



CEPS POLICY BRIEF
GI-NI H2020 PROJECT

SHAPING TOMORROW'S WORKFORCE: EU POLICY PRIORITIES FOR SKILLS

Cinzia Alcidì

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Key points

While the European Year of Skills ended this month, skills will remain a key topic of discussion in the years to come, paving the way for a 'Decade of Skills.' This juncture provides an opportunity to reflect on the current understanding of skills and their impact on labour market dynamics, a topic which fully aligns with the GI-NI project's aim to study the impact of technological transformation on the labour market.

As structural transformations catalysed by technological advancements and shifting EU policy priorities continue to unfold, progress is necessary to i) clarify concepts like jobs, skills, tasks and occupations, ii) create standardised, but flexible, taxonomies, and iii) properly integrate different, reliable data sources. Building on these innovations and the recent findings of the literature on the impact of artificial intelligence (AI) on skills and work, we can distil four recommendations:

- **Anticipate Future Skills Demands:** Utilise skills intelligence to identify upskilling and reskilling needs, address shortages, and develop proactive education and training programmes. Promote occupational mobility to boost productivity and create pathways for vulnerable workers.
- **Promote and Embrace Lifelong Learning:** Encourage continuous learning and adaptation to new technologies and industry changes. Ensure access to lifelong learning opportunities, as job retention and growth depend on this capability.
- **Enhance Labour Market Integration:** Align skills training with industry demands to integrate newcomers and foster entrepreneurship and innovation. Modernise education and training systems and incentivise industry-specific training in key sectors.
- **Address Redistribution Impacts:** Understand and mitigate the redistribution impacts of AI. Ensure equal access to quality education, training, and employment opportunities to prevent inequality. Enhance redistributive policies to address ex-post income disparities.

In conclusion, the future of work can be shaped for the better. Policy and business decisions, as well as workers' engagement today, will determine the future landscape and create good opportunities for shared prosperity.



DrCinzia Alcidi is a Senior Research Fellow at the Centre for European Policy Studies (CEPS), where she is also head of the Economic Policy Unit and the Jobs and Skills Unit. She is grateful to Steven Dhondt, Gerben Hulsege and Laura Nurski for their insightful comments. CEPS Policy Briefs present concise, policy-oriented analyses of topical issues in European affairs. As an institution, CEPS takes no position on questions of European policy. Unless otherwise indicated, the views expressed are attributable only to the authors in a personal capacity and not to any institution with which they are associated. This Policy Brief is a deliverable of the Horizon 2020 GI-NI project (grant agreement number 101004494). Some of its reflections are inspired by an expert meeting jointly organised by CEPS and the European Commission's DG Employment, Social Affairs & Inclusion in the context of the European Year of Skills.

As the [European Year of Skills](#) officially concluded on 8th May 2024, the academic community and stakeholders within the field of skills foresee that skills will remain a key topic of discussion in the years to come, paving the way for a 'Decade of Skills.'

This juncture provides an excellent opportunity to reflect on the current understanding of skills and their impact on labour market dynamics and competitiveness and to anticipate future policy challenges. It also prompts a re-evaluation of how policymakers can strategically focus their efforts on key areas to drive progress and innovation in the realm of skills development and skills use in the workplace. These issues are closely related to the GI-NI project's work on the impact of technological transformation on labour market outcomes and the project's purpose to contribute to forward-looking thinking to support EU policymakers' decisions.

Context

In today's ever-evolving workforce landscape, leveraging data and insights about individuals' skills has become a vital tool for navigating the complexities of the labour market. Known as skills intelligence, this approach involves systematically collecting, analysing, and applying insights related to the skills landscape, including in-demand skills, emerging trends, and the diverse skill sets of the current workforce. Organisations, both public and private, have increasingly recognised the importance of investing in skills intelligence but also in knowledge about effective skills development and effective skills use in the workplace. This investment reflects a growing understanding of the pivotal role that data-driven decision-making plays in fostering organisational agility, sustainability, economic competitiveness, labour market inclusivity and, not least, effective policymaking.

In the EU, initiatives related to skills intelligence trace back to 2010 when the European Commission introduced the [ESCO \(European Skills, Competences, Qualifications and Occupations\)](#) classification. ESCO categorises skills, competences, and occupations relevant to the EU labour market and education and training to facilitate the alignment of skills with occupations and qualifications and enhance labour mobility and employment prospects. As structural transformations catalysed by technological advancements and shifting EU policy priorities (e.g. greening the economy or global competitiveness) continue to unfold, the ESCO system (and other international systems) must evolve and adapt to capture dynamic relationships between different concepts. This is just one example of how current changes are challenging the capacity of established concepts, indicators and data sources to provide a good representation of the labour market dynamics.

Amidst these developments, informed decision-making about education and training policies, industrial strategies, and technology adoption requires identifying areas experiencing skills shortages, forecasting skill needs, and addressing mismatches. A comprehensive skills intelligence system, characterised by robust data, well-defined concepts, and standardised, but flexible, taxonomies, can support such a process.

For this purpose, three steps, which represent the focus of the rest of this policy brief, are key. First, progress is necessary to clarify concepts like jobs, skills, tasks and occupations, and how they relate to and depend on each other. The existence of a standardised taxonomy would facilitate the task. Second, reliable information is of key importance, and the strengths and limitations of different data sources should be well understood. Third, it is time to take stock of the key messages from recent literature on labour market developments, particularly about exposure to artificial intelligence (AI). Drawing on such insights, we can distil some messages for the EU policymakers to direct efforts in key areas to shape the labour force of tomorrow and promote shared prosperity.

Need to clarify concepts and build standardised taxonomies

Over the last decade, skills have gradually emerged as a crucial unit of analysis for understanding labour market dynamics, offering a more nuanced view of workforce capabilities, compared to established concepts. The focus on **skill**, defined as ‘the ability to perform a task well’¹, reflects several key developments.

First, while [mismatches between the supply of and demand for skills](#) are a labour market feature in normal circumstances, they can grow in the context of major changes like the twin transition, demographic changes, and globalisation, as is the case today. When skills mismatches become substantial and persistent, they can significantly impact labour productivity, firm innovation, unemployment rates, wages, and job satisfaction. This can lead to suboptimal economic and social outcomes.

Second, in labour markets, formal qualifications are increasingly supplemented by individual skills and knowledge, making skills more important than in the past. This trend has emerged with the so-called [great resignation](#) and expanded during Covid-19, in response to labour market shortages in many sectors. Recent evidence from employers' surveys and job postings, points to a decline in the value (premium on) institutionalised learning, as companies are increasingly prioritising hiring based on skills rather than

¹ This definition is borrowed from the [JRC](#). In their definition, one skill relates to one task while competencies (that include bundles of skills, knowledge, attitudes and expertise) relate to bigger task domains (or bundles of tasks, that could be jobs). Following [Autor \(2010\)](#), a task is the unit of work activity that produces output.

formal degrees. The [skills-first approach](#), by favouring hiring based on individual skills and knowledge often acquired outside formal qualifications, boosts the number of applicants but often also the matching and even the duration of the working relations. The attractiveness of this approach is being reinforced by a growing demand for soft and transversal² skills across the professional landscape. Such skills are gradually being integrated into organisations' skills development and educational and training systems but do not yet appear in formal qualifications systematically.

Interestingly, the skills-first approach has the potential to support the integration of persons who may face obstacles pursuing high-quality formal education into the labour market and can benefit those traditionally disenfranchised. This is particularly important in the context of digital transformation, which appears to most prominently affect lower-skilled jobs³.

Third, the focus on skills allows for a detailed and nuanced analysis that cannot be achieved by focusing on **occupations**⁴ or educational achievements, two more traditional indicators of labour market dynamics. Typically, thousands of skills can be identified and classified. However, it is important to recall that a **job**⁵ is not defined by a single skill and jobs are empirical manifestations of the theoretical construct of occupations. Hence, the concept of occupation remains key from both an analytical and policy point of view. Despite the advantages of focusing on skills, occupations remain a fundamental concept in the context of collective bargaining and social protection – and therefore for understanding labour market institutions. Occupations, skills, and qualifications, all have value depending on the purpose of the analysis. This reinforces the value of a skill intelligence system that links and investigates them. Similarly, the role of education systems in offering relevant skills and preparing young individuals for the labour market is central, hence educational achievements must remain part of the labour markets analysis.

² According to the ESCO Member States Working Group on terminology for transversal skills and competences, “Transversal skills and competences are learned and proven abilities which are commonly seen as necessary or valuable for effective action in virtually any kind of work, learning or life activity. They are “transversal” because they are not exclusively related to any particular context (job, occupation, academic discipline, civic or community engagement, occupational sector, group of occupational sectors, etc.).

³ There is strong empirical evidence that jobs that involve repetitive tasks that can be automated easily, with machines or algorithms, typically lower-skilled jobs, are more exposed to automation and hence to displacement.

⁴ According to [ISCO](#), occupation refers to the work performed in a job. Occupation is defined as a ‘set of jobs whose main tasks and duties are characterised by a high degree of similarity’. A job is defined as a set of tasks and duties performed, or meant to be performed, by one person, including for an employer or in self-employment’.

⁵ A job is a specific position or role within an organisation that involves specific tasks, responsibilities, and duties. It is defined by the functions and responsibilities assigned to an individual.

The impact of the green and digital transitions

In practice, one coherent categorisation of skills and how they relate to occupations and tasks does not exist yet. As multiple skills taxonomies exist⁶, the comparison or combination of different data sources and empirical findings is complex and can lead to different diagnoses of a problem. Taxonomies are particularly important and challenging in the context of **green and digital transitions**. As new jobs emerge, the skills needed to perform the tasks defining those jobs are yet unknown. For instance, in the context of the green transition⁷, while ‘green jobs’ and ‘green skills’ are receiving attention in the media and policy discussions, there remains a lack of consensus on their precise definitions. Different skills, occupations, or tasks may contribute to the green transition without being inherently ‘green’. For these reasons experts are increasingly replacing the taxonomy of ‘green skills’ with one of ‘skills for the green transition’, but there is no single green taxonomy for the labour market. Additionally, taxonomies inevitably tend to be outdated by the time a consensus has been reached to create or update them. A way forward is to develop **taxonomies that combine bottom-up flexibility with sound top-down conceptualisations**.

In the context of the digital transition, the impact of new technologies, like **Generative AI**, on skills, and the labour market is still unfolding and not fully understood. Whilst initially thought to accelerate the dis/re-placement of repetitive jobs, Generative AI has proven able to replace more ‘intellectual’ tasks, like reading or deductive reasoning. Furthermore, AI could replace but also enhance certain categories of tasks (i.e. project or creative). This implies that to disentangle the impact of Generative AI on labour markets, one must look at tasks and their interdependence within organisational processes rather than jobs or individual skills.

Integrate different data sources

The digital transformation is reshaping the skill intelligence landscape through innovative data collection methods and advanced analytical tools – notably leveraging ‘big data’ and AI technologies. This transformation is fuelled by the abundance of information sourced from online job postings, which contain labour *demand* information, and platforms hosting CVs and professional data from individuals worldwide, offering insights into labour *supply*. The integration of these sources, coupled with the ability to swiftly and cost-effectively generate analytics, heralds significant changes in skills intelligence. Compared

⁶ In some cases, they are linked to different underlying occupational taxonomies that can be mapped to ISCO but might have different degrees of detail.

⁷ See for instance [Urban et al. \(2023\)](#).

to conventional sources like surveys and administrative data, these new data sources offer two significant advantages over their forebears.

First, they are far more **timely** than traditional data sources, which are often published with significant delays. These new sources provide real-time insights into the evolution of skills and job demand. Given the rapid pace of change in the labour market, this timeliness is vital to ensure that policymakers and business leaders have the most up-to-date and accurate evidence. The emergence of new sources has already prompted providers of traditional data to streamline release schedules, often leveraging advanced analytical tools to do so.

The second advantage of such new data sources is the **scope**. Most conventional data sources tend to cover a country or, at best, a region, and samples are often small – particularly when looking at occupational or skill-based breakdowns. New sources very often have much larger geographical coverage, even global, as well as a wider spectrum of information about occupations and skills.

Nonetheless, new data collection methods also suffer some limitations. New data sources rely on unsystematised data available on the internet⁸, which, unlike survey data, were not collected for statistical purposes. As such, they often contain unwanted information that must be filtered out.⁹

While this limitation raises a challenge in balancing real-time access with data reliability, the academic consensus is converging towards the need to integrate new and traditional data sources. Such a combination can provide new opportunities for analysis that draws on the strengths of both kinds of sources. The main challenge in integrating different sources is the absence of a '**common language**' for skills. While this is a pressing issue, it is not new. As mentioned above, in the EU, ESCO has been working towards this goal, but more effort is needed.¹⁰ A major step forward would be the adoption of the ESCO system in the private sector or, more reasonably, the establishment of a co-creation process that includes the private sector.

Furthermore, the current status of **data linking skills to jobs** is inadequate. The existence of different skills classifications and systems, such as O*NET/ESCO/UNESCO/ISCO-08, hampers the ability to leverage complementarities between data sources. Progress crucially requires coordinating efforts, seeking consent for data linkage between

⁸ There are still vacancies that are not published online, and distributed through mail, paper, or verbally. Because of this, sampling may be biased. However, non-online vacancies are likely to represent a limited part of the total and decline further in the future.

⁹ [They are also not representative of all types of skills and all occupations.](#)

¹⁰ Another challenge is related to the [GDPR](#) (General Data Protection Regulation). While it has the key role of protecting data privacy, its enforcement can act as a barrier to accessing administrative data and prevents effective integration.

databases, and establishing minimum procedural standards. Implementing these changes would represent a clear advance towards greater interoperability and more effective labour market analysis.

Importantly, one of the core objectives of skills intelligence and improved data collection is to better prepare companies, educational systems, and policymakers for the future, anticipating the skills needs. With new data sources and AI modelling capabilities, the supply of skills forecasts has surged to meet an expanding demand. Whilst experts agree that forecasting is an important tool, reliable forecasts should properly consider several contextual factors like upcoming technological advancements, demographic changes, economic conditions, and shifts in industry demand. This is a sizeable challenge, even when making use of novel predictive AI models and the increased sample size of new data sources, and it is not always done. Skills forecasts, therefore, should be engaged with critically. Many organisations favour forecasting skills trends over predicting specific skill needs in isolation, relying on skills foresight and different scenarios, which can better consider the uncertainties of tomorrow's labour market.

The impact of AI technologies on tasks, skills and work

Drawing on the large set of insights above and the burgeoning literature focusing on the impact of AI, we can identify three main messages that can help to navigate the complexities of a shifting workforce driven by AI.

AI-driven automation will lead to increased displacement of routine and repetitive tasks within jobs, well beyond manufacturing jobs, but [not necessarily to net job losses](#).¹¹ AI is likely to automate specific tasks within jobs rather than entire occupations. Instead of job losses, this can result in more tasks done by machines and in the augmentation of existing tasks, as workers can focus on higher-value tasks that require human capabilities. Furthermore, AI will create entirely new job categories, such as AI ethicists, machine learning engineers and data scientists. These jobs require human skills such as creativity, critical thinking, and emotional intelligence.

[The adoption of AI is leading to shifts in the types of skills demanded](#). Evidence points to a greater emphasis on technical skills, data literacy, and digital proficiency. There is a growing need for professionals with expertise in AI, machine learning, and data science, as well as skills in programming languages (such as Python and R) and skills related to big data processing, statistical analysis, and data visualisation, among others. At the same time, hybrid skill sets and non-technical skills are gaining importance. There is a rising demand for individuals who combine technical AI skills with domain-specific knowledge.

¹¹ See also Rademakers and Zierahn-Weilage (2024) forthcoming.

For example, combining AI expertise with finance or healthcare. The same holds for professionals who can bridge the gap between AI research and practical application, including those skilled in AI system integration, deployment, and maintenance. On a parallel track, typical human skills like critical thinking and creativity, which cannot be replaced by machines, have increased in value. For instance, for humans, it will be key to critically engage with AI to be able to judge when to trust and when not to trust a certain process and how to monitor the outputs of algorithms. Similarly, as AI takes over more mechanical tasks, human creativity becomes an invaluable skill, especially in fields like design, content creation, and strategic planning.

The increased adoption of [AI technologies requires job redesign](#), not only new skills. As an increased number of tasks are taken over by machines, organisations need to reconfigure tasks to combine human and machine capabilities and, hence, redesign jobs to improve the efficiency and productivity of work processes as well as the motivation and engagement of workers. For instance, AI can efficiently handle some routine tasks, enabling employees to handle more tasks or dedicate time to strategic planning and decision-making. Furthermore, collaboration between humans and AI will increase and is expected to develop further. For example, customer service representatives might use AI tools to provide faster and more accurate responses and data analysts might use AI to process large datasets and derive insights. All such changes require assessing the potential and desirability of automation and, more broadly, AI adoption, reconstructing the remaining tasks into new jobs and charting pathways from old to new jobs.

Where should policymakers focus efforts on?

Such insights must inform strategies, initiatives, and policy decision-making related to education, training, employment, and competitiveness. Companies must be prepared to shape the future of labour and workers are equipped to be part of such changes, to ensure engagement and prevent harm to job quality, and hence enjoy the benefits of the transformations. For this to occur, we identify four areas where policymakers' efforts should concentrate.

Anticipate future skills demands: insights from skills intelligence should be used to anticipate future skills demands and trends in the job market. This goes beyond short-term specific needs. Skills anticipation is about identifying areas where upskilling and reskilling are needed to address shortages and enable the proactive development of targeted education and training programs. Policies should also focus on increasing occupational mobility in sectors with growing demand to boost productivity and, above all, to generate viable pathways for vulnerable workers to secure employment. Extensive upskilling and reskilling programmes will be needed to help workers transition to new

roles and industries, as well as support to upgrading public and private employment services to facilitate skill matching.

Promoting and embracing lifelong learning: In the era of AI, it is fundamental to constantly learn and adapt to new technologies and ways of working. This means taking courses and keeping up-to-date with the latest trends to adapt to technological advancements, industry changes, and evolving job requirements. This is key for employers, as productivity will depend on it, and workers should be offered opportunities to access lifelong learning, Both on the job and off the job. Yet, governments should monitor and ensure that this is the case, as the ability to keep jobs and grow will largely depend on such capacity to adapt.

Enhance labour market integration: Enhancing the integration of newcomers, like students, graduates, and young workers, into the labour market by aligning skills training with industry demands is key. It also fosters new entrepreneurship and innovation. To meet these new needs, both the EU and member states should focus on modernising education and training systems, incentivising industry-specific training in key sectors.

Address redistributive impacts: Concerns about the fact that AI may exacerbate income inequality need to be better understood. While the net effect of AI on jobs is unlikely to lead to mass job losses, redistribution impacts are inevitable. Not everyone will benefit from transformations. Workers with more advanced skills and education may benefit from automation and AI applications, while lower-skilled, more vulnerable workers face greater risks of job displacement and income insecurity. However, as AI increasingly handles complex intellectual tasks, the potential for displacement is likely to extend beyond low-skilled workers to high-skilled workers. To address skills disparities, equal access to quality education, training, and employment opportunities is critical, but the role of redistributive policies to compensate for income disparities will increase in importance.

In conclusion, the future of work can be shaped for better outcomes. Policy and business decisions as well as workers' engagement today will determine the future landscape and good opportunities for shared prosperity.

Further reading

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Place du Congres 1

B-1000 Brussels