.ec.europa.eu/policies-and-activities/skills-and-qualifications/working-together/blueprint-sectoral-cooperation-skills_en); Erasmus+ Programme Guide 2026; Pact for Skills Guidance Handbook (2025 update).

— **Operational:** identification of which specific occupational profiles face recruitment difficulties, which emerging skills are not yet covered by existing training programmes, and which qualification pathways need updating.
— **Certain degree of intelligence integration with ESCO and Cedefop:** Blueprint Alliances are required to make use of EU tools including EQF, ESCO, Europass, and EQAVET, and to feed their skills intelligence findings into Cedefop's Skills Intelligence tool. This creates a feedback loop between bottom-up sectoral intelligence and the centralised Cedefop system described in Section 3.

6.2.2. Limitations

— No harmonised methodology. Each LSP and Blueprint Alliance uses its own approach to skills intelligence, not enabling cross-sectoral or cross-country comparison . There is no common taxonomy of 'skills gap' severity, no standardised measurement of shortage intensity, and no shared data infrastructure across partnerships.
— No structured, publicly accessible data. Skills intelligence outputs from LSPs are disseminated as reports, case studies, and internal working documents — not as structured datasets with defined variables, units, and metadata. Blueprint Alliance deliverables are published as project outputs but without a standardised data format.
— Self-selection and representativeness bias. The Pact members are self-selected organisations that have voluntarily joined the initiative. They are not a representative sample of firms or sectors.. The 2025 Annual Survey (N=1,534) represents a 49% response rate from 3,154 contactable members — itself a subset of total membership.
— Qualitative and narrative rather than quantitative. Skills gap assessments within LSPs are typically expressed in qualitative terms ('significant shortage of welding technicians with Industry 4.0 competences') rather than as measurable indicators.
— Project-based and time-limited. Blueprint Alliances are projects funded by Erasmus+ grants, typically for four years. The long-term sustainability of skills intelligence depends on the willingness and capacity of consortium partners to continue beyond the project's duration.
— Integration with Skills Intelligence data systems remains limited. Beyond the requirement for Blueprint Alliances to feed intelligence into Cedefop's Skills Intelligence tool, there is no automated or systematic linkage between Pact-generated intelligence and the statistical infrastructure described earlier in this report.

6.2.3. Net-Zero Industry Academies and EU Skills Academies

The Net-Zero Industry Act[40] mandates the European Commission to support the launch of Net-Zero Industry Academies in certain strategic net-zero technology sectors (listed in the regulation) based on an assessment of skills needs.

Where launched, these Academies are required to perform continuous skills intelligence in the sector combining market research, innovation trends and industry insights related to skills, skill gaps, new job profiles and talent needs for the solar value chain. This activity is performed involving key players and projects in the industry and in cooperation with relevant stakeholders listed in the Net-Zero Industry Act, as well as by consulting the governance body of the regulation: the Net-Zero Europe Platform.

[40] Regulation (EU) 2024/1735 of the European Parliament and of the Council of 13 June 2024 on establishing a framework of measures for strengthening Europe's net-zero technology manufacturing ecosystem and amending Regulation (EU) 2018/1724Text with EEA relevance.

The results of the skills intelligence should inform the development of the Academy's learning content. As of June 2026, these academies exist in the Batteries[41], Solar[42] and Raw Materials[43] sectors. New academies in Wind and Hydrogen are under preparation.

[41] European Battery Academy

[42] European Solar Academy

[43] European Raw Materials Academy | EIT RawMaterials - Developing raw materials into a major strength for Europe

7. Other Relevant Sources

7.1. Eurobarometer

7.1.1. Description

The Eurobarometer programme, managed by the European Commission's Directorate-General for Communication, conducts periodic Flash and Special surveys on policy-relevant topics, including skills-related themes.

A key survey is[44]: **Flash Eurobarometer 537: SMEs and Skills Shortages** (September 2023; published March 2024). This survey covered approximately 13,000 SMEs across all EU Member States, asking employers directly about their experience of recruitment difficulties, hard-to-fill vacancies, skills gap perceptions, and retention strategies[45].

Key findings include: two-thirds of SME respondents reported that soft/transversal skills had become 'somewhat more important' (20%) or 'much more important' (48%); digital skills were the second most frequently cited growing need; and average hiring time for skilled employees varied significantly across Member States.

7.1.2. Strengths

Eurobarometer provides the employer demand perspective at a scale that many other enterprise surveys (CVTS, JVS) do not. It directly asks firms about their subjective experience of skill shortages and the strategies they employ to address them (including training, wage adjustment, automation, and recruitment from abroad). This can complement the supply-side household survey data from the EU-LFS.

7.1.3. Limitations

1. Eurobarometer surveys are ad hoc. There is no guaranteed periodicity for skills-related modules.
2. The sampling frame targets SMEs (which face different shortage dynamics than large firms).
3. The questionnaire design changes between waves, preventing consistent time-series construction.
4. While microdata from Eurobarometer surveys are publicly accessible via the GESIS Data Archive (Eurobarometer Data Service), these are typically available with a lag of 6–12 months.

7.2. 7.2 European Higher Education Sector Observatory (EHESO)

7.2.1. Description

The European Higher Education Sector Observatory (EHESO) is a comprehensive, user-focussed platform providing data and insights on higher education across Europe. Designed to serve a diverse range of stakeholders, the Observatory facilitates comparative analysis and performance assessment of the higher education sector. It enables users to explore, analyse, and visualize key trends, metrics, and developments across institutions, systems, and thematic areas, fostering a deeper understanding of the sector's dynamics and challenges.

It functions as part of the broader EU skills intelligence ecosystem, contributing to initiatives such as the European Skills Agenda, the Pact for Skills, and the European Education Area (EEA). Its

[44] There are others such as Barriers for European SMEs in recruiting workers from outside the EU - June 2026 - Eurobarometer survey

[45] SMEs and skills shortages - November 2023 - Eurobarometer survey.

relevance for the mapping of skills mismatches and gaps is the future-proof skills pillar which flags vertical mismatch — the degree to which graduates end up in jobs that don't require their level of qualification — by cross-referencing employment status against field and level of study and Eurograduate's skills-match-of-graduates data. allowing to connect educational outputs (degree type, institution) to labour market outcomes (employment quality, relevance of work), giving a longitudinal read on whether skills produced by HE systems are landing where they're needed or flowing elsewhere.

EHESO builds upon a comprehensive range of established EU data platforms and analytical resources, integrating insights from EHESO's predecessor projects the European Tertiary Education Register (ETER) and U-Multirank (multidimensional university benchmarking), and the Erasmus+ database (tracking student and staff mobility, as well as transnational collaborations among higher education institutions). It also draws on the Database of External Quality Assurance Results (DEQAR) (accreditation outcomes), Eurostudent (social dimensions of higher education), Eurograduate (graduate employment and career trajectories), and Eurydice (policy data, including Bologna Process Implementation Reports, the Mobility Scoreboard, and national higher education system profiles).

By consolidating and cross-referencing these diverse data sources, the EHESO facilitates rigorous comparative analysis, enabling stakeholders to assess and highlight performance trends within the higher education sector. This empowers institutions and policymakers to bolster their evidence-based decision-making on critical issues—such as inclusive access, learning outcomes, and advancements in digital, green, and entrepreneurial competencies, as well as technology transfer, graduate employability, and alignment with labour market demands. In doing so, EHESO strengthens the role of higher education institutions as key drivers of innovation ecosystems while fostering cross-border collaboration within the sector.

EHESO is designed as a modular platform comprising five instruments at different stages of deployment[46]:

— European Higher Education Sector Scoreboard (EHESS) — launched January 2025: an interactive visualisation platform tracking EU higher education policy objectives at country level through a comprehensive set of thematic indicators.
— Institutional Benchmarking Tool — enabling higher education institutions (HEIs) to benchmark against peers across EU and OECD countries, drawing on U-Multirank methodology and ETER data.
— European Student Hub — planned for late 2026: a major tool to inform students about study options and programme diversity across European institutions; feasibility analysis and roadmap are underway.
— Open-Access Data Centre: offering researchers and stakeholders micro-level data on institutions, programmes, and students, complementing the aggregate-level scoreboard and benchmarking tools.
— A Strategic Transformation Toolbox with tools and resources by or for stakeholders, supporting the strategic transformations of the European higher education sector.

The European Higher Education Sector Scoreboard (EHESS) structures its indicators across five thematic pillars aligned with EU higher education policy objectives. The reference year for the inaugural edition is calendar year 2022 (academic year 2021/2022), with time series available from 2015. The geographical coverage encompasses EU-27, EEA-EFTA countries (Iceland, Liechtenstein, Norway, Switzerland), several candidate countries, and the United Kingdom. Data sources include

[46] The European Higher Education Sector Observatory, Handbook for institutional-level indicators Handbook for institutional-level indicators, 2026

Eurostat educational statistics, ETER, U-Multirank, EUROSTUDENT, Eurograduate, and Erasmus+ mobility databases. The data collection for the Eurograduate 2026 survey is carried out by EHESO, with new survey module on general, green and digital skills. The survey will cover graduates for the cohorts graduated in 2024/2025 (T+1) and 2020/2021 (T+5). Results will be available in Autumn 2027.

Table 16 summarises the five pillars and their principal indicator clusters.

Table 16. Key indicators in EHESO, by thematic pillar

Thematic Pillar	**Key Indicators**
1. Future-Proof Skills	Key indicators to compare European higher education systems according to six dimensions: — perceived value of teaching and pedagogical innovation; — strengthening quality and relevance of future-proof skills; — cooperation with industrial ecosystems; — promoting entrepreneurship; — engagement in green transition; — engagement in digital transition.
2. Transnational Cooperation	Key indicators to compare European higher education systems according to three dimensions: — transnational mobility of staff; — transnational mobility of students; — cooperation of institutions in education, research and innovation.
3. EU Values	Key indicators to compare European higher education systems according to three dimensions: — institutional autonomy and academic freedom; — gender balance; — diversity and inclusiveness.
4. International Cooperation	Key indicators to compare European higher education systems according to two dimensions: — global role in education; — global role in research and innovation.
5. Context Indicators	Key contextual indicators allowing to better compare European higher education systems according to available resources, system composition, activities and outputs. Expenditure for higher education R&D (% of GDP); student-to-staff ratios; among others.

Source: Authors' elaboration

7.2.2. Strengths

— **Integration of existing infrastructure.** EHESO does not duplicate but consolidates proven EU data tools (ETER, U-Multirank, Eurostat, Eurydice) into a single coherent platform, improving accessibility and reducing the fragmentation that previously characterised European higher education data.

— **Policy relevance and alignment.** The Scoreboard's five thematic pillars map directly onto the European Education Area and Union of Skills objectives, ensuring that monitoring outputs are directly usable by policymakers at national and EU level without extensive reinterpretation.

— **Multi-actor utility.** The platform is explicitly designed for heterogeneous user groups — policymakers, institutional leaders, researchers, and students — with tools calibrated to each audience (Scoreboard for national policy monitoring; Benchmarking Tool for institutional strategy; European Student Hub for prospective students).

— **Longitudinal depth.** Time series data going back to 2015 enables trend analysis, not merely static comparison, supporting evaluation of reform effects over time.
— **Open-access micro-data.** The Data Centre component provides researchers with underlying datasets, extending the value of the platform beyond pre-defined indicator views and stimulating independent secondary analysis.
— **Broad geographic scope.** Coverage extends beyond EU-27 to EEA-EFTA countries, several candidate countries, and the UK, reflecting the reality that European higher education mobility and cooperation is not bounded by EU membership.

7.2.3. Limitations

— **Data lag.** The inaugural Scoreboard uses 2022 as its reference year, a two-to-three year lag from publication that reduces the platform's utility for near-real-time policy monitoring. Administrative data collection cycles are difficult to accelerate without major national-level reforms.
— **Inherited data quality constraints.** EHESO's outputs are only as reliable as the underlying national reporting to Eurostat and ETER. Inconsistencies in how Member States classify institutions, student categories, and expenditure items persist, limiting strict comparability at the institutional level.
— **Survey-based indicator volatility.** Indicators derived from U-Multirank institutional surveys depend on voluntary HEI participation. Response rates vary significantly across countries and institution types, introducing selection bias that may skew benchmarking results toward more internationally engaged, resource-rich institutions.
— **Limited sub-national granularity.** The Scoreboard primarily operates at national level, which masks significant intra-country heterogeneity — particularly relevant for federal or regionally diverse Member States (Germany, Spain, Italy, Belgium) where higher education systems are largely governed at sub-national level.

7.3. Education and Training Monitor

The Education and Training Monitor is an annual publication presenting the latest data and insights on education and training systems across the EU. Serving as a key resource, it highlights recent developments and emerging trends in learning—from early childhood education and care to adult participation in training and lifelong learning. The Monitor comprises three core components:
— A comparative report
  • Assessing progress toward the EU's 2030 education and training targets
  • Integrating supporting evidence to provide context
— Country-specific analyses
  • Examining policy advancements in all 27 EU Member States
  • Assessing national education system performance
— An interactive toolbox: Providing an overview of the key indicators and sources used in the report and country pages to see how countries compare to others.

7.3.1. Key Indicators in the Education and Training Monitor

The ET Monitor utilises a set of indicators categorized by thematic area. These indicators are designed to be quantifiable and comparable across the heterogeneous education systems of the EU. The indicators (a selection of them is presented below) are structured around the following domains:
— **Early Childhood Education and Care (ECEC):** Participation rates of children in ECEC.
— **Basic Skills:** Student performance in reading, mathematics, and science (measured via PISA) and level of digital skills (via ICILS survey) and citizenship skills (via ICCS survey).

— **Early Leavers from education and training:** The percentage of individuals (aged 18–24) with at most lower secondary educational attainment and no longer in formal or non-formal education or training.
— **Teachers and teaching profession:** Indicators capturing the attractiveness and status of the teaching profession, including salary, working conditions, and professional development.
— **Equity in school education:** Indicators capturing how a disadvantage background and features of school systems affect school performance.
— **Vocational education:** Share of VET graduates who experienced work-based learning as part of their VET programmes.
— **STEM:** Enrolment in STEM fields for initial medium-level VET and tertiary programmes
— **Tertiary Education:** Tertiary attainment rates among the 25-34 population.
— **Adult Learning and skills:** Participation in life-long learning.

7.3.2. Primary Data Sources

The Monitor relies on robust, international data sets to ensure comparability:
— **Eurostat:** Labour Force Survey is the primary source for early leavers from education and training, and tertiary educational attainment levels. The UNESCO/OECD/Eurostat (UEO) joint data collection is the main source for enrolment, graduates, teachers, learning mobility and participation in ECEC.
— **OECD Programme for International Student Assessment (PISA):** The core source for comparative data on student performance in reading, mathematics, and science and equity at school level.
— **International Association for the Evaluation of Educational Achievement (IEA)[47] ICILS (International Computer and Information Literacy Study)**: the core source for digital skills.
— **International Association for the Evaluation of Educational Achievement (IEA) ICCS (International Civic and Citizenship Education Study)**: the main comparable source for citizenship skills.
— **OECD Teaching and Learning International Survey (TALIS)**: Provides insight into teacher working conditions and professional development.

In addition, the Monitor also relies on the system-level information collected through Eurydice (see Section 7.6).

7.3.3. Strengths

— **Policy Steering:** By making available comparable and country evidence, the Monitor allows policy makers to identify common challenges and best practices, representing a key source for policy making and for identifying funding priorities at national and EU level.
— **Comparability:** The use of harmonized data sources (e.g., Eurostat and PISA) enables a comparative analysis that would otherwise be impossible.

7.3.4. Limitations

— **Data Latency:** While the Monitor provides essential data, there is often a significant “time lag” between policy implementation at the national level and the reflection of that policy in the EU-wide statistical data. This limits the ability of the Monitor to provide real-time guidance on emerging crises or rapid systemic changes.

[47] See: About IEA | IEA.nl

7.4. Research and Innovation Careers Observatory (ReICO)[48]

The Research and Innovation Careers Observatory (ReICO), launched in September 2024 as a joint initiative of the European Commission (DG Research and Innovation) and the OECD, is a six-year project that provides international data, analytical tools, and resources focussed specifically on research and innovation (R&I) careers. Hosted by the OECD and supported by a network of national contact points and an expert advisory group, ReICO responds to the Council Conclusions of 28 May 2021 on "Deepening the European Research Area" and the Council Recommendation on a European framework to attract and retain research, innovation, and entrepreneurial talents in Europe.

ReICO tracks and analyses trends in R&I talent development, employment, mobility, and career paths across EU and OECD countries, as well as other major economies including China, India, and the United States. Its first set of data was released in the first half of 2025 and will be updated annually.

7.4.1. Key data dimensions

— **Researcher population and density:** The EU population of researchers has doubled over two decades, reaching 9.7 researchers per thousand employed in 2022 — matching the OECD average and approaching the US rate (10.5). ReICO tracks this metric across countries and over time.
— **Doctoral enrolment trends:** The EU doctoral enrolment index (2015 = 100) reached 112 in 2022, while the equivalent US index fell to 89.4. ReICO monitors this divergence, including the rapid expansion in China.
— **Cross-border researcher mobility:** Tracking where researchers move, the duration of stays, return rates, and the relationship between mobility and career outcomes (publications, patents, career advancement).
— **Career pathways and working conditions:** Data on the transition from doctoral training to permanent research positions, the prevalence of fixed-term contracts, career exits from research to private sector or non-R&I roles, and gender disparities in career progression.
— **Skills and competences:** Analysis of the skills developed through research training and their transferability to non-academic labour markets — addressing the question of whether doctoral holders are 'over-qualified' or possess specialist skills that standard mismatch indicators do not capture.

7.4.2. Strengths

ReICO addresses a specific and strategically important dimension of mismatch that is poorly captured by general labour market surveys: the gap between the supply and demand for research and innovation talent. Standard mismatch indicators do not distinguish between a doctoral physicist working as a data scientist (which may represent effective skills transfer) and one working as a secondary school teacher (which may represent genuine mismatch). ReICO's granular career-pathway data can illuminate these distinctions.

Integration with other EU data infrastructure. ReICO is accessible via the ERA Talent Platform (ec.europa.eu/era-talent-platform/reico/), which also links to EURAXESS (the pan-European researcher mobility portal covering 43 countries). The Observatory's data complements EHESO's graduate outcomes data at the post-graduate career stage, and potentially Cedefop's Skills Forecast projections for ISCO major group 2 (Professionals), which includes researchers.

[48] Source: https://www.oecd.org/en/networks/research-and-innovation-careers-observatory.html , and https://ec.europa.eu/era-talent-platform/reico/

7.4.3. Limitations

— ReICO is in its early operational phase (first data released in 2025); its scope is limited to researchers and innovators — a small (approximately 1.9 million in the EU, or roughly 1% of total employment) though strategically critical segment of the workforce.
— Limited scope: The Observatory does not cover non-R&I occupations and is not designed for general skills mismatch analysis.
— Its OECD hosting means that data harmonisation follows OECD statistical standards (Frascati Manual for R&D statistics[49]), which differ in some respects from Eurostat's classification systems (ISCO, ISCED).
— Time-limited. The six-year project timeframe (2024–2030) means long-term sustainability beyond EU funding is not guaranteed.

7.5. The European Data Space for Skills

Launched in January 2025, the DS4Skills project brings together 22 partners under the coordination of DIGITALEUROPE, with co-funding from the European Commission.

D4Skills (Data Space for Skills) is an initiative focussed on creating a decentralised data ecosystem. The project centres on the skills and education sector and is primarily concentrated on enabling GDPR-compliant data exchange in this sector, facilitating access to the data catalogue and services.

The project takes a 'use cases first' stance, addressing concrete workforce challenges through practical, sustainable use cases. It is anchored in the EU Digital Strategy, working toward a data ecosystem for education and employment that is secure, ethical, and respectful of privacy.

The use cases that are explored are:
— Student mobility and lifelong learning — Uses AI to surface learning opportunities across European university alliances, cutting manual data handling and improving data quality for a more connected education area.
— Soft skills assessment automation — A tool for managers and employees to evaluate and build soft skills, aligning assessment with real workplace needs and supporting ongoing development.
— Mind the gap: strategic workforce development — Targeted, personalised upskilling driven by data insights, building a more resilient and adaptable workforce through smarter training design.
— Mind the gap: job market-aligned training — Custom learning pathways shaped by market demand, closing skill gaps and boosting employability for lifelong learners.
— Connecting personal skills-data to the Data Space — Secure data sharing between personal skills ecosystems and the EU Skills Data Space, strengthening job search and recruitment across borders and sectors.
— Student learning experiences and skills — A framework to share and analyse student experiences, helping institutions tailor curricula and improve training effectiveness.
— Dataspace for manufacturing skills — Bridges theory and practice in advanced manufacturing with personalised learning paths, helping close skills shortages by aligning education with industry needs.

From a skills data-and-indicator standpoint, the DS4Skills project´s contribution is expected to be structural: it aims at tackling the fragmentation and incomparability that constrain European skills intelligence, through data sharing between participants. This open and federated design opens the

[49] The internationally recognised methodology for collecting and using R&D statistics, the OECD's Frascati Manual (OECD, 2015) is an essential tool for statisticians and science and innovation policy makers worldwide.

door to timelier, more granular, and more outcome-oriented indicators than are widely available today.

However, its main purpose is to facilitate matching, not to provide skills intelligence.

7.6. The Eurydice network

Eurydice[50], coordinated by the European Education and Culture Executive Agency (EACEA), is a network of 37 national units covering all EU Member States, EEA countries, and candidate countries. It provides comparative overview of European education systems and policies, publishes thematic reports, country profiles, and policy briefs on topics ranging from teacher working conditions to higher education governance.

7.6.1. Strengths

Eurydice's contribution is mainly institutional rather than statistical. Its reports on national education structures, providing the regulatory and institutional context within which skills supply is shaped.

7.6.2. Limitations

— Eurydice does not produce quantitative skills mismatch indicators.
— Its outputs are mainly descriptive and policy-analytical, rather than statistical.
— There is no structured dataset to download. The information is presented in narrative reports and country fiches. Its value lies in contextualising the quantitative indicators produced by Eurostat, Cedefop, and ELA.

7.7. OECD: PIAAC Survey of Adult Skills and PISA

Unlike most household and enterprise surveys reviewed above—which proxy skills through qualifications—these sources measure cognitive proficiency directly. PIAAC (the Survey of Adult Skills) is an internationally comparable instrument that measures the skills of the working-age population itself, and therefore a source that supports a genuine skills-mismatch measure rather than a qualification-mismatch proxy.

PISA measures the foundational skills of 15-year-olds and functions as an upstream, pipeline indicator of the skill supply that will reach the labour market over the following decade or before. Both are supply-side and proficiency-based: neither carries a demand side, and both are designed for group-level reporting rather than fine disaggregation.

7.7.1. Survey of Adult Skills (PIAAC)[51]

7.7.1.1. Description

OECD computer-based household survey of adults aged 16–65 that directly assesses literacy, numeracy and adaptive problem solving[52]. It runs on a decadal cycle: Cycle 1 (2011–18, 39 countries, 245,000 adults) and Cycle 2 round 1 (2022–23, 31 countries and economies, 1.2 million adults). A background questionnaire covers skill use at work, education and training, and earnings. It is the only internationally comparable source measuring adult skills directly.

[50] Source: eurydice.eacea.ec.europa.eu

[51] Sources: https://www.oecd.org/en/about/programmes/piaac.html, and https://www.oecd.org/en/about/programmes/piaac/piaac-data.html.

[52] Adaptive problem solving is in Cycle 2. It replaced the Cycle 1 problem-solving-in-technology domain.

7.7.1.2. Methodological note

PIAAC supports three distinct mismatch measures on the same individuals:
- Qualification (vertical) mismatch: highest attainment versus the qualification the worker reports being usually required for the job, giving over- and under-qualification.
- Field-of-study (horizontal) mismatch: workers employed outside the occupational field of their highest qualification, via a normative crosswalk to ISCO.
- Skills mismatch (over-/under-skilling): assessed proficiency (plausible values) outside the minimum–maximum band of self-reported well-matched workers in the occupation, plus over-/under-use of skills. The OECD treats this as a developmental measure, not for strict international comparison.

7.7.1.3. Strengths

- Combining direct proficiency, skill use, qualification, occupation (ISCO), industry and earnings on the same respondent enables triangulation of vertical, horizontal and skill mismatch.
- Harmonised sampling and plausible values give comparable literacy and numeracy scores.
- Microdata are available as country Public Use Files.

7.7.1.4. Limitations

- Decadal frequency (only two cycles; adaptive problem solving not back-comparable), so no cyclical monitoring.
- Incomplete and shifting country coverage (39 → 31), with not all EU members in every cycle.
- Regional identifiers generally absent from the Public Use Files, precluding NUTS-2 spatial-mismatch analysis.
- ~5,000 respondents per country limit disaggregation and small cells may be unreliable.
- The skills-mismatch indicator is developmental and sensitive to the well-matched anchor; cross-sectional, with finest occupation/region detail requiring restricted access.

7.7.2. Programme for International Student Assessment (PISA)[53]

7.7.2.1. Description

OECD assessment of 15-year-olds' functional literacy in reading, mathematics and science near the end of compulsory schooling, run since 2000 with a rotating major domain. PISA 2022 (the 8th

[53] Sources: https://www.oecd.org/en/about/programmes/pisa.html, and https://www.oecd.org/en/publications/pisa-2022-results-volume-i_53f23881-en.html.

[54] Additional to PISA there exists also two sources of data managed by the International Association for the Evaluation of Educational Achievement (IEA) that provide data on math, science and reading competencies. The first in TIMSS (Trends in International Mathematics and Science Study), which assesses the mathematics and science knowledge of fourth- and eighth-grade students. Conducted every four years since 1995, it involves over 70 education systems. Similar to PISA, it measures attitudes toward science and mathematics. Because education systems vary in structure and in policies and practices regarding school-starting age and promotion and retention, there are differences across countries in how the target grades are labelled and in the average age of students. In addition, some countries choose to administer TIMSS to a different grade than the fourth year of formal schooling. In TIMSS 2023, data on 4th-graders are available for 21 EU MS, while on 8th graders they are available for 13 EU Member States. An important distinction between PISA and TIMSS lies in their assessment philosophy. PISA adopts a literacy-based approach, measuring students' ability to apply knowledge and skills to real-world situations, regardless of what is taught in school curricula. TIMSS, by contrast, is curriculum-based: its assessment framework is built upon the curricula of participating countries, measuring the extent to which students have learned the content prescribed by their education systems. This difference has practical implications for interpreting results: TIMSS scores more closely reflect what has been taught in schools, while PISA scores reflect students' capacity to transfer and apply knowledge across diverse contexts. As a consequence, a country may perform differently on the two assessments depending on the alignment between its curriculum and the skills measured.

cycle; mathematics major) covered 690,000 students across 81 countries and economies[54]. Performance is reported on described proficiency levels, with Level 2 the baseline.

7.7.2.2. Methodological note

PISA is not designed as a labour-market mismatch instrument; it is a leading, pipeline indicator of the foundational skill supply entering the workforce over the following decade[55]. It surfaces upstream inefficiencies through the share below baseline Level 2 (future low-skilled adults), the share at Levels 5–6 (high-skill supply), the socio-economic gradient (efficiency and equity of skill formation), and cross-cycle trends such as the post-2018 decline. Like PIAAC it uses matrix sampling and plausible values, so scores are for group-level reporting. Key derived indicators include:

— The average scores in mathematics, reading and science.
— The share of underachieving students (less than level 2). This is a forward-looking indicator of potential skills gaps.
— The share of top performers (levels 5 and 6). This indicates the supply of high-skill talent.

7.7.2.3. Strengths

— The largest and most established comparable assessment of foundational skills, with a trend series since 2000 across 80+ systems.
— Direct cognitive assessment with robust psychometrics.
— Rich contextual microdata (socio-economic status, school factors) to diagnose drivers and equity.
— Early-warning value, since the share below Level 2 anticipates the low-skilled adult share later measured by PIAAC.
— Microdata public and free.

7.7.2.4. Limitations

— It assesses 15-year-old students, not the labour force. Therefore, it measures potential labour supply, not realised mismatch, and carries no demand side, occupations or wages. It cannot measure mismatch in the labour-market sense.
— It is a repeated cross-section, not a panel, by design.
— It excludes out-of-school youth, with sampling-standard caveats flagged for several countries in 2022.
— Designed for system-/country-level reporting, with reliable sub-national estimates only where regions are oversampled.

The second source of data, also managed by IEA is PIRLS (the Progress in International Reading Literacy Study). Conducted every five years since 2001, PIRLS provides internationally comparative data on how well children read and offers policy-relevant information for improving learning and teaching. PIRLS provides trends and international comparisons of fourth grade students' reading achievement and students' competencies in relation to goals and standards for reading education. 21 EU Member States participated to PIRLS 2026.

[55] There exists a specific source of data on students' digital competencies. ICILS (International Computer and Information Literacy Study), conducted by IEA, evaluates the computer and information literacy of 8th-grade students. It assesses how students use information and communications technology (ICT) to research, create, and communicate. Two main measures of knowledge and skills for digital competences are used in ICILS: the Computer and Information Literacy (CIL) scale and the Computational Thinking (CT) scale. The CIL scale captures one's ability to use computers to search for, acquire, and process information, to create content and to communicate with others, while the CT scale measures critical and abstract thinking and problem solving competencies, as it involves one's ability to identify, test and implement possible solutions to the problem at hand and to analogous problems that might arise in a new context or situation. In 2023 measures for CIL scores and related variables are available for 21 EU Member States, while the CT scores and related variables are available only for 16 EU Member States.

7.8. European Training Foundation (ETF)

The European Training Foundation (ETF) is an EU agency supporting human capital development in countries neighbouring the European Union. Established in 1994 and based in Turin, Italy, its mission is to support countries bordering the EU in reforming their education, training, and labour market systems to improve human capital development, with a focus on enhancing employability, boosting competitiveness, and promoting social inclusion. The ETF's data and indicators are primarily designed for neighbourhood countries so their direct relevance to EU skills intelligence is indirect and operates through specific channels (e.g. through collaboration with CEDEFOP, notably the second European Skills and Jobs Survey (ESJS2, 2023), where Cedefop joined forces with the ETF to expand the survey's scope beyond EU Member States to include neighbourhood countries — making ETF data directly comparable with EU-internal benchmarks).

7.9. Private-sector data: Lightcast, LinkedIn

Beyond the public-sector institutional infrastructure described in previous sections, two private-sector data providers have become increasingly influential in European skills intelligence: Lightcast (formerly EMSI Burning Glass) and LinkedIn Economic Graph.

7.9.1. Lightcast[56]

Lightcast is a global labour market analytics company that collects and processes online job advertisements (OJAs) from job boards, corporate career sites, and public employment service portals across Europe and worldwide.

Its European coverage spans all EU-27 countries plus the UK, Switzerland, and Norway. Lightcast operates its own proprietary collection and NLP pipeline. Lightcast's taxonomy maps extracted skills to both ESCO and O*NET frameworks, and its historical database extends back to approximately 2012 in many European countries, enabling trend analysis.

7.9.1.1. Strengths

— Longer historical time series, compared to those in the Web Intelligence Hub (WIH);
— access to OJA microdata (including of the job ad's full text);
— fine occupational granularity (proprietary taxonomy mappable to ISCO 4-digit and SOC codes);
— firm-level identifiers enabling linkage with company-level datasets;
— salary data extraction from job ads where available.

7.9.1.2. Limitations

— Proprietary and commercial — access requires institutional licensing agreement, and the underlying algorithms (deduplication, skill extraction, occupation classification) are not fully documented in the public domain.
— Coverage bias : under-representation of offline recruitment channels, SME informal hiring, agriculture, care work.
— No governance framework ensuring methodological transparency or comparability standards.

7.9.2. LinkedIn Economic Graph[57]

LinkedIn's Economic Graph Research programme publishes aggregate statistics on workforce composition, hiring rates, skill migration patterns, and talent flows, derived from approximately 65

[56] Source: https://lightcast.io/

[57] Source: https://economicgraph.linkedin.com/

million EU-based member profiles and employer postings. LinkedIn publishes a monthly Workforce Report for several European countries.

Relevance: LinkedIn data captures dimensions that no official source covers: real-time hiring rates by occupation and skill cluster; geographic talent migration flows between cities and countries; the diffusion speed of new skills (e.g. generative AI, green hydrogen engineering) as measured by profile skill additions; and employer brand attractiveness metrics.

7.9.2.1. Limitations

— Demographic and occupational selection bias: LinkedIn's membership skews heavily toward white-collar professional, managerial, and technical workers, with very low penetration among manual, agricultural, service-sector, and public-administration workers.
— Geographic coverage is non-uniform: LinkedIn penetration is said to exceed 50% of the working-age population in the Netherlands, Ireland, and the Nordic countries, but falls below 20% in many Eastern and Southern European countries.
— The data is derived from self-reported profiles, not administrative records or employer submissions.
— Methodological documentation is limited, and LinkedIn periodically changes its algorithms and data access policies, creating reproducibility challenges.

7.10. National Administrative Data

Administrative data — records generated as a by-product of regulatory, fiscal and social protection processes — represent a high-potential source of skills intelligence within the EU. Unlike survey-based instruments, which are periodic and resource-intensive, administrative data are collected continuously, cover entire populations rather than mere samples, and can be linked across registers to produce multi-dimensional pictures of the labour market. The most analytically powerful configuration for these purposes is the **linked employer-employee dataset** (LEED). By combining firm-level metrics (e.g., sector, size, productivity, technology adoption, and wage bill) with individual worker records (e.g., occupation, earnings, tenure, qualifications, and employment transitions), LEEDs provide a granular view of labour dynamics.

Prominent European examples include the Finnish FLEED, the Danish IDA database, the Swedish LISA register, the German IAB Linked Employer-Employee Data (LIAB), the French DADS-EDP.

7.10.1. Strengths of Administrative LEEDs

Administrative LEEDs offer distinct advantages over survey-based intelligence and Online Job Advertisements (OJAs):
— Comprehensive Coverage: Full population coverage eliminates sampling error, allowing for highly granular disaggregation across occupational, sectoral, and regional levels (including NUTS-3 and below) that surveys cannot support.
— Temporal Precision: Continuous collection enables near-real-time monitoring, moving beyond the limitations of periodic snapshots.
— Longitudinal Depth: The longitudinal nature of social insurance records facilitates the analysis of individual career trajectories, enabling the identification of long-term trends such as skills depreciation and occupational displacement.
— Multidimensionality: where data can be linked across registers to produce multi-dimensional pictures of the labour market.

7.10.2. Limitations

Despite these benefits, there is a notable gap in comparable, cross-EU skills intelligence indicators derived from administrative data. This is primarily driven by the following factors:

- Purpose Mismatch: Administrative datasets are designed to satisfy regulatory and fiscal requirements rather than for the specific purpose of skills intelligence.
- Low international comparability: Unless the data are explicitly linked to common statistical frameworks, they mainly reflect national frameworks for which they are collected, mostly in the official languages of the relevant country.
- Limited data access: Access to and the usage of these detailed and personal data are limited in view of data protection.

7.11. EU-funded research Projects (Horizon Europe, Erasmus+)

The EU has mobilised significant research and cooperation funding through two complementary programmes: Horizon Europe and Erasmus+.

The comparison table in the Annex 1. It includes an (illustrative) selection of EU-funded projects launched since 2023 that contribute directly to skills intelligence in Europe.

The evidence generated in these projects can complement the monitoring and analytical work of EU agencies — notably Eurofound, Cedefop and the European Labour Authority — and may generate open-access tools, composite indicators, occupational profiles and transferable policy frameworks that national governments, regional authorities, social partners and education providers can integrate into their own skills planning and anticipation systems.

For each project, the table in the Annex provides the programme and call reference, duration, primary skills perspective (supply, demand or both), key objectives and methods, expected outputs, policy framework links, and direct hyperlinks to the project website and CORDIS or Erasmus+ portal entry.

8. Criteria for the Selection of Indicators for the ESIO Dashboard

The sources reviewed in the preceding sections yield more candidate indicators than a single dashboard can usefully and meaningfully present. This section sets out the criteria used to prioritise among them. The criteria are intended to be **transparent** and **reproducible**, so that the rationale for including or omitting any given indicator can be made clear to ESIO stakeholders.

Two points define how the criteria are to be read. First, they assess the suitability of an indicator for the specific purpose of the ESIO Dashboard, namely the regular monitoring of skills demand, supply, and mismatch across the EU. An indicator may be excellent for its original purpose and still score relatively low for dashboard use, for example because it is updated infrequently or is not available on a comparable basis across Member States. Second, the criteria are applied comparatively, to rank candidate indicators relative to one another rather than as fixed thresholds that an indicator must clear. The appropriate balance among them depends on the policy question, so an indicator that scores moderately on several criteria may still be retained where it fills a gap that no better-scoring alternative covers.

Box 4. How to read the score for each indicator

> Each indicator is scored from 1 to 3 on each of the seven criteria, where 3 is most favourable for dashboard use and 1 least favourable. The scores are descriptive markers of fitness for purpose, not quality ratings, and the score for each indicator is recorded alongside it so that the basis for its inclusion or omission is transparent and can be revisited as data sources evolve.

The dashboard applies seven transparent selection criteria.

1. Coverage

Indicates the geographical, sectoral, or occupational scope of the data. Wider coverage ensures the indicator can be applied for comparative studies across countries, industries, or regions.

3: Available for all or nearly all Member States on a harmonised basis, permitting direct comparison.

2: Available for a substantial subset of Member States, or available widely but with some definitional differences across units.

1: Available for few Member States, or on bases that are not readily comparable.

2. Timeliness / Update Frequency

Assesses how current the indicator is and how often it is updated. This criterion concerns the publication cadence of the indicator. Frequency is often fixed by survey design or legal mandate.

3: Updated at least annually and released with a short lag.

2: Updated every two to three years, or annually but with a long lag.

1: Updated less often than every three years, or on an irregular basis.

3. Granularity

Refers to the level of detail at which the indicator is available, such as task, occupation, sector, educational levels, or regional breakdowns. Finer granularity supports more precise policy targeting. Where an indicator is available at several levels, the level used in the dashboard is recorded.

3: Detailed breakdowns available, for example 3-digit occupation, detailed sector, or sub-national region.

2: Intermediate breakdowns available, for example 1- to 2-digit occupation or broad sector.

1: Available only at aggregate or headline level.

4. Accessibility / Availability

Evaluates whether the underlying data are openly available, available on request, or subject to restriction, licensing, or purchase. This is recorded because it affects how the indicator can be updated and reused, not as a judgement on the source. Restricted access does not by itself exclude an indicator.

3: Openly and freely available, supporting straightforward reuse and reproduction.

2: Available on request or under conditions that permit regular updating.

1: Subject to purchase, licensing, or access controls that constrain routine updating.

5. Computability

Measures the amount of processing required to derive the indicator from available data. This records the effort and methodological transparency involved, not the merit of more complex indicators, which may be retained where the information they provide is not otherwise available.

3: Available directly or with minimal transformation.

2: Requires moderate processing, such as standard aggregation, mapping, or combination of sources.

1: Requires extensive mapping, integration, or modelling, with a correspondingly higher need for documentation.

6. Relevance and interpretability

Assesses how directly the indicator measures skills demand, supply, or mismatch, and how readily a policymaker can interpret what it conveys. This is an indicator-content-related criterion. It is considered because a well-formed indicator that speaks only indirectly to skills imbalances is of limited use on the dashboard. An online-vacancy skill frequency and a qualification-mismatch rate may score identically on every formal criterion yet differ sharply in what they tell a policymaker, and this criterion is what distinguishes them.

3: Measures skills demand, supply, or mismatch directly, with a clear and unambiguous interpretation.

2: Measures a closely related construct or measures the target indirectly and requires some interpretation.

1: An indirect proxy whose link to skills imbalances is weak or open to competing interpretations.

7. Reliability and methodological transparency

Measures whether the indicator construction is documented and stable over time or instead depends on limited methodological information or frequently revised methods. This criterion is distinct from computability, which records the effort of producing an indicator rather than the soundness of the result. It matters particularly for a dashboard intended to track trends, where an undocumented change in method can resemble a genuine change in the labour market. The criterion rewards documentation and stability rather than judging the merit of any method.

3: Construction is well documented, methodologically stable, and consistent across releases.

2: Documented but subject to periodic methodological revision, or with some breaks in series.

1: Poorly documented or methodologically unstable, so that changes over time are difficult to interpret.

Each candidate indicator is assessed against these seven criteria, the seven scores are recorded together, and the resulting profile informs whether the indicator is included in the dashboard and at what level of detail. The profile is retained so that selection decisions remain auditable and can be updated as sources change.

9. Conclusions

The evidence reviewed shows that the EU already possesses many highly relevant information sources on skills intelligence: official statistical sources, dashboards and forecast systems, online job advertisement intelligence, established taxonomies such as ISCO, ISCED, NACE and ESCO, and a growing set of EU-funded projects generating new methods, composite indicators and analytical tools. This report aims to lay the groundwork for a systematic mechanism selecting, combining and governing these components in a way that supports the Union of Skills and the Skills High-Level Board.

A practical next step is to operationalize this mapping towards a well-functioning data platform and dashboard, periodically updated and used to provide early warning signals on skills gaps and shortages.

A second conclusion concerns indicator governance. The report's seven-criterion scoring model provides discipline to the design of a dashboard because it makes explicit the trade-offs that are otherwise left implicit in many monitoring systems. No indicator is universally best. High-frequency online vacancy indicators provide early warning and fine detail but suffer from representational distortions and unequal cross-country coverage. Survey-based and administrative indicators offer stronger harmonisation and statistical legitimacy but are less timely and often coarser in occupational or skills resolution. Model-based forecast tools extend the time horizon but depend on assumptions and are not substitutes for current-state measurement. This report's contribution is to spell out these tensions so that inclusion decisions are transparent, revisable and tied to policy purposes. For ESIO, this means that dashboard construction should remain modular, with different layers serving different functions: a core layer of highly comparable EU-wide indicators; a supplementary layer of early-warning and experimental indicators; and a methodological register, to which this report belongs, documenting the strengths, limits of indicators and updating characteristics of each source.

A third conclusion is that both synthesized evidence (that is comparable and stable over time) and more forward-looking and implementation-oriented intelligence is available. Indicator scorecards can help determine which measures are suitable for recurring strategic monitoring. Occupational profiles and ESCO-linked skills evidence can connect labour market signals to education and training responses. The report thus provides a concrete basis for strengthening links between technical analytics and political governance.

At the same time, the report underscores that important gaps remain. The current infrastructure does not yet fully overcome fragmentation across institutions and source types. Comparability remains weak for some of the most policy-relevant high-frequency signals. Existing mismatch metrics still rely heavily on education or occupational proxies and do not adequately capture task change, competency intensity, or skills utilisation. While there is no perfect data on the horizon, ESIO could contribute to a staged maturity model for indicators and evidence products.

The report points towards a practical technical roadmap.

First, apply the seven-criterion indicator assessment as a permanent governance instrument, so dashboard choices remain auditable and updateable.

Second, organise platform data-outputs into interoperable layers built around common classifications, especially ISCO, ISCED, NACE and ESCO, to allow cross-source linking and more coherent drill-down from aggregate indicators to occupational and skills details..

Third, use established indicators as the backbone for harmonised monitoring, while incorporating, with time, online vacancy intelligence and funded-project outputs in a controlled supplementary layer to enhance timeliness and experimentation.

Fourth, treat EU-funded projects as a structured innovation pipeline, with regular review of whether their tools, composite measures or analytical models can be included into Observatory services.

Fifth, strengthen documentation of limitations alongside all published metrics, especially where cross-country comparability is constrained or conceptual proxies are being used.

In sum, the report concludes that the value of ESIO will depend less on creating a new standalone architecture than on establishing a functional system for evidence integration, transparent indicator governance, and policy-facing analytical delivery. The technical work presented here advances that objective by specifying what can be mapped, how indicators should be selected, how diverse sources can be joined through common classifications, and how outputs can support governance under the High-Level Board in the context of the Union of Skills. This makes the report not only an analytical review, but a practical blueprint for the Observatory's data platform and dashboard.

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List of abbreviations and definitions

Abbreviations	Definitions
AES	Adult Education Survey
AMECO	Annual Macro-Economic database
CORDIS	Community Research and Development Information Service
CVT	Continuing Vocational Training
CVTS	Continuing Vocational Training Survey
Cedefop	European Centre for the Development of Vocational Training
DG	Directorate-General
DG COMM	Directorate-General for Communication
DG EAC	Directorate-General for Education, Youth, Sport and Culture
DG EMPL	Directorate-General for Employment, Social Affairs and Inclusion
DigComp	Digital Competence Framework for Citizens
E3ME	Energy-Environment-Economy Macro-Econometric model
EC	European Commission
ECEC	Early Childhood Education and Care
ECS	European Company Survey
EEA	European Economic Area
EFTA	European Free Trade Association
EHESO	European Higher Education Sector Observatory
EJM	European Jobs Monitor
ELA	European Labour Authority
EQF	European Qualifications Framework
EQLS	European Quality of Life Survey
ESCO	European Skills, Competences, Qualifications and Occupations
ESIO	European Skills Intelligence Observatory
ESJS	European Skills and Jobs Survey
ETER	European Tertiary Education Register
ETF	European Training Foundation
ETLS	European Training and Learning Survey
EU	European Union
EU-27	European Union (27 Member States)
EU-LFS	European Union Labour Force Survey
EU-SILC	European Union Statistics on Income and Living Conditions
EURES	European Employment Services

Abbreviations	Definitions
EWCS	European Working Conditions Survey
EWCTS	European Working Conditions Telephone Survey
Eurofound	European Foundation for the Improvement of Living and Working Conditions
GDP	Gross Domestic Product
HEI	Higher Education Institution
ICCS	International Civic and Citizenship Education Study
ICILS	International Computer and Information Literacy Study
ICT	Information and Communication Technology
IEA	International Association for the Evaluation of Educational Achievement
IESS	Integrated European Social Statistics
ISCED	International Standard Classification of Education
ISCED-F	International Standard Classification of Education: Fields of Education and Training
ISCO	International Standard Classification of Occupations
ISCO-08	International Standard Classification of Occupations, 2008 revision
JRC	Joint Research Centre
JVR	Job Vacancy Rate
JVS	Job Vacancy Statistics
LEED	Linked Employer-Employee Dataset
LFS	Labour Force Survey
LSP	Large-Scale Skills Partnership
LSSI	Labour and Skills Shortage Index
NACE	Statistical Classification of Economic Activities in the European Community
NCO	National Coordination Office
NEET	Not in Employment, Education or Training
NLP	Natural Language Processing
NSI	National Statistical Institute
NUTS	Nomenclature of Territorial Units for Statistics
O*NET	Occupational Information Network
OECD	Organisation for Economic Co-operation and Development
OJA	Online Job Advertisement
PES	Public Employment Service
PIAAC	Programme for the International Assessment of Adult Competencies
PIRLS	Progress in International Reading Literacy Study

Abbreviations	Definitions
PISA	Programme for International Student Assessment
ReICO	Research and Innovation Careers Observatory
SME	Small and Medium-sized Enterprise
SOC	Standard Occupational Classification
STAS	Skills Trends and Anticipation System
STEM	Science, Technology, Engineering and Mathematics
Skills-OVATE	Skills Online Vacancy Analysis Tool for Europe
TIMSS	Trends in International Mathematics and Science Study
UK	United Kingdom
US	United States
UoS	Union of Skills
VET	Vocational Education and Training
WIH	Web Intelligence Hub

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Annexes

Annex 1. EU-Funded Research Projects

Table 17. Selected EU-funded Horizon Europe projects on skills intelligence (2023 onwards)

Acronym	**Full Title**	**Duration**	**Key Objectives & Skills Focus**	**Links**
SkillsPULSE	Skills — Predicting, Understanding, and Locating Shortages in Europe	Jun 2024 – May 2027	Develops a comprehensive framework integrating traditional LMI with online job vacancy data and AI analytics to identify emerging skills, measure shortages and assess how education/training systems respond. Builds a composite Skills Shortage Index.	Project site CORDIS
SKILLAB	Monitoring the Demand and Supply of Skills in the European Labour Market	Jan 2024 – Dec 2026	Designs an intelligent platform for monitoring labour market skills and gaps. Uses LLMs and AI to extract skill/ occupation data from job postings, extend the ESCO taxonomy, identify skills at risk, and align curricula with labour market needs.	Project site CORDIS
SkiLMeeT	Skills for Labour Markets in the Green and Digital Transition	Jan 2024 – Dec 2026	Generates indicators quantifying labour and skills shortages and mismatches, explores drivers (digital/green transitions, demographics), and analyses pathways to reduce skill gaps. Focuses on	Project site CORDIS

Acronym	Full Title	Duration	Key Objectives & Skills Focus	Links
			how technological progress shapes educational choices.	
TRAILS	Training and Labour market AI-enabled Skills System	2024–2027	Creates novel tools and databases harnessing AI for skills mismatch. Develops AI real-time skill profiling and matching, analyses AI training in VET/adult learning, identifies behavioural biases, and links VET providers to employer needs.	Project site CORDIS
Link4Skills	Linking Fair Skill Matching — Global Research on Skill Shortages	2024–2027	Assesses existing and emerging required skills; evaluates four responses to shortages (upskilling, wages, automation, migration) across four continents. Develops an AI-Assisted Skill Navigator (open-access expert system).	Project site CORDIS
GS4S	Global Strategy for Skills, Migration, and Development	2024–2027	Addresses global skills shortages in the digital, care and construction sectors. Examines MNE/SME strategies and global mobility schemes. Co-creates a global strategy to address shortages and propose alternatives to migration.	Project site CORDIS
SKILLS4JUSTICE	Skill Partnerships for Sustainable and	Nov 2023 – Oct 2026	Systematic analysis of skills	Project site CORDIS

Acronym	Full Title	Duration	Key Objectives & Skills Focus	Links
	Just Migration Patterns		shortages in five EU destination countries (DE, FR, IT, PL, LT) and six non-EU countries. Examines skill partnerships, qualification recognition, sustainable migration and workforce integration.	
SKILLS2CAPABILITIES	From Skills to Capabilities: Understanding Skills Systems for Labour Market Transitions	Jan 2023 – Dec 2025	Examines how skills systems can reduce mismatch by equipping individuals with capabilities for frequent labour market transitions. Addresses demand-side (current/future skills) and supply-side (VET programmes' reflection of capabilities). Provides a methodology and tool for decision-makers.	Project site CORDIS
DocTalent4EU	Transforming Europe Through Doctoral Talent and Skills Recognition	2023–2025	Enhances PhD employability through ESCO-based recognition of transferable skills. Builds a machine learning prototype to predict in-demand skills at EQF level 8 from job offer data. Develops local talent management centres with a multi-actor approach.	Project site CORDIS

Acronym	Full Title	Duration	Key Objectives & Skills Focus	Links
VETprep	VET Participation, Retention, and Educational Policies in the Wake of COVID-19	Jan 2025 – Dec 2027	Examines challenges in VET related to student identification, participation and retention. Focuses on students from diverse backgrounds and COVID-19 impact. Informs policy on improving VET as a pathway to labour market integration for young people.	Project site CORDIS

Source: Authors' elaboration

Table 18. Selected EU-funded Erasmus+ projects on skills intelligence (2023 onwards)

Acronym / Alliance	Full Title / Sector Alliance	Action Type / Industrial Ecosystem	Duration	Key Objectives & Skills Focus	Links
AEQUALIS4TCLF	Addressing Skills Gaps in the European Textile, Clothing, Leather and Footwear Industries (Equality, Innovation, Resilience)	Lot 2 Blueprint Alliance — 2023 call; Textiles-Clothing-Leather-Footwear	Feb 2024 – Jan 2028	Seeks to bridge the skills gaps in the Textile, Clothing, Leather and Footwear (TCLF) sectors by focusing on advancing sustainability, digital transformation and innovation. Aims to equip HEI students and TCLF industry professionals with the knowledge and skills needed in a rapidly changing industry landscape.	Project site Erasmus+ portal
ASSETs+	Alliance for Sectoral Skills in Emerging	Lot 2 Blueprint Alliance; Sector Skills Alliances	2020–2024	Aimed to build a sustainable human	Project site Erasmus+ portal

Acronym / Alliance	Full Title / Sector Alliance	Action Type / Industrial Ecosystem	Duration	Key Objectives & Skills Focus	Links
	Technologies in Defence	in vocational education and training; Aerospace and defence		resources supply chain for the European defence industry: (1) exploring emerging trends in technologies and skills in robotics, autonomous systems, AI, cybersecurity and C4ISTAR; (2) translating results into concrete concepts as a basis for new education and training programmes; (3) conceiving a European Defence Qualification System covering pedagogical and technical aspects while complying with education requirements and industrial needs.	
spaceSUITE	SpaceSUITE — Space Downstream Skills Development and User Uptake through Innovative Curricula in Training and Education	Alliances for Sectoral Cooperation on Skills (implementing the 'Blueprint'); Aerospace	2024–2027	The main objective is to empower a skilled workforce in the downstream space sector.	Project site Erasmus+ portal

Acronym / Alliance	Full Title / Sector Alliance	Action Type / Industrial Ecosystem	Duration	Key Objectives & Skills Focus	Links
AI4VET4AI	AI-Powered Next Generation of VET — Centres of Vocational Excellence for AI Skills	Centres of Vocational Excellence; Cross-sectoral (AI/Digital)	2024–2027	Addresses the skills gap in AI technologies by incorporating AI content and methods into VET curricula across 11 European countries. Maps AI skills demand; develops standardised AI competency frameworks; builds VET-industry partnerships for AI apprenticeships.	Project site Erasmus+ portal
GreenSkills4H2	Green Skills for Hydrogen — VET Alliance for Hydrogen Competences	Alliance for Education and Enterprises; Energy/ Hydrogen	Jul 2022 – Jun 2026	Designs and implements a hydrogen skills strategy for Europe to ensure the skills needs of the expanding hydrogen value chain can be met in the short, medium and long term. Addresses the skills needs of workers in declining sectors and transition regions, providing upskilling and reskilling opportunities to access new employment within the	Project site Erasmus+ portal

Acronym / Alliance	Full Title / Sector Alliance	Action Type / Industrial Ecosystem	Duration	Key Objectives & Skills Focus	Links
				hydrogen sector.	

Source: Authors' elaboration

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