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HUMAN-CENTRED DIGITAL TRANSITIONS AND SKILL MISMATCHES IN EUROPEAN WORKPLACES

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Cedefop working papers are targeting primarily researchers, policymakers, and European stakeholders in vocational education and training (VET), skills, and qualifications.

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Executive summary

Cedefop's second European skills and jobs survey

Technological change, most recently in the form of new digital and artificial intelligence (AI) technologies, are fast reshaping skill requirements in the EU labor market, potentially leading to mismatches between workers' capabilities and the demands of their jobs. These mismatches can impose significant economic and social costs by depressing wages, diminishing job satisfaction, and leading to suboptimal allocation of human capital (Cedefop, 2015; McGuinness et al., 2017). The COVID-19 pandemic and corresponding social distancing measures, along with the subsequent EU and national policies aimed at fostering a 'digital transition', have accelerated this transformation process. Concerns have been particularly raised about the adverse consequences of machine automation on employment, as well as the lagging productivity and competitiveness that is partly an outcome of skill shortages and skill gaps affecting European economies. It is hence widely claimed that unless individuals engage in significant reskilling or upskilling, they will have difficulty adapting to the new economic landscape.

To deepen understanding of how digitalisation affects the nature of work and skill mismatches in European labour markets, Cedefop carried out the second wave of the European skills and jobs survey (ESJS2), its main adult worker skills survey, in 2021 (see Box 1). The ESJS2 is a unique and rich EU data set containing comparative information from all 27 EU Member States plus Iceland and Norway focused on the intensity of digital technologies used by adult workers at their jobs, the level of job-skills required, the type of skill mismatches affecting them and the extent to which they engage in remedial adult education or training to mitigate their skill gaps. The survey contains novel information on the actual impact of digital technology on workers' job tasks, its automation risk and the consequences on workers' well-being and job quality. In its Setting Europe on course for a human digital transition flagship report, Cedefop engaged in a first in-depth empirical analysis of the ESJS2 data, highlighting the opportunities but also risks of the digital transformation.

In this special edition of Cedefop's working paper series, original research contributions have been drafted in which experts utilise, for the first time, the ESJS2 microdata. In ten relatively short and comparable articles, the reader can benefit from a wealth of focused and robust empirical analyses, covering a wide range of different aspects focused on how the digital transition is affecting the world of work and skills in Europe.

Box 1. **In brief: Cedefop's second European Skills and Jobs Survey (ESJS2)**

(a) The ESJS2 is the second wave of Cedefop's main skills survey collecting information on the job-skill requirements, digitalisation, skill mismatches and workplace learning of representative samples of European adult workers. It builds on the first wave carried out in 2014 and aims to inform the policy debate on the impact of digitalisation on the future of work and skills, also in the context of the COVID-19 pandemic.
(b) Fielded in summer 2021, the ESJS2 collected information about 46 213 adult workers in the EU-27 Member States plus Norway and Iceland (EU+). In 2023, Cedefop joined forces with the European Training Foundation (ETF) and the ESJS2 was carried out in an additional six EU periphery countries.
(c) The ESJS2 collects complete information on the socio-demographic and job profile of EU+ adult workers. It maps the task structure of EU+ jobs and uses it to proxy job-skill requirements in labour markets. The focus is on literacy (reading, writing), numeracy, physical, interpersonal, and problem-solving tasks, along with digital activities carried out at work and the incidence and impact of technological change for work. ESJS2 also collects information characterising the nature of work and its organisation (e.g., routine, autonomous, standardised, learning-intensive). The extent to which skill mismatches affect digital and overall productivity at work and efforts to mitigate them via education and training, is also measured.
(d) The ESJS2 aspires to become a key tool for evidence-based policymaking in VET. Its design incorporates the growth, sustainability and resilience ambitions of the EU Skills Agenda and European Digital Strategy and acknowledges the importance of digital skills in VET put forward in the 2020 Council Recommendation on VET and the Osnabrück Declaration.
(e) More information on the European skills and jobs survey (ESJS) is available on Cedefop's web portal and data access is provided via the dedicated ESJS2 online tool.

Source: Cedefop.

Impact of digital technology on tasks and skill mismatch

Zhu and Yang's first contribution uniquely estimates causal effects of rapid technological change on skill mismatches and training demand. It does so by using a country-level COVID-19 policy stringency measure, interacted with an occupation-level AI exposure variable, to generate exogenous variation in digital adoption. This then serves as an instrument for the self-declared impact of COVID-19 on workers' jobs and skill demands, as detected by the Cedefop ESJS2.

Their analysis shows that accelerated digitalisation substantially increases training demand by individuals, with affected workers 15.7 percentage points more likely to request general training and 39.7 percentage points more likely to seek IT-specific training. Employees hence tend to recognise skill upgrading needs in response to technological shocks.

In addition, the results indicate that digitalisation reduces skill underutilisation by 17.5 percentage points, suggesting that on average, digital technologies enhance employment match quality rather than creating displacement. However, COVID-19-induced digitalisation is also found to significantly reduce positive attitudes toward digital technologies. This highlights that for workers, direct exposure to rapid digitalisation might generate implementation difficulties, increased performance pressures, or recognition of technology's limitations in practice.

The paper also draws attention to the marked heterogeneous effects of digitalisation, as its benefits concentrate among already-advantaged workers (males, urban residents, highly educated workers, and non-routine workers). In contrast, potentially vulnerable groups show limited adaptive responses despite potentially facing greater displacement risks as automation advances. These differential distributional consequences are likely to exacerbate labor market inequalities in EU labour markets.

Key lesson for policy 1
Successful digital training programs and policies may require attention to both technical skills development and individuals' psychological adaptation to technological change.

The second paper by Curci et al. explores how technological transformation affects outcomes related to skills matching among white- and blue-collar workers. They conceptualise technological transformation as the relationship between knowledge inputs and innovation outputs, stressing the key role of the *Learning capacity of the organisation* in facilitating workers' skills adaptability to technological change. The authors combine two novel data sources, the 2019 Cedefop-Eurofound European Company survey (ECS) and the 2021 European skills and jobs survey (ESJS2). They create a unique merged company-employee dataset at the level of a 2-digit industry.

The analysis shows that R&D engagement, the adoption and use of digital technologies and the learning capacity of the organisation are powerful drivers of enterprises' innovativeness. While digital technology adoption and use does not have a direct effect on skills mismatches, the study shows that the learning capacity of organisations can be a powerful countervailing force to labour shortages and skill mismatches and a major contributor to business resilience. Organisations that set up the right conditions for learning may particularly enable less-educated, blue-collar workers in successfully navigating and performing increasingly complex tasks, hence lowering their skills underutilisation and real overqualification.

Key lesson for policy 2
Effective adaptation to digital transformation, particularly for lower-skilled workers, can be achieved by fostering the learning capacity of organisations, in addition to designing individual training programs.

In the third contribution, Leitner and Zilian address the disproportional effects of digitalisation across age. This research is particularly valuable considering the demographic crisis facing the European continent and the need to augment the employment participation of older-aged, skilled workers. Using Cedefop's ESJS2 data, the authors show that age segregation and gender gaps are prevalent in the digital skill intensity of tasks performed in EU workers' jobs. Even after controlling for a rich set of variables, young adults (aged 25-34) are found to be much more likely to perform high digitally intensive tasks than are middle aged or older employees; meanwhile older generations are much more likely to be non-users or to perform tasks of low digital content. There is also a clear gender gap: men generally have a higher probability than women of doing digitally skill intensive tasks at work, whereas women – and in particular older women – are more likely to be non-users or to perform low-skilled digital tasks. Employees in more digitally intensive jobs obtain more ICT training, but no pronounced pattern of age or gender gap in digital upskilling is found. Higher digital skill intensity in jobs is further associated with higher hourly wages. Gender wage gaps are sizable across all digital skill intensity categories and additionally widen in the 55–65 age group.

Key lesson for policy 3
To tackle age segregation in digital skill intensity of jobs, greater access to training is needed for older workers. Currently, training participation varies by the digital intensity of jobs, but not by age or gender, putting older workers and females at disadvantage.

Digitalisation and drivers of worker upskilling

The next two papers focus on understanding how technological change and other, sometimes unconventional, drivers can influence workers' participation in training.

In Chapter 4, McGuinness et al. measure the impact of technological change on work-related training. The value added of their paper is that they use novel ESJS2 information that distinguishes whether new digital technology led to the automation or augmentation of workers' job tasks. With those exposed to new digital technology mostly experiencing task disruption – both task creation and some slight task displacement – it is evident that digitalisation increases the need for worker upskilling.

The analysis shows that employees in jobs impacted by new digital technologies are more likely to have to react to unpredictable situations, thus demonstrating a positive link between technologically driven task disruption and job complexity. There is also a strong linear relationship between technologically driven job task disruption and the need for job-related training. Employees in jobs were new technologies resulted in both task displacement and task creation are over 26 percentage points more likely to have undertaken job-related training in the previous 12 months, relative to those unaffected by new technologies.

Key lesson for policy 4
Upskilling policies need to better equip adult workers to cope with higher job complexity and digital intensity in labour markets. This can be done by investing in their problem-solving, creativity and agility skills. They should also target specific population groups such as older and lower-educated workers in part-time jobs, who are less likely to engage in job-related training as a reaction to new digital technology in their jobs.

Using a unique ESJS2 variable that measures whether EU workers invested in the improvement of their digital skills, Bertoni et al. (Chapter 5) analyse the different drivers of employee participation in digital skills training. The results draw attention to the fact that in addition to key job design features (e.g. the extent to which a worker's job requires him to leverage a high skill level, autonomy or job complexity), workers' perceptions about the impact of technological change on their jobs can also influence their digital skills training decisions. For instance, workers who fear thar digital technology can automate (part of) their job, or will affect their job-skill requirements, tend to engage in digital skills training more than those who are not fearful. The paper also shows that approximately 13 % of EU workers experience a significant digital skills mismatch, highlighting the need for upskilling and reskilling to adapt to new digital technologies. Employers have an important role to play: workers in organisations with a more systematic approach to training, including skill needs awareness raising, are more likely to participate in digital skills training.

Key lesson for policy 5
Policy efforts should focus more on workers who are not engaged in digital skills training even though they have a digital skill gap or are at high risk of job reallocation due to these technologies. Education and training initiatives must consider job-specific skills but also

individual perceptions/attitudes and other workplace motivational levers and incentives to be effective.

Skill shortages and the digital transition

Four original research articles shift the attention to the nature of skill shortages that prevail as a response to technological and organisational change in EU labour markets and explore the, potentially socially exclusive, hiring practices of European firms.

In ‘Hiring from the margins’, Lima and Korkut (Chapter 6) investigate how firm-level technological and organisational restructuring influences hiring patterns of workers with distinct prior employment statuses. Using ESJS2 information, they analyse the relationship between offshoring, digital technology adoption, automation exposure, and training, and the likelihood that a worker transitioned into their current job from education, unemployment, or self-employment, relative to having been employed in another job. By modelling hiring outcomes rather than post-employment trajectories, this article shifts focus to the demand side of labour transitions, asking not only who finds jobs, but which firms hire whom.

The paper’s insights are highly relevant for policy, as they suggest that existing recruitment practices in dynamic EU firms tend to exacerbate structural vulnerabilities in job markets. While training in dynamic firms is shown to be a key mediating mechanism that allows those without continuous employment histories (i.e. from education or training pathways) to transition into the job market, those with past unemployment spells face greater barriers. This selection process risks deepening patterns of labour market segmentation. Self-employed individuals are, by contrast, more likely to be hired into tech-adopting and offshoring firms, especially into non-routine roles. This finding points to a potential complementarity between entrepreneurial experience and the demands of restructured or flexible work environments. Overall, the paper points to a highly differentiated landscape of hiring decisions in the EU labour market, one in which prior employment histories, task content, and access to training interact to shape who is integrated into the evolving structure of work.

Key lesson for policy 6
EU skills activation policies need to more explicitly target the firm-side of skills matching

mechanisms, given that training does not serve as an effective re-entry channel into technologically advanced firms for those workers with a history of unemployment.

In Chapter 7, McGuinness et al. argue that despite the sparsity of the research base, with skill shortages accounting for just 5 % of the skills mismatch literature, they remain the principal concern of policy makers in the realm of skill mismatches. The authors highlight the multiple difficulties associated with measuring skill shortages using either subjective or objective data approaches. They subsequently develop a new indicator of ‘potential skill shortages’, one that employs an objective measurement approach using online job vacancy data, that is however benchmarked to a subjective measurement approach using ESJS2 survey data with detailed job characteristics. The multi-dimensional approach used identifies several conditions / job characteristics that are likely to be associated with potential skill shortages at an occupational level and subsequently calculate the share of jobs that are likely to be difficult to fill by employers.

In this way, it is estimated that the overall EU share of jobs facing potential skill shortages stands at around 3.5 % and it is around 2 % of all vacancies across the EU and the UK. High shares of potential skill shortages are located among professional occupations (Science and Engineering, ICT, Business and Teaching Professionals), but are also evident among other managerial positions (Administrative and Hospitality Managers) and across the occupational spectrum.

Key lesson for policy 7
Understanding and measuring skill shortages in EU labour markets requires a multi-dimensional and harmonised approach that is anchored to the ‘objective’ distribution of skill demands and job characteristics within occupations, although real-time job postings data can provide reasonably regular insights into their occupational distribution.

With many shortage occupations being heavily influenced by the digital transition, policy attention has been increasingly directed to the growing impact of artificial intelligence (AI) on labour markets. AI is now widely recognised as a general-purpose technology with transformative implications for productivity, business models and skill requirements. Leveraging real-time data extracted from online job advertisements (OJAs), Gsavalia et al. (Chapter 8) deliver granular evidence on the types of AI skills requested, their sectoral and occupational distribution, and their association with various business strategies, from innovation and product development to process optimisation and change management.

The article stresses that AI’s rapid diffusion extends beyond specialised or IT-focused roles, permeating diverse occupations and reshaping both the nature of work and the competencies demanded by employers. The data also show a shift in AI adoption from internal efficiency to outward-facing innovation and product development, with more employers now investing in building new AI-based products and capabilities. The insights reveal a nuanced picture of how AI is reshaping work: not as a blanket disruptor, but as a layered and evolving transformation across occupations and sectors.

Key lesson for policy 8
The diffusion of generative and applied AI tools across non-technical occupations and the diversity of roles adopting AI – from creative professions to technical and managerial ones – underscores the need for designing interdisciplinary curricula and lifelong learning frameworks in vocational education and training (VET). The design of training pathways should be customised to the degree and type of AI exposure (e.g. Build, Enable or Improve AI processes). Basic AI awareness should be integrated into general education, vocational training, and adult learning.

With the EU in need to attain a greater degree of strategic autonomy than in the past, given current geopolitical tensions, attention is also shifting to the need to meet the high skill needs of sectors of strategic significance for the continent. One such sector is the technologically intensive Aerospace and Defence (ASD), one of the 14 key industrial ecosystems identified by the EU and which Large Skill Partnerships are involved. The ASD industry, driven by AI, Internet of Things (IoT), and advanced manufacturing, requires a highly skilled workforce to stay competitive and meet global market demands.

In Chapter 9, Farinha et al. hence investigate, using ESJS2 data, how digitalisation and automation in this sector are affecting individual workers' well-being and skill mismatch. Their research shows that workers in the ASD industrial ecosystem, regardless of education level, country, or occupation, are more motivated to upskill/reskill due to a fear of lacking necessary knowledge or skills following the onset of new digital technology in their company or organisation. Training, including ICT training, improves job satisfaction through better worker attitudes and skill use, not through reducing job insecurity.

Key lesson for policy 9
Large-scale skills partnerships aligned with European agenda goals can further bolster

organisations' efforts to provide well-targeted continuous trainings and create a more engaged and stable workforce, especially in high-tech sectors like ASD.

A human digital transition in teaching

The special issue concludes with a paper focused on the teaching profession. For Cedefop, having launched in 2025 the EU's first European Vocational Teacher Survey (EVTS), the issue of teacher shortages and understanding how teaching practices and skill needs are being reshaped by digital technologies is paramount. In his study (Chapter 10), Serodes argues that the education sector has undergone significant changes over the last few decades following the emergence of the pandemic and the spread of new technologies, such as AI. Nevertheless, this sector has some specific characteristics and is by its nature less affected by digitalisation, as the mediating role of teachers remains key, particularly at primary and secondary levels. In the EU, this transition has been slow and has encountered several barriers, often attributed to personal attitudes, a lack of skills and adequate training, and the desire to maintain a direct, lively, human relationship between teacher and student. Digital technologies offering direct access to knowledge and information, without the need for mediation, are hence sometimes seen as jeopardising the human element of teaching.

In the article, the author uses ESJS2 information on digital skill needs and the perceived impact of digital technologies albeit focused on samples of primary and secondary school teachers. With 75 % of them having had to use new digital tools for their work during the first year of the coronavirus pandemic, it is noteworthy that a resounding majority of teachers anticipates only a minimal impact of digital technology on their future employment. This seems to reflect that most teachers possess fundamental computer skills, which they can utilise to a large extent in their job. A significantly higher share of teachers also attended training courses compared to other professional groups during the 2020-21 period, which may underpin the high resilience they exhibited during the pandemic.

Despite such positive reactions, the analysis points to the need for heightened awareness among teachers about the future risks of systematically integrating new digital technologies in their profession.

Key lesson for policy 10
Continuous policy efforts are required to raise awareness among professionals, even those in good command of basic digital skills, about the potential future challenges associated with the digital transition.

Chapter 1.
Accelerated digital transformation, demand for training and skill mismatch: evidence from Europe

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1.1. Introduction

Technological change reshapes the skill requirements of the labor market, potentially leading to mismatches between workers' capabilities and the demands of their jobs. These mismatches can impose significant economic and social costs by depressing wages, diminishing job satisfaction, and leading to suboptimal allocation of human capital (Cedefop, 2015; Leuven & Oosterbeek, 2011, McGuinness et al., 2017). Digital technologies have accelerated these concerns by transforming work across industries, with the COVID-19 pandemic and the corresponding social distancing measures compressing what might have been years of gradual change into months of rapid adoption (Acemoglu et al., 2022; Agarwal et al., 2020; Brynjolfsson & McAfee, 2014). Existing research has largely overlooked whether employees are able to reskill or upskill in response to rapid technological transitions. This setting creates a unique opportunity to study how individuals adapt to abrupt technological change.

Understanding these rapid transitions is particularly important, as digital automation increasingly affects occupations that were previously considered less affected by technological displacement (Acemoglu & Restrepo, 2019; Frey & Osborne, 2017). This expansion generates competing theoretical predictions. Technology-skill complementarity theories predict that accelerated digitalisation should reduce skill mismatches and increase training demand, as workers adjust their skills to complement new technologies (Acemoglu & Restrepo, 2018; Autor et al., 2003). In contrast, displacement theories predict that rapid technological change should exacerbate skill mismatches and undermine the effectiveness of training, as workers struggle to keep pace with evolving job requirements. (Arntz et al., 2016; Bessen, 2016). The COVID-19 pandemic provides a unique natural experiment to test these competing theories by accelerating digital adoption across industries and occupations.

We leverage this unique setting to address three research questions:

(a) How does the accelerated digital transformation affect workers' demand for training and skill mismatches?

(b) What are the potential mechanisms that drive these effects?
(c) Do these effects differ systematically across different categories of workers?

These questions allow us to evaluate competing theoretical frameworks and inform policy responses to technological change.

We analyze comprehensive data from 46 000 workers across 28 EU countries in the European Skills and Jobs Survey (ESJS2), which provides detailed information on job characteristics, workplace digitalisation, and COVID-19 impacts. Our identification strategy exploits the pandemic as a natural experiment, using country-level COVID-19 policy stringency interacted with occupation-level AI exposure to instrument for the impact of the COVID-19 in workplace. This approach generates exogenous variation in digital adoption, allowing us to estimate causal effects of rapid technological change on skill mismatches and training demand.

Our results provide a critical reassessment of conventional predictions about technological displacement. We find that accelerated digitalisation substantially increases training demand, with affected workers 15.7 percentage points more likely to request general training and 39.7 percentage points more likely to seek IT-specific training. This training response aligns with human capital theory's prediction that workers invest in skills when returns are high (Mincer, 1974) and suggests that employees can recognise skill upgrading needs in response to technological shocks (Chen et al., 2022). In addition, our results indicate that digitalisation reduces skill underutilisation by 17.5 percentage points, suggesting that on average, digital technologies enhance employment match quality rather than creating displacement. These findings support technology-skill complementarity theories over displacement framework (Acemoglu & Restrepo, 2020; Autor et al., 2003). Furthermore, in line with previous literature (Akerman et al., 2015), we find significantly negative effects on job satisfaction, supporting the evidence of negative well-being impacts of technological changes.

To understand what drives these patterns, we explore four potential mechanisms: attitudes toward digital technologies, perceived job displacement risk, rise in task complexity, and new digital tasks in the workplace. Among these channels, we find evidence that positive attitudes toward digital technologies play a significant role in shaping outcomes. Employees who experienced accelerated digitalisation are 53.0 percentage points less likely to hold positive attitudes towards digital technologies, while those who hold positive attitudes are 1.4 percentage points less likely to report skill underutilisation and 54.7 percentage points higher in job satisfaction. Other mechanisms show no significant effects, suggesting that technology acceptance is crucial for realizing the benefits of digital transformation.

Heterogeneous analysis demonstrates that benefits of digitalisation are unevenly distributed across worker types. Improvements in skill utilisation concentrate among non-routine workers, while routine workers show no significant changes. This pattern supports theories that digital technologies complement complex cognitive and interpersonal tasks more than routine work (Acemoglu & Restrepo, 2019; Autor, 2015; Autor & Dorn, 2013; Goos et al., 2014), highlighting concerns about inclusive growth during digital transformation.

This paper makes three contributions to the literature on technological change and labor markets. First, we provide the first causal evidence that rapid digitalisation can reduce skill underutilisation, directly contradicting displacement-focused theories that dominate policy discussions (Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017). Second, we identify the role of worker attitudes in mediating digitalisation effects, extending research on technology adoption barriers (Akerman et al., 2015), and suggesting that technology acceptance policies are as important as skill training policies. Third, we demonstrate significant inequality in digitalisation benefits across worker types, contributing to the literature on polarisation and technological change (Autor & Dorn, 2013; Goos et al., 2014;), with implications for inclusive growth policies in the EU's Digital Decade framework (European Commission, 2021; European Parliament, 2021). These findings directly inform the EU's Digital Decade strategy and its goal of ensuring 80 % of adults have basic digital skills by 2030 (European Commission, 2022). Our evidence on differential training effectiveness and heterogeneous benefits provides guidance for implementing the Council's recommendations on digital skills education (Council of the European Union, 2022).

1.2. Data and empirical methodology

1.2.1. Data and variables

We use the second wave of the European Skills and Jobs Survey (ESJS2) collected by the Cedefop to examine how COVID-19-induced digitalisation affects training demand and skill mismatch. ESJS2 provides a representative sample of 46 000 adult workers aged 24 to 65 from the 28 Member States of the EU and EU neighborhoods ([1]). The survey focuses on the changes in skill needs and job tasks due to digitalisation and the EU workers' adaptability to technological change through initial education and on-the-job training. Carried out in 2021, this data set gives us a unique opportunity to explore

([1]) In total, about 46 000 adult employees are surveyed using a mixed online-telephone methodology. The list of countries is: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

the impact of COVID-19 and its corresponding induced digitalisation at the individual level. All individuals in the final sample are currently employed and are residents of the sample country.

Our analysis uses several key variables from the survey. We extracted self-reported skill mismatch and whether the individuals were affected by COVID-19 from the survey ([2]) ([3]). We also identified variables such as socio-demographics (age, gender, residence, work experience), workplace characteristics (industry, firm size, work location, digital tools, tasks performed at work), education level, and on-the-job-training information.

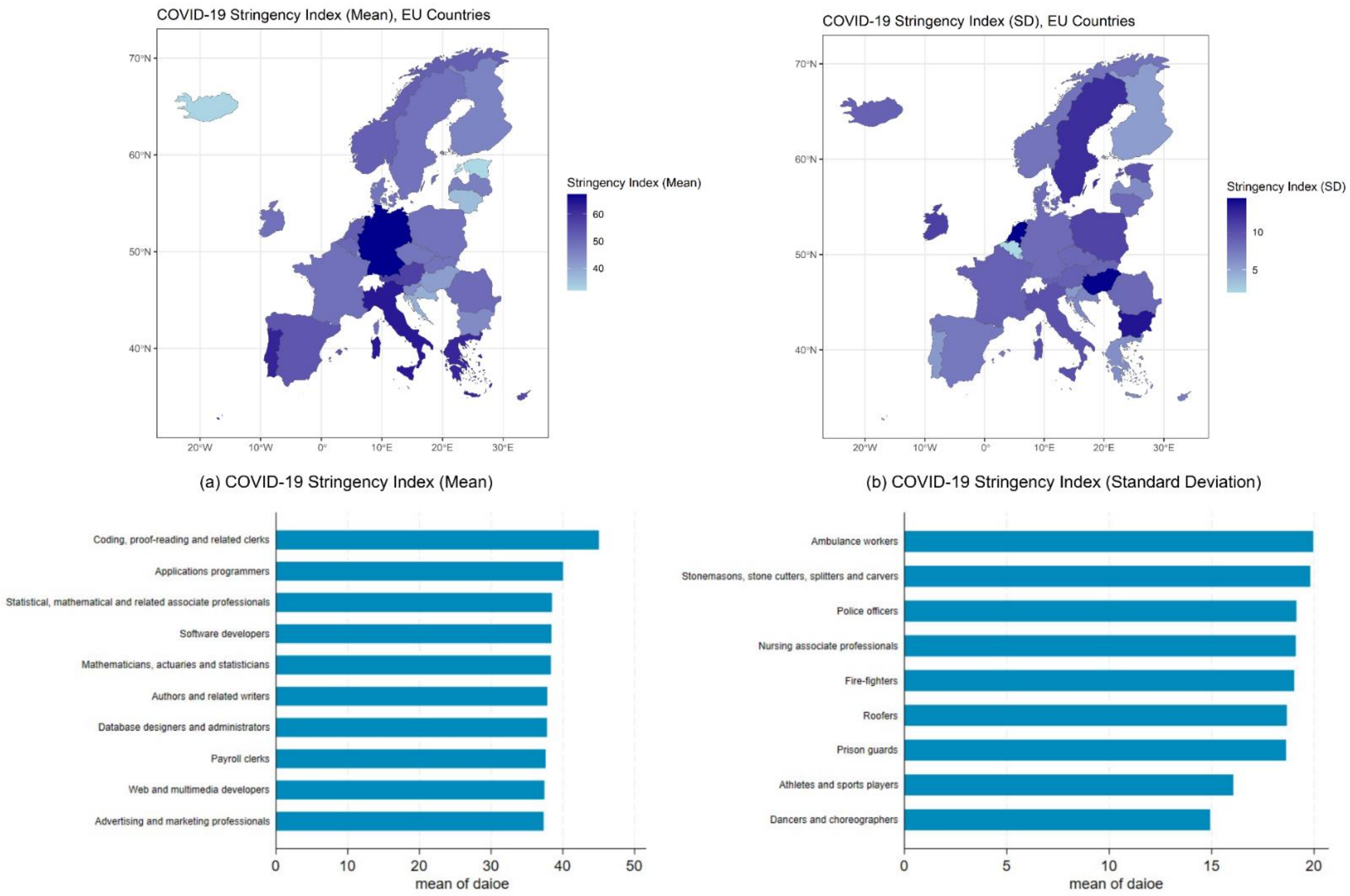
We construct instrumental variables using COVID-19 stringency variation across countries and AI exposure variation across occupations. The COVID-19 Stringency Index, calculated by the Oxford Coronavirus Government Response Tracker (OxCGRT), provides a composite measure of the strictness of the pandemic policies ([4]). On a scale of 0 to 100, where a higher score indicates a stricter response. To build our measures, we took the average of the daily COVID-19 Stringency Index from May to August 2021. Figure 1 (a) and (b) illustrate the differences in the mean and standard deviation of the COVID-19 stringency index among European countries. The average represents the level of stringency, and the standard deviation represents the magnitude of change in the policy. To the best of our knowledge, this index is the most comprehensive and publicly available collection of data on COVID-19 stringency, and it has been widely used in research fields such as medical science and economics. The AI exposure indices are obtained from Engberg et al. (2024) and provide a dynamic AI occupational exposure measure (DAIOE) at the ISCO 4-digit occupational-year level. This panel dataset spans 2010–2023, a period of rapid AI advancements. We use the index of 2021 to construct our measure. Figure 2 panel (c) presents the most AI-exposed occupations as coding, proofreading and related clerks; panel (d) shows the least exposed occupations as ambulance workers.

([2]) Our main dependent variables include horizontal skill mismatch and skill underutilisation. Horizontal skill mismatch is defined as a mismatch between a worker's field of study or training and the type of job they are doing. Skill underutilisation is defined as the extent to which a worker can apply their existing skills and knowledge in their current job.

([3]) Example questions: 'Did you experience any of the following as a result of the COVID-19 (or coronavirus) pandemic?' and 'Compared with the situation before the COVID-19 pandemic, do you now experience any of the following situations in your main job?'

([4]) The measure is calculated out of nine response metrics, such as school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls. If policies vary at the subnational level, the index is shown as the response level of the strictest sub-region. Since government policies may differ by vaccination status, a stringency index at the national level is weighted based on the share of people that are vaccinated.

Figure 1. **Illustration of the COVID-19 Stringency Index and the DAIOE AI Exposure Index**



(a) COVID-19 Stringency Index (Mean)

(b) COVID-19 Stringency Index (Standard Deviation)

(c) Occupations Most Exposed to AI Technologies

(d) Occupations Least Exposed to AI Technologies

Source: Oxford Coronavirus Government Response Tracker (OxCGRT) and Engberg et al. (2024)

1.2.2 Empirical strategy

We exploit COVID-19-induced digitalisation as an exogenous variation to identify causal effects on skill mismatch and training demand. Our key treatment variable measures self-reported impact of COVID-19 in the workplace including job loss, reduced working time, changes in remote work, digital tool usage, and digital skill requirements, and thus a negative answer to the question does not mean the individual was not affected by COVID-19, but their work was more or less affected. Additionally, even if the answers are self-reported, individuals can easily differentiate whether they experienced the changes induced by COVID-19, and hence, we expect little measurement error.

To establish credible causal estimates, we use AI exposure and its interaction with the COVID-19 stringency index as instruments for being affected by COVID-19 induced digitalisation in the workplace. Note that COVID-19 as a disease does not have any direct effect on skill mismatches or demand for on-the-job training, and the instrument satisfies the exogeneity condition. The instrument by construction satisfies the relevance condition. The interaction term also satisfies the relevance and exogeneity conditions. The estimations are described below:

$$Y_{ijc} = \beta_0 + \beta_1 \cdot \widehat{D_{ijc}} + Controlled_{ijc} + \varepsilon_{ijc},$$
$$D_{ijc} = \alpha_0 + \alpha_1 \cdot Stringency_c \cdot DAIOE_j + Controlled_{ijc} + \epsilon_{ijc},$$

where i denotes individual worker, j denotes occupation, and c denotes country. In the second equation above, $Stringency_c \cdot DAIOE_j$ is our instrumental variable. $Stringency_c$ presents the country-level stringency index, taking the average of the index values from May to August 2021. $DAIOE_j$ is the occupation-level AI exposure index, taking the value in 2021. D_{ijc} is the dummy variable that indicates whether the employee is affected by the pandemic in the workplace. The dependent variables Y_i are a set of labor market outcomes: horizontal skill mismatch, skill underutilisation, demand for general and IT-specific training, and job satisfaction. Among these dependent variables, except for job satisfaction that ranges from 1-10, the rest are dummy variables that indicate whether individuals report skill mismatches or demand for training. ε_{ijc} and ϵ_{ijc} are the error terms in the estimations. The covariates include individual characteristics (gender, age, urban or rural residence, education level, occupation, position, work experience, contract type), workplace characteristics (company sector, company size, remote work indicator, digital devices in the workplace), tasks performed at work (reading and writing tasks, manual tasks, mathematics tasks, social tasks, problem solving tasks, and advanced-skilled tasks), monthly wage, and phone use information.

We explore mechanisms underlying our main effects through two steps. First, we estimate treatment effects on potential mediating variables: worker attitudes toward digital technologies, perceived job displacement risk, rise in task complexity, and new digital tasks in the workplace. Second, we test mediation by including these channel variables as controls in our main specifications and examining coefficient changes. To examine heterogeneous effects, we perform subgroup analyses by estimating the main specification separately across several dimensions, including gender, educational attainment, urban versus rural residence, satisfaction with career prospects, task routineness, and high-skill occupational status.

1.3. Main empirical findings

1.3.1 Main effects of accelerated digitalisation

Table 1 presents our instrumental variable estimates examining how COVID-19-induced digitalisation affects skill mismatch, demand for training, and job satisfaction. Panel A shows our main results, while Panel B includes the control for workers' attitudes toward digital technologies.

Our estimates reveal significant effects across skill mismatch dimensions. Accelerated digitalisation reduces skill underutilisation by 17.5 percentage points ($p < 0.05$), indicating workers perceive their existing knowledge and capabilities as better aligned with job requirements following digital transformation. This effect represents a substantial improvement and suggests that digital technologies enhance rather than diminish workers' performance to meet job requirements. Conversely, the same digitalisation process increases horizontal mismatch by 16.6 percentage points ($p < 0.05$). This finding indicates that while workers feel higher skill utilisation in performing their jobs, their previous knowledge acquired from formal education have become less relevant to current job content. The contrasting effects across mismatch types illuminate how technological change simultaneously improves skill utilisation while shifting job requirements away from previous educational training. In addition, employees respond to digitalisation with substantial increases in demand for training, demonstrating forward-looking behavior consistent with optimal human capital investment theory. The treatment increases general skills training demand by 15.7 percentage points ($p < 0.05$) and IT skill-specific training demand by 39.7 percentage points ($p < 0.001$). The differential magnitude, with IT training responses 2.5 times larger than general training, reveals that workers strategically prioritise skills most complementary to digital technologies. These training responses provide evidence that workers can accurately identify high-return skill investments during periods of rapid technological change.

Despite improvements in skill matching, digitalisation significantly reduces job satisfaction by 3.08 points ($p < 0.001$). This result aligns with existing study that technological transitions impose psychological costs even when economically beneficial, possibly reflecting increased work intensity, adaptation stress, or concerns about future job security despite current improvements (Kim & Kim, 2024).

Table 1. **Instrumental Variable Estimation Results**

COVID-19 impact in the workplace	Horizontal mismatch	Skill underutilisation	General skill training demand	IT skill training demand	Job satisfaction
Panel A. Main results					
Estimates	0.166**	-0.175**	0.157**	0.397***	-3.083***
Robust SE	(0.0745)	(0.0858)	(0.0708)	(0.0896)	(0.6439)
Controlled	Yes	Yes	Yes	Yes	Yes
No. Obs	30,213	30,213	30,213	30,213	29,761
F Statistics	97.57	97.57	97.57	97.57	92.70
Panel B. Results with the mechanism					
Estimates	0.166**	-0.182**	0.155**	0.394***	-2.790***
Robust SE	(0.0730)	(0.0842)	(0.0694)	(0.0878)	(0.6144)
Positive Attitude	-0.001	-0.014***	-0.003	-0.007	0.547***
Robust SE	(0.0044)	(0.0050)	(0.0042)	(0.0053)	(0.0370)
Controlled	Yes	Yes	Yes	Yes	Yes
No. Obs	30,213	30,213	30,213	30,213	29,761
F Statistics	101.65	101.65	101.65	101.65	96.69

NB: This table reports treatment effects from COVID-19 induced digitalisation on various labor market outcomes from separate regressions. Robust standard errors in parentheses. Control variables include individual characteristics (gender, age, urban or rural residence, education level, occupation, position, work experience, contract type), workplace characteristics (company sector, company size, remote work indicator, digital devices in the workplace), tasks performed at work (reading and writing tasks, manual tasks, math tasks, social tasks, problem solving tasks, and advanced-skilled tasks), monthly wage, and phone use information. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Source: Cedefop second European skills and jobs survey (ESJS2).

1.3.2 Mechanisms

We further investigate potential channels mediating our main results by examining whether COVID-19-induced digitalisation affects theoretically motivated intermediate outcomes. We test four hypothesised mechanisms: worker attitudes toward digital technologies, perceived job displacement risk, rise in task complexity, and the emergence of new digital tasks in the workplace.

The treatment effect results on mediators are presented in Table 2. The mechanism analysis yields a striking finding: COVID-19-induced digitalisation significantly reduces positive attitudes toward digital technologies by 53.0 percentage points ($p < 0.001$). This result challenges conventional assumptions that technology adoption necessarily improves worker perceptions. Instead, direct exposure to rapid digitalisation might generate skepticism, reflecting on implementation difficulties, increased performance pressures, or recognition of technology's limitations in practice. Other hypothesised mechanisms show no statistically significant effects. We find no evidence that digitalisation affects perceived job displacement risk (estimated coefficient: 0.065, $p > 0.10$), task complexity (0.079, $p > 0.10$), or emergence of new digital tasks (0.170, $p > 0.10$). These null results suggest that workers' subjective assessments of job content changes may not capture the objective shifts in skill demands in the workplace.

The robustness of our main treatment effects when controlling for the one significant mechanism indicates that workers' attitude do not fully explain the observed improvements in skill utilisation or increases in training demand (Panel B of Table 1). The coefficients remain statistically significant with similar magnitudes: skill underutilisation (-0.182, $p < 0.05$), demand for general training (0.155, $p < 0.05$), and demand for IT training (0.394, $p < 0.001$). Notably, positive attitudes toward digital technologies significantly reduce skill underutilisation reports (-0.014, $p < 0.001$) and increase job satisfaction (0.547, $p < 0.001$), suggesting that technology acceptance plays an independent role in labor market outcomes. This pattern suggests our results operate primarily through direct modifications to task content and skill requirements rather than shifts in employees' perceptions towards technology.

Table 2. **Treatment effects on mediator**

COVID-19 impact in the workplace	Positive attitude towards digital technologies	Job displacement risk	Rise in task complexity	New digital tasks
Estimates	-0.530***	0.065	0.079	0.170
Robust SE	(0.1347)	(0.0711)	(0.1241)	(0.1142)
Controlled	Yes	Yes	Yes	Yes
No. Obs	30 213	30 213	30 213	30 213

NB: This table reports treatment effects on the four mediating channels from separate regressions. Robust standard errors in parentheses. Control variables include individual characteristics (gender, age, urban or rural residence, education level, occupation, position, work experience, contract type), workplace characteristics (company sector, company size, remote work indicator, digital devices in the workplace), tasks performed at work (reading and writing tasks, manual tasks, math tasks, social tasks, problem solving tasks, and advanced-skilled tasks), monthly wage, and phone use information. $*$ $p < 0.1$; $**$ $p < 0.05$; $***$ $p < 0.01$.

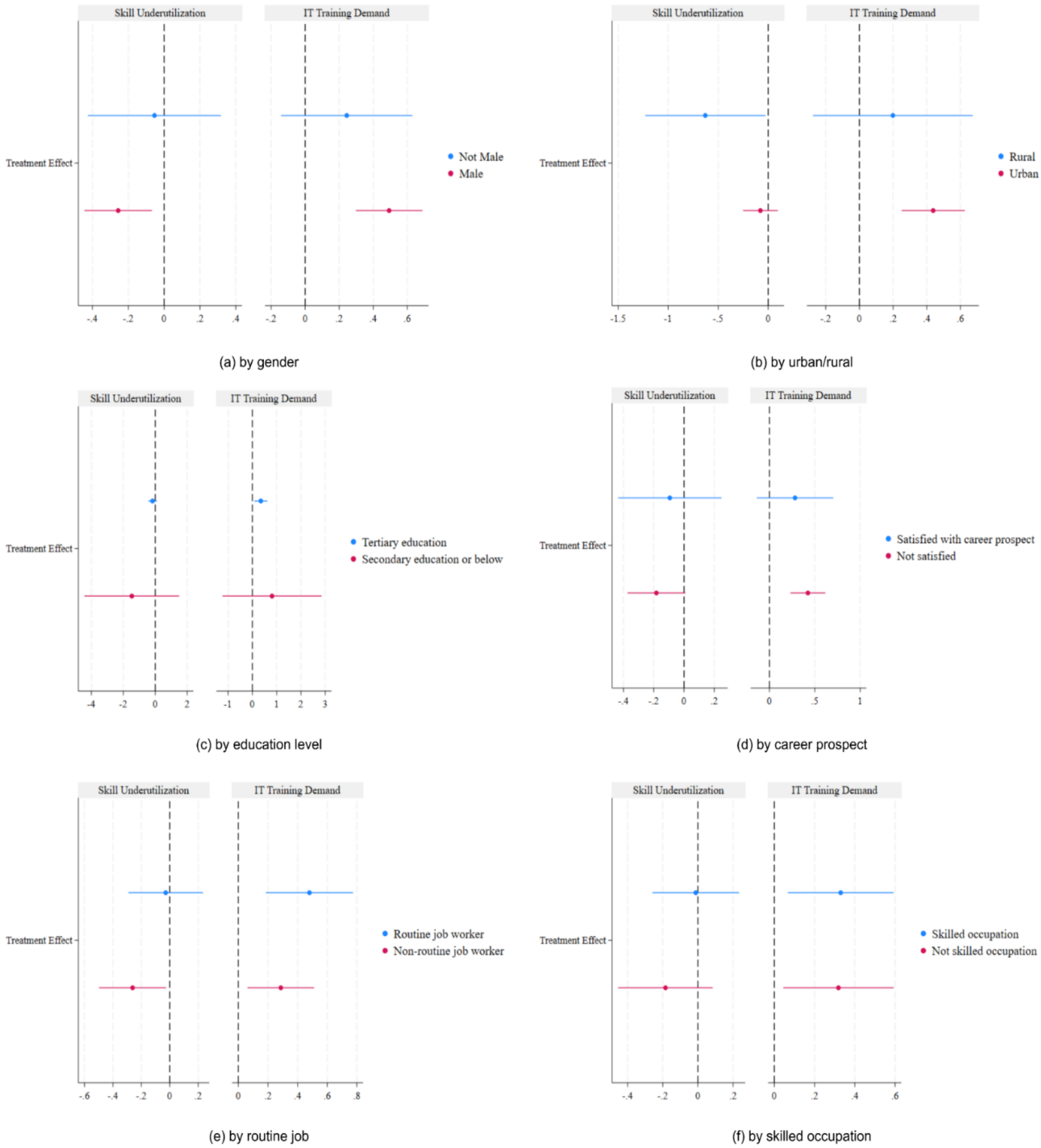
Source: Cedefop second European skills and jobs survey (ESJS2).

1.3.3 Heterogeneous treatment effects

Figure 2 reveals heterogeneity in accelerated digitalisation impacts across multiple worker characteristics, providing insights into the distributional consequences of technological change. We examine the variations of treatment effect across six dimensions: gender, educational attainment, urban versus rural residence, satisfaction with career prospects, task routineness, and high-skill occupational status.

Panel (a) shows that the effects are concentrated among male employees, who experience significant reductions in skill underutilisation, while female employees show smaller and statistically insignificant effects. Male employees also increase demand for IT skill training substantially, while still no significant effects for females. Panel (b) demonstrates that urban workers primarily drive the effects, with significant increases in demand for training, while rural workers show minimal responses across both outcomes. Panel (c) reveals differences by educational attainment: workers with tertiary education experience significant reductions in skill underutilisation and increases in demand for IT skill training. In contrast, workers with secondary or lower education show noisy and insignificant results. Panel (d) indicates that workers who are not satisfied with their career prospects respond more strongly to digitalisation, showing larger training request responses compared to those who are satisfied with their career trajectory. Panel (e) confirms our theoretical predictions about task complementarity. Non-routine workers experience significant reductions in skill underutilisation and substantial increases in demand for IT skill training, while routine workers show statistically insignificant effects for skill underutilisation. This differential response aligns with theoretical predictions that digitalisation complements complex cognitive and interpersonal tasks while offering fewer immediate benefits for codifiable routine work. Panel (f) demonstrates that there is no statistically significant difference between workers in skilled occupations and non-skilled occupations, suggesting that it is the task content of the job instead of skill level of occupation that captures the heterogeneous effects.

Figure 2. **Heterogeneous treatment effects across subgroups**



Source: Cedefop second European skills and jobs survey (ESJS2).

These heterogeneous effects reveal a consistent pattern where digitalisation benefits concentrate among already-advantaged workers: males, urban residents, highly educated workers, and non-routine workers. In contrast, potentially vulnerable groups show limited adaptive responses despite potentially facing greater displacement risks as automation advances. With digitalisation continuously improving aggregate production, these differential distributional consequences might exacerbate labor market inequalities. These findings underscore the need for targeted policies ensuring digitalisation benefits extend beyond already-advantaged workers, particularly as disadvantaged groups face greater automation risks without investing in skills that could protect against job displacement.

1.4. Summary and policy relevance

Using the COVID-19 pandemic as a natural experiment for accelerated digitalisation, we find three key results on technological disruption in labor markets. First, digitalisation substantially increases demand for training, with affected workers 15.7 percentage points more likely to request general training and 39.7 percentage points more likely to seek IT skill-specific training. Second, digitalisation reduces skill underutilisation, with affected workers 17.5 percentage points less likely to report skill underutilisation. Third, these beneficial effects are concentrated among male, urban, and non-routine workers.

The increased demand for training reveals that workers can accurately identify which skills offer the highest returns with new technologies. The targeted response challenges models that assume workers face significant information costs in recognizing valuable training opportunities. While these results align with human capital theory’s prediction that workers invest in skills when returns are high (Mincer, 1974), the speed of adjustment occurs much more rapidly than traditional models assume. The immediate training response suggests that when technological benefits are clear, human capital markets can adjust with remarkable efficiency during technological transitions. The willingness of firms to support this rapid training likely reflects the immediate productivity gains and competitive advantages that digital competencies provide in the transforming work environment.

Beyond increasing training demand, digitalisation reduces skill underutilisation that challenges the widespread assumption that technological change creates temporary skill gaps and displacement effects (Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017). Digital technologies appear to enhance existing human capabilities while workers simultaneously adapt through training, creating better alignment between skills and job requirements. However, these effects operate differently across worker types. Non-routine workers benefit immediately as digital tools complement their cognitive and interpersonal tasks, while routine workers show no effects on skill utilisation. In line with the expectations that AI should threaten codifiable work most directly, routine workers are also aware of the new automation risk and are more likely to request training in IT skills as compared to non-routine workers.

1.4.1 Policy implications

Our results have implications for digital transformation policy design, particularly for the EU's Digital Decade framework discussed above, though we caution that the specific context of COVID-19 may limit generalizability. The finding that digitalisation reduces skill underutilisation while increasing training demand challenges displacement-focused policy approaches that emphasise protecting workers from technological change. The EU’s strong emphasis on privacy and regulatory safeguards, while normatively valuable, may be contributing to a slower pace of digital adoption and innovation relative to more flexible global counterparts. Our evidence suggests that there is a high demand for digital skill training from employee side, suggesting a high degree of willingness to adapt to technological change despite the potentially restrictive regulatory environment.

The heterogeneous effects we document raise questions about the distributional consequences of uniform digital skills policies. Benefits concentrated among advantaged worker groups (male, urban, and non-routine workers) suggest that standard policy approaches may not achieve inclusive growth objectives without targeted interventions for routine workers, rural residents, and women who show minimal adaptive responses. However, the welfare implications of these distributional effects depend on general equilibrium responses and longer-term adaptation dynamics beyond the scope of our analysis.

The role of worker attitudes in mediating digitalisation effects points to an underexplored dimension of technology policy. The disconnect between objective skill matching improvements and subjective technology acceptance (with digitalisation reducing positive attitudes by 53 percentage points) suggests that successful digital transformation may require attention to both technical skills development and psychological adaptation to technological change, rather than focusing solely on technical training programs.

1.4.2 Conclusions

This study demonstrates that employees can adapt to rapid technological change promptly and effectively than typically assumed, but with important differences across worker types. By leveraging the COVID-19 pandemic as a natural experiment, we provide the first large-scale causal evidence that accelerated digitalisation substantially increases demand for training while reducing skill underutilisation. Our findings challenge displacement-focused models of technological change and support theories emphasizing technology-skill complementarity. Our results extend our understanding of human capital adaptation during technological disruption and offer insights for European policymakers seeking to ensure that digital transformation benefits a wide range of workers. With the ongoing acceleration of digitalisation, the patterns we document suggest that the key policy challenge lies not in preventing technological displacement but in addressing information gaps and ensuring that all workers can access the training necessary to benefit from human-technology complementarity.

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Chapter 2.
The path toward a human-centric digital transformation: what the learning capacity of organisations can do for jobs' skills matching?

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2.1. Introduction

This study ([5]) explores how technological transformation affects outcomes related to skills matching among white- and blue-collar workers. We conceptualise technological transformation as the relationship between knowledge inputs and innovation outputs, stressing the role of the *Learning capacity of the organisation* in reducing the burden on workers who need to develop new skills and competencies to adapt to technological changes.

Technological revolutions usually raise concerns about job displacement and inequalities. However, the predicted massive skills and job destruction due to automation, robotics and AI has not yet materialised. Empirical analyses increasingly suggests that technology tends to automate specific tasks rather than entire occupations. Digital transformation is nevertheless profoundly reshaping work practices and job content (Cedefop, 2022), affecting workers across all occupational ranks and all sectors.

Hence, the transition towards more digitally oriented production systems carries a significant risk of skills mismatches and highlights the need for substantial reskilling of more vulnerable workers. This evidence calls for a massive reorientation of the education system and for a more intensive focus on vocational training and lifelong learning programs. But what role can organisations play in facilitating a smoother and more inclusive transition?

This paper argues that organisations can have a dual strategic function by investing in increasing their stock of productive knowledge. On the one hand, they can drive innovation creation while, on the other hand, they simultaneously improve quality of work, employment relationship and skills development. Therefore, we conceptualise

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technological transformation as a relationship between knowledge inputs, which encompass both tangible and intangible investments aimed at enriching the stock of productive knowledge (R&D engagement, digital technologies adoption and use, and the learning capacity of the organisation), and innovation outputs (Greenan & Napolitano, 2023). Then, we explore how this technological transformation affects outcomes related to on-the-job skills matching, where a discrepancy between the qualification level of a jobholder and the requirements for that particular job exist. Our research ultimately aims to assess whether investing in the knowledge inputs might mitigate the skills mismatches arising from the digital transformation.

Bodrožić and Adler (2018) and Franco and Landini (2022) suggest that pursuing advanced innovation strategies requires revising organisational paradigms to fully leverage technological opportunities. A learning organisation succeeds by carefully balancing the exploration of new ideas with the exploitation of existing knowledge, while continuously adapting strategies to respond to changing demands (Greenan & Napolitano, 2021). Such organisation cultivates individual learning by promoting cognitive challenges and worker autonomy and by providing training opportunities, while also implementing organisation-wide knowledge sharing practices and nurturing an innovative culture (Greenan & Napolitano, 2023). Investing in the learning capacity of the organisation can improve workers' well-being in multiple ways, including by reducing skills mismatches. The alignment between skills and job requirements is crucial in the context of rapid technological change, where continuous learning and skills development are essential for staying competitive and mitigate the effects of job loss due to digitalisation (Cedefop, 2022).

In this paper we focus on three manifestations of skills mismatch: a) skills underutilisation, a form of on-the-job mismatch that may be exacerbated by digital transformation and has been linked to negative outcomes for workers' well-being (Green & Zhu, 2010); b) education underqualification, which may signal the need for workers to upgrade their skills and qualifications through the education system to better align with evolving job requirements and labour market demands; and c) real overqualification, which occurs when workers possess higher levels of education than their job requires and are unable to use or develop their skills at work. Real overqualification always has a negative connotation, as it often results in frustration, dissatisfaction with job's match and a sense of waste potential which may ultimately lead to reduced motivation and productivity losses (McGuinness & Pouliakas, 2017). In contrast, education underqualification could reflect a positive dynamic of labour market participation, particularly when individuals lacking formal qualification gain employment through alternative pathways such as non-formal education (Vandeplas & Thum-Thysen, 2019).

To operationalise this framework, this paper adopts an original empirical strategy by building an innovative EU-wide cross-country dataset combining the employer level European Company Survey of 2019 (ECS, Eurofound and Cedefop) and the employee level European Skills and Jobs Survey of 2021 (ESJS, Cedefop). We leverage these complementary data sources to analyse the relationship between the technological transformation of firms and employees' skills matches.

The integration of these two data sources (henceforth referred to as ECS-ESJS) is achieved through data aggregation at a common level: the 2-digit industry classification according to Nace Rev. 2 within each country, which serves as the matching key between datasets.

2.2 Data and empirical methodology

The 2019 ECS data provides a comprehensive picture to describe the technological transformation in the digital era. We adopt a framework proposed by Greenan and Napolitano (2023) and already applied to the ECS's data in Greenan and Napolitano (2025). It builds on the idea that, while the adoption of emerging technologies does create favourable conditions for change, true transformation requires organisations to creatively embed these technologies in their production processes, breaking from conventional business practices to foster innovation. It links organisations' investments to increase their productive knowledge to their innovation outputs. While traditional models such as the one by Crépon-Duguet-Mairesse (CDM) (1998) focus primarily on R&D investments, we incorporate a broader range of knowledge inputs. Notably, in line with recent studies that augment the CDM model (Mohnen et al. 2019, Nicoletti et al. 2020; Venturini, 2015) we recognise the crucial role of digital technologies in driving innovation.

Therefore, we construct a direct measure of investments in *Technology adoption and use* that considers the diversity of ICTs and digital technologies as well as their continual renewal. It encompasses four sub-dimensions: e-commerce, e-business software, data analytics and robots. The indicator is weighted by the inverse of each technology's European diffusion rate, accounting for the technological advancement stage of emerging technologies. It can range from 0 (adoption of basic technologies) to 1 (adoption of frontier technologies) at the industry-country level.

Furthermore, we introduce a composite indicator of the *Learning capacity of the organisation* as a distinct argument of the knowledge production function of firms that captures the implementation of management tools concerned with the improvement of individual and organisational learning. The indicator equals the average of seven sub-dimensions: a) The cognitive dimension of work; b) Training opportunities; c) Autonomy of workers in cognitive tasks; d) Motivation backed by the organisation; e) Autonomous teamwork; f) Social support; g) Direct participation. Its value at the industry-country level may vary from 0 (no *Learning capacity*) to 1 (maximum *Learning capacity*).

In terms of innovation outputs, we consider product, process, marketing and organisational innovation. The 2019 ECS defines product, process and marketing innovations according to the Oslo Manual. As the survey lacks a specific question on organisational innovation, we use a proxy measure capturing employees' significant influence on management decisions about work process organisation and efficiency. It is, therefore, a definition of organisational innovation focused on employee-driven changes in work processes or workplace innovation ([6]).

The ESJS provides employee level data to measure the outcomes of the digital transformation related to skills mismatches. We identify three key indicators: a) skills underutilisation, which identifies whether workers use their current knowledge and skills to a small extent or not at all in their main job: b) education underqualification, which identifies whether the highest level of education completed by the worker is lower than the level of qualification usually needed in the job; c) real overqualification, which identifies situations of unexploited human capital due to education overqualification associated with skills underutilisation (Pouliakas & Souto-Otero, 2022). To capture possible heterogeneous patterns in how digital transformation impacts cognitive-oriented occupations vs manually oriented occupations, we compute these indicators for two distinct sub-populations: white-collar workers in skilled and semiskilled occupations (professional, managerial, technical, and clerical roles); and blue-collar workers in manual and elementary occupations (craft, machine operation, and basic labour).

Table 3 reports the ESJS survey questions used to approach our outcomes and the recodification criteria that we applied. Table 4 presents descriptive statistics about the key measures of technological transformation and skills mismatches from the ECS-ESJS dataset. The final dataset covers employees aged 25-65 in enterprises with more than 10 employees across 27 EU Member States, and 68 industries (sections B to N of the Nace Rev. 2 classification). With some cells missing due to industry coverage gaps, we have a total of 1 314 cells spanning between 2018 (the reference year in the ECS) and 2021 (the year the ESJS was conducted).

([6]) See Greenan & Napolitano (2025) for details on the construction of knowledge input indicators and innovation outputs.

Table 3. **Construction of key indicators of skill mismatches with the 2021 ESJS**

Indicator	Questionnaire question(s)	Recodification criteria
Skills underutilisation	E_SKILLU: To what extent can you use your current knowledge and skills in your main job?	1 if Small extent/Not at all 0 otherwise
Education underqualification	E_HIGHED/ What is the highest level of education you have completed? E_REQED/ What is the level of education usually needed nowadays to do a job like your main job?	1 if E_HIGHED < E_REQED 0 otherwise
Real overqualification	Combination of education overqualification and skills underutilisation	1 if Skill underutilisation =1 & E_HIGHED > E_REQED 0 otherwise

Source: Authors' elaboration.

Table 4. **Summary statistics of key variables**

Variable	Obs.	Mean	Std. Dev.	Min	Max
R&D engagement	1314	0,52	0,36	0	1
Digital technology adoption and use	1314	0,36	0,17	0	1
Learning capacity of the organisation	1314	0,55	0,11	0,2	0,9
Share of product innovative enterprises	1314	0,38	0,32	0	1
Share of process innovative enterprises	1314	0,37	0,31	0	1
Share of organisation innovative enterprises	1314	0,21	0,26	0	1
Share of marketing innovative enterprises	1314	0,28	0,28	0	1
Skill underutilisation – white-collar workers	1175	0,10	0,18	0	1
Skill underutilisation – blue-collar workers	856	0,17	0,27	0	1
Education underqualification – white-collar workers	1250	0,13	0,18	0	1
Education underqualification – blue-collar workers	930	0,11	0,21	0	1
Real overqualification – white collar workers	1175	0,04	0,11	0	1
Real overqualification – blue collar workers	856	0,08	0,19	0	1

NB: Coverage: Enterprises with more than 10 employees in 68 industries (B to N of Nace Rev.2) in EU 27 (ECS) and their employees (ESJS2).

Source: Cedefop European Company Survey-Second European skills and jobs survey dataset

We employ a Structural Equation Model (SEM) to simultaneously estimate the complex relationship between investments in knowledge inputs and innovation outputs, and between knowledge inputs, innovation outputs and skill mismatches outcomes among white- and blue-collar workers. This empirical strategy also allows assessing whether organisations' innovation strategies mediate the relationships between the knowledge inputs and the skills mismatch outcomes. We identify complete mediation when a knowledge input effect becomes non-significant after introducing a mediator (e.g. product innovation), and partial mediation when the effect size is reduced but not nullified (Iacobucci et al., 2007).

Our systems include the following equations:

$$\begin{cases} Product\_Inno_{ij} = \beta_{01} + \beta_{11} R\&D_{ij} + \beta_{21} Tech_{ij} + \beta_{31} Learn_{ij} + Y_{ij} + \varepsilon_{1ij} \\ Process\_Inno_{ij} = \beta_{02} + \beta_{12} R\&D_{ij} + \beta_{22} Tech_{ij} + \beta_{32} Learn_{ij} + Y_{ij} + \varepsilon_{2ij} \\ Organisation\_Inno_{ij} = \beta_{03} + \beta_{13} R\&D_{ij} + \beta_{23} Tech_{ij} + \beta_{33} Learn_{ij} + Y_{ij} + \varepsilon_{3ij} \\ Marketing\_Inno_{ij} = \beta_{04} + \beta_{14} R\&D_{ij} + \beta_{24} Tech_{ij} + \beta_{34} Learn_{ij} + Y_{ij} + \varepsilon_{4ij} \\ \\ Skills\ mismatch_{ijs} = \beta_{05} + \beta_{15} R\&D_{ijs} + \beta_{25} Tech_{ijs} + \beta_{35} Learn_{ijs} + X_5 (Inno - type)_{ijs} + Y_{ijs} + Z_{ijs} + \varepsilon_{5ijs} \end{cases}$$

where *i* are industries according to the Nace Rev. 2 classification at 2-digit level, *j* are countries and *s* are skilled categories (white- and blue-collar workers).

In the first set of regressions, $R\&D_{ij}$ measures the share of establishments in an industry within a country that engage in the design of new products or services, $Tech_{ij}$ is the *Digital technology adoption and use* indicator and $Learn_{ij}$ is the *Learning capacity of the organisation* indicator. The variables $Inno_{ij}$ represent the sector level share of firms in an industry within a country that introduced new or significantly improved products or services, production processes, organisational methods influenced by employees, marketing concepts or strategies.

The second set of regressions analyses how the technological transformation relates to our three indicators of $Skills\_mismatch_{ijs}$: skills underutilisation, education underqualification and real overqualification. Each indicator is calculated separately for the category of white-collar workers (skilled and semi-skilled occupations) and blue-collar workers (manual and elementary occupations), that we created using the ESJS variable B_ISCOD1_CAT. We estimate each indicator simultaneously for the two worker categories, allowing for potential covariances between their error terms and to account for unobserved factors that may jointly affect both groups.

In this second set of regressions, we include the input indicators computed, which we expect to interact directly with the outcomes, as well as the four innovation types $X(Inno\text{-}type)_{ij}$ that are the dependent variables in the first set of regressions.

All specifications include a set of controls (Y_{ijs}): a dummy that distinguishes between secondary sectors (sections B to F), tertiary sectors (sections G to J) and other services involving information and communication, intellectual, administrative, and financial activities (sections K to N of the Nace Rev. 2 classification); dummies indicating the percentage of enterprises in the industry-country cell that have 11 to 49 employees, 50 to 249 employees or more than 250 employees; dummies for different welfare regimes ([7]). In the second set of regressions, we also control for some socio-demographic characteristics, by adding for each category of workers (Z_{ijs}): a variable to control for the pre and post COVID habits in terms of use of digital technologies, the average age of employees and the percentage of women.

2.3 Main empirical findings

The first set of regressions that describe the technological transformation (Table 5, panel 1) shows that the three knowledge inputs that we consider are significantly associated with all types of innovation outputs ([8]), with two exceptions.

Table 5. **SEM estimation results (panel 1)**

	Skill underutilisation	Education underqualification	Real overqualification
Product innovative enterprises			
R&D engagement	**0.444*** **	**0.428*** **	**0.444*** **
	(0.029)	(0.029)	(0.029)
Digital technology adoption and use	**0.339*** **	**0.376*** **	**0.339*** **
	(0.061)	(0.062)	(0.061)
Learning capacity of the organisation	**0.267** **	**0.280** **	**0.267** **
	(0.121)	(0.115)	(0.121)
Constant term	-0.099	-0.131*	-0.099
	(0.082)	(0.078)	(0.082)
Process innovative enterprises			
R&D engagement	**0.300*** **	**0.299*** **	**0.300*** **
	(0.032)	(0.032)	(0.032)
Digital technology adoption and use	**0.323*** **	**0.355*** **	**0.323*** **
	(0.062)	(0.062)	(0.062)

(7) Nordic countries are Denmark and Finland. Conservative countries are Austria, Belgium, Germany, France, Ireland, Luxembourg and the Netherlands. Eastern-European countries post-communist are Bulgaria, Czech Republic, Croatia, Hungary, Poland, Romania, Serbia and Slovakia. Southern European countries are Cyprus, Greece, Spain, Italy, Malta and Portugal. Former USSR (Baltic) countries are Estonia, Lithuania and Latvia.

(8) The results for this first set of regressions are similar in column (2) and (4) and slightly different in column (3) because the number of observations is larger in column (3).

	Skill underutilisation	Education underqualification	Real overqualification
Learning capacity of the organisation	**0.354*** **	**0.302*** **	**0.354*** **
	(0.117)	(0.111)	(0.117)
Constant term	-0.100	-0.109	-0.100
	(0.082)	(0.077)	(0.082)
Organisation innovative enterprises			
R&D engagement	0.045*	0.051*	0.045*
	(0.027)	(0.027)	(0.027)
Digital technology adoption and use	0.072	0.044	0.072
	(0.057)	(0.057)	(0.057)
Learning capacity of the organisation	**0.772*** **	**0.776*** **	**0.772*** **
	(0.098)	(0.093)	(0.098)
Constant term	-0.376***	-0.351***	-0.376***
	(0.070)	(0.067)	(0.070)
Marketing innovative enterprises			
R&D engagement	**0.180*** **	**0.173*** **	**0.180*** **
	(0.027)	(0.026)	(0.027)
Digital technology adoption and use	**0.357*** **	**0.370*** **	**0.357*** **
	(0.061)	(0.060)	(0.061)
Learning capacity of the organisation	**0.244** **	**0.308*** **	**0.244** **
	(0.097)	(0.093)	(0.097)
Constant term	-0.025	-0.082	-0.025
	(0.068)	(0.064)	(0.068)

SEM estimation results (panel 2)

	Skill underutilisation	Education underqualification	Real overqualification
White-Collar Workers			
Product innovative enterprises	**0.091*** **	-0.022	**0.075*** **
	(0.027)	(0.024)	(0.019)
Process innovative enterprises	-0.007	-0.034	0.010
	(0.028)	(0.022)	(0.015)
Organisation innovative enterprises	**-0.040** **	**-0.052** **	-0.023*
	(0.020)	(0.025)	(0.014)
Marketing innovative enterprises	-0.040*	**0.063*** **	0.002
	(0.023)	(0.023)	(0.016)
R&D engagement	-0.036*	0.038	**-0.041*** **
	(0.022)	(0.023)	(0.014)
Digital technology adoption and use	0.002	0.002	-0.028
	(0.032)	(0.037)	(0.023)
Learning capacity of the organisation	-0.040	**0.142*** **	-0.082*
	(0.069)	(0.054)	(0.047)
Constant term	0.275***	-0.240***	0.135**
	(0.086)	(0.082)	(0.059)
Blue-Collar workers			
Product innovative enterprises	0.019	**0.066** **	-0.013
	(0.037)	(0.032)	(0.023)
Process innovative enterprises	-0.048	-0.048*	0.034
	(0.036)	(0.029)	(0.023)
Organisation innovative enterprises	**-0.079** **	-0.028	-0.020
	(0.032)	(0.033)	(0.022)
Marketing innovative enterprises	0.056	-0.005	0.019
	(0.040)	(0.032)	(0.030)
R&D engagement	**0.065** **	-0.039	0.023
	(0.029)	(0.024)	(0.018)
Digital technology adoption and use	-0.010	0.011	-0.018
	(0.053)	(0.047)	(0.042)
Learning capacity of the organisation	**-0.249** **	**0.312*** **	**-0.274*** **
	(0.112)	(0.084)	(0.082)
Constant term	0.612***	-0.245***	0.474***
	(0.124)	(0.090)	(0.090)
Controls	Yes	Yes	Yes

	Skill underutilisation	Education underqualification	Real overqualification
Observations	781	866	781
Chi-square	0.88	0.53	0.88

NB: authors' elaboration on ECS-ESJS2 dataset, aggregated by industry (Nace Rev. 2, 2-digit level) within a country. Coverage: Enterprises with more than 10 employees in 68 industries (B to N of Nace Rev.2) in EU 27 (ECS) and their employees (ESJS).

Source: Cedefop European Company Survey-Second European skills and jobs survey dataset

Indeed, in line with the literature in economics of innovation, the share of firms engaged in R&D activities and the *Digital technologies adoption and use* synthetic indicator are positively and significantly correlated with the share of all types of innovative enterprises, except for organisation innovative enterprises. Notably, neither R&D (which is only weakly significant at the 10 % level) nor digital technologies are significantly associated with organisational innovation, a result that is unsurprising, considering our use of an employee-driven measure for the latter. The *Learning capacity of the organisation* captures a third powerful innovation driver typically absent from conventional models. This factor is highly significant across all types of innovative enterprises and particularly relevant – in terms of magnitude – for the share of firms implementing organisational innovation.

The second part of Table 5 (panel 2) presents, for white- and blue-collar workers, the results of the second set of regressions, where the dependent variables are one of the indicators of skills mismatches computed for white- and blue- collar workers.

Our analysis of the relationship between the technological transformation and outcomes of skills mismatches reveals that the *Digital Technology Adoption and Use* indicator has no direct effect on skills mismatches, for either occupational group. By contrast, *R&D engagement* has a positive direct effect on white-collar workers as it reduces real overqualification, and an opposite one on blue-collar workers, as it increases skills underutilisation. Finally, the *Learning capacity of the organisation* has significant direct effects for both occupational groups, although these effects are more pronounced among blue-collar workers. For this group, it reduces skills underutilisation while simultaneously showing a positive association with education underqualification. Notably, it also lowers real overqualification, where workers are both overqualified and experience skills underutilisation. For white-collar workers, it displays a direct increasing effect solely on education underqualification. These findings signal that organisations with stronger learning capacities create environments where workers – particularly those in blue-collar positions – can better utilise their skills despite potential formal educational gaps, effectively mitigating skills mismatches through workplace learning opportunities rather than formal credentials alone.

The innovation strategy of the firm significantly influences the genesis of skills mismatches across different worker categories. Organisations operating in sectors with higher share of product innovative enterprises present challenges for white-collar workers, manifesting in higher probabilities of skills underutilisation and real overqualification. Furthermore, product innovation completely mediates the *Learning capacity of the organisation* and the *Digital technology adoption and use* investments. For blue-collar workers, conversely, product innovation is associated with more underqualification, and it partially mediates the investments in the *Learning capacity*, while completely mediating investments in R&D and digital technologies. These results suggest that white-collar workers in product innovative enterprises often struggle to apply their existing knowledge and skills in the workplace. By contrast, blue-collar workers typically possess educational qualifications that fall below formal job requirements, suggesting opportunities for skills development through experiential learning and structured on-the-job training interventions.

Marketing innovation presents a different pattern compared to product innovation. Among white collars, higher shares of marketing innovative enterprises are positively associated with education underqualification. This form of innovation completely mediates the effect of R&D engagement and *Digital technology adoption and use*, whilst partially mediating the influence of the *Learning Capacity*. Furthermore, marketing innovation demonstrate no significant association with skills mismatches among blue collar workers.

Alternatively, higher concentration of organisational innovative enterprises is associated with beneficial outcomes for both white- and blue-collar workers. For the former occupational group, organisational innovation is associated with reduced skills underutilisation and education underqualification (and even diminished real overqualification, if we consider 10 % level of significance), whilst for the latter it yields decreased levels of skills underutilisation. Given that our measure of organisational innovation relates to employee driven changes in work processes and considering that organisational innovation partially mediates the *Learning capacity of the organisation* by amplifying its positive effects on skills matches, our findings indicate that organisational innovation plays a pivotal role in adapting new knowledge and skills to rapid technological transformation.

Finally, process innovation shows lower levels of significance, hence it has no mediating effects. Nevertheless, if we consider 10 % level of significance, it is negatively associated to education underqualification among blue-collar workers.

2.4 Summary and policy relevance

While technological advances spark fears of job loss, research shows that automation targets specific tasks rather than entire occupations. The current technological transformation is nonetheless reshaping work across all sectors and workforce levels, creating potential skills gaps. Though education systems, vocational training and lifelong learning must adapt to teach new skills, organisations themselves may play a crucial role in facilitating a digital transition that does not burden workers, especially vulnerable ones.

We model technological transformation as a relationship between knowledge inputs and various forms of innovation. We consider three primary knowledge inputs: engagement in R&D, digital technologies adoption and use, and the *Learning capacity of organisations*. Our approach extends beyond merely embedding digital technologies such as artificial intelligence or robotics into the production process. We argue that a genuine technological transformation occurs when the application of new knowledge to production yields tangible innovation. In addition, we argue that the way in which enterprises organise the learning process of their employees, so that it contributes in improving collective knowledge, is essential for innovation. However, this aspect is often underestimated or even ignored in the existing literature.

The main objective of this paper is to assess whether investing in the knowledge inputs might mitigate the skills mismatch as indicator of the scale of the disruptions suffered by workers in the technological transformation. To empirically test our hypothesis, we integrate data from the ECS 2019 (Eurofound & Cedefop) with data from the ESJS 2021 (Cedefop) to reconcile information on technological transformation collected at the employer level with employee level information on skills mismatches. Our unit of observation is a Nace rev. 2 2-digit industry within a EU27 country.

Our empirical analysis first provides evidence of the consistency of our model of the technological transformation. In particular, R&D engagement, the adoption and use of digital technologies and the *Learning capacity of the organisation* are powerful drivers of enterprises' innovativeness. The sole exception pertains to the non-significant relationship between digital technologies and organisational innovation, measured here as employee-initiated modifications to work processes.

Second, we find that, while the *Digital technology adoption and use* indicator has no direct effect on skills mismatches and R&D engagement has contrasting effects on white- and blue-collar workers, the *Learning capacity of the organisation* demonstrates significant efficacy in mitigating the challenges associated with technological transformation.

Indeed, we observe that the *Learning capacity of the organisation* serves to alleviate the burden of skill adaptation among blue-collar workers. This kind of investment probably enables less-educated workers to successfully navigate and perform increasingly complex tasks. It is in fact associated with lower skills underutilisation, and lower real overqualification. It is also associated with higher rates of education underqualification, suggesting that sectors with stronger learning capacity cultures organise work in ways that enable less educated employees to successfully perform complex tasks and update their skills. For white-collar workers, the *Learning capacity of the organisation* shows no direct effects on skill mismatches, except for a positive association with education underqualification.

Firm innovation strategies influence skill mismatches and usually mediates knowledge inputs.

Sectors with high product innovation intensity exhibit a tendency to underutilise white-collar workers' skills and increase their overqualification rates, while raising the shares of underqualified blue-collar workers. As product innovation mediates the investments in knowledge inputs, this suggests that white-collar workers in product innovative enterprises acquire new knowledge and on-the-job skills that subsequently remain underutilised in their professional activities. Meanwhile, blue-collar workers appear more likely to develop and apply new skills within their operational context.

Marketing-innovation-heavy sectors presents a different pattern than product innovation: marketing innovation is positively associated with education underqualification among white-collar workers, mediating the effects of knowledge inputs and unrelated with skills mismatches among blue-collar workers.

By contrast, higher shares of organisational innovative organisations benefits both white- and blue-collar workers in terms of skill underutilisation and additionally lowers education underqualification among the white-collar workers. As organisational innovation – reflecting employee-driven changes in work processes – partially mediates the organisation's *Learning capacity*, our findings highlight its central role in enabling the adaptation of knowledge and skills to rapid technological change.

Education underqualification manifests distinctly divergent implications for white-collar and blue-collar workers. For individuals occupying skilled or semi-skilled positions that demand advanced expertise, education underqualification reflects a misalignment between higher education provision and contemporary labour market requirements. This misalignment indicates that academic institutions may be insufficiently equipping graduates with the specialised knowledge and competencies sought by employers in knowledge-intensive sectors.

By contrast, within traditionally manual occupational contexts, education underqualification embodies an entirely different narrative. In these environments, underqualification frequently signifies that the organisation has implemented robust innovation strategies and cultivated substantial learning capacity, thereby enabling personnel with limited formal qualifications to upskill and successfully execute relatively complex tasks. This observation highlights how the *Learning capacity of the organisation* can function as an effective substitute for formal educational credentials, bridging qualification gaps through experiential and contextual development opportunities.

The *Learning capacity of the organisation* might also function as a strategic response to labour shortages, particularly in sectors experiencing recruitment difficulties. By developing effective internal training mechanisms and knowledge-sharing practices, companies can transform underqualified workers into valuable contributors, thereby expanding their potential talent pool beyond conventionally qualified candidates.

Ultimately, these findings underscore how the *Learning capacity of the organisation* contributes substantially to business resilience, enabling companies to adapt more effectively to potential labour market disruptions. By reducing dependency on formally qualified personnel and creating systems that facilitate skill development across diverse educational backgrounds, organisations can sustain operational continuity despite fluctuations in workforce availability and skills distribution.

Overall, results from our study indicates that investments in the *Learning capacity of the organisation* are key in contributing to innovation as well as to human empowerment. Hence, they are a necessary complement to investments in Industry 4.0 technologies.

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Chapter 3. Digitalisation of jobs and age segregation in digital tasks: cross-country evidence based on ESJS2 data

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3.1. Introduction

The world of work is changing rapidly ([9]), and particularly due to demographic challenges, the EU is exposed to labour shortages as well as skill shortages. Subsequently, in 2015-2020, the age group 65+ recorded the fastest increase in labour-market participation (Bertelsmann Stiftung & wiiw., 2023). Changes on the supply side are coupled with important developments on the labour demand side. Automation and digital technologies are transforming the world of work, and reskilling and upskilling are crucial if we are to adapt to these changes. However, not all workers are equipped with the skills and abilities needed to adjust to the ongoing shift in job tasks and expanding digitalisation. Specifically, in the EU every third person at work lacks the proper digital skills ([10]), resulting in (i) major skill shortages; and (ii) widening inequalities, as labour-market returns to skills, particularly digital skills, have increased (Falck et al., 2021; Frey, 2019; DiMaggio & Bonikowski, 2008).

However, as the demographic shift is coupled with rapid digitalisation, the job skill requirements and the rising importance of digital skills may appear challenging to older workers, who often experience a sharp digital divide both at work and in everyday life. Older generations tend to have lower digital literacy and consequently less experience with digital devices and computerised machinery (Falck et al., 2021; Bejaković & Mrnjavac, 2020). Indisputably, older workers possess other invaluable skills and competencies, largely stemming from their long labour-market experience. Yet, increasing digitalisation and automation change the content and organisation of work, with most job tasks inevitably being affected and requiring some degree of digital skills.

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([10]) European Commission. Digital skills and jobs

As a result, especially older workers – who are now staying in the labour market for longer and who possess, on average, lower digital skills – need to engage in upskilling and reskilling because of the extra difficulties they face in adapting to technological change (European Commission, 2021).

A widening age gap in digital skills will inevitably amplify age segregation in job tasks that require digital skills, as older workers opt out of these because of their lack of digital skills; they may also be reluctant to engage in additional training, given the smaller life-long returns to be gained from acquiring digital skills (Peng et al., 2017). Age segregation in jobs has long been documented in the literature, and substantial entry barriers to occupations with steep wage profiles, pension benefits and computer usage have been among the major factors driving age segregation (Biagi et al., 2011; Hirsch et al., 2000). However, rapid automation and digitalisation, may result in even more persistent job-task selection patterns across older and younger workers, largely driven by differential digital skill profiles ([11]). Furthermore, opting out of digital tasks can be even more pronounced among older women, as the persistent gender gap in digital skills and the use of digital skills may reinforce age segregation with regard to digital tasks in the case of older women (Siddiq *& Scherer, 2019). Given the increasing wage returns to digital skills, this could widen the gender wage gap even further. Data from the European Skills and Jobs Survey highlight that older workers tend to be less exposed to digital technologies at work, but this varies by educational attainment and occupation, which may be related to labour market segmentation patterns (Cedefop, 2022).

While research consistently points towards the digital vulnerability of older adults, results of the ESJS2 show that a substantial share of older workers invests in digital skill development. Moreover, they tend to direct their training activities more often at digital skill development compared to younger workers (Cedefop, 2022).

Without presenting a comprehensive literature review in this Cedefop working paper we can emphasise that the previous and most recent literature shows clear evidence that older workers are disadvantaged in terms of digital skills and they tend to be less engaged in digitally intensive work compared to younger workers. However, research further shows that older workers are not homogenous and socioeconomic inequalities in terms of skills and ICT use and associated labour market outcomes also prevail within this age group. Reskilling programs for older adults need to consider

([11]) It is worth mentioning that digital skill gaps between age groups may also shrink over time as overall technology adoption increases and because the current young generation is the old generation of the future. Zilian and Zilian (2020) find mixed results for Austria using Eurostat data from 2015 and 2019: while the gap between older and younger adults with advanced digital skills has decreased over time, the gap has widened for those with low and basic digital skills.

these inequalities as well as the particular challenges they encounter when learning new technologies.

To date, however, there has been limited internationally comparable evidence on within-job age selection in digital tasks. This is largely due to a lack of international surveys of workers that would allow researchers to derive harmonised and comparative measures of digitalisation at the job-task level.

Our analysis makes some contributions in this respect to the existing literature. It will provide one of the first comprehensive evidence on age selection into digital tasks within similar jobs in the EU context, by harnessing the very detailed measures of digital tasks of Cedefop's second European Skills and Jobs Survey (ESJS2). Aiming to investigate how older workers are adjusting to the shift in work tasks towards greater digital intensity, it answers the following research questions:

(a) Is there within-job age selection into more digitally demanding tasks?
(b) Do older workers tend to engage more or less in digital upskilling by training than younger workers in similar jobs? This question is linked to the potential widening or shrinkage of age gaps in digital skills.
(c) Are there within-job age disparities in wage returns to the performance of digital tasks?
(d) Are the aforementioned age-related disparities even stronger among women than men? This highlighted gender wage gap within jobs might be driven by older women opting out of digitally intensive job tasks and differences in participation in digital upskilling.

3.2. Data and empirical methodology

3.2.1 Data

The data used in this analysis stems from Cedefop's second European Skills and Jobs Survey (ESJS2) which was conducted in 2021. The data allows us to look at how skills needs are changing as a consequence of digitalisation and technological progress, and how workers are adapting their skills to respond to such transformations. The ESJS2 covers all EU-27 countries, Iceland and Norway and has a sample of over 45 000 adult employees. It provides comprehensive information on the socio-demographic characteristics of respondents (age, gender, education, urbanisation) and detailed job profiles (e.g. industry, occupation, employment tenure, firm size, type of contract, work hours, earnings, job satisfaction).

Most importantly, the survey maps the task structure of jobs and uses that to proxy job–skill requirements in labour markets. The second wave of the ESJS places the digital demands of jobs in the spotlight. As a result, it allows to capture the wider use of digital skills and the greater digital demands of jobs across a broad range of occupations, by collecting data on (i) on-the-job use of various digital devices; (ii) the performance of diverse job tasks requiring digital skills and the use of digital devices; and (iii) operation of various computerised machinery. This is a major advantage of the ESJS2 survey, as it measures the use of digital skills at work very comprehensively, covering multiple applications and numerous devices that require digital competence. The ESJS2 data includes a broad range of 10 digital job tasks ([12]) performed by employees, from simple tasks, i.e. using the internet up to complex tasks like advanced programming for AI.

Based on the information collected on digital tasks within jobs, the Cedefop digital skills intensity (DSI) index is derived. This index relies on a composite indicator approach to characterise jobs in terms of the intensity of on-the-job use of digital technology (non-users, low, medium, high). The index combines quantitative intensity and qualitative complexity measures – the number of computer applications used in jobs and their skill complexity. Furthermore, the survey provides a proxy for the digital upskilling of workers, by eliciting whether respondents had education or training activities to develop their computer/IT skills needed for their job in the last year.

3.2.2 Methodological approach

The empirical analysis is structured into three parts. In the first part, we analyse within-job age selection into digital tasks. To derive a unified measure of digital job-task intensity, we apply the digital skills intensity (DSI) index, which takes into account all the 10 digital job tasks, with two sub-components – quantitative digital intensity (number of digital tasks performed and digital devices used) and qualitative digital complexity (a judgement on the intensity of digital knowledge and skills, based on the complexity of the activities performed). Out of the information on digital job tasks performed, the DSI index is derived as a categorical variable differentiating between non-users, low-intensity users, medium- and high-intensity users. To approximate same jobs, we construct industry-occupation pairs and employ a multinomial ordered logistic weighted regression of the following form:

$$P\{y_i = \{0,1,2,3\} \big| A_{ij}, G_{ij}, Job_{ij}, X_{ij}^n\} = \alpha + \beta A_{ij} + \mu G_{ij} + \sigma A_{ij} \times G_{ij} + \rho Job_{ij} + \gamma_n X_{ij}^n + \varepsilon_{ij}$$

([12]) The 10 digital job tasks in the ESJS2 survey by qualitative complexity categories: Low intensity users: 1: Using internet for browsing, sending emails, etc.; 2: Writing or editing text with word processing program; 3: Preparing presentations with specialised software; 4: Using spreadsheets, using specialised software; Medium intensity users: 5: Using more advanced functions of spreadsheets (e.g., macros or complex formulas); 6: Working with specialised, sector or occupation-specific software; 7: Managing and merging databases with specialised software, etc.; High intensity users: 8: Writing codes using a computer language, e.g. C++, Python; 9: Writing programs using AI methods; 10: Developing or maintaining IT systems, hardware or software.

In specification (1) the dependent variable $y_i \in \{DSI_{ij}\}$ refers to the digital complexity of tasks performed on the job by individual i in country j. Respondents' age $A_{ij}$is a categorical variable with ten-year age categories, G_{ij} stands for gender, Job_{ij} implies industry–occupation pairs, and the vector X_{ij}^n includes a broad range of demographic (education, urbanisation, etc.) and employment controls (employment tenure, firm size, type of contract, work hours). Moreover, we add an interaction term between age and gender, allowing us to investigate gender disparities in age segregation in digitalised tasks.

In the second part of the analysis, we will analyse age disparities in digital upskilling. As measure of upskilling we employ whether, within the last year (or since the start of employment), an individual has learned new computer programs or software to do the main job: We will employ a specification similar to (1), but with the upskilling variable $y_i \in \{ICT\ Training_{ij}\}$ as dependent variable. We will estimate the model using weighted logistic regression based on ESJS2 data.

In the third part, we investigate differentials in within-job wage returns to digital tasks across older and younger workers by gender. We employ a weighted linear regression of the following form:

$$lnW_{ij} = \alpha + \omega DSI_{ij} + \beta A_{ij} + \mu G_{ij} + \sigma A_{ij} \times G_{ij} + \quad \rho Job_{ij} + \gamma_n X_{ij}^n + \varepsilon_{ij}$$

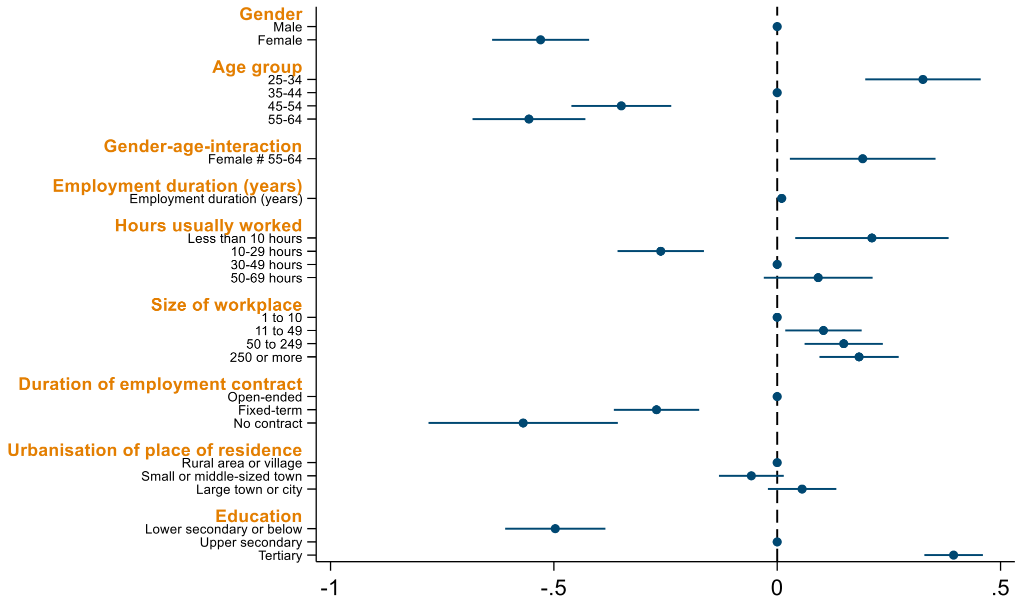
We regress the logarithm of the hourly wage W_{ij} of individual i in country j on age (A_{ij}), on gender (G_{ij}) and the digital skills intensity index of the job (DSI_{ij}), derived within ESJS2, industry–job pair (Job_{ij}) and a set of the same demographic and employment controls X_{ij}^n as in specification (1). Specification (2) contains also an interaction term between age and gender to identify potential gender differences of within-job age related disparities in wage returns to the performance of digital tasks.

3.3. Main empirical findings

3.3.1 Age segregation of digital skill intensity of jobs

In this section we present the main results of the analysis on age segregation in digital skill intensity in jobs performed by employees. We apply an ordered logistic regression and use survey weights. The first dependent variable is the categorial variable of the DSI index, which comprises the categories: non-user of digital devices, low, medium or high level of digital skills intensity of the main job. In our preferred regression specification, we control in addition to the different explanatory variables ([13]) including an interaction term between age groups and gender presented below, also for countries and jobs, i.e. for occupation-industry pairs. First, we present raw coefficients (Figure 3), i.e. we can only observe if an explanatory variable is associated significantly or not with a higher probability of being in a higher DSI category, but not by how much. Marginal effects will be presented in Figure 4.

Figure 3. **Digital skill intensity of jobs: raw coefficients of ordered logit regression**



NB: Authors' own calculations: robust standard errors, weights Pan_Country_weight_v2.
Source: Cedefop second European skills and jobs survey (ESJS2).

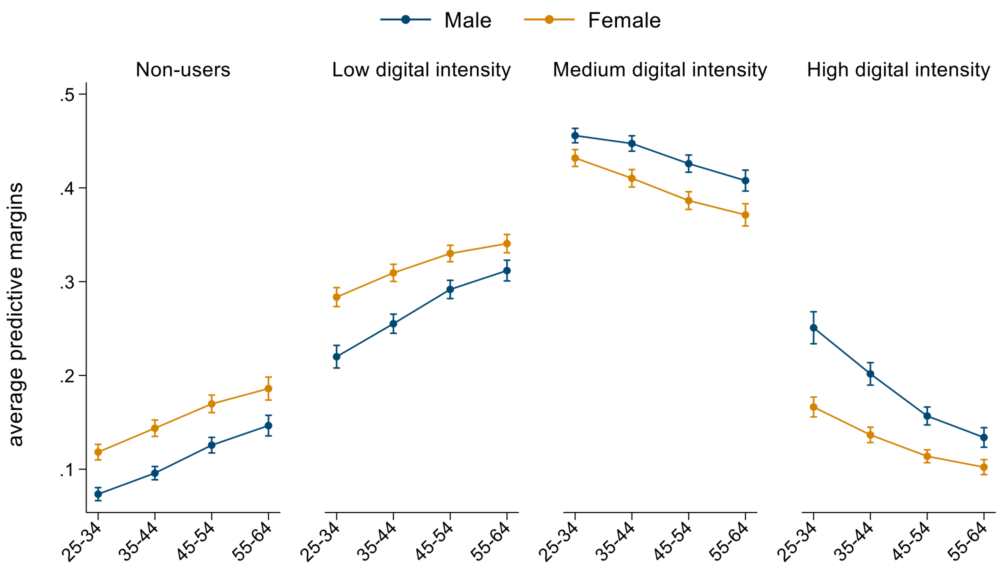
The raw coefficients show that women are less likely to fulfil tasks of a higher DSI category within jobs. We can also observe the expected age differences where higher age is associated with a lower likelihood of falling into a higher DSI category. The interaction term between age groups and gender shows that the prevalent gender gap of digital skill intensity within jobs decreases with rising age, but significantly only for the age group 55-64. Thus, we show in Figure 3 only this category and not those with insignificant coefficients. The probability of a higher DSI category is higher for those working on average full-time (30-49 hours per week) or even more (50-69 hours) in comparison to part-time (10-29), while the group of employees with less than 10 working hours per week seem to have rather different characteristics and is also more likely to perform more complex digital tasks. The likelihood of a higher DSI category

([13]) Most of the explanatory variables include, in addition to the presented categories, a category for 'Don't know' and another for 'No answer', which we included in our regressions. However, we suppressed these categories in the presentation of the results.

increases with more employees working in an enterprise but does not differ by degrees of urbanisation of the place of residence of the employee.

Employees with open-ended contracts are more likely to have a higher DSI index than those with fixed-term or no contracts at all. Also, those employees that have tertiary education and those with upper secondary education show a higher probability compared to those with education below upper secondary level.

Figure 4. **Digital skill intensity of jobs: average predicted probabilities by age group and gender**



NB: Authors' own calculations: robust standard errors, weights Pan_Country_weight_v2.
Source: Cedefop second European skills and jobs survey (ESJS2).

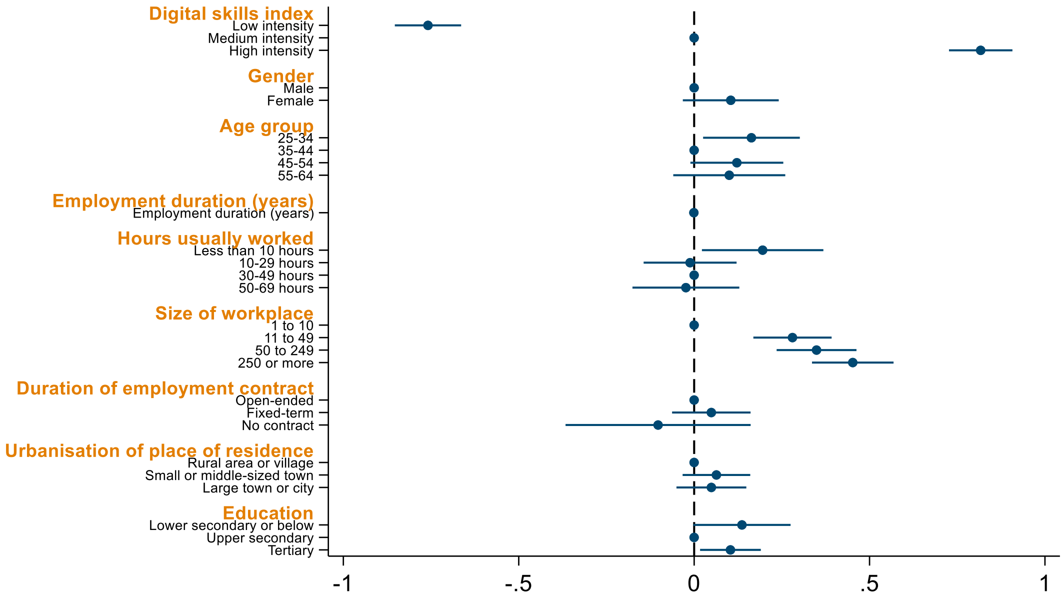
To illustrate how gender and age group are associated with the likelihood of belonging to the different categories of DSI (all other covariates being held constant), in Figure 4 we plot the average adjusted predictions (y-axis) of any given individual falling into each of the four DSI categories for the four age groups (x-axis), differentiated by gender (blue represents men, orange women). Figure 4 highlights a significant divide between age groups that is most pronounced in the high DSI category. Thus, even after controlling for a rich set of variables, young adults (aged 25-34) are much more likely to perform high DSI tasks than are middle aged or older employees; meanwhile older generations are much more likely to be non-users or to perform tasks of low DSI. There is also a clear gender gap: men generally have a higher probability than women of falling into the category of high DSI, whereas women – and in particular older women – are more likely to be non-users or to perform low DSI tasks. The gender gap in jobs of high digital skills intensity is the largest of all DSI categories – with younger age it even tends to increase, i.e. it might even aggravate the ongoing digital transformation of the economy.

3.3.2 Age segregation of training participation

In the following we present the results of the analysis on the participation of employees in ICT training. We applied a logistic regression using survey weights. The dependent variable indicates if the employee took part in a course, etc. in the past 12 months in which she or he could enhance her or his digital skills. Again, we first present raw coefficients (Figure 5); thus, we can only observe if an explanatory variable is associated with a higher probability of having participated in a training measure. In our regression model we control for all explanatory variables presented in Figure 5, which includes an interaction term between gender and age as well as for countries and jobs, i.e. occupation-industry pairs. As expected, employees in jobs of higher DSI categories obtain more ICT training, while we don't find a pronounced pattern of age segregation; however, the middle age group 35-44 is less likely to receive ICT training. In addition, women show a higher probability of participating in digital skills training measures. The interaction between age group and gender was not statistically significant and is omitted from Figure 5 for conciseness.

The likelihood of participating in training increases with more employees working in an enterprise, while between individuals living in more urbanised areas the differences aren't statistically significant as well as between those with open-ended contracts, fixed term or no contracts. Employees with tertiary education show a higher probability compared to those with education below upper secondary level, while no difference is found between the latter group and those with upper secondary education. Longer employment duration in a company is also associated with a higher likelihood of training participation.

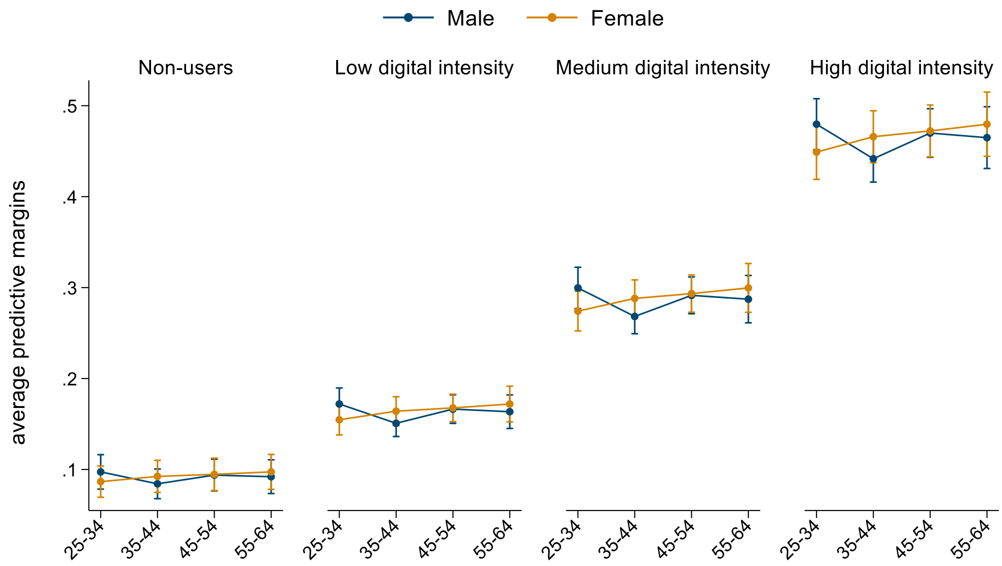
Figure 5. **Training participation by digital skill intensity of jobs: raw coefficients**



NB: Authors' own calculations: robust standard errors, weights Pan_Country_weight_v2.
Source: Cedefop second European skills and jobs survey (ESJS2).

Figure 6 illustrates how the likelihood of participation in IT training diverges between jobs of different task categories of DSI (all other covariates being held constant). We plot the average adjusted predictions (y-axis) of any given individual falling into each of the four DSI categories for the four age groups (x-axis), differentiated by gender (blue represents men, orange women). Obviously, in jobs of higher DSI categories IT training is a permanent built-in process. Employees in the high digital intensity group have a 40 %-50 % chance of participating in training with no significant differences between genders and age. Surprisingly, IT training probability differs a lot between DSI categories but hardly between age groups. There exist no significant gender training gaps if we apply the rich set of control variables in our regression analysis. This however also indicates that a narrowing of the gender DSI gap is not likely to take place, given the non-existence of preferential training measures at the workplace.

Figure 6. **Training participation by digital skill intensity of jobs: average predicted probabilities by age groups and gender**

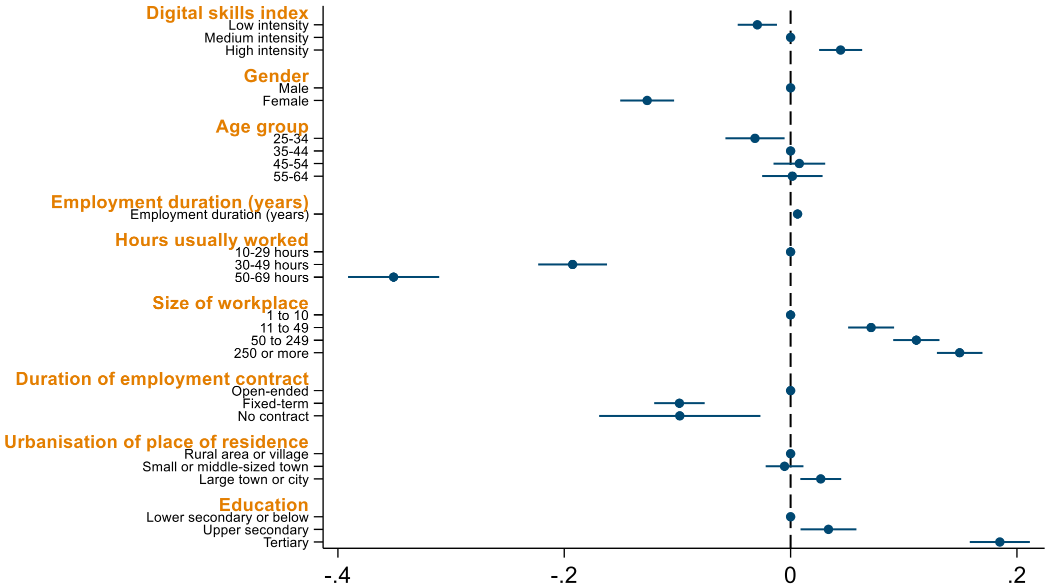


NB: Authors' own calculations: robust standard errors, weights Pan_Country_weight_v2.
Source: Cedefop second European skills and jobs survey (ESJS2).

3.3.3 Age segregation of within-job wage returns to digital tasks

The next part of our analysis covers age differentials in within-job wage returns to digital tasks by applying linear regressions and using survey weights. The dependent variable is the logarithm of the hourly wage of employees. The coefficients describe the percentage change in wage associated with a one-unit change in the respective explanatory variables. In addition to the explanatory variables presented in Figure 5, we again control for countries and for jobs, i.e. occupation-industry pairs. The results show that wages rise with higher digital skill intensity of jobs. As expected, we also find a gender wage gap in the ESJS2 data after controlling for several important explanatory variables. Hourly wages increase up to the age group 45-54 but decrease thereafter; however, these differences are not statistically significant. Thus, no significant differences can be detected between the age groups 35-44, 45-54 and 55-64. However, longer employment duration in a company is associated with significantly higher hourly wages, which could partially compensate for the decline in wages with age.

Figure 7. **Within-job wage returns by digital skill intensity: raw coefficients**



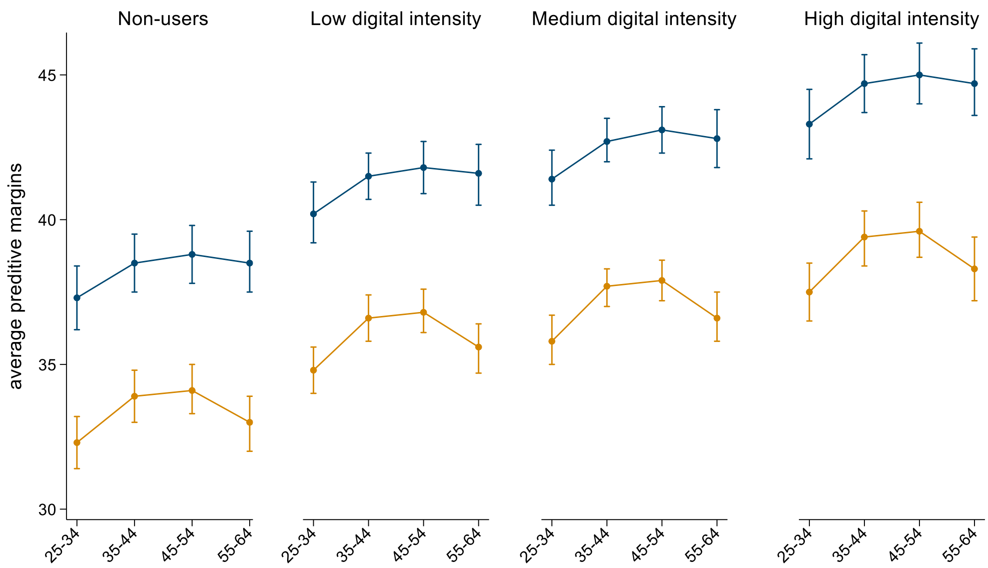
NB: Authors' own calculations: robust standard errors, weights Pan_Country_weight_v2.
Source: Cedefop second European skills and jobs survey (ESJS2).

The more hours employees work per week, the lower their hourly wage (possibly due to unpaid overtime). Higher wages are more likely in firms with more employees and for individuals living in large towns and cities. Employees with open-ended contracts earn higher hourly wages than those with fixed-term or no contracts. Also, individuals with upper secondary and tertiary education earn higher wages compared to those with education below the upper secondary level. We also include an interaction term between gender and age group. However, we do not find any significant differences in wages across age groups by gender.

Figure 8 illustrates how hourly wages diverge within jobs (i.e. for occupation-industry pairs) by task categories of different digital skill content, i.e. by different DSI index groups (all other covariates being held constant) and how those outcomes are associated with gender and age group. We plot the average adjusted predictions (y-axis) of any given individual falling into each of the four DSI categories for the four age groups (x-axis), differentiated by gender (blue represents men, orange women). Obviously, a large part of wage differences between jobs of the four DSI categories are already eliminated when applying the set of control variables, particularly occupation categories and NACE sectors. Moreover, part of the age differences is also captured by the variable documenting the duration of employment in a specific company. Nevertheless, jobs with tasks of higher DSI categories show a more generous hourly renumeration. In jobs of all DSI categories hourly wages increase with age, but decrease again for the age group 55-64, slightly in the case of men, while more pronounced in the case of women. Of course, employees do not experience a decline in wage in their job in an enterprise over their career. However, as shown by Charni and Bazen (2017), who compared wage developments using cross-sectional and panel data, younger cohorts still experience faster wage growth, whereas older cohorts no longer do. On average, the younger generation also surpasses the previous one in terms of wage levels. Moreover, for younger workers, job changes and periods of unemployment do not generally lead to wage decline but increases, while for older workers, such events are more likely to result in wage losses.

Figure 8 also shows an enormous gender wage gap across all DSI categories. While these wage gaps are somewhat smaller in the two middle age groups (35-54) they increase again for the older aged group (55-64). This is likely also due to the reasons described above for the kink in the wage curve by age. The steeper decline observed among women may be because more women than men in the 55–64 age group have already retired.

Figure 8. **Within-job wage returns by digital skill intensity: average predicted estimates by age group and gender, in EUR**



NB: Authors' own calculations: robust standard errors, weights Pan_Country_weight_v2. Estimation results presented in EUR, not logs.

Source: Cedefop second European skills and jobs survey (ESJS2).

3.4. Summary and policy relevance

In our analysis, we address the disproportionate effects of digitalisation across age by investigating within-job age segregation in tasks by digital intensity, within-job age disparities in digital upskilling, age inequalities in wage returns to digital job tasks as well as the role of gender in these age segregation and inequality patterns. We use data from Cedefop's second wave of the European Skills and Jobs Survey (ESJS2), conducted in 2021, and employ weighted (multinomial ordered) logistic regressions as well as weighted linear regressions.

In the first part of our analysis, we look at within-job age selection into digital tasks. To derive a unified measure of digital job-task intensity, we apply the digital skills intensity (DSI) index of Cedefop, which takes into account 10 different less and more complex digital job tasks and derives four different DSI categories. This DSI categorial variable (non-users, low, medium, high intensity users due to digital tasks performed) is our dependent variable, while the explanatory variables are socio-demographic characteristics of respondents (age, gender, education, urbanisation) and detailed job profiles (e.g. industry and occupation pairs, employment tenure, firm size, type of contract, work hours). Our main results are:

(a) Younger workers are more likely to work in positions requiring frequent and complex use of digital technology, while older workers tend to occupy roles needing lower or no digital skills.
(b) Women are less likely to perform medium to high digital intensity roles then men; the gender gap is highest in jobs with high digital intensity tasks.
(c) The gender gap decreases with age for low and high digital intensity tasks while it increases slightly for medium digital intensity tasks.

In the second part of the analysis, we investigate age disparities in digital upskilling. We apply a weighted logistic regression with participation in ICT training in the past twelve months as dependent variable, using the same explanatory variables as in the previous specification, but also including the DSI index categories as an independent variable. Our main result is that, when controlling for a large set of job characteristics:

(a) The probability of training participation increases with digital skills intensity, but there are no significant gender or age gaps.

In the third part of the analysis, we investigate differences in within-job wage returns to digital tasks across older and younger workers by gender. We employ a weighted linear regression with the logarithm of hourly wage as the dependent variable, using the same explanatory variables as in the previous specification, including the DSI index categories as independent variables. Our main results are:

(a) Jobs with higher digital skill intensity are associated with higher hourly wages.

(b) In jobs of all DSI categories hourly wages increase with age, but decrease again for the age group 55-64, slightly in the case of men, while more pronounced in the case of women. This is largely not the result of declining wages among older workers, but of younger workers advancing toward higher wage levels than those of previous generations.
(c) We find a substantial gender wage gap across all DSI categories. The gaps are smaller in the two middle age groups (35-54) but increase again for the older aged group (55-64).

The policy conclusion of this paper is straightforward. In order to tackle the existing within-job age segregation in digital skill intensity of tasks, more training is needed for older workers. Currently, training participation (controlling for jobs) varies by DSI categories of jobs, but not by age or gender. In order to reduce both age and gender gaps, these groups would require even greater access to training. The same applies to efforts aimed at reducing gender wage gaps. However particularly in this case, inequalities and underlying gender norms have to be tackled by measures in other areas, e.g. family policies, etc.

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Chapter 4. Technological change and the upskilling of European workers

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4.1. Introduction

The past decade has seen growing research and policy interest on the actual and prospective impact of advanced digital technologies on labour market outcomes. The bulk of the academic literature initially focused on the overall employment impact of technologically induced automation, spurred by the advent of artificial intelligence (AI) technologies and advanced robotics. Frey and Osborne (2013, 2017) is an often cited study, predicting that close to a half of all jobs in advanced economies are susceptible to replacement by machine learning. Subsequent studies that account for task heterogeneity within occupations have shown that the share of all jobs considered to be at high risk of automation is much lower, ranging between 9-14 % within the labour markets studied (Pouliakas, 2018; Nedelkoska & Quintini, 2018; Arntz et al., 2017).

While it has often been asserted that digital technologies tend to crowd out routine jobs and foster labour market polarisation (Autor et al., 2003), recent studies have highlighted that newer AI technologies have wider task displacement effects within occupations, also reducing demand for non-routine, abstract tasks (Gathmann et al., 2024). Indeed, the ability of Generative Pre-trained Transformers (GPTs) to partially perform cognitive tasks (e.g. analysing text, drafting documents and messages, or searching through private repositories and the web for additional information) is increasingly recognised, resulting in a new wave of automation affecting ‘knowledge workers’. A recent AI skills survey carried out by Cedefop (2025) has shown that while the use of AI has resulted in the destruction of some job tasks for about one in three European workers, four in ten ended up doing some new or different tasks. As a result, the most important impact of GPTs is likely to be the augmentation of existing jobs with a new blend of tasks, as opposed to fully or partially automating them.

While the literature on the impact of technological change on jobs has been expanding rapidly in recent years, there has been scarce evidence on the associated implications for job-related training. In the face of significant task churning associated with technological change, as argued above, it is expected *a priori* that the requirement for learning and training among workers will be greater. An OECD (2023) survey revealed that training indeed plays an important role in enabling workers to adapt to AI's integration in the workplace. Employers tend to opt for training current employees, or outsourcing, over hiring and firing to overcome AI related skill gaps (ibid, 2023). Innocenti and Golin (2022) point out that in addition to actual exposure to new digital technology, the fear of automation can by itself act as a spur towards the take-up of more training by workers. Nevertheless, it is generally the case that occupations at high risk of automation tend to consistently have a lower likelihood of participation in job-related adult education and training (Ioannidou & Parma, 2022), although more training can result in the switch of workers towards less exposed jobs (Gathmann et al., 2024; Zeyer-Gliozzo, 2024). Falck et al. (2024), for instance, use a large internationally harmonised dataset and show that job training reduces workers' automation risk by 4.7 percentage points.

Firm-level studies have, by contrast, shown that technological change tends to have a negative relationship with employers' investment in continuing training (Brunello et al., 2023), particular for incumbent workers (Muehlemann, 2024). It is argued that digital technology and training are substitutes within firms, as a higher use of the former reduces the marginal product of the latter, particularly in lower-skilled jobs.

Understanding the extent to which technology will alter the composition of jobs and the likely need for employers and workers to adjust to technologically driven job disruption via (formal, non-formal and informal) training is therefore an important topic for policymaking.

4.2. Data and empirical methodology

In this paper, we use data from the second wave of the Cedefop European Skills and Jobs Survey (ESJS2) for 29 European countries to address these issues. The ESJS is an adult employee survey, with both waves collecting core information such as socio-economic and job characteristics, job skill requirements, skill mismatches, training and labour market outcomes. The second wave of the survey is particularly focused on the impact of new digital technologies and technological change on the future of work. In this paper, we focus particularly on the survey questions related to (a) the adoption of new digital technologies in the current job during the year preceding the survey, captured by the respondent's need to learn either new computer software or computerised machinery to do the job (b) the impact of such technological adoption on task composition, namely if some of the worker's tasks were made redundant or new ones created as a result of new digital technology at the job and (c) participation in education or training activities to learn new job-related skills in the last year. The key goals of the study are to uncover the relationships between these three aspects of the survey.

A key feature of our study is that we separate out workers into the following five categories:

(a) workers who have not seen any change in the use of new technologies, digital or computerised, within their main job;
(b) worker who have experienced new technologies, digital or computerised, within their main job and have not experienced any change in job tasks as a consequence of these new technologies;
(c) worker who have experienced new technologies, digital or computerised, within their main job and have only experienced task displacement as a consequence of these new technologies;
(d) worker who have experienced new technologies, digital or computerised, within their main job and have only experienced task creation as a consequence of these new technologies;
(e) worker who have experienced new technologies, digital or computerised, within their main job and have experienced both task displacement and task creation as a consequence of these new technologies.

Our empirical strategy first identifies the job characteristics of workers in Categories 2, 3, 4 and 5 relative to the reference Category 1 (i.e. workers who have not seen any change in the use of new technologies in their job), using Equation 1. *TaskΔ* is a binary variable indicating the degree to which a worker's tasks have been changed as a result of new technologies, X1 is a vector of individual and job characteristics, X2 are sectoral and country level fixed effects while $\varepsilon_i$denotes the error term.

$$TaskΔ_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \varepsilon_i \qquad (1)$$

A key objective of the paper is to assess the extent to which training participation varies depending on how new technologies affect a job's task composition. To capture this, we estimate Equation 2, where *Train* indicates the extent to which workers were in receipt of job-related training in the 12 months prior to the survey, *TaskΔ* is a binary variable indicating the degree to which a worker's tasks have been changed as a result of new technologies, X1 is a vector of individual and job characteristics, X2 are sectoral and country level fixed effects while $\varepsilon_i$denotes the error term.

$$Train_i = \beta_0 + \beta_1 TaskΔ_i + \beta_2 X_{1i} + \beta_3 X_{2i} + \varepsilon_i \qquad (2)$$

To obtain unbiased estimates from Equation 2, one needs to be wary of the potential impact of selection bias, whereby the treatment variable is non-randomly correlated with another right-hand side covariate that also influences the outcome variable. For example, employers may disproportionately implement new technologies in posts staffed by more educated employees, who are also more likely to be selected for training. In such circumstances, the coefficient on task composition may also be incorporating some of the influences of educational attainment on the probability of training and it will be biased.

To account for this, we also estimate the relationship between training and changing task content using Propensity Score Matching (PSM). The propensity score is defined as the conditional probability of receiving a treatment given certain determining characteristics (Equation 3): D indicates exposure to the treatment and X is a vector of determining characteristics. For the probit and PSM models, the treatment group will be employees in each of the four technological change and task composition categories (Categories 2-5), and the control group will be those workers who have not experienced any new technologies in their main job (Category 1). In the second stage of the PSM estimation procedure, individuals in the treatment group (experiencing technological change) are 'matched' with counterparts in the control group (that have experienced no new technologies) that have similar propensity scores of being subject to the treatment effect and their actual outcomes (job related training) are compared.

$$P(X) = \Pr(D = 1|X) = E(D|X) \tag{3}$$

4.3 Main empirical findings

4.3.1 Descriptive statistics

According to the ESJS2 data, 58 % of employees did not experience any change in the use of new computer technologies at their main job during the 12 months preceding the survey. Of the 42 % who had to learn new digital technology for their job, 14 % reported no impact on job composition, 10 % only experienced task creation and 5 % only saw some task displacement. The remaining 13 % underwent both task displacement and task creation. Overall, levels of technological task disruption are highly dispersed internationally and both rates of task creation and task disruption are positively correlated with each other at country level (Table 6).

Table 6. **Technological change and task content changes (% of total country sample)**

Country	No Technological Change	Technological Change, No Task Changes	Technological Change, Displacement Only	Technological Change, Creation Only	Technological Change, Displacement & Creation
Austria	60.90 %	12.90 %	4.40 %	10.90 %	10.90 %
Belgium	58.00 %	14.30 %	5.60 %	7.60 %	14.30 %
Bulgaria	56.00 %	11.40 %	4.60 %	11.60 %	16.00 %

Croatia	59.60 %	13.40 %	4.50 %	10.10 %	12.10 %
Cyprus	64.40 %	19.80 %	3.80 %	6.70 %	5.10 %
Czechia	61.00 %	16.70 %	4.80 %	8.10 %	9.20 %
Denmark	48.40 %	19.10 %	6.90 %	12.10 %	12.60 %
Estonia	61.70 %	15.30 %	3.60 %	10.00 %	8.30 %
Finland	43.80 %	22.60 %	6.50 %	13.50 %	12.60 %
France	64.90 %	9.30 %	4.50 %	8.30 %	13.00 %
Germany	67.40 %	11.40 %	3.70 %	6.90 %	10.50 %
Greece	55.50 %	16.90 %	8.00 %	8.00 %	11.40 %
Hungary	59.90 %	16.60 %	5.50 %	7.30 %	10.60 %
Iceland	51.40 %	25.80 %	7.60 %	8.10 %	6.30 %
Ireland	54.00 %	9.30 %	4.20 %	10.60 %	21.60 %
Italy	58.40 %	14.20 %	4.40 %	10.70 %	12.20 %
Latvia	61.90 %	11.80 %	3.80 %	10.70 %	11.70 %
Lithuania	52.20 %	12.10 %	4.00 %	13.10 %	17.50 %
Luxembourg	58.40 %	17.80 %	4.10 %	9.70 %	9.70 %
Malta	51.70 %	15.00 %	4.10 %	16.70 %	11.70 %
Netherlands	61.20 %	16.80 %	3.50 %	8.40 %	10.10 %
Norway	47.90 %	24.00 %	6.10 %	10.90 %	10.40 %
Poland	59.10 %	9.50 %	2.90 %	12.70 %	15.60 %
Portugal	58.00 %	14.70 %	6.30 %	9.80 %	11.20 %
Romania	54.90 %	10.00 %	3.40 %	10.90 %	20.60 %
Slovakia	59.70 %	15.50 %	4.70 %	8.50 %	10.90 %
Slovenia	57.00 %	14.20 %	4.00 %	10.40 %	14.30 %
Spain	54.70 %	12.40 %	4.50 %	11.60 %	16.80 %
Sweden	48.50 %	16.30 %	5.10 %	12.00 %	17.70 %

Source: Cedefop second European skills and jobs survey (ESJS2).

The data further indicate a strong relationship between technologically driven job task disruption and the need for job-related training. Across the entire sample, approximately 64 % of employees report undertaking some job-related training in the 2020-2021 period. However, this varies substantially with technological job penetration. Just 51 % of workers in jobs not impacted by new technology were in receipt of job-related training, increasing to 74 % for jobs where new technologies were adopted but there was no impact on job tasks. The incidence of job-related training increases further among employees in jobs where tasks were disrupted because of new technologies, rising to 81 % where tasks are displaced only, 84 % where tasks are created only and 88 % in jobs where new technologies have both displaced and created tasks.

Table 7. Summary statistics by technological change

Variable	No Technological Change	Technological Change, No Task Changes	Technological Change, Displacement Only	Technological Change, Creation Only	Technological Change, Displacement & Creation	Total Sample
Training	0.514 (0.500)	0.744 (0.436)	0.810 (0.392)	0.842 (0.364)	0.878 (0.327)	0.641 (0.480)
Female	0.521 (0.500)	0.506 (0.500)	0.424 (0.494)	0.503 (0.500)	0.446 (0.497)	0.503 (0.500)
Repetitive	0.271 (0.445)	0.204 (0.403)	0.218 (0.413)	0.229 (0.420)	0.264 (0.441)	0.254 (0.435)
Uncertain	0.252 (0.434)	0.296 (0.457)	0.302 (0.459)	0.317 (0.465)	0.349 (0.477)	0.280 (0.449)
Employment Duration (Years)	10.411 (9.408)	9.924 (9.633)	10.024 (9.384)	9.439 (9.432)	8.893 (8.714)	10.027 (9.370)
Part Time	0.222 (0.416)	0.188 (0.391)	0.187 (0.390)	0.182 (0.386)	0.207 (0.405)	0.210 (0.407)
Highest Level of Education						
Low	3,089 (11.6 %)	355 (5.4 %)	145 (6.7 %)	237 (5.1 %)	480 (8.0 %)	4,306 (9.3 %)
Medium	10,980 (41.2 %)	1,842 (28.0 %)	630 (29.1 %)	1,376 (29.5 %)	1,773 (29.5 %)	16,601 (36.0 %)
High	12,537 (47.0 %)	4,363 (66.4 %)	1,387 (64.0 %)	3,035 (65.1 %)	3,757 (62.5 %)	25,079 (54.4 %)
Don't Know/No Answer	61 (0.2 %)	13 (0.2 %)	4 (0.2 %)	14 (0.3 %)	5 (0.1 %)	97 (0.2 %)
N	26,667 (57.9 %)	6,573 (14.3 %)	2,166 (4.7 %)	4,662 (10.1 %)	6,015 (13.1 %)	46,083 (100.0 %)

Source: Cedefop second European Skills and Jobs Survey

4.3.2 Empirical analysis

We next empirically assess the characteristics of our four technologically impacted treatment groups, relative to workers in jobs not influenced by technology, by estimating Equation 1. We estimate probit models and marginal effects are reported in Table 8.

The results from our models confirm that females are between one and four percentage points less likely to be employed in jobs impacted by technological change, with the marginal effects highest for jobs experiencing both task displacement and task creation. Employees with third level qualifications are also more likely to be in jobs impacted by technology. However, this is particularly the case for those employees in jobs where task content is not changed following the introduction of new technologies. This implies reversely that the adoption of new digital technology is more likely to have a non-neutral, marginal impact on task content for workers with lower levels of education. Workers on part-time hours and those with more tenure are generally less likely to be employed in jobs impacted by technological change.

Workers in three of the four categories impacted by new technologies are between one and three percentage points less likely to undertake repetitive tasks. However, employees in jobs were technological change resulted in both task displacement and task creation are no less likely to undertake repetitive tasks, compared to the reference category. Finally, relating to job complexity, workers impacted by new technologies are much more likely to have to respond to unpredictable situations with the marginal effect, at approximately seven percentage points, being highest in jobs where new technologies result in both task displacement and task creation.

Table 8. **Determinants of technological change (Probit estimates, dY/dX)**

VARIABLES	Technological Change, No Task Content Changes	Technological Change, Displacement Only	Technological Change, Creation Only	Technological Change, Displacement & Creation
Female	-0.0128**	-0.0249***	-0.0119*	-0.0424***
	(0.00535)	(0.00376)	(0.00690)	(0.00467)
Repetitive	-0.0304***	-0.00826**	-0.0102**	0.00349
	(0.00571)	(0.00360)	(0.00471)	(0.00601)
Uncertain	0.0327***	0.0181***	0.0345***	0.0672***
	(0.00488)	(0.00351)	(0.00405)	(0.00516)
Employment Duration (Years)	-0.00118***	-0.000400**	-0.00173***	-0.00252***
	(0.000260)	(0.000186)	(0.000224)	(0.000322)

VARIABLES	Technological Change, No Task Content Changes	Technological Change, Displacement Only	Technological Change, Creation Only	Technological Change, Displacement & Creation
Part Time	-0.0222***	-0.00583	-0.0252***	-0.00544
	(0.00688)	(0.00513)	(0.00576)	(0.00931)
Education				
Low (ISCED 0-2)	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Medium (ISCED 3-4)	0.0347***	0.0116**	0.0371***	0.00334
	(0.00919)	(0.00501)	(0.00760)	(0.00888)
High (ISCED 5-8)	0.121***	0.0470***	0.0989***	0.0768***
	(0.0101)	(0.00530)	(0.00684)	(0.00965)
Observations	32,790	28,403	30,891	32,217

NB: Standard errors (clustered at the country level) in parentheses. Marginal effects for industry and country not reported for brevity.

Source: Cedefop second European skills and jobs survey

The results from a probit model following estimation of equation (2) are reported in Table 9, largely confirming the results of our descriptive analysis of job-related training. Being cautious of unobserved factors that might potentially bias our result, we introduce into our model a rich set of additional controls specifically collected by the ESJS2 survey, that capture the extent to which employees have skill sets that are complementary to new technologies. We add the following three additional controls to our specification (a) Digital Intensity ([14]) (b) Tech Savvy ([15]) and (c) an ICT skill gap ([16]). The results from a pooled model containing all controls

([14]) We derive this from the question: ‘Did you use any of the computing devices from the previous question to do the following activities as part of your main job in the last month?’ (Q37). We construct a simple index variable using the eight digital tasks captured in the question, weighting each task based on its technical complexity. For the first three tasks (i.e. web browsing, word processing and presentations), we assign a weight of one. For the second three tasks (i.e. using spreadsheets, using advanced formulae in spreadsheets and working with occupation-specific software), we assign a weight of two. For the last two, more advanced tasks (i.e. managing databases and writing code), we assign a weight of three. For each respondent, we simply aggregate the total value of each task, dependent on the respondent stating that they carried out such tasks in their daily work, giving us the $Digital\ Intensity$ value.

([15]) This is a binary variable denoting whether respondents reported that *their friends* would say that they were technologically savvy (Q76).

([16]) This is derived from the question ‘*To what extent do you need to further develop your computer/IT skills to do your main job even better?*’ (Q61). We code this variable as a binary, where respondents who responded ‘Great extent’ or ‘Moderate extent’ were assigned a one, and those who responded ‘Small extent’ or ‘Not at all’ were assigned a zero.

indicate that, relative to workers in jobs not impacted by new technologies, those in jobs affected by new technologies and no task disruption are 14 percentage points more likely to receive job-related training. The marginal effects increase with the extent of technological task disruption, rising to 20 percentage points for task displacement only and 23 percentage points for task creation only. Employees in jobs were new technologies resulted in both task displacement and task creation are over 26 percentage points more likely to have undertaken job-related training in the previous 12 months, relative to those unaffected by new technologies. In terms of the other control variables, our three variables for worker technological complementarity are all positive and significant. Training is also more likely to be carried out by workers who are full time, with lower tenure and with third level qualifications.

Table 9. **Marginal effects of probit models predicting the likelihood of training**

Variables	**(1) Training**	**(2) Training**
Technological Change		
No Technological Change	*Ref.*	*Ref.*
Technological Change, No Task Changes	0.231***	0.136***
	(0.0124)	(0.008)
Technological Change, Displacement Only	0.296***	0.197***
	(0.0151)	(0.013)
Technological Change, Creation Only	0.328***	0.228***
	(0.0119)	(0.007)
Technological Change, Displacement & Creation	0.364***	0.256***
	(0.0136)	(0.009)
Female		-0.003
		(0.006)
Repetitive		-0.002
		(0.006)
Uncertain		0.047***
		(0.007)
Skill Gap		0.033***
		(0.006)
Tech-Savvy		0.025***
		(0.006)
Digital Intensity		0.015***
		(0.001)

Variables	(1) Training	(2) Training
Employment Duration (Years)		-0.001***
		(0.000)
Part Time		-0.026***
		(0.008)
Education		
Low (ISCED 0-2)		*Ref.*
Medium (ISCED 3-4)		-0.018*
		(0.011)
High (ISCED 5-8)		0.044***
		(0.015)
Country Included	NO	YES
Industry Included	NO	YES
Observations	45,986	40,605
Pseudo R-Squared	0.09	0.13

NB: Standard errors (clustered at the country level) in parentheses. Marginal effects for industry and country not reported for brevity.

Source: Cedefop second European skills and jobs survey

As further robustness tests, we first re-estimate the models on a sub-sample of data collected through a Computer Assisted Web Interview (CAWI) mode. This is done to include additional controls for technological complementarity, which are available in this online sample, such as employees' satisfaction with the technologies used in the workplace ([17]) and a measure of change in their use of technology in the workplace post-COVID19 ([18]). The results of this model, with more extensive controls for technological complementarity, are wholly consistent with our main results presented in Table 9.

In addition, results from a PSM estimation as shown in equation (3) fully align with our parametric estimates. We implement post-estimation checks to measure how strongly unobserved effects must influence the selection process to undermine the propensity score matching results (Becker & Caliendo, 2007). The

([17]) This is derived from the question 'On a scale from 0 to 10, where 0 is completely dissatisfied, 5 moderately satisfied and 10 is completely satisfied, how satisfied are you with the following aspects of your job? – Digital or computer technologies you use.' (Q64). Where respondents answered between seven and ten, they were coded as being 'Satisfied', with values of zero to three corresponding to being 'Unsatisfied' and four to six being 'Moderately satisfied'.

([18]) This is derived from the question 'Compared with the situation before the COVID-19 pandemic, do you now experience any of the following situations in your main job? – You more often use digital technologies to perform some of your work tasks' (Q78).

results from the tests indicate that the estimated impacts of technologically driven task change on training are highly robust. They would remain statistically reliable even in the presence of an unobserved variable that would cause the odds ratio of treatment assignment to increase by a factor of between 2 and 4.5.

4.4 Summary and policy relevance

Understanding the extent to which technology will alter the composition of jobs and the likely associated costs for employers in assisting workers to adjust to technologically driven job disruption is important for policymakers. In this paper, we use data from the second wave of the ESJS to address these issues among adult employees in Europe.

Our analysis shows that workers with higher levels of education are over-represented in jobs impacted by technological change. Contrary to the predictions of previous research, we find no evidence that workers who experienced technologically driven task displacement are more likely to be in jobs with high levels of repetitive tasks. Employees in jobs impacted by new technologies are more likely to have to react to unpredictable situations, thus demonstrating a positive link between technologically driven task disruption and job complexity, confirming previous evidence by McGuinness et al. (2023).

The results from our empirical models indicate that, relative to workers in jobs not impacted by new technologies, those affected by new technologies and no task disruption are 14 percentage points more likely to receive job-related training. The marginal effects, with respect to job-related training, increase substantially with the extent of technological task disruption. Employees in jobs where new technologies only displaced tasks are 22 percentage points more likely to have undertaken training, with the probability of those seeing only task creation being 25 % higher. Employees in jobs were new technologies result in both task displacement and task creation are over 26 percentage points more likely to have undertaken job-related training in the previous 12 months, relative to employees in jobs not impacted by new digital technologies. Our robustness checks confirm that our results are not sensitive to the impacts of sample selection bias and potential unobserved heterogeneity.

Overall, our study highlights that the major impact of new digital technology on jobs is likely to be one of task disruption that increases the need for worker upskilling. Such efforts need to better equip adult workers to cope with higher levels of job complexity and digital intensity in labour markets by investing in their problem-solving, creativity and agility skills. They should also target specific population groups such as older and lower-educated workers in part-time jobs, for whom there appears to be a lower propensity to engage in job-related training as a reaction to the onset of new digital technology in their jobs.

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Chapter 5.
What drives workers' participation in digital skills training? Evidence from Cedefop's second European skills and jobs survey

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5.1. Introduction

Digital skills mismatches ([19]) have been high on the EU policy agenda for some time. Skills mismatches are a concern for policymakers and researchers as they are closely associated with negative labour market outcomes such as wage penalties, absenteeism, high turnover, and lower levels of job satisfaction. Training is one policy instrument that can be implemented to address skills mismatches.

In the economic literature, the concept of skills mismatch is multifaceted and encompasses a variety of types which are very different in terms of their measurement, determinants and impact. In this study, we focus on digital skills mismatch and on training as a policy instrument that can be implemented to mitigate skills mismatches, particularly when there are skills deficiencies and also when it may contribute to higher job quality and better skills utilisation.

Training has been shown to reduce skills mismatches (Pouliakas & Wruuck, 2022), although the positive effect of training on skill mismatches can vary across occupations, industries or regions (Messinis & Olekalns, 2007; Ferreira et al., 2017; Brunello & Wruuck, 2021). Additionally, training has significant, positive short- and long-term effects on job match quality (Zhang et al., 2021); and is positively associated with job satisfaction and negatively associated with turnover intention (Haepp, 2022; Park & Luo, 2022; Wen et al., 2023).

Existing research which has identified factors related to participation in training shows that low-skilled workers are less likely than high-skilled ones to participate in adult learning (OECD, 2020, 2023). Aside from the policy priority to increase the

([19]) An earlier version of this work was published as: Bertoni, E., Cosgrove, J., Pouliakas, K., & Santangelo, G. (2024). *What drives workers' participation in digital skills training? Evidence from Cedefop's second European Skills and Jobs Survey*. European Commission – Joint Research Centre and Cedefop. JRC137073.

level of basic skills in the population, this finding is of concern when we consider that low-skilled workers are also at increased risk of displacement due to job automation (Lassébie & Quintini, 2022; Nedelkoska & Quintini, 2018; Pouliakas, 2018). Furthermore, even though fear of automation is positively associated with individuals' intentions to undertake training (Innocenti & Golin, 2022), the low-skilled are also less likely to be concerned about the potential negative consequences of digital technology compared to those exposed to digitalisation (Cedefop, 2022b). Finally, when looking at institutional factors, it appears that workers in occupations at high risk of automation are consistently less likely to participate in job-related adult education and training, irrespective of welfare regime (Ioannidou & Parma, 2022).

Recent literature on automation has investigated the implications of different technologies on employment share (Hu et al., 2023; Klenert et al., 2022), and on the changing structure of skills and job tasks (Fernández-Macías & Bisello, 2022; Guo et al., 2022; Fernández-Macías et al., 2023). Evidence shows that automation, robotics and information technologies in general affect industries heterogeneously, inducing employment growth in some and decline in others (McGuinness et al., 2021; Fossen & Sorgner, 2022; Restrepo, 2023). Risk of automation is higher for those occupations that rely on tasks that can be more easily carried out by computers or machines, such as those with high focus on routine-middle-skilled, manual-routine and manual-non-routine tasks ([20]).

The advent of new digital technologies in EU workplaces, including AI and other Industry 4.0 computerised machines, has been associated with positive labour market outcomes, such as growing workplaces and better overall markers of job quality (Cedefop, 2022b), higher job satisfaction and safety, reduction in repetitive tasks, and wage increases (Lane et al., 2023), as well as with negative impact on specific dimensions of job quality, such as work intensity (Antón et al., 2022).

For digital skills specifically, it is often claimed that the labour market for IT occupations is tight, with increasing demand for IT professionals who are in scarce supply. However, digital skill needs far transcend IT occupations. In recent years, fostered also by the COVID-19 pandemic, a growing number of sectors and occupations have been rapidly experiencing a digital transformation, resulting in growing demand for digital skills in non-IT jobs (Cedefop, 2023). Even prior to the pandemic, evidence existed of a digital skills gap that is broader than that associated with IT professions. A study on digital skills gaps in the EU that used

([20]) This means that the job-specific knowledge of medium-skilled or manual workers is likely to become obsolete more rapidly, while the skill content of cognitive-non-routine and cognitive-routine occupations is less exposed to automation.

data collected prior to the pandemic has confirmed priority groups for policy support, which go well beyond the IT sector (Centeno et al., 2022).

In terms of policy targets and implementation, the European Year of Skills, launched in May 2023 and running until May 2024, provided a new momentum to reach the EU 2030 target of ensuring that at least 60 % of adults are in training every year (with 2022 rates estimated at 39.5 %). The Digital Decade skills targets of 80 % of the adult population having at least basic digital skills by 2030; reaching 20 million employed ICT specialists in the EU; and promoting the access of women to the ICT sector to close the persistent gender gap.

Moreover, the European Commission's Digital Education Action Plan 2021-2027 considers the development of digital skills and competences as a strategic priority; the Skills Agenda supports the development of digital skills at all levels; and the 2022 European Declaration on Digital Rights and Principles for the Digital Decade states that everyone 'should be able to acquire all the basic and advanced digital skills they need'.

In November 2023, under the Digital Education Action Plan, the Council adopted two sets of recommendations on improving the provision of digital skills and competences in education and training; and on enabling factors for a successful digital education. The latter recommends that Member States agree on national/regional strategies for digital skills (competences), invite them to set or review national objectives for the provision of skills, take measures targeting 'priority or hard-to-reach groups', give adults opportunities to acquire digital skills, and address the shortage of ICT professionals.

Furthermore, the Council recommendation on vocational education and training (VET) for sustainable competitiveness, social fairness and resilience (2020) underlines the importance of a modern and digital provision of VET, according to the current and future requirements of the labour market, while the 2020 Osnabrück declaration defines VET as an enabler of recovery and just transitions to digital and green economies.

The ongoing policy debate on the future of work is featured in the above policy initiatives. A strong theme in this debate is the impact of AI and automation on jobs and skills (Arregui Pabollet et al., 2019). On one hand, job losses are predicted, although estimates vary widely. On the other hand, new technologies also create new job opportunities with strong policy implications for upskilling and reskilling.

This article contributes to policy on the provision of digital skills of the workforce. By focusing on analysis of Cedefop's second European Skills and Jobs Survey (ESJS2, 2021), it provides new information and evidence on the theme of AI and automation, by examining the extent to which both fear and experience of automation and digital skills mismatch drive adult workers' participation in education and training to improve their digital skills.

5.2. Data and empirical methodology

5.2.1 Data

The European skills and jobs survey (ESJS) is a Cedefop periodic EU-wide survey. It provides robust information from representative samples of adult workers on a core set of measures, including sociodemographic characteristics, job characteristics, job-skill requirements (literacy, numeracy, digital, analytical, manual and interpersonal skills), skill mismatches (vertical, horizontal, mismatches in specific skills, skill gaps), initial and continuing vocational education and training participation, and labour market outcomes (wages, job insecurity, job satisfaction).

The second wave of the survey (ESJS2), carried out in 2021, aims to inform the ongoing policy debate about the impact of digitalisation on the future of jobs and the changing nature of work, as well as heightened concerns about the long-term effect of the COVID-19 crisis on EU digital skill needs and new forms of digital and distance learning. It does so by analysing comparative information from 46 213 adult employees from all EU Member States plus Norway and Iceland (EU+) (Cedefop, 2022a, 2022b) ([21]).

Among others, the ESJS2 provides new evidence on the following areas:

(a) what tasks EU+ workers do in their jobs and the skill needs implied, with particular emphasis on digital skill needs;

(b) the exposure of EU+ adult workers to new digital and automating technologies in a cross-country comparative context;

(c) the extent of technological change and digitalisation in EU workplaces and its impact on workers' skill needs, skill mismatches and overall job quality; and

(d) the extent to which EU+ workers are adapting to digitalisation via continuing learning and supportive workplace practices ([22]).

Novel information collected in the ESJS2 aimed at measuring job-skill requirements, following a task-based approach, allows us to construct the following scales (which are categorised into very low, low, medium and high levels):

([21]) In partnership with the European Training Foundation (ETF), the ESJS2 has been carried out in 2022-23 in an additional five Western Balkan countries plus Israel, collecting information from paid adult workers from a total of 35 EU and neighbourhood countries.

([22]) An [online data explorer for the ESJS2 is available](#).

(a) basic job-skill requirements (literacy and numeracy);
(b) social/interpersonal job-skill requirements;
(c) manual/physical job-skill requirements;
(d) digital job-skill requirements;
(e) job complexity;
(f) work routinisation.

Below we report the main concepts and ESJS2 survey questions the analysis is based on:

(a) **General training participation**: Based on answering 'yes' to participation during the past 12 months to any of the following (formal or non-formal) education or training activities: (a) Courses; (b) Workshops or seminars; (c) On the job training with the support of a designated trainer.
(b) **Digital skills training participation**: [Following from the previous question and asked to those answering 'yes' to it] 'And was at least one of these education or training activities done to further develop your computer/IT skills needed for your job?'
(c) **Experience of technological change:** Based on answering yes to the question 'In the last 12 months, have you had to learn any new computer software or computerised machinery to do your main job?'. Whether such technological upskilling is associated with job-task automation or augmentation is captured as follows: 'As a result of the new ([23]) computer programs or software/new computerised machinery you learnt for your main job in the last 12 months, did your job tasks change in the following way:
    (i) With task replacement: 'You now do not do some tasks you did before?'
    (ii) Without task replacement: (a) 'You now do some different or new tasks; (b) 'You now do some of your tasks at a faster pace than before?'
(d) **Digital skills:** The digital skill level of adult workers is defined on the basis of their use of computing devices or related computerised machinery as part of their main job, as well as the intensity of the digital activities users regularly carry out when doing their work. Non-users are also asked about their knowledge in carrying out specific digital activities.
(e) **Digitally under-skilled**: Defined at the level of the individual worker by asking respondents 'To what extent do you need to further develop your computer/IT

([23]) From the ESJS2 survey questionnaire: 'By 'new' we mean those you started using for your main job in the last 12 months. The ESJS2 includes guidelines and examples of both software and machines and advises respondents to include only major updates.

skills to do your main job even better?' Throughout this analysis when we refer to 'digital under-skilled workers' we focus on workers who responded 'a great extent' ([24])

(f) **Qualification mismatch:** Has a lower, higher or matched qualification compared to that needed for the job, based on a comparison between respondents' highest level of education and that required for the job.

In 2021, 62 % of EU+ workers participated in some form of (formal or non-formal) training (i.e. courses, seminars, on-the-job training) ([25]). Overall, in the EU+ workforce, 26 % participated in digital skills training, 36 % in non-ICT training and the remaining 38 % do not participate in any training.

Around 13 % of EU+ workers reported being digitally under-skilled to a great extent (and another 39 % to a moderate extent). Of the 13 % with marked digital underskilling, 73 % participated in some form of training (46 % in digital skills training and 27 % in non-ICT training) while 27 % did not participate in any training.

On average, workers who report being digitally under-skilled are more likely to be younger, male, living in urban areas and highly educated. They are mostly employed in the ICT or education sectors or in skilled occupations. They are, overall, more experienced workers, in larger organisations, under a permanent contract and on higher salaries. This finding illustrates that many digitally under-skilled workers are highly digitally skilled and are in jobs with high or changing digital job-skill requirements. Indeed, the digitally under-skilled measure relates to both a person's digital skills and his/her job-skill requirements and so is distinct from the low digitally skilled, which is inferred from an assessment of digital skill/competence levels in absolute terms.

5.2.2 Empirical methods

To identify which characteristics are associated with undertaking digital skills training, we run a multivariate logit model on a sample of around 42,000 observations where the dependent variable takes on three values: 0 for no training – baseline outcome; 1 for digital skills training; and 2 for non-ICT training.

([24]) Answer options are: 'great extent'; 'moderate extent'; 'small extent'; 'not at all'; 'don't know'; 'no answer'. This relative measure of digital underskilling differs to other measures aiming to detect the digital skill/competence level of individuals in more absolute terms, such as Eurostat's Digital Skills Index (DSI 2.0), which comprises five competence areas that are based on the European Digital Competence Framework for Citizens (DigComp).

([25]) Note that this is not identical to the measure on which the EU social target of 60 % is based, since the ESJS2 measure used here includes on- the-job training, while the EU social target measure excludes it.

We include in the model the following covariates:

(a) Individual: Age, gender, rural/urban area, highest education completed, vocational/other qualification, perception of losing job, fear of automation, need to digitally upskill/reskill, attitude towards technology (consider technology to increase performance at work, to be useful for learning at work, to be easy to learn to use at work, to be enjoyable to use at work) individual experience of technological change (with task replacement vs task alteration);

(b) Job-skill requirements: Cedefop's digital skills intensity index, basic skill needs of job (reading, writing, mathematics), interpersonal skill needs, manual skill needs; job complexity, job routinisation;

(c) Job characteristics: industry (NACE1), occupation (ISCOD1), tenure, private/public sector, workplace size, contract status, hours worked per week, monthly net pay band; organisation's approach to training (training needs are systematically reviewed, job performance is formally appraised and pay varies according to job performance);

(d) Institutional characteristics: Digital Economy and Society Index dimensions (Connectivity, Human capital, Integration of digital technology, Digital public services), GDPpc PPP, share of working age population (25-64).

5.3. Main empirical findings

We analyse the data on training participation in the EU workforce to find out whether individual perceptions and the experience of technological change make EU workers more likely to undertake digital skills training. The estimated results show that workers' perceptions on the impact of technological change on their jobs influence their digital skills training decisions. Indeed, workers who fear automation (i.e. who believe new digital, or computer technologies have the potential to do part or all their job) engage in digital skills training by 4 percentage points more than those who are not fearful of potential job automation. Additionally, workers who believe new digital or computer technologies will help them to upskill and reskill participate 14 percentage points more in digital skills training. General sense of job insecurity has a smaller positive impact on participation in digital skills training (Table 10).

Around 35 % of EU+ workers experienced some form of technological change, and among them, those who actually experienced task automation are 4 percentage points more likely to engage in training to develop digital skills than those who experienced digitalisation without task replacement.

Table 10. **Digital skills training for workers who experienced technological change**

		Digital skills training		
	Full sample	Workers who experienced tech change		
	(1)	(2)	(3)	(4)
Job-skill mismatch				
Digital under-skilled	0.0984***	0.1343***	0.0924***	0.0897***
Matched in ed. Qualification				
Over-educated	-0.0030		-0.0084	-0.0050
Under-educated	0.0194***		0.0375***	0.0342**
Perceptions of automation				
Fear of automation-None				
Fear of automation-Small/Moderate	0.0387***	0.0481***	0.0435***	0.0349***
Fear of automation-Great	0.0474***	0.0706***	0.0458***	0.0364**
Need to upskill/reskill-None				
Need to upskill/reskill-Small/Moderate	0.0545***	0.1066***	0.0768***	0.0842***
Need to upskill/reskill-Great	0.0957***	0.1858***	0.1364***	0.1496***
Experience of automation				
Exp tech change without task replacement				
Exp tech change with task replacement		0.0538***	0.0391***	0.0421***
N.	41663	15280	14034	13412
Country FE	Yes	Yes	Yes	
Sample FE	Yes	Yes	Yes	Yes
Individual characteristics	Yes		Yes	Yes
Job-skill requirements	Yes		Yes	Yes
Job characteristics	Yes		Yes	Yes
Institutional characteristics				Yes

NB: Marginal effects of multinomial logit regression (at sample mean values). Weighted estimates. * p<0.10 ** p<0.05 *** p<0.01; **Individual:** Age, gender, rural, highest ed. completed, vocational qualification, perception of losing job. **Job-skill requirements:** Industry (NACE1), Occupation (ISCOD1), Scales (Digital intensity index, Basic skills (Read, Write, Math), Interpersonal skills, Manual skills, Job complexity, Job routinisation). **Job characteristics:** Tenure, private/public sector, workplace size, contract status, hours worked (week), monthly net payband. **Institutional:** Digital Economy and Society Index dimensions (Connectivity, Human capital, Integration of digital technology, Digital public services), GDPpc PPP, share of working age population (25-64).

Source: Cedefop second European skills and jobs survey (ESJS2).

Another important question on participation in digital skills training is whether the overall workplace environment and practices offer fertile ground for upskilling and reskilling. Indeed, workers in organisations where training needs are systematically reviewed are 9 percentage points more likely to participate in digital skills training than those in organisations without such a system in place. Appraisal of job performance and salary varying according to job performance are also positive correlates of digital skills training by around 5 percentage points and 3 percentage points, respectively (Table 11). Additionally, having a positive attitude towards technology increases the chances of undertaking digital skills training between 1 to 3 percentage points (Table 12).

Table 11. **Digital skills training by job environment**

Digital skills training (CAWI sample)			
	(1)	**(2)**	**(3)**
Job-skill mismatch			
Digital under-skilled	0.0912***	0.0898***	0.0681***
Matched in ed. Qualification	0.0000	0.0000	0.0000
Over-educated	-0.0056	-0.0045	0.0003
Under-educated	0.0243***	0.0227***	0.0504***
Job environment			
Training needs are system. Reviewed	0.0913***	0.0946***	0.1041***
Job performance is formally appraised	0.0422***	0.0390***	0.0650***
Pay varies according to job performance	0.0348***	0.0343***	0.0189
Perceptions of automation			
Fear of automation – None			
Fear of automation – Small/Moderate			0.0382***
Fear of automation -Great			0.0419**
Need to upskill/reskill – None			
Need to upskill/reskill – Small/Moderate			0.0641***
Need to upskill/reskill – Great			0.1109***
Experience of automation			
Exp tech change without task replacement			
Exp tech change with task replacement			0.0417***
N.	29374	28423	9453
Country FE	Yes		Yes
Individual characteristics	Yes	Yes	Yes
Job-skill requirements	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes
Institutional characteristics		Yes	

NB: Marginal effects of probit regression (at sample mean values). Weighted estimates. * p<0.10 ** p<0.05 *** p<0.01; **Individual:** Age, gender, rural, highest ed. completed, vocational qualification, perception of losing job. **Job-skill requirements:** Industry (NACE1), Occupation (ISCOD1), Scales (Digital intensity index, Basic skills (Read, Write, Math), Interpersonal skills, Manual skills, Job complexity, Job routinisation). **Job characteristics:** Tenure, private/public sector, workplace size, contract status, hours worked (week), monthly net payband. **Institutional:** Digital Economy and Society Index dimensions (Connectivity, Human capital, Integration of digital technology, Digital public services), GDPpc PPP, share of working age population (25-64).

Source: Cedefop second European skills and jobs survey (ESJS2).

Table 12. **Digital skills training by attitude towards technology**

Digital skills training (CAWI sample)			
	(1)	**(2)**	**(3)**
Job-skill mismatch			
Digital under-skilled	0.0949***	0.0941***	0.0717***
Matched in ed. Qualification			
Over-educated	-0.0094*	-0.0086	-0.0084
Under-educated	0.0253***	0.0231***	0.0496***
Attitude towards technology			
Increase performance at work	0.0361***	0.0356***	0.0449***
Useful for learning at work	0.0262***	0.0260***	0.0403**
Easy to learn to use at work	0.008	0.0076	-0.0098
Enjoyable to use at work	0.0342**	0.0340***	0.0345**
Perceptions of automation			
Fear of automation – None			
Fear of automation – Small/Moderate			0.0516***
Fear of automation -Great			0.0592***
Need to upskill/reskill – None			
Need to upskill/reskill – Small/Moderate			0.0659***
Need to upskill/reskill – Great			0.1107***
Experience of automation			
Exp tech change without task replacement			
Exp tech change with task replacement			0.0429***
N.	29399	28445	9464
Country FE	Yes		Yes
Individual characteristics	Yes	Yes	Yes
Job-skill requirements	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes
Institutional characteristics		Yes	

NB: Marginal effects of probit regression (at sample mean values). Weighted estimates. * p<0.10 ** p<0.05 *** p<0.01; **Individual:** Age, gender, rural, highest ed. completed, vocational qualification, perception of losing job. **Job-skill requirements:** Industry (NACE1), Occupation (ISCOD1), Scales (Digital intensity index, Basic skills (Read, Write, Math), Interpersonal skills, Manual skills, Job complexity, Job routinisation). **Job characteristics:** Tenure, private/public sector, workplace size, contract status, hours worked (week), monthly net payband. **Institutional:** Digital Economy and Society Index dimensions (Connectivity, Human capital, Integration of digital technology, Digital public services), GDPpc PPP, share of working age population (25-64).

Source: Cedefop second European skills and jobs survey (ESJS2).

5.4. Summary and policy relevance

Based on ESJS2 data, 62 % of EU workers have participated in some forms of formal or non-formal education and training (courses, seminars, on-the-job training) in the 12 months prior to the survey. Excluding on-the-job training, this figure corresponds to 50 % ([26]) therefore the EU still needs to exert significant efforts to reach the EU 2030 target of 60 % of adults participating in training every year. The findings underline the importance of actions under Recommendation 9 to Member States in the Council Recommendation on improving the provision of digital skills and competences in education and training ([27]).

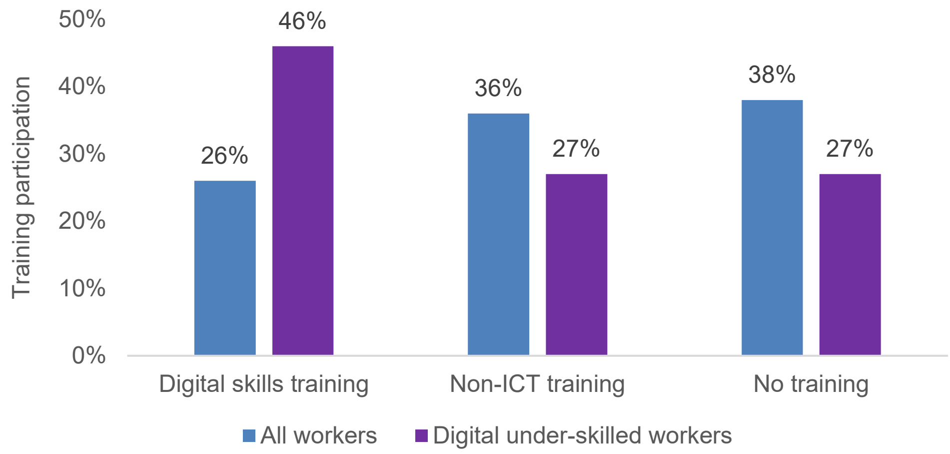
Digital under-skilling, measured in the ESJS2 based on awareness of one's skill development needs, tends to affect about one in eight EU workers to a great extent. This share is compatible with existing evidence from other skills surveys (e.g. OECD PIAAC; Cedefop ESJS1) (see Centeno et al., 2022). Policy efforts should hence be targeted to those reporting a digital skills mismatch but who receive no digital skills training (Figure 9).

Even though there are important digital divides between different population groups (e.g. by gender, age, education level, geographical area, sector or occupation), digital skills training appears generally well targeted to the ones who are aware that they need it, although the evidence suggests that there is room to increase digital skills training participation (Figure 10). Indeed, workers who report being digitally under-skilled are more likely to undertake digital skills training than workers who do not. Nonetheless, policy attention is required to stimulate the uptake of digital skills training by workers who are (or are unaware they are) underskilled, to prevent an overall widening in the digital divide (UNESCO, 2022).

([26]) Although this 50 % is higher than the 39.5 % estimate from the 2022 AES, recall that the AES includes all adults aged 25-64 while the ESJS2 covers only those in the workforce.

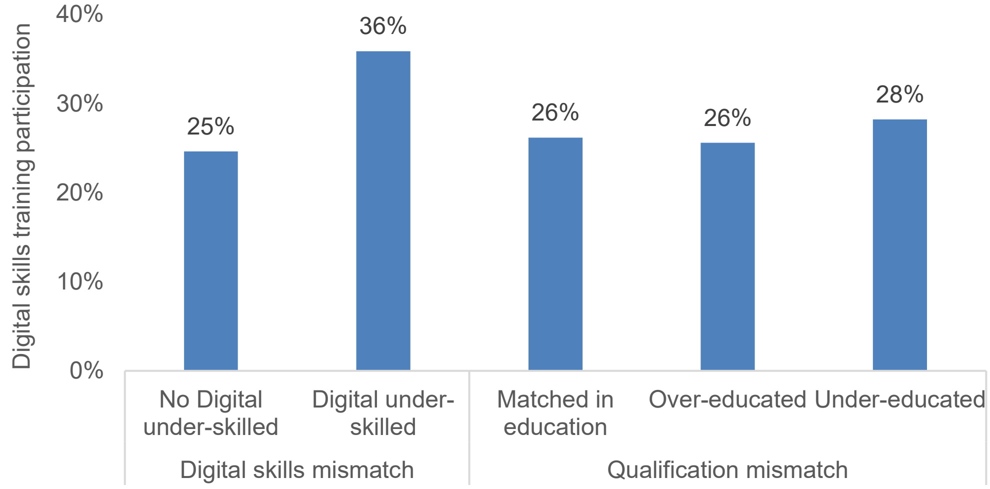
([27]) Recommendation 9 emphasises the importance of developing digital skills of adults, and of offering equal opportunities, by: mainstreaming digital skills opportunities across the adult learning system; promoting public-private partnerships in digital skills initiatives; running targeted awareness-raising; promoting and recognise digital skills training; strengthening efforts to embed SMEs in the existing ecosystems; and promoting Digital Skills and Jobs Coalitions.

Figure 9. **EU+ workers training participation**



Source: Cedefop second European Skills and Jobs Survey (ESJS2).

Figure 10. **Digital skills training participation by skill mismatch**



Source: Cedefop second European Skills and Jobs Survey (ESJS2).

ESJS2 analysis reveals that female workers who are employed in jobs with similar job-skill requirements and characteristics as those of men, are more likely to undertake training in digital skills. Given the lower presence of females in high-skilled, complex jobs, including in ICT, the policy challenges are to get them in such jobs and retain them.

Digital skills mismatch rates are generally lower among people with an initial VET qualification. While this may suggest that VET provides a better fit to digital (and overall) skills needs in the workplace, further research on this is needed such as how to strengthen links between employers and VET systems (see e.g. Herrero, 2023).

Job-skills requirements, i.e., the level of skills demanded in individuals' jobs, are the strongest drivers of participation in training. Our results indicate that we need to consider several job characteristics to accurately understand the main drivers of digital skills training participation and, by extension, design suitable digital skills policies. These should focus on digital skill development from the supply side as well as spurring digital workplace practices from the demand side.

The importance of individual-level attitudes and perceptions (e.g. fear of automation) towards technology should not be overlooked: training institutions and employers should take these seriously into account when designing education and training initiatives. This is the case since both fear and actual experience of automation are relevant drivers of training participation.

New technologies imply a need for upskilling and reskilling of workers who are likely to face marked changes in their job tasks. Even in cases with limited displacement effects, policy reactivity is continuously needed to facilitate the retraining, upskilling and reskilling of workers and the adoption of new skills in industries and occupations affected by automation (Bessen, 2019). The introduction of new digital technologies in workplaces is associated predominantly with new task generation and growing staff size (Cedefop, 2022b).

Employers and educational institutions have an important role to play: workers in organisations with a more systematic approach to training, including skills' needs awareness raising, are more likely to participate in digital skills training. ESJS2 results also further confirm the need to support SMEs, which may face challenges in providing a systematic approach to training. This is consistent with recent findings from the European Company Survey (Eurofound 2019) ([28]). Some of our findings align with recent studies (Cedefop, 2020; OECD, 2022), which highlight time constraints as a relevant factor in the decision to participate in training, which needs to be convenient and accessible.

Nonetheless, more information on motivation and incentives to train, as determined also by the quality of the workplace environment (e.g. learning communities of practice, reciprocity between managers-workers, relations with peers) and quality and impact of training is needed.[29]

([28]) The 2019 European Company Survey by Eurofound-Cedefop shows that small establishments are most likely to train less than 20 % of their workers during working time or to provide on-the-job training, relative to medium-sized and large establishments. SMEs also present the lowest proportion of managers adjusting work schedules so that workers can participate in training.

([29]) Cedefop's European Training and Learning Survey (ETLS), carried out in Fall 2024, is expected to provide novel evidence on such determinants of in-work, non-formal and informal learning.

Large differences between countries in training participation also merit further study, as they may be related to national digital skills/training policies and/or distinct institutional characteristics. The 2023 Council recommendation on improving the provision of digital skills and competences in education and training, suggests the need for Member States to set or review national objectives for the provision of digital skills and competences and ensure their regular review and update. This should also serve to identify 'priority or hard-to-reach groups' (e.g. those living in rural areas, disadvantaged or marginalised groups, or not in education, employment or training) and establish appropriate measures to facilitate their participation in digital skills education and training, considering accessibility, territorial and socio-economic gaps in digital skills.

There is a need to clearly understand measures of digital skills across various sources of data as well as to align them where possible. This would enable us to integrate the analysis of different sources of information towards a common policy goal (e.g., using DigComp as a reference framework) (Centeno et al., 2022). In doing so, it will be important to distinguish between relative and absolute digital skill deficiency measures, which have complementary policy functions. For example, the ESJS2 measure is relative, as it is measured taking the skill needs in a respondent's current job as yardstick. In contrast, the DSI 2.0 measure is absolute, since it is calculated in the same way across individuals, regardless of their job or other characteristics.

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Chapter 6.
Hiring from the margins? How dynamic firms select workers across European labour market pathways

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6.1. Introduction

Technological and organisational transformation is altering the structure of labour markets across Europe. Firms are navigating a complex environment shaped by offshoring, digitalisation, and automation, each of which reshapes job content, skill requirements, and the channels through which workers enter employment. While these trends have boosted productivity and accelerated the reorganisation of work, they have also intensified labour market segmentation, exposing specific groups, particularly unskilled, new entrants and those with fragmented employment histories, to heightened risk of exclusion.

This paper investigates how firm-level restructuring influences hiring patterns across distinct prior employment statuses. Using the 2021 wave of the European Skills and Jobs Survey (ESJS2), we analyse the relationship between offshoring, digital technology adoption, automation exposure, and training, and the likelihood that a worker transitioned into their current job from education, unemployment, or self-employment, relative to having been employed in another job. By modelling hiring outcomes rather than post-employment trajectories, we shift focus to the demand side of labour transitions, asking not only who finds jobs, but which firms hire whom.

A growing body of research has examined how labour market shocks, particularly those driven by automation and global trade, reshape the demand for skills and reallocate employment across sectors and occupations. Exposure to rising import competition from low-wage countries, especially China, has been linked to substantial declines in manufacturing employment and wages in affected U.S. local labour markets, with particularly strong effects on low- and middle-skill workers (Autor et al., 2013). Technological change has contributed to job polarisation by displacing routine-intensive occupations and expanding both high-skill, non-routine and low-skill service roles, a pattern observed across Western Europe and the United States (Acemoglu & Restrepo, 2020; Goos et al., 2014).

These dynamics raise important questions not only about which jobs are eliminated or created, but also about who gains access to the newly emerging roles, and whether firms undergoing transformation tend to exclude or include workers with fragmented employment histories. Yet most of this literature focuses on post-hire effects, such as wage trajectories or occupational content, rather than on the hiring phase itself. We add to this literature by examining the entry dynamics that channel individuals with different prior employment statuses into firms undergoing organisational or technological change.

Our analysis also speaks to the political economy of skills. Research has shown that firms' responses to skill mismatches depend on the institutional environments in which they are embedded. Coordinated skill formation systems, characterised by strong employer associations, sectoral bargaining, and vocational training regimes, facilitate long-term investment in workforce development and reduce poaching risks (Busemeyer & Trampusch, 2012). At the firm level, training responses to skill gaps are shaped not only by the existence of deficiencies but also by whether these gaps are mutually recognised by both employers and workers. McGuinness and Ortiz (2016) show that mutual recognition, enabled by human resource practices and institutionalised channels of worker representation, is critical for aligning training provision with actual needs. Our findings support this perspective: workers who report recent exposure to job-related training, whether through courses, seminars, or on-the-job learning, are significantly more likely to have transitioned from education backgrounds into dynamic firms. In contrast, unemployed individuals are consistently underrepresented in these firms, across all occupational types. While our measure does not differentiate between self-initiated and employer-provided training, the evidence indicates that access to skill development opportunities plays a central role in structuring who enters more dynamic workplaces.

Labour market transitions represent a critical analytical lens for understanding exclusion. While much empirical research has emphasised occupational mobility or wage trajectories, the process by which individuals re-enter employment, particularly from unemployment or education, often exposes structural vulnerabilities. As Darby et al. (1986) argue, it is the 'ins,' not just the 'outs,' of unemployment that shape labour market dynamics. Their findings show that fluctuations in unemployment are primarily driven by inflows, both their volume and composition, rather than changes in the probability of exiting unemployment. Workers with discontinuous employment histories, especially those entering during downturns, are disproportionately represented in these inflows and often face higher structural barriers to reintegration. These transitions are thus not random or frictional but deeply patterned by broader institutional and macroeconomic forces.

Our analysis builds on this framework by examining how firm-level practices mediate access to employment at precisely these critical moments, offering potential pathways to counteract exclusion.

Our findings reveal three core patterns. First, firms undergoing technological transformation, are significantly more likely to hire individuals who transitioned from education or training. This pattern is most pronounced in non-routine occupations, where skill requirements are more compatible with post-hire learning. Second, self-employed workers are more likely to be recruited by firms engaged in offshoring or digital adoption, suggesting complementarities between entrepreneurial experience and the flexibility required in dynamic organisational environments. Third, unemployed individuals are systematically underrepresented in technologically dynamic firms, especially in routine roles, highlighting how firm-side selection mechanisms may entrench labour market exclusion even in contexts of innovation and restructuring.

These patterns speak directly to ongoing EU policy concerns surrounding labour market polarisation, skills mismatches, and unequal access to upskilling opportunities (Cedefop, 2022). By linking firm-level practices, including offshoring, automation, digital technology adoption, and exposure to training, to prior employment status at the point of hiring, our analysis identifies critical forces where technological and organisational change may either exacerbate or mitigate structural vulnerabilities. We find that individuals reporting recent training, are more likely to be integrated into dynamic firms, particularly from education pathways. In this context, training emerges as a key mediating mechanism, increasing the likelihood of entry for those without continuous employment histories.

This paper contributes to labour economics in three ways. First, it shifts analytical focus to the entry phase of employment, offering new evidence on how sorting processes happen under conditions of organisational change. Second, it documents how inclusion varies across task types, reinforcing the importance of occupational segmentation, particularly the distinction between routine and non-routine work, in understanding labour demand. Third, it provides policy-relevant insights into the role of training in enabling more inclusive transitions, with clear implications for European skills strategies aimed at fostering economic resilience and labour market inclusion.

In sum, we offer an empirically grounded account of how firms undergoing restructuring allocate opportunity across diverse labour market entrants. Our findings challenge the view that digital transformation and organisational change necessarily reinforce insider advantages. Instead, they point to a more differentiated landscape, one in which prior employment histories, task content, and access to training interact to shape who is integrated into the evolving structure of work in Europe's markets.

6.2. Data and empirical methodology

This paper draws on data from the second wave of the European Skills and Jobs Survey (ESJS2), conducted by Cedefop in 2021 across 29 European countries. The survey includes approximately 46 000 employed individuals, providing a rich dataset on workers' educational background, employment trajectory, and current job characteristics. As all respondents were employed at the time of the survey, we operationalise labour transitions retrospectively, based on respondents' self-reported status before entering their current job.

The dependent variable categorises respondents according to their employment status prior to their current job. We distinguish four categories:

(a) education/training;
(b) self-employment;
(c) unemployed/other;
(d) employed in another job (used as the reference category).

Because the firm-level explanatory variables are measured post-transition, our empirical strategy is descriptive and does not aim to establish causal relationships. Instead, we assess how current firm characteristics correlate with the types of workers firms end up hiring, offering insights into patterns of labour market sorting and structural exclusion.

Table 13. **Descriptive statistics**

Variable Name	Type	Description	Category	Mean/pr oportion	S.D
Depedent Variable	Catego rical	Employment status before current job	Employee in another job (b)	22.8%	0.4
			Education/Training	57.2%	0.5
			Self-employed	4.0%	0.2
			Unemployed/Other	16.0%	0.4
Contract type	Catego rical	Employment contract type	Indefinite contract (b)	84.5%	0.4
			Part-time/Fixed	13.0%	0.3
			No contract	2.5%	0.2
Industry	Catego rical	Industry classification	Services (b)	52.0%	0.5
			Agriculture/Industry	14.5%	0.4

Variable Name	Type	Description	Category	Mean/proportion	S.D
			Public sector	33.5%	0.5
Offshoring	Binary	Firm has offshored tasks		19.8	0.4
New tech	Binary	Firm has implemented new digital tech		48.8	0.5
Automation	Binary	Automation exposure		22.6	0.4
Training	Binary	Employer provides job training		64.0	0.5
Female	Binary	Sex	1 = Female, 0 = Male	50.6	0.5
Firm size	Binary	Firm size	1 = Large, 0 = Small	51.9	0.5
Age	Continuous	Age		19.4	10.4

NB: (b) = base category
Source: Cedefop second European Skills and Jobs Survey (ESJS2).

Descriptive statistics in Table 13 summarise the variables used in the analysis. The main explanatory variables reflect firm-level features likely to influence or correlate with hiring practices. These include indicators for whether the firm has offshored tasks, implemented new digital technologies, or is exposed to automation, as well as whether it provides job-related training to employees. Each of these variables is operationalised as a binary measure, facilitating interpretation within a multinomial logit framework. To account for individual-level heterogeneity, we include controls for gender, age, firm size (large vs. small), industry classification (services, agriculture/industry, public sector), and contract type (indefinite, fixed-term, or informal/no contract).

Table 13 shows that 57.2 % of respondents transitioned from education or training, while 22.8 % were already employed, 16.0 % were previously unemployed, and only 4.0 % were formerly self-employed. Among the firms where these individuals are now employed, 19.8 % engage in offshoring, 48.8 % have adopted new digital technologies, and 22.6 % are exposed to automation, with 64 % providing training opportunities. These baseline distributions already suggest significant heterogeneity in both firm-level practices and the worker populations they attract, motivating our investigation into patterns of sorting across transition pathways and organisational types.

We employ multinomial logistic regression to model the association between a worker's prior employment status and the characteristics of the firm they are currently employed in ([30]). Given the categorical and non-ordered nature of the dependent variable, this is the most suitable regression technique (Greene, 2020). The dependent variable categorises individuals by whether they transitioned into their current job from education/training, self-employment, unemployment/other, or from another job (the reference category). The independent variables describe features of the current firm, such as whether it has adopted automation, offshored tasks, implemented digital technologies, or provided formal training.

The model estimates Relative Risk Ratios (RRRs), which indicate the likelihood that a worker comes from a particular prior employment status relative to the base category (employed at another job), conditional on the characteristics of the firm they currently work for. In other words, the RRR tells us: how likely is it that this type of firm hires from unemployment or self-employment, relative to hiring workers already in employment? For instance, an RRR < 1 for the unemployment category suggests that unemployed workers are underrepresented in that type of firm, relative to workers who transitioned from another job.

This modelling strategy is particularly suited to contexts in which firm characteristics are observed ex post yet still convey meaningful information about the types of workers certain firms are more likely to hire. It allows us to uncover patterns of selection and exclusion in hiring, without imposing a structural interpretation.

We begin by estimating baseline models on the full sample, isolating the relationship between each firm-level variable (offshoring, automation, digital technology adoption, training provision) and workers' prior employment status. A final, complete model includes all predictors simultaneously to understand their joint explanatory power.

To further explore heterogeneity in hiring patterns, we stratify our analysis by job type, distinguishing between routine and non-routine occupations. This distinction is grounded at empirical literature showing that routine tasks, both cognitive and manual, are more easily automated or offshored, whereas non-routine tasks, particularly those requiring abstract reasoning, problem-solving, or interpersonal communication, are more complementary to new technologies and less susceptible to displacement (Autor et al., 2003; Goos et al., 2014). Routine-Biased Technological Change (RBTC) has been a major driver of job polarisation across advanced economies, reducing demand for middle-skill, routine-intensive jobs while expanding both high-skill and low-skill employment. Given that

([30]) One way to interpret this setup is to imagine standing inside a firm and asking: *'Looking at our current workforce, how did people get here?'* This approach lets us uncover **patterns of hiring** based on firm type: are they selecting from education pipelines, re-integrating the unemployed, or mostly recycling already-employed workers?

automation and technological adoption may affect routine and non-routine occupations differently, we estimate separate models for each subgroup. This approach enables us to assess whether the relationship between prior employment status and current firm characteristics varies by task content, and whether patterns of structural exclusion, such as the underrepresentation of unemployed workers in tech-adopting firms, are more acute in certain segments of the labour market.

Together, these models allow us to map how firms undergoing technological and organisational change draw from different segments of the labour supply, highlighting not only demand for specific skills, but also the exclusionary dynamics embedded in contemporary patterns of hiring.

6.3. Main empirical findings

We begin by examining how firm-level technological and organisational practices correlate with the prior employment status of newly hired workers. The four firm-level variables included in our models capture key dimensions of organisational and technological restructuring. Offshoring indicates whether part of the respondent's current workplace activities has been relocated to another region or country, reflecting global integration strategies. Digital technology adoption captures whether the firm has introduced new computer systems, devices, or software, signalling ongoing digital transformation. Training provision is operationalised as a binary variable indicating whether the worker received any job-related training, i.e., courses, seminars, or on-the-job learning, within the past 12 months, serving as a proxy for firms that invest or value employee skill development. Lastly, automation exposure is a composite measure identifying workers in firms that have adopted new digital technologies and whose roles involve repetitive or procedural tasks, which are more susceptible to automation. These variables, while measured post-transition, provide insight into the types of firm's workers with different prior labour market statuses are entering.

Table 14 reports Relative Risk Ratios (RRRs) from five multinomial logit models, where the outcome variable is whether a worker transitioned into their current job from education/training, self-employment, or unemployment/other, relative to the reference category: employed in another job. Each column corresponds to a separate regression specification. The first four columns isolate the effects of offshoring, digital technology adoption, training provision, and automation exposure respectively, while the final column presents a fully saturated model that includes all predictors simultaneously. Standard errors are shown in parentheses; statistical significance is denoted at the conventional levels.

The results reveal a consistent pattern: firms undergoing technological or organisational transformation are more likely to hire workers who were previously not in employment. Specifically, firms that report offshoring are 23.1 % more likely to have hired a worker from education/training rather than from another job, relative to firms that do not offshore. Similarly, technology-adopting firms, those that report implementing new digital technologies, are 28.8 % more likely to have recruited from education/training than from the employed pool.

Table 14. **Baseline models**

Variable	Offshoring	New tech	Training	Automation	Complete
Offshoring	1.231 ***				1.116 **
	(0.036)				(0.042)
New tech		1.288 ***			1.194 ***
		(0.03)			(0.048)
Training			1.301 ***		1.225 ***
			(0.032)		(0.036)
Automation				1.231 ***	1.031
				(0.037)	(0.051)

* p<0.05 **p<0.01 ***p<0.001
Source: Cedefop second European Skills and Jobs Survey (ESJS2).

The results are even more pronounced for the training variable, which captures whether the worker received any form of training in the past 12 months. The training model suggests a 30.1 % higher likelihood of hiring from education/training versus prior employment. This finding indicates that firms that integrate less experienced workers may do so by offering training opportunities, either directly or through task-based learning. Rather than signalling institutionalised firm-level training programs per se, this pattern may reflect a broader openness to developing worker competencies post-hire, particularly among recruits without prior job experience.

The automation model also yields a statistically significant association: firms exposed to automation are 23.1 % more likely to hire from education/training than from another job. This aligns with theories of skill upgrading and occupational restructuring, where automation may create demand for workers who can be trained or shaped internally, rather than those locked into specific prior job routines.

The complete model (Column 5) includes all four firm-level variables simultaneously. While the coefficients are smaller, as expected due to multicollinearity, the core associations remain significant. Offshoring (1 116) new technology adoption (1 194), and training provision (1 225) each retain independent, positive associations with hiring from education/training. In contrast, the coefficient for automation becomes statistically insignificant, suggesting that its baseline effect may be partly mediated by co-occurring practices like training or digital investment.

Beyond transitions from education, the baseline models also reveal meaningful variation across other prior employment statuses. Unemployed workers are significantly less likely to be hired by firms that offshore or adopt new technologies, suggesting a pattern of exclusion from dynamic or globally integrated firms. In contrast, self-employed workers are more likely to be absorbed by firms exposed to automation and digital transformation, possibly reflecting complementarities between entrepreneurial skillsets and adaptive roles in more dynamic workplaces. The training variable, while positively associated with transitions from education, is also linked to higher likelihoods of hiring from unemployment and self-employment, indicating that post-hire training may act as a mechanism to integrate candidates with more fragmented employment histories. These findings underscore the heterogeneity in hiring preferences across firm types and point to how organisational practices, particularly training and technology adoption, can shape the structure of labour market inclusion.

These findings suggest that firms undergoing technological or organisational transformation are not exclusively recruiting from incumbent workers but are also drawing from pools with less continuous employment histories, particularly individuals transitioning from education or training. This challenges the conventional view that technology adoption systematically favours already-employed, high-skill insiders. Instead, the results point to a more complex pattern of transitional labour market integration, in which even dynamic or restructuring firms may absorb new entrants, especially where post-hire training mechanisms are present.

To account with heterogeneity in sorting mechanisms, we estimate separate models for routine and non-routine occupations. This allows us to examine whether the relationship between firm characteristics and prior employment status differs across jobs with varying exposure to automation and task restructuring. Table 15 displays the RRRs from these stratified models. In each specification, the dependent variable remains the same, prior employment status relative to current employment, but the sample is restricted by task characteristics.

Table 15. Stratification analysis

Variable	Offshoring /Non routine	Offshoring/ Routine	New tech/ Non routine	New tech/ Routine	Training/ Non routine	Training/ Routine	Automation/Non routine	Automation/ Routine	Complete/ Non routine	Complete/Routine
Offshoring	1.218 *** (0.041)	1.275 ** (0.077)							1.083 (0.048)	1.243 * (0.09)
New tech			1.311 *** (0.034)	1.199 ** (0.065)					1.234 *** (0.055)	1.066 (0.104)
Training					1.309 *** (0.037)	1.236 ** (0.070)			1.233 *** (0.041)	1.179 * (0.077)
Automation							1.282 *** (0.042)	1.035 (0.083)	1.048 (0.058)	0.947 (0.112)

* p<0.05 **p<0.01 ***p<0.001

Source: Cedefop second European Skills and Jobs Survey (ESJS2).

Across all specifications, firms with dynamic organisational practices consistently exhibit stronger associations with hiring from education or training in non-routine jobs. The clearest example is among firms that have implemented new digital technologies: these firms are 31.1 % more likely to hire into non-routine roles from education/training compared to the employed pool, versus only 19.9 % more likely in routine roles. A similar pattern emerges for training exposure: workers in non-routine jobs who received training are 30.9 % more likely to have transitioned from education/training, relative to those who came from another job, while the effect is smaller but still significant in routine occupations.

Importantly, we also observe robust and significant effects of automation in the non-routine subsample (1.282), whereas automation is statistically insignificant in routine roles. This may seem counterintuitive, given that routine tasks are classically viewed as more susceptible to automation. However, this divergence likely reflects differential selection processes: in tech-adopting firms, non-routine jobs may be newly created or restructured roles, open to candidates without continuous job experience. Routine positions, by contrast, may be more standardised and filled through conventional recruitment channels. Also, this result may reflect the nature of the automation proxy used at the estimations, that also captures part of technologic adoption.

The complete model reinforces these dynamics. The joint influence of offshoring, technology adoption, and training remains significant in non-routine occupations, with particularly strong associations for digital technology (1.234) and training (1.233). In contrast, the routine specification yields smaller and more fragile effects, with only offshoring (1.243) and training (1.179) reaching marginal significance.

Looking further into the routine jobs' stratification, previously unemployed workers face substantial exclusion: they are significantly less likely to be hired by offshoring firms (0.23), by firms adopting new technologies (0.76), or by firms providing training (0.77). These effects are consistently negative and statistically robust, suggesting that hiring into routine roles in dynamic firms remains highly selective. In contrast, self-employed workers are more likely to be absorbed by routine firms that values training (1.48).

In non-routine jobs, the picture is more mixed. Firms that offshore or adopt new technologies are significantly more likely to hire self-employed workers, 1.83 and 1.46, respectively, indicating a potential synergy between entrepreneurial experience and the skill demands of non-routine, tech-intensive work. However, unemployed workers still face barriers, especially in firms adopting digital technologies (0.75) or reporting automation exposure (0.72). Across both routine and non-routine segments, the variable capturing workplace training remains negatively associated with hiring from unemployment, suggesting that these firms may prioritise candidates with either educational continuity or entrepreneurial experience over those with recent employment gaps.

The stratified results suggest that firms navigating technological change do not apply uniform hiring strategies across their occupational structure. Instead, they appear more likely to recruit from non-traditional sources, including the unemployed, the self-employed, and new labour market entrants, when staffing non-routine roles, particularly in contexts where post-hire learning or adaptability is required. This reinforces the view that non-routine job creation under technological transformation is not inherently exclusionary and may in fact offer important points of re-entry into employment, conditional on organisational support structures like training.

To ensure the reliability of the multinomial logistic regression results, we conducted several robustness checks focusing on model specification, stability across statistical approaches, and diagnostic tests. First, we re-estimated all 15 models using Probit regressions, which assume a normal distribution of the error term, in contrast to the logistic distribution used in the main models. The signs, magnitudes, and significance levels of the key coefficients were largely consistent across Probit and MNL models, supporting the validity of our results independent of distributional assumptions.

Second, we compared McFadden's Pseudo R^2 across both sets of models. While MNL models typically exhibited slightly higher R^2 values (e.g. 0.21 for the full model versus 0.18 for its Probit counterpart), the overall ranking of model performance remained stable. This suggests a structurally consistent explanatory power across model types.

Third, we assessed multicollinearity via correlation matrices across all independent variables. No concerning levels of multicollinearity were identified, except for a modestly high correlation between New Tech and the constructed Automation variable, an expected outcome due to shared underlying constructs. This informed our interpretation, though we opted to retain both variables due to their conceptual distinctiveness. In sum, the results presented in this study are supported by a range of robustness checks, all of which indicate a high degree of internal consistency and model stability across statistical assumptions and specifications.

6.4. Summary and policy relevance

This paper has examined how organisational and technological restructuring at the firm level shapes patterns of hiring across different prior employment statuses in Europe. Drawing on the European Skills and Jobs Survey (ESJS2), we model transitions into current employment from education or training, self-employment, and unemployment, using a multinomial logit framework. While our analysis is descriptive, given that firm characteristics are observed after the transition occurred, it reveals systematic sorting patterns that are relevant to ongoing policy debates around inclusion, training, and labour market segmentation. Three central findings emerge from the analysis.

First, firms undergoing restructuring through offshoring, digital technology adoption, and training provision are more likely to hire individuals who transitioned directly from education or training. This association is particularly strong in non-routine occupations. The consistent pattern across models suggests that organisational transformation is not uniformly biased in favour of incumbent or continuously employed workers. Rather, under certain conditions, dynamic firms appear open to integrating new entrants, especially where post-hire learning or adaptability is feasible.

Second, self-employed individuals are more likely to be hired into tech-adopting and offshoring firms, especially into non-routine roles. This finding points to a potential complementarity between entrepreneurial experience and the demands of restructured or flexible work environments. These workers may bring adaptive or transferable skills that are valued in contexts of technological change.

Third, across all models, unemployed individuals are systematically less likely to be hired into firms engaging in offshoring, adopting digital technologies, or providing training. This pattern holds even when disaggregating by job type: in both routine and non-routine roles, the likelihood that unemployed individuals enter restructuring firms is significantly lower than for other transition pathways. In several models, this effect is especially pronounced in routine jobs. These findings indicate that firms undergoing transformation often avoid hiring from unemployment pools, even when providing internal training.

These results have important policy implications. Most immediately, they call into question the assumption that firms engaging in technological upgrading or restructuring will naturally contribute to inclusive hiring. On the contrary, our findings suggest that such firms tend to draw from labour market segments characterised by educational continuity or entrepreneurial backgrounds, while systematically excluding unemployed individuals. This selection process risks deepening patterns of labour market segmentation, especially in countries or regions where unemployment is longer or more structurally embedded.

At the same time, the positive association between training provision and transitions from education backgrounds suggests that training, whether formal or task-based, can mediate access to dynamic firms. However, this effect does not extend to unemployed workers. Despite widespread EU investment in upskilling and active labour market policies, training does not appear to serve as a re-entry channel into technologically advanced firms for those with recent employment gaps.

In light of this, policy interventions may need to more explicitly target the firm-side of matching mechanisms. While much emphasis has been placed on individual skill deficits, our results indicate that employer-side selection remains a major barrier to inclusive transitions. Recruitment incentives, de-risking mechanisms, or targeted hiring subsidies for unemployed individuals in firms undergoing restructuring may help address this bottleneck.

Finally, the routine/non-routine divide remains relevant. Our results reinforce the idea that non-routine job creation under digitalisation may offer more inclusive pathways, conditional on firms' openness to candidates without continuous employment. In contrast, routine occupations remain more rigidly stratified, with unemployed candidates facing consistent exclusion.

Taken together, these findings highlight that access to dynamic firms is not merely a function of individual readiness or skills, but also of firm-level filtering processes. Understanding and addressing these selection mechanisms is critical for designing effective and equitable labour market policies in the context of digital and organisational transformation.

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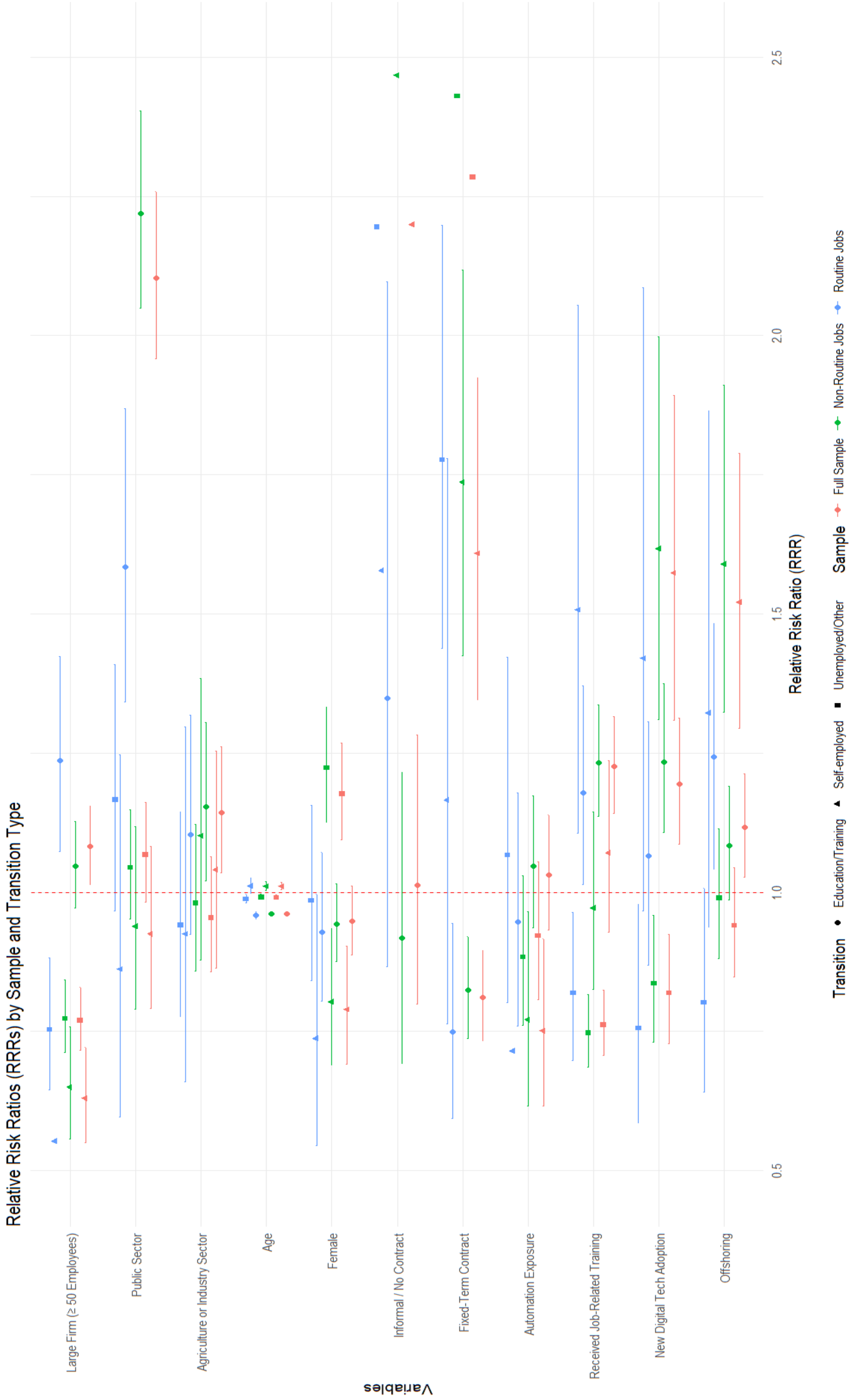
6.6. Annex

The complete regression tables (including full coefficients, standard errors, and robustness checks), replication code, and a clean version of the processed dataset used in this analysis are available from the authors upon request. The next figure summarises selected results from multinomial logistic regression models estimated on the full sample, as well as routine and non-routine occupations, using the 2021 Cedefop European Skills and Jobs Survey (ESJS2). Each model includes controls for gender, age, firm size, contract type, and industry sector. Country fixed effects are included but not shown.


Relative Risk Ratios (RRRs) by Sample and Transition Type
Large Firm (≥ 50 Employees)
Public Sector
Agriculture or Industry Sector
Age
Female
Informal / No Contract
Fixed-Term Contract
Automation Exposure
Received Job-Related Training
New Digital Tech Adoption
Offshoring
Variables
0.5
1.0
1.5
2.0
2.5
Relative Risk Ratio (RRR)
Transition
Education/Training
Self-employed
Unemployed/Other
Sample
Full Sample
Non-Routine Jobs
Routine Jobs

Chapter 7.
Measuring potential skill shortages in Europe

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7.1. Introduction

Skill shortages ([31]) describe a situation whereby employers are unable to fill existing vacancies due to a lack of suitably qualified and skilled external candidates. Skill shortages have the potential to inhibit firm level productivity and, if pervasive enough, can negatively feed through to macroeconomic variables such as economic growth and wage inflation. However, even though it is common to see policies implemented at both a national and European level to combat skill shortages, there is remarkably little empirical research on their impacts (McGuinness et. al, 2018) and even less agreement on how to measure the phenomenon. The scarcity of evidence related to skill shortages is demonstrated in McGuinness et al. (2025), which summarise the skill mismatch peer reviewed literature published between 2006 and 2022, with just 14 studies on skill shortages published over a 16-year period. According to McGuinness et al. (2025), skill shortages account for just 5 % of the skills mismatch literature. However, despite the sparsity of the research base, skill shortages remain the principal concern of policy makers in the realm of skill mismatches. This paper reviews the existing methodological approaches to measuring skill shortages before going on to propose an empirical measurement approach that we believe will effectively capture potential skill shortages in a way that can be easily replicated across countries and over time.

As previously mentioned, the evidence regarding impacts of skill shortages is thin and somewhat mixed. Few studies have been able to measure the impact of skill shortages on companies proving that they negatively impact firms' productivity (Bennett & McGuinness, 2009; Haskel & Martin, 2006; Forth & Mason, 2006; Mason et al., 1994; Sharma et al., 2016; Tang & Wang, 2005). Other studies proved that skill shortages negatively affect R&D investments and innovation projects (Horbach &

([31]) This research was funded by the Horizon 2023 Europe project SkillsPULSE.

Rammer, 2022; Nickell & Nicolitsas, 1997). Some find no evidence that skill shortages negatively affect firms' performance, measured in terms of sales (Healy et al., 2015). A key conclusion that we can take away from this literature is that the lack of measurement consistency across studies makes it extremely difficult to draw concrete conclusions regarding the impacts of skill shortages.

This study is more closely aligned to another strand of literature that seeks to measure skill shortages. As organisations and policymakers strive to align workforce capabilities with evolving market demands, the accurate identification and quantification of skills shortages have become increasingly important. The consistent measurement of skill shortages is vital to ensure well-informed policy measures. Within the literature, there are two main approaches to measuring skill shortages: (1) Employer-reported (subjective) data: containing subjective measures of skills shortages or gaps, offering valuable first-hand insights into workplace challenges, and (2) Objective indicators: which bring together various statistics and data to develop generally indirect measures of skill shortages.

Table 16 reports the studies that use subjective methodologies; specifically, we report the firm-level survey data used in the studies, and the specific questions asked to employers on skills shortages. The first thing that becomes apparent is that no two survey approaches adopt the same measurement approach. Some surveys ask only about hiring difficulty, without directly quantifying the shortages (Ho, 2016) and in instances where skill shortages are referred to they are associated with varying definitions of recruitment difficulty, e.g. difficult to hire (Tang & Wang, 2005), hard-to-fill vacancies (Gambin et al, 2016; Horbach & Rammer, 2019; Watson et al, 2006), unfilled vacancies (Bellman & Hubler, 2014; Horbach & Rammer, 2019; Sharma et al, 2016). Some measurement approaches set various time parameters (i.e., online vacancy duration) around the skill shortage (Watson et al. 2006; Healy et al.2015; Sharma et al., 2016; Weaver & Osterman, 2017; Chang-Richards et al, 2017; Beerli et al., 2020) while others do not (Tang & Wang, 2005; Bellmann & Hübler, 2014; Gambin et al. 2016; Ho, 2016; Mergener & Maier, 2019; Horbach & Rammer, 2022). In general, despite the lack of consistency, subjective, firm-level survey measures are an important source of information as they are a primary indicator of skill shortage. They are, however, associated with a number of weaknesses including potential measurement error, whereby employers wrongly attribute hiring difficulties to skill shortages. Other, non-skill related factors influencing hiring difficulties include unattractive working conditions, uncompetitive wages and ineffective Human Resource Management (HRM) processes. The existing limited evidence suggests that these biases are likely to be substantial. Drawing on the Eurobarometer Flash Survey 304, Cedefop (2015b) shows that while 47 % of employers report difficulties in recruiting suitably skilled graduates, the total proportion of graduate employers deemed to be facing genuine skill shortages was 12 %.

Table 16. **Summary of employer-based skill shortages – subjective measures**

Year	Author(s)	Data used	Country	Sector	Actual question for skill shortages
2005	Tang and Wang	Statistics Canada Survey of Innovation	Canada	Manufacturing	*It is difficult to hire qualified staff and workers; It is difficult to retain qualified staff and workers*
2006	Watson et al.	1998 Dorset Employer Survey	UK	Various	*Did you experience hard-to-fill vacancies due to skill shortages in the past 12 months?*
2014	Bellmann and Hübler	IAB Establishment Panel Survey	Germany	Various	*How many unfilled qualified jobs does your firm have?*
2015	Healy et al.	Business Longitudinal Database	Australia	SMEs	*Did this business have skill shortages during the last year?*
2016	Gambin et al.	UK Employer Skills Survey	UK	Various	*Hard-to-fill vacancies; Skill shortages vacancies*
2016	Ho	Survey administered by the author(s)	Hong Kong	Construction	*Indirectly assessed through expert consensus on the existence and severity of skill shortages*
2016	Sharma et al.	Survey administered by the author(s)	Australia	Various	*How many unfilled job vacancies have you encountered over the preceding 12 months?*
2017	Weaver and Osterman	Survey administered by the author(s)	US	Manufacturing	*How many core production worker vacancies have persisted for three months or more?*
2017	Chang-Richards et al.	Survey administered by the author(s)	New Zealand	Construction	*Have you experienced a shortage for specific skills in your company since the earthquake?*
2019	Mergener and Maier	Survey administered by the author(s)	Germany	Various	*What are your expectations regarding future recruitment difficulties?*
2020	Beerli et al.	Swiss Employer Survey	Switzerland	Various	*Have your innovation efforts been negatively affected by a shortage of specialised personnel in the last year?*
2022	Horbach and Rammer	Community Innovation Survey	Germany	Various	*How many job vacancies could not be filled or hard to be filled with workers lacking the desired qualifications?*

NB: The actual questions presented are either directly extracted from the papers or have been indirectly inferred based on the authors' descriptions.

Source: Author's elaboration.

With significant advances in data analysis techniques, such as web scraping, artificial intelligence and big data analytics, that have occurred over the last years, the use of objective methodologies that capture skill shortages has become increasingly widespread. Such objective methodologies aim to provide quantifiable and data-driven insights into labour market dynamics and potential skill shortages. Objective approaches mainly employ job vacancy data; however, they also use various indirect indicators (such as unemployment, wages, undereducation etc.) to gauge labour market tightness and potential skill shortages. Some of the key examples of objective measures published are presented in Table 17.

A recent objective indicator that attempts to provide a cross-country measure of skill shortages has been developed by the OECD (2017, 2018, 20222). The OECD 'Skills for Jobs' database stands as the most prominent example of a more comprehensive objective method used to assess skill shortages. The OECD method utilises a range of indicators, including undereducation levels and wage rates, to assess the potential rate of skill shortage within an occupation.

The ILO (2020) also recently published long-term projections for ICT skill shortages in Canada, Germany, China and Singapore, developed through models based on various assumptions that, ultimately, compare labour supply and demand. The ILO study summarises the current forecasting methods employed in these four countries and publishes estimates of projected ICT skill shortages. Despite these various efforts, the ILO report highlights challenges in accurately measuring skill shortages, stemming from differing definitions of 'ICT specialists' across countries, the lack of detailed and comparable data, and the rapid pace of technological change.

Other examples of the construction of objective measures of skills shortages include Gambin et. al (2016) for the UK, Dawson et. al (2019) for Australia, Hertrich and Brenner (2024) for Germany and Aksenova et al. (2024) for the EU countries. It is also worth noting that in 2024 Cedefop launched their European Skills Index (ESI), which is designed to measure the performance of skills formation and matching systems within EU member states. While the index is not designed to measure the incidence of skill shortages and gaps, it will at least partially reflect these.

Table 17. **Summary of studies on skill shortages – objective measures**

Year	Author(s)	Data used	Country	Sector	Measures Used
2016	Gambin et al.	Labour Force Survey, Annual Survey of Hours and Earnings	UK	Various	Employment and unemployment rates, wage levels and occupational skill profiles
2019	Dawson et al.	6.7 million Australian online job ads (2012-2019)	Australia	Data Science and Analytics	Skill co-occurrence patterns, DSA skill intensity, Relative Comparative Advantage (RCA)
2020	ILO	Canada's ESDC; Germany's BiBB and IAB; Singapore’s skills framework; China’s CCW	Canada, Germany, Singapore, China	ICT	Long-term labour market forecasts, labour supply and demand projections
2024	Hertrich and Brenner	Federal Employment Agency job vacancy data	Germany	Skilled workers, specialists, experts	Average vacancy time (days), spatial vector autoregressive (VAR) model
2017, 2018, 2022	OECD	Skills for Jobs database, Lightcast (EBG) data	OECD, EU countries	Various sectors, with a focus on ICT and digital skills	Occupational Shortage Indicator, skill imbalance index, RCA
2024	Aksenova et al.	OECD Skills for Jobs, Eurostat ICT data (2011-2021)	34 European countries	Digital skills, ICT	Paired regression analysis, skill shortage indicators, growth rate of ICT specialists

NB: The measures are directly extracted from the papers.
Source: Author’s elaboration.

As was the case with the subjective indicators, a key weakness of the objective approaches is a lack of consistency in the measurement methodology and, with some notable exceptions, the indicators tend to be country-specific and not easily replicable for multiple countries. There is also a good deal of subjectivity associated with some of the indicators selected as potential drivers of skill shortages, and it is unclear the extent to which selected indicators are actually related to the key outcome variable. Changes in these indicators can be driven by factors beyond skill availability, such as broader economic trends, changes in labour market regulations or technological disruptions all of which will be related to skill shortages to varying degrees. This complexity necessitates sophisticated statistical analysis and careful control of multiple variables to establish meaningful correlations between observed patterns and actual skill shortages. However, it is almost impossible to ascertain the extent to which such objective approaches are generating accurate estimates of skill shortages.

Another limitation of objective methodologies for estimating skill shortages, as acknowledged by Dawson et al. (2019), is their focus on labour demand data and the reliance on proxies to estimate labour supply. This approach is unlikely to capture the complete picture of skill shortages in the labour market. Furthermore, the use of online job postings as a primary data source introduces potential biases in skill requirement analysis. Employers utilising online platforms might disproportionately seek candidates with specific skill sets, which may not accurately reflect the skill sets required across all positions within an occupation. Also, extended vacancy durations, which have been used as inputs to some measures, may result from internal factors unrelated to genuine skill shortages, such as unattractive wages or inefficient recruitment practices. These confounding variables can potentially lead to an overestimation of actual skill shortages in the labour market.

7.2. Data and empirical methodology

We attempt to develop an indicator of potential skill shortages using an approach that (a) is built on job characteristics that can reasonably be associated with a skill shortage and (b) can be easily replicated for all countries across time. To do this, we employ an objective measurement approach using online job vacancy data, that is benchmarked to a subjective measurement approach using survey data with detailed job characteristics. Our approach is multi-dimensional, as it employs a broad set of variables, and we identify and impose several conditions / job characteristics that are likely to be associated with potential skill shortages within the two different datasets.

First, we use data from the 2021 European Skills and Jobs Survey (ESJS), which is a broad employee-based survey on adult employees aged 24 to 65 in the EU countries, plus Iceland and Norway, with a total sample of over 46 000 observations. We identify several job characteristics that are likely to be associated with potential skill shortages at an occupational level (at ISCO 2-digit) and calculate the share of jobs that are likely to be difficult to fill, at an EU level and at member state level. It should be noted that the ESJS2 approach effectively measures the proportion of jobs that are likely, in our view, to be difficult to fill, should openings become available to the labour market.

Second, we employ 2021 job advertisement data from Lightcast. Lightcast is a private labour market analytics company that aggregates millions of job advertisements worldwide on a daily basis; they extract over 50 elements from the job postings descriptions and classify them according to standard labour market classifications. In a similar manner to our use of the ESJS, we identify several characteristics that are likely to be associated with difficult to fill vacancies and the proportion of jobs in each ISCO category that are difficult to fill across the EU and at member state level. Therefore, our approach will measure the proportion of current vacancies that we estimate will be hard to fill. While the Lightcast measure is solely demand-based and may not precisely reflect the skill requirements of jobs, it is replicable over time.

We then validate our Lightcast approach against the ESJS estimates to ensure that our skill shortage measure based on vacancy data broadly reflects the current distribution of skills and jobs employed within the labour market and helps to ensure that any policy measures designed on the basis of job vacancy estimates will be more likely to align with actual labour market needs. We validate our Lightcast approach by calculating the correlation between the potential skill shortage estimates in the two datasets within 2-digit ISCO occupation. Following our validations, we estimate the share of potential skill shortages at 2-digit ISCO level for the EU and for all member states for 2022 and 2023 using Lightcast data. The benchmarking of an objective measurement approach to a dataset reflecting the current distribution of skills and competencies being utilised within the labour market is, in our view, a substantial advancement in the measurement of skills shortages at both a national and European level.

7.3.1 European Skills and Jobs Survey (Wave 2)

Within the 2021 European Skills and Jobs Survey, we identify and impose several conditions/job characteristics that are likely to be associated with potential skill shortages. We develop a set of indicators that capture explicit measures of job complexity, competency and experience requirements as well as higher wages. To distinguish skill from labour shortages, for many of our indicators we set the condition that various metrics exceed both the respective occupational average and the economy wide average. This implies that jobs with a relatively low skill content that lie above their occupational average are not identified as potential skill shortages.

The rationale for our approach is that genuine skill shortages should only appear in jobs with specific characteristics. For example, a job that has little complexity and requires very few skills is unlikely to be associated with a genuine skill shortage. By definition, a skill shortage implies that an employer cannot recruit a candidate with the required skills. If the job itself does not require complex skills, then genuine skill shortages should not be present. Of course, employers may sometimes find it difficult to recruit candidates for low-skilled and low-wage jobs, but this is likely not due to the pool of potential candidates not having the skills required to do the job. Rather, it may simply be that potential employees are unwilling to work in such a role at the advertised pay and conditions. Therefore, in order to be identified as an area of potential skill shortage, a job must meet each of the following criteria:

(a) Complex job within occupation: We construct a composite index that attempts to identify more skill-complex jobs within occupations. When the level of job complexity is higher than the average calculated at occupational level, the job has a high level of complexity, and it is considered to have met a requirement for being a potential skill shortage.
(b) Economy-wide complex job: When the level of job complexity is higher than the average for the general labour market, the job is deemed to have met a requirement for being a potential skill shortage.
(c) High volume of task requirements within occupation: We compute the average value of the task index at an ISCO 2-digit occupational level. When the value of the index is higher than the average calculated at occupational level, the job has a high number of tasks, and it is considered to have met a condition for being a potential skill shortage.
(d) Economy- wide high task requirement: When the value of the task index is above the average calculated at country level, the job is considered to be a hight task demanding job within the general economy/labour market, and the job has met a condition for being a potential skill shortage.
(e) Long tenure: We impose the condition that jobs with tenure longer than one year are likely to be considered potential skill shortages.
(f) High wage within occupation: When an employee's monthly net wage is higher than the average calculated at occupational level, the job is considered to have met a condition for being a potential skill shortage.
(g) Economy wide- high wage: When an employee's monthly net wage is above the average calculated at country level, the job is considered to be a potential skill shortage.

When all seven conditions above hold simultaneously, a job is identified as a potential skill shortage within the 2021 European Skills and Jobs Survey ([32]).

7.3.2 Lightcast data

While the ESJS provides insights into the experiences of employees in the European labour market (labour supply), it is equally important to understand skills shortages from the perspective of employers (labour demand). As stated, the key advantage of developing a measure of potential skill shortages using this data is that estimates can be updated annually as new Lightcast data is published, and, due to the large sample sizes involved, replicated for individual member states. This considered, we use online job vacancy data from Lightcast (formerly Burning Glass Technologies) to

([32]) Note that in our analysis we exclude armed force and agricultural occupations (Armed Forces; Skilled agricultural, forestry and fishery workers; Agricultural, forestry and fishery labourers).

identify potential skill shortages using metrics that, as far as is possible given the differences in the datasets, correspond to those set in the ESJS data.

We adopt a similar approach to our classification of skills shortages using the ESJS, in that we identify specific job vacancy conditions that are likely to be associated with potential skill shortages. Specifically, six criteria – relating to required competencies, experience requirements, salary requirements and vacancy duration – must all be met. These criteria are outlined in turn below.

(a) High competency requirements within occupation: We consider a vacancy to be a potential shortage if a vacancy contains an above average (mean) number of competency requirements within its relevant occupational category.
(b) Economy wide high competency requirements: We also consider a vacancy to be a potential shortage if a vacancy contains an above average (mean) number of competency requirements in their respective national economy.
(c) Previous Experience: Similar to the ESJS condition, since skill shortages are more likely to occur among experienced workforces, rather than among entry level positions, we consider a vacancy to be a potential skill shortage if it requires at least one year of experience.
(d) High wage within occupation: Similar to the ESJS condition, if employers experience difficulties in recruiting qualified candidates for their vacancies, then this is likely to be reflected in a higher salary. We consider a vacancy to be a potential skill shortage if a vacancy posts a higher-than-average salary in the corresponding ISCO 2-digit occupation.
(e) Economy wide- high wage: We also want to take into account jobs with a higher-than-average posted salary within the general economy, not only at an occupational level. Therefore, we consider a vacancy to be a potential skill shortage if a vacancy posts a salary higher-than-average computed at country level. This condition is set in order to exclude potential labour shortages, which may have above average wages for the occupation, from potential skill shortages.
(f) Duration Condition: We consider a vacancy to be a potential shortage if the job vacancy remains published for a duration greater than 30 days (and less than 120 days).

In summary, positions with high skill requirements both at an occupational level and at country level, that require experience, that post above-average salaries both within occupation and within an economy and are published online for extended periods of time are associated with potential skill shortages / hard-to-fill vacancies. Where all six of these conditions apply to job vacancies, we identify them as potential skill shortages.

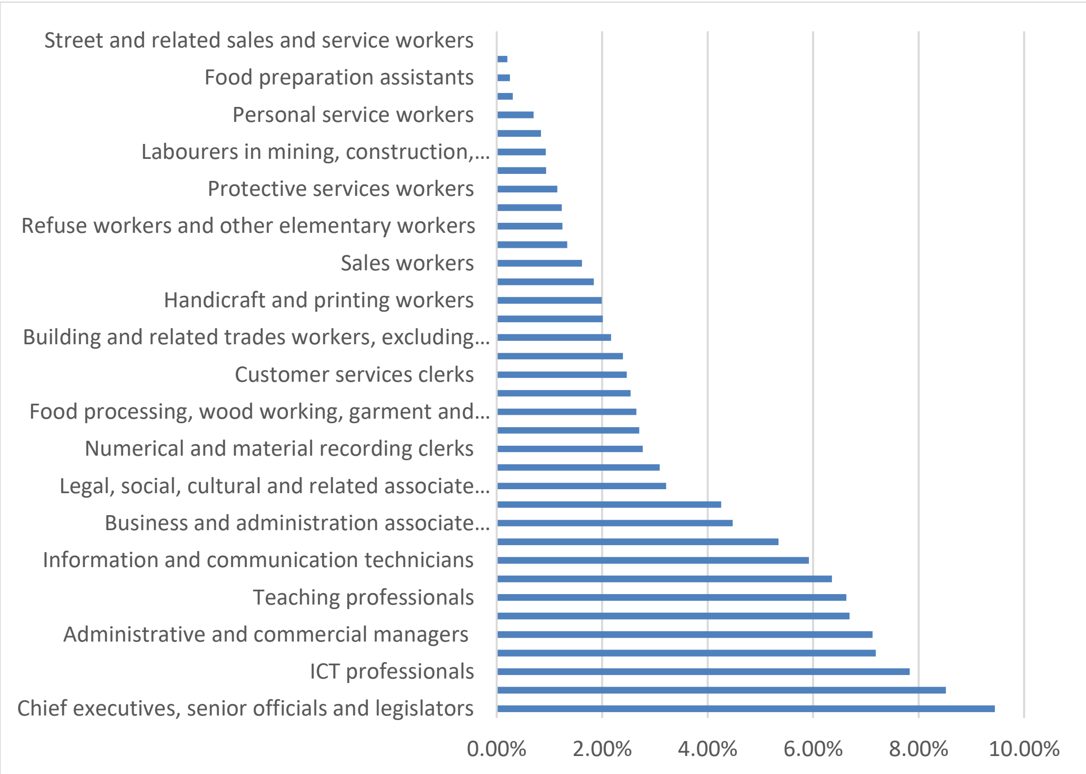
We apply the following restrictions to the Lightcast data for the purpose of analysis. First, we only include data where both salary information and experience requirements are available. Second, we only include data for which at least one ‘Hard Skill’ or ‘Language’ is present in the competency requirements. This is because we want to take into account the technical skills related to jobs, rather that soft and transversal skills. Third, we do not include vacancies that exhibit a duration (i.e. the number of days that the vacancy remains open to applicants) of 120 days or more.

7.3. Main empirical findings

7.3.1 EU incidence of skill shortages across ISCO 2-digit occupation level based on the 2021 ESJS

When all seven job conditions presented above hold simultaneously, a job is identified as a potential skill shortage in the 2021 European Skills and Jobs Survey. According to our methodology, the overall EU share of jobs estimated to be potential skill shortages stands at around 3.5 %. We want to investigate in which occupations potential skill shortages are more likely to occur. The first thing that is striking is that the overall incidence of potential skill shortages is relatively low and below 3 % for most occupations.

Figure 11. **Potential skill shortages across ISCO 2-digit level occupations, ESJS2**



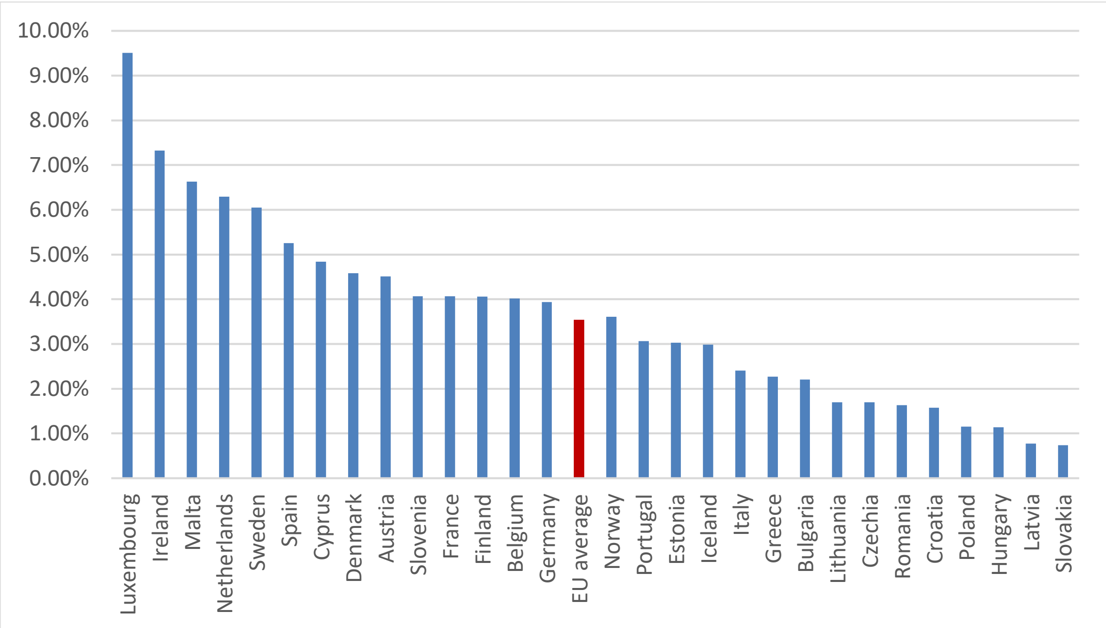
NB: Armed Forces, Skilled agricultural, forestry and fishery workers and Agricultural, forestry and fishery labourers are excluded from the analysis.
Source: Cedefop second European Skills and Jobs Survey (authors' elaboration).

To get a clearer idea of the occupations at highest (lowest) risk of potential skill shortages, in Figure 11 we graphically show the occupational distribution of potential skill shortages. The distribution makes sense intuitively, with many of the occupations typically thought of as having skill related hiring difficulties emerging at the top end of the distribution. The highest share of potential skill shortages appears within Chief executives, senior officials and legislators (over 9 %). High shares of potential skill shortages are located among professional occupations (Science and Engineering, ICT, Business and Teaching Professionals) as well as other managerial positions (Administrative and Hospitality Managers); but potential skill shortages do exist along all the occupational distribution. As expected, elementary and service occupations have the lowest predicted incidences of potential skill shortages.

7.3.2 Cross-country shares of potential skill shortages based on 2021 ESJS

We present the cross-country distribution of potential skill shortages in Figure 12. There is substantial heterogeneity across member states, indicating that the issue of skill shortages is much more problematic in some countries than in others. Shortage rates range from over 9 % to less than 1 %. Countries such as Luxembourg, Ireland, Malta and the Netherlands appear to have the highest share of potential skill shortages, while Slovakia, Latvia, Hungary, and Poland have the lowest.

Figure 12. **Cross-country shares of potential skill shortages, ESJS**



Source: Cedefop second European Skills and Jobs Survey (authors' elaboration).

7.3.3 EU incidence of skill shortages across ISCO 2-digit occupation level based on 2021 Lightcast data

When all six job posting conditions analysed above hold simultaneously, a vacancy is identified as a potential skill shortage within 2021 Lightcast data. According to our methodology, the overall EU + UK share of jobs estimated to be potential skill shortages stands at around 2 % (40 996 potential shortages out of a total 2 023 357 vacancies in 2021). The estimated rates of potential skill shortage are comparatively lower than ESJS estimates. While the ESJS is a representative survey of all adult employees in Europe, Lightcast data represents the number of job openings over a period. Given that many high-skilled roles are filled internally within organisations, it is not surprising that such positions account for a lower share of total job advertisements relative to their employment shares.

In Figure 13, we graphically show the occupational distribution of potential skill shortages and, again, these make intuitive sense. ICT professionals exhibited the highest potential skill shortage rate in 2021 (over 5 %), followed by Business and administration Professionals, and Administrative and Commercial Managers (over 4 %). Potential skill shortages are located among other professional and managerial occupations.

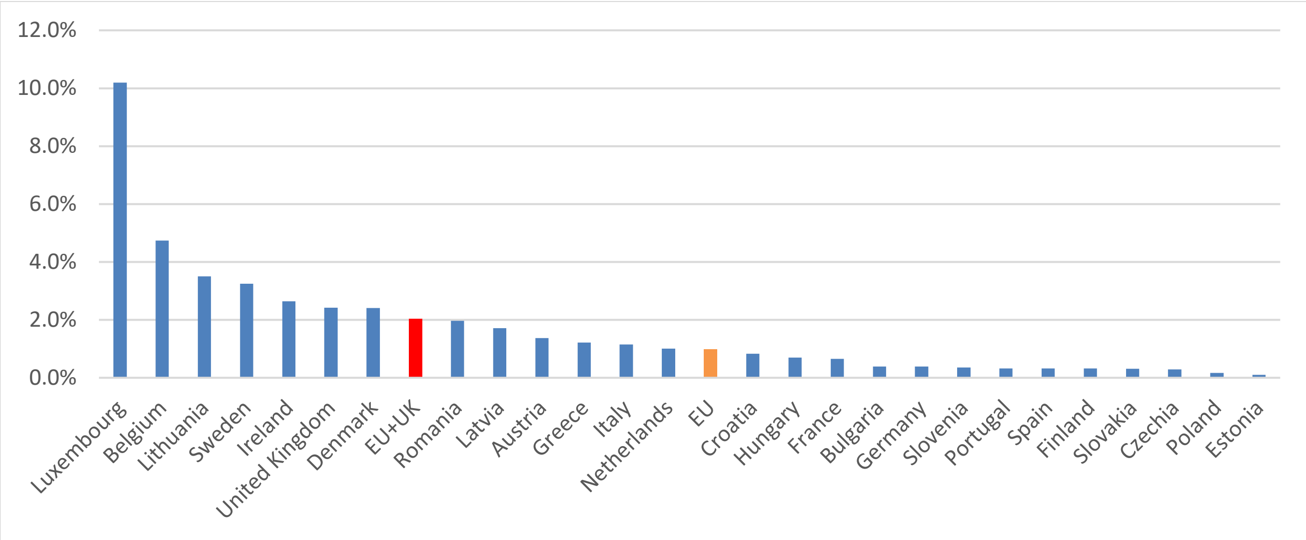
Figure 13. **Potential skill shortages across ISCO 2-digit level occupations, Lightcast data**

Source: 2021 Lightcast data (author's elaboration).

7.3.4 Cross-country shares of potential skill shortages based on 2021 Lightcast data

We also calculate the potential shortage rates for each individual country across the sample, which we graph in Figure 14 below. Luxembourg seems to display the highest shares of potential skill shortages, followed by Belgium and Lithuania; Estonia, Poland and Czechia display the lowest shared of potential skill shortages vacancies. The EU + UK average stands at 2 %, while if we consider only the EU 27 countries, the average is halved. Note that Cyprus and Malta are not included in the analysis due to small sample sizes.

Figure 14. **Country-level rates of potential skill shortages (EU-27+UK; 2021, Lightcast)**

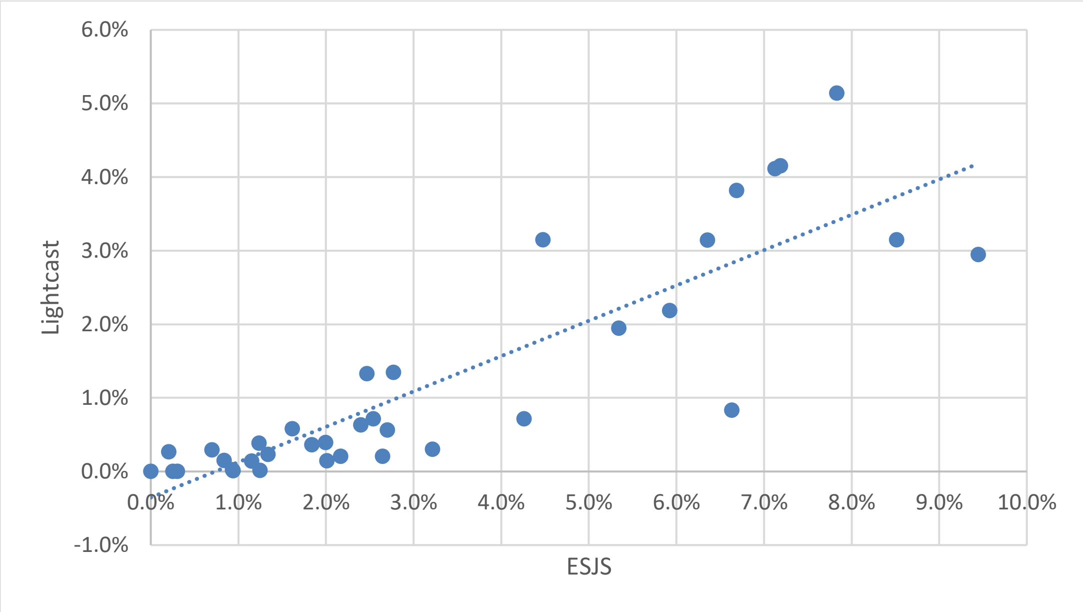


NB: Cyprus and Malta are not included due to small sample size.
Source: 2021 Lightcast data (author's elaboration).

7.3.5 Benchmarking ESJS skill shortages estimates against Lightcast skill shortages estimates

We validate our Lightcast approach against the ESJS estimates, by calculating the correlation between the potential skill shortages estimates in the two datasets. In Figure 15, we plot potential skill shortages rates in ESJS against potential skill shortages in Lightcast, at an occupational level. We observe a positive correlation (ρ = 0.87): occupations with high (low) shares of potential skill shortages in ESJS data, generally have high (low) rates of potential skill shortages in Lightcast data, although with some outliers. This is a critical finding as it confirms that our Lightcast approach predicts the vacancies that are likely to be most difficult to fill in a way that is reflective of the current distribution of competencies and skills being demanded, and utilised, in the labour market, as measured by the ESJS. When the country level estimates of skill shortage are compared with each other, the two sets of estimates are found to be strongly positively correlated ($\rho = 0.60$), albeit the correlation is weaker than the EU level ISCO correlations.

Figure 15. **Potential skill shortages by occupation- ESJS estimates against Lightcast estimates**



Source: Cedefop second European Skills and Jobs Survey and 2021 Lightcast data (author's elaboration).

7.3.6 Potential skill shortages rates across ISCO 2-digit occupations using the 2022 and 2023 Lightcast data

As stated, the principal advantage of the Lightcast approach is that it can be replicated across years and countries, as new Lightcast data becomes available. As a robustness check, we next examine the incidence of potential skill shortages in later years of Lightcast data. Specifically, we identify potential skill shortages by applying the same conditions explained before using job vacancy data from 2022 and 2023. It is important to assess whether potential skill shortages identified in Lightcast data in 2021 persist, increase or decrease in subsequent years. It is also important to confirm that subsequent Lightcast estimates continue to closely align with the distributions of skills and human capital being utilised within the labour market. Generally, potential skill shortage rates are stable across time, with most occupational categories fluctuating within a band of ±1 percentage point between 2021 and 2023. Information and Communications Technology professionals, Business and Administration Professionals and Administrative and Commercial Managers display the highest share of potential skill shortages across the years, although ICT Professionals exhibited a decline of approximately 2 percentage points over the period of interest (from 5.1 % to 3.1 %).

7.4 Summary and policy relevance

While policymakers and governments are continually alert to the potential risks of skill shortages and routinely implement policies designed to combat them, there is no consensus on how to measure them. The limited literature contains a number of subjective and objective measurement approaches to skill shortages. However, each of these has their weaknesses and very few can be easily replicated over time and/or across countries due to data constraints.

The objective of this study is to produce a meaningful indicator of potential skill shortages, based on vacancy data, that can be replicated annually at both EU and member state level, while distinguishing skill from labour shortages. Our approach uses the second wave of the European Skills and Jobs Survey (ESJS2) to identify within each occupation the proportion of jobs that are likely to be difficult to fill should they come to the labour market. The ESJS2, is an employee survey with detailed information on job characteristics. We use a multi-dimensional approach, by identifying several conditions that are likely to be associated with potential skill shortages. However, the ESJS2 is a periodic cross-section, and while any measure of potential skill shortage will reflect the distribution of jobs in 2021, it also has drawbacks in that (a) the flow of jobs that are advertised may not accurately mirror the stock of existing jobs, particularly, as many high skilled vacancies could be filled internally, and (b) the estimates of potential skill shortages cannot be replicated for years subsequent to 2021.

In order to overcome these limitations, we attempt to replicate our measure of potential skill shortages based on the ESJS2 using job advertisement data from Lightcast, which will reflect the distribution of current vacancies and can be estimated on an annual basis at an EU and member state level. The benchmarking of an objective measurement approach to a dataset reflecting the current distribution of skills and competencies being utilised within the labour market is, in our view, a substantial advancement in the measurement of skills shortages at both a national and European level.

The results of our analysis produce a meaningful indicator that aligns to prior expectations regarding the likely occupational distribution of skill shortages. The incidences of potential skill shortage are found to be generally much lower, at around 2 % of all vacancies across the EU and the U.K., relative to estimates produced using other approaches. Many of the occupations typically thought of as having skill-related hiring difficulties emerge at the top end of the occupational distribution. Our robustness checks are highly encouraging as they suggest that our Lightcast based estimates closely reflect the distribution of skill and competencies being employed within the labour market, and these relationships are stable as the Lightcast estimates extend beyond 2021.

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Chapter 8.
Mapping AI adoption in the EU labour market: evidence from online job postings

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8.1 Introduction

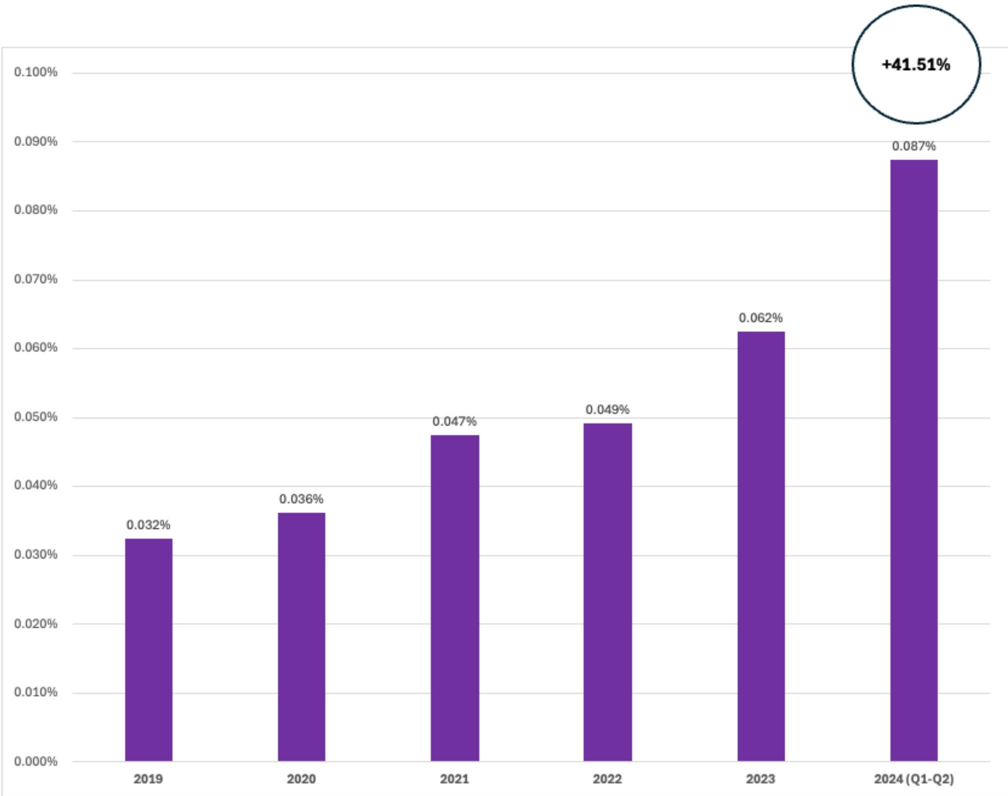
Artificial Intelligence (AI) is increasingly recognised as a general-purpose technology with transformative implications for productivity, business models, and skill requirements across the European labour market. Its rapid diffusion extends beyond specialised roles, permeating diverse occupations and reshaping both the nature of work and the competencies demanded by employers. Understanding the evolving role of AI in the workplace has thus become a policy priority within the European Union, particularly in the context of the Digital Decade and initiatives related to digital and green transitions ([33]).

The data (Figure 16) indicates a significant increase in AI-related job postings from 2019 to mid-2024. Unique postings grew from 10 270 in 2019 to 36 935 in 2024 (Q1-Q2), with the percentage rising from 0.032 % to 0.087 %. The highest yearly increase was observed in 2024, with a 41.51 % delta from the previous year (comparing the 2023Q1Q2 with 2024Q1Q2). This trend highlights the growing demand for AI skills in the job market.

This paper contributes to the expanding literature on AI's impact on labour markets by offering a novel empirical analysis of AI-related skills and occupations, utilizing real-time data extracted from online job advertisements (OJAs). While existing research often emphasises potential job displacement based on model-based forecasts of automation, this study analyses current labour demand across EU and neighbouring countries, providing a unique perspective on how AI is being integrated into organisational structures and daily job tasks. By leveraging the Lightcast dataset, one of the most comprehensive sources of structured job posting data in the EU, the paper delivers granular evidence on the types of AI skills requested, their sectoral and occupational distribution, and their association with various business strategies, from innovation and product development to process optimisation and change management.

([33]) Shaping Europe’s digital future: European approach to artificial intelligence

Figure 16. **Job postings for AI titles as % of total EU job postings**



Source: Lightcast Global Postings

Our analysis advances the empirical literature in three key ways. First, we present a clustering of occupations based on the functional role of AI within job tasks. Using the intensity and nature of AI skills in job postings, we categorise occupations into three broad clusters: Build (new product development), Enable (implementation of new processes), and Improve (optimisation of existing operations). This framework allows for a nuanced interpretation of AI adoption across different organisational levels and departments.

Second, we apply a Revealed Comparative Advantage (RCA) ([34]) approach to identify job-specific AI skills within each occupation. This method, adapted from trade economics, enables us to distinguish between general AI skills (used broadly across roles) and those particularly important in specific occupational contexts. The RCA methodology allows policy stakeholders to target upskilling and reskilling interventions with greater precision.

Third, our findings contribute to the policy debate by offering timely, bottom-up evidence of the shifting demand for AI-related competencies. Notably, the results

([34]) Hidalgo, César A. 'The dynamics of economic complexity and the product space over a 42-year period.' CID Working Paper Series (2009).

have implications for EU-level strategies such as the Pact for Skills, the Digital Education Action Plan, and the European Skills Agenda. The data presented in this paper can assist policymakers in aligning education and training systems with emerging industry needs, especially in domains such as data science, robotics, and generative AI. Moreover, the diversity of roles adopting AI – from creative professions to technical and managerial ones – underscores the need for interdisciplinary curricula and lifelong learning frameworks.

This research aligns closely with the European Commission's March 2025 ([35]) Union of Skills Communication, which underscores the necessity of investing in human capital to bolster the EU's competitiveness and resilience. The Communication identifies critical challenges, including skills shortages, insufficient transformation speed, and fragmented governance, which impede productivity growth and innovation. It emphasises the importance of enhancing skills intelligence at the EU level to inform effective and targeted policies.

From a methodological standpoint, this study reinforces the value of online job postings as a near real-time source of Labour Market Intelligence (LMI). Although limitations remain, particularly in representing low-skilled occupations or smaller employers, OJAs offer a unique lens to capture emerging skill trends and provide foresight that complements traditional surveys and administrative data. This is especially important in a fast-moving technological environment, where policy decisions must be agile and evidence based.

8.2 Methodology

This study draws on online job postings (OJPs) data to examine how Artificial Intelligence (AI) is integrated into occupations across the European labour market. The methodology is designed to extract insights from a large-scale, real-time dataset, and identify how AI-related skills are distributed across roles and sectors. The approach combines text mining, skill clustering, and statistical profiling, allowing for a detailed and policy-relevant picture of AI's impact on jobs.

8.2.1 Data sources

The analysis is based on Lightcast's proprietary online job postings database, which includes millions of ads collected daily from thousands of sources, including job boards, corporate career pages, and public employment portals. Postings are deduplicated and cleaned using natural language processing and machine learning

([35]) Union of Skills: Investing in people for a competitive European Union techniques to ensure consistency. Each ad is then classified using the Lightcast Occupation Taxonomy (LOT), as well as tagged with location, sector, and skills data.

While job posting data may underrepresent lower-skilled or non-digitised sectors, it provides unparalleled granularity and timeliness, making it a valuable tool for monitoring fast-changing trends, especially in technology adoption. The dataset includes job postings from EU Member States and associated countries, covering the period from January 2019 to mid-2024 ([36]).

8.2.2 Defining artificial intelligence skills

To identify AI-related job postings, we leverage the Lightcast Open Skills Taxonomy, which includes over 30 000 distinct skills organised into categories and sub-categories. A curated list of AI skills was selected for this analysis, covering the following clusters ([37]):

(a) Artificial Intelligence (general), e.g. AI systems, cognitive automation, ethical AI;
(b) Machine Learning, e.g. Scikit-Learn, TensorFlow, boosting algorithms;
(c) Natural Language Processing (NLP), e.g. ChatGPT, sentiment analysis, BERT;
(d) Generative AI, e.g. large language models, GANs, prompt engineering
(e) Robotics & Autonomous Systems, e.g. robotic operating systems, LiDAR, autonomous vehicles
(f) Neural Networks, e.g. deep learning, autoencoders, convolutional networks
(g) Computer vision/Visual recognition, e.g. image segmentation, facial recognition.

A job posting is defined as ‘AI-related’ if it mentions at least one of the identified AI skills in its text. These postings are further analysed to identify the occupations and business functions in which AI is being deployed.

8.2.3 Clustering of occupations

To understand the functional use of AI in different occupations, we developed a three-cluster framework:

(a) Build: Occupations that use AI to develop new products or services (e.g. Data Scientists, Robotics Engineers)
(b) Enable: Occupations that apply AI to activate or transform business processes (e.g. HR Managers, Compliance Officers)
(c) Improve: Occupations that integrate AI to enhance existing workflows or efficiency (e.g. Logistics Engineers, Administrative Managers)

([36]) Vermeulen, Wessel, and Fernanda Gutierrez Amaros. ‘How well do online job postings match national sources in European countries?: Benchmarking Lightcast data against statistical and labour agency sources across regions, sectors and occupation.’ (2024).

([37]) HAI - AI Definitions

The classification is based on the share of AI job postings per occupation. Using percentiles, occupations in the top quartile were assigned to the 'Build' cluster, the middle quartiles to 'Enable,' and the lower quartile to 'Improve'.

8.2.4 Identifying job-specific AI skills using revealed comparative advantage

To identify the most relevant AI skills within each occupation, we used a Revealed Comparative Advantage (RCA) approach. RCA is typically applied in international trade but here is adapted to measure the relative importance of a given AI skill within an occupation compared to its importance across all occupations. The RCA index is calculated as:

$$RCA_{ij} = \frac{(S_{ij}/T_i)}{(S_j/T)}$$

where S_{ij} is the number of job postings in occupation i requiring skill j, T_i is the total number of job postings for occupation i, S_j is the total number of job postings requiring skill j across all occupations, and T is the total number of job postings.

Skills with RCA values significantly above 1 (and scaled between 0 and 5) are interpreted as job-specific AI skills: those that are disproportionately important within a given role. This approach allows us to go beyond generic trends to map the unique skill signatures associated with different occupations, which can be used to guide curricula design and training investments.

8.3 Main empirical findings

The analysis reveals a steady and significant rise in employer demand for AI-related skills. The share of AI-related job postings has increased from 0.032 % in 2019 to 0.087 % in mid-2024, more than doubling over five years. Although the share remains relatively low in absolute terms, the growth rate indicates a clear structural shift in skills demand.

The COVID-19 pandemic temporarily slowed growth in 2020, but AI job postings rebounded strongly in subsequent years, particularly in fields such as machine learning, natural language processing (NLP), and generative AI.

The most rapid increase occurred in Generative AI, which grew from 0.03 % in 2019 to 0.13 % in 2024, driven by tools like ChatGPT, DALL·E, and other large language models. This reflects a broader diffusion of AI into non-technical fields such as communications, design, and education.

8.3.1 Clustering occupations by AI integration: build, enable, improve

To understand how AI is deployed across different jobs, we grouped occupations into three categories (Build, Enable, Improve) based on the intensity and purpose of AI use as described above (Table 18). These clusters reflect how AI is not just concentrated in technical fields, but increasingly embedded in decision-making, people management, and logistics roles.

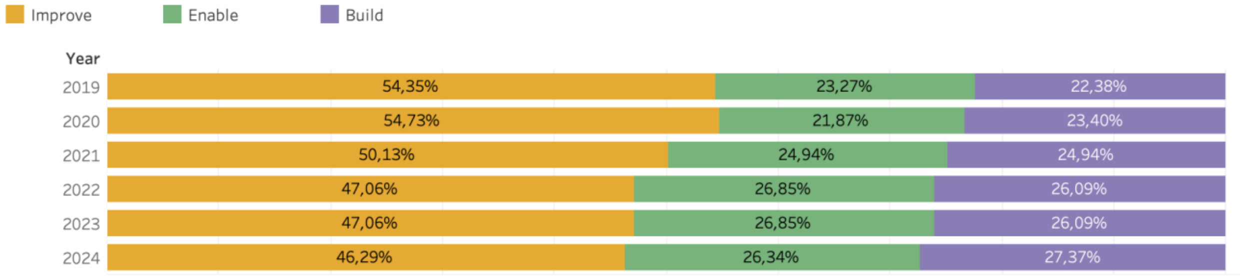
The share of postings in the Build cluster has increased over time – 22.4 % of AI jobs in 2019 to 27.4 % in 2024 – suggesting that more employers are investing in new AI-based products and capabilities (Figure 17). The Improve cluster, once dominant, declined from 54.3 % to 46.3 %, as more organisations moved from optimisation to innovation. This trend underlines a shift in AI adoption from internal efficiency to outward-facing innovation and product development.

Table 18. **Examples of occupations by cluster and AI adoption levels (EU, 2024)**

Cluster	Occupation	% of AI job postings	Primary AI Use
Build	Data Scientist	73 %	Model development, LLM training
Build	Robotics Engineer	23 %	AI integration in machines
Enable	HR Manager	0.90 %	Chatbots, AI-driven hiring
Enable	Operations Manager	0.80 %	Workflow automation
Improve	Office Manager	0.60 %	AI tools for scheduling
Improve	Logistics Engineer	0.50 %	Route optimisation

Source: Lightcast Global Postings

Figure 17. **Share of occupations in the different cluster by year – EU countries**



Source: Lightcast Global Postings

8.3.2 Composition of AI skill demand

Beyond the presence of AI, it is essential to understand which AI skills are in demand and how these vary by role (Table 19). Using the Revealed Comparative Advantage (approach, we identified which AI skills are uniquely associated with specific occupations.

Table 19. **Examples of job-specific AI skills using RCA (EU, 2023-24) – Top skills for selected occupations (RCA scaled 0-5)**

Occupation	AI Skill	RCA Score
Data Scientist	Scikit-Learn	5
Robotics Engineer	Robotic Systems	4.6
Graphic Designer	Generative AI	5
Compliance Analyst	Generative Adversarial Nets	4.4
Logistics Engineer	Autonomous Vehicles	5

Source: Lightcast Global Postings

For instance, data scientists most often request Scikit-learn, PyTorch, and TensorFlow, while robotics engineers are associated with robotic operating systems and computer vision. Meanwhile, communications specialists increasingly rely on ChatGPT and Generative AI tools to produce tailored content.

These results help differentiate between jobs that create AI tools (e.g. engineers, scientists) and those that apply them in context (e.g. designers, managers, educators). This distinction has important implications for curricula design, training investments, and career guidance.

8.3.3 Occupational use-cases: from innovation to efficiency

Using AI-related job ad text, we extracted illustrative use-cases across the three clusters. These show how AI is deployed in practice:

(a) Build:

A Data Scientist role described building predictive models using PyTorch and TensorFlow, managing end-to-end pipelines via MLOps.

A Robotics Engineer position required integrating AI vision systems for automated defect detection.

(b) Enable:

A Communications Specialist job ad requested experience with Generative AI and ChatGPT to streamline content production.

A Compliance Analyst was tasked with assessing ethical implications of AI deployment in regulated industries.

(c) Improve:
An Administrative Manager was expected to implement AI-based scheduling and chatbot support tools.
A Warehouse Worker role included interaction with robotic operating systems and autonomous vehicles for inventory handling.

These examples illustrate AI’s practical impact – not just automating tasks, but augmenting workers' roles with new tools and responsibilities.

8.3.4 AI in the workplace: how European jobs are adapting

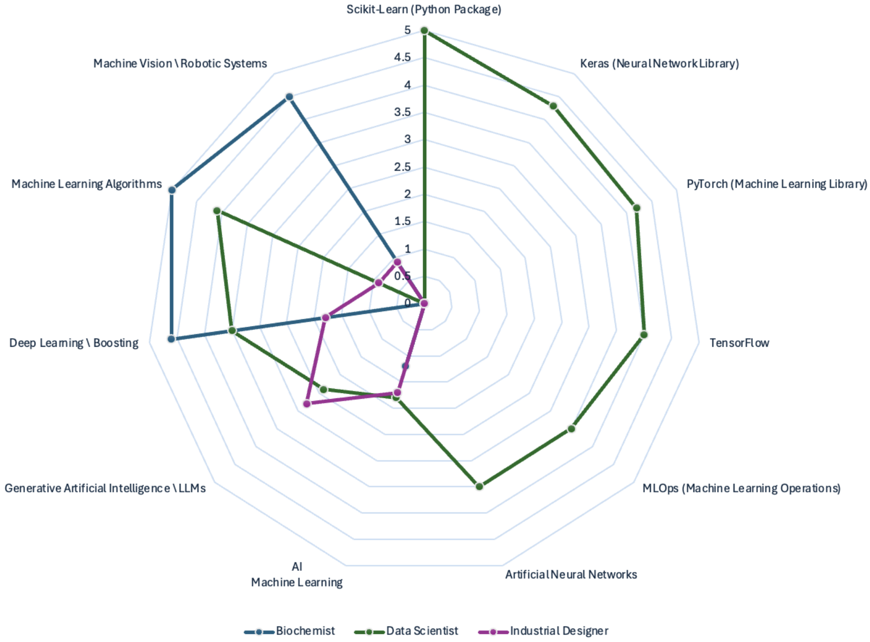
In roles such as Data Scientists, Robotics Engineers, and Biochemists, AI drives innovation. These jobs are at the forefront of AI development, applying technologies like machine learning, generative AI, and neural networks to create entirely new tools and services. Designers and content creators are also using AI for creative generation, blending art and automation. Developers rely on frameworks like TensorFlow and PyTorch to build scalable, intelligent systems. These professionals don’t just use AI: they invent what AI can do next.

In the cluster ‘Enable’, AI is woven into workflows to enhance processes. Project Managers, Compliance Officers, and Communications Specialists use AI to automate tasks, optimise resource allocation, and inform decisions. Tools like ChatGPT and computer vision systems are becoming everyday utilities for these roles. Rather than creating new technologies, these professionals use AI to rethink how work gets done.

Finally, AI is helping traditional roles become more efficient. Warehouse workers, administrative managers, and logistics engineers use AI to streamline tasks, from inventory tracking to routing deliveries. Even in education and construction, AI supports decision-making and productivity. Here, AI is not disruptive, but supportive – augmenting human effort rather than replacing it.

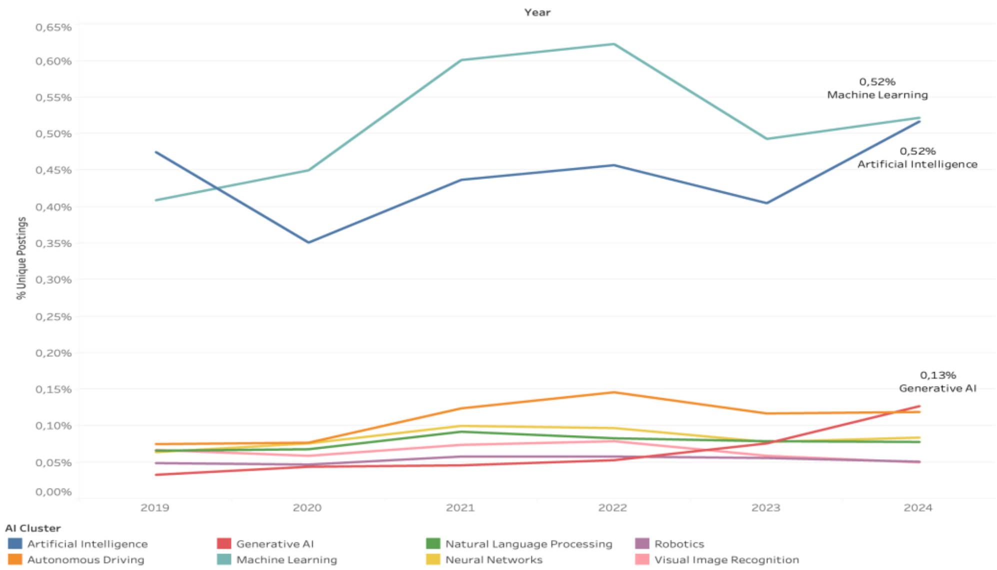
Across these clusters, the common thread is adaptation. Whether building, enabling, or improving, European workplaces are integrating AI in ways that respond to the unique demands of each occupation. As these trends accelerate, they underscore the need for updated skills policies that foster both innovation and inclusion in the AI-powered labour market.

Figure 18. **More relevant skills in the build occupations cluster**



Source: Lightcast Global Postings

Figure 19. **Job postings requesting AI skills as a % of total job postings, by skills clusters in EU countries**



Source: Lightcast Global Postings

8.4 Summary and policy relevance

This study provides new empirical evidence on the integration of Artificial Intelligence in European workplaces, using large-scale data from online job advertisements to assess how AI is reshaping skills needs, job profiles, and occupational dynamics. By analysing over five years of job postings across EU and neighbouring countries, we trace the emergence, diffusion, and diversification of AI-related demand within the labour market.

Key Findings:

(a) AI demand is growing rapidly, with AI-related postings more than doubling from 0.032 % in 2019 to 0.087 % in 2024. This growth is particularly strong in generative AI, computer vision, and machine learning roles.
(b) AI is no longer limited to highly technical or IT-focused roles. It is now embedded across diverse occupations, including human resources, communications, operations, finance, and education.
(c) Occupations are adopting AI in three distinct ways:
(d) To build new products and services (e.g. Data Scientists, Robotics Engineers);
(e) To enable new processes and organisational transformation (e.g. Project Managers, Compliance Officers);
(f) To improve efficiency in existing workflows (e.g. Logistics Engineers, Office Managers).

Job-specific AI skills vary widely, with a clear distinction between skills needed to design and train AI systems (e.g. neural networks, MLOps) versus those used to apply AI tools in domain-specific contexts (e.g. ChatGPT in communications, machine vision in manufacturing).

Together, these insights reveal a nuanced picture of how AI is reshaping work: not as a blanket disruptor, but as a layered and evolving transformation across occupations and sectors.

The findings speak directly to several ongoing EU policy priorities, particularly those outlined in the Communication on the Union of Skills (European Commission, 2025). This initiative highlights the urgency of responding to skill mismatches, accelerating digital transitions, and ensuring inclusive, coordinated action across Member States.

(a) **Strengthen EU-level skills intelligence systems.** This research demonstrates the value of using real-time, web-based data to complement traditional labour market statistics. Job postings provide granular and timely information about employer demand: essential for anticipating future skill gaps. EU-level bodies in cooperation with Member States and platforms like the SkillsOVATE and the Pact for Skills, can integrate such insights into policy dashboards and foresight exercises.

(b) **Support targeted reskilling and upskilling programmes.-** The occupational clustering in this study, 'Build, Enable, Improve', offers a useful framework for designing training pathways based on the degree and type of AI exposure. For Build roles, emphasis should be placed on deep technical competencies (e.g. machine learning engineering, data architecture). For Enable roles, training should focus on hybrid skill sets that blend digital tools with business and communication skills. For Improve roles, workers may benefit from foundational digital skills, change management training, and AI tool adoption (e.g. productivity software, scheduling tools).

(c) **Embed AI literacy across education and lifelong learning.** The diffusion of generative and applied AI tools across non-technical occupations suggests that basic AI awareness should be integrated into general education, vocational training, and adult learning. Initiatives like the Digital Education Action Plan and European Year of Skills can play a key role in mainstreaming AI understanding in both formal and informal learning settings ([38]).

(d) **Monitor inclusive and ethical AI deployment.** AI's impact is not uniform. Some occupations (particularly those with low digital intensity or high regulatory complexity) remain less exposed to AI. These include sectors such as healthcare, crafts, and manual services. Policymakers should ensure that AI transitions are inclusive by investing in accessibility, rural outreach, and SME adoption. The rising demand for roles such as AI compliance officers and ethical AI strategists highlights the importance of embedding trustworthiness and transparency into AI deployment, in line with the AI Act.

(e) **Foster cross-sectoral cooperation.** Finally, the study underlines the importance of cross-sector collaboration. Developing AI-relevant skills requires coordinated action between public employment services, industry actors, training providers, and educational institutions. National Skills Strategies and European-level platforms can help broker these partnerships, ensuring alignment between labour market needs and training provision.

As AI technologies evolve rapidly (particularly with the mainstreaming of generative AI) the need for agile, evidence-based skills governance becomes more urgent. This study contributes to a better understanding of what employers currently expect and how those expectations are shifting. Future monitoring efforts should

([38]) Felten, E., Raj, M., & Seamans, R. (2021). The Variable Impact of Artificial Intelligence on Labor: The Role of Complementary Skills and Technologies. Management Science, 68(7), 5308-5328.

expand the use of granular data sources like OJAs, invest in deeper profiling of AI-related jobs, and continue building forward-looking skills intelligence to guide policy development.

The EU's AI, digital and green transitions will depend not only on technological readiness but on human capital that is adaptable, well-informed, and equipped with the right skills. AI is not just reshaping the labour market, it is redefining what it means to learn, adapt, and work in Europe.

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Chapter 9.
Job satisfaction and the digital transition: ESJS2 evidence for the aerospace and defence industrial ecosystem

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9.1 Introduction

Industry 5.0 foresees a human-centred digital transition, integrating advanced technologies with human creativity to encourage collaborative work where robots enhance human capabilities rather than replacing them. This shift affects the work environment, prompting changes in methods and work processes (Suciu et al., 2023). Nevertheless, there are still some concerns about job insecurity and losses driven by a substitutability of human skills by technology. As fields in science, technology, engineering, and mathematics (STEM) evolve rapidly, the risk of skills obsolescence has become a significant concern (Deming & Noray, 2020). Updating skills is key to navigating and overcoming these challenges with 50 % of the workforce requiring reskilling within the next five years (Li, 2022).

Digitalisation and automation can also affect individual workers' subjective well-being, particularly their job satisfaction, but the process is yet to be fully understood. To explore this gap, the present study aims to investigate the impact of training to develop skills on job satisfaction and factors such as attitudes towards technology, skill utilisation, and job security. It also examines the need for various skill improvements in a high technological intensive sector, particularly in jobs/sectors related with aerospace and defence (ASD).

Job satisfaction is essential for retaining workers and reducing absenteeism (Martin & Omrani, 2015). The new industrial revolution can enhance job satisfaction by creating engaging work experiences. However, rapid technological changes can

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cause job insecurity and skill obsolescence, negatively impacting satisfaction. Digital technologies significantly interact with human resource management and skill utilisation, emphasizing continuous skill development to mitigate job insecurity and mismatches (Sanjayyana et al., 2024). Thus, job satisfaction, influenced by digital technologies, is a key indicator of workers' well-being and attitudes towards work. Attitudes towards new digital technologies and their impact on job satisfaction is also crucial to be explored, as workers attitudes greatly impact performance, motivation, and productivity: when workers are required to implement certain technologies to improve production, they are more motivated to use the technologies and, thus, be reskilled, if they have a positive attitude towards them.

Skills shortages are a significant issue in the EU (Krzywdzinski, 2022). With only 55.6 % of the population having basic digital skills, the Digital Decade goals remain unmet. By 2030, the EU is expected to have around 12 million ICT specialists, with a persistent gender imbalance. To address these gaps, the EU's Pack for Skills initiative focuses on upskilling and reskilling workers through training programs, partnerships with educational institutions, and incentives for companies. Large-Scale Skills Partnerships (LSPs) support workforce development by facilitating cooperation among industry players, public authorities, and SMEs. Among the 14 key industrial ecosystems identified by the EU, the ASD sector is a relevant area where LSPs are actively involved. The ASD industry, driven by AI, IoT, and advanced manufacturing, requires a highly skilled workforce to stay competitive and meet global market demands. It employs approximately 600,000 individuals across the EU, including companies involved in aircraft, spacecraft, and defence systems, as well as related services (European Commission, 2023).

The present study explores the effect of various types of training on job satisfaction, examining how attitudes towards technology, skills use, and perceived job security influence this relationship in the ASD industry. Specifically, the study aims to: (1) assess how different skills improvements contribute to job satisfaction, (2) identify key predictors of job satisfaction, and (3) propose and test a joint model to explain how IT/computer training influences job satisfaction through attitudes towards technology and the application of skills. The study also explores how the interaction between humans and technology, management practices, and investment in ongoing skill development impact job satisfaction.

9.2 Data and empirical methodology

Data from the second wave of the ESJS (Cedefop, 2022) were used to address the objectives outlined. The sample used for the purpose of this study corresponds to those who agreed to participate in the study and are included in the ISCO-4th level and NACE-2nd level codes compatible with ASD, validated by a panel of specialised recruiters working in aerospace. The subsample under analysis (n=1953) includes workers aged from 25 to 64 years old (*M*=42.26, *SD*=10.24), from 27 countries. Most (77 %) are male, and 23 % are female.

Only workers in skilled occupations (93.3 %) and manual occupations (6.7 %) appeared, with none from elementary occupations or semi-skilled ones. Jobs in this sample are tendentially highly paid, with 43.2 % earning above the national highest pay quartile and 21.7 % between the median and highest quartile. As to the size of their current organisation, only 38.5 % work in companies with more than 250 workers, which is suggestive of the prevalence of SMEs in this ecosystem.

Thematic variables were used based on the established objectives. Whenever feasible and upon checking for internal consistency, those items were aggregated in composite scores, for a closer approximation to continuous variables. Variables used in the analyses include:

(a) training received in the past 12 months, training in IT/ computer skills; training in new software/machinery;
(b) Use of computerised machines; machinery activity;
(c) Need to further develop numeracy skills, social skills, technical skills or job-specific skills;
(d) skill use in job;
(e) need to develop computer skills; need to develop overall skills;
(f) technology may replace jobs*;* technology requires new skills;
(g) likelihood of losing job/job insecurity;
(h) job satisfaction ($\alpha = .96$);
(i) attitudes towards technology ($\alpha = .83$);
(j) problem-solving ($\alpha = .82$),*);*
(k) social skills *(*$\alpha = .80$);
(l) dynamic/autonomous work organisation (monotonous/repetitive work);
(m) digital intensity.

The analyses were conducted considering the defined objectives and the nature of the variables themselves, adapting the statistical techniques accordingly, and having as statistical significance a probability value <= .05. Variables showing effects on job satisfaction were included as covariates. For assessing the variables for which it is possible to measure association with job satisfaction, correlation analyses were conducted, taking Pearson correlation for the variables resulting from composite scores, and non-parametric correlation (Spearman’s Rho) for the single items with ordinal scale.

Among the significant associations, to test jointly which is the best predictor of job satisfaction, hierarchical multiple regression was used, including the covariates in a first step, and the predictors in a second step, and having job satisfaction as the criterion/outcome variable.

For testing mediation as an additional analysis, the SPSS macro-PROCESS (version 4.3) was used, created and documented by Hayes (2018) (model 4 for simple mediation, with 10 000 bootstrap samples to estimate indirect effects, and statistical significance interpreted using confidence intervals, being significant if 0 is not in the interval).

9.3 Main empirical findings

9.3.1 Effects of the Digital on job satisfaction

Even accounting for covariates, training for new job-related skills in the last 12 months significantly impacted job satisfaction, $F(1, 1485)=25.18$, $p<.001$, $\eta^2_p=.02$. Those who received training were more satisfied ($M=7.62$, $SD=2.08$) than those who did not ($M=6.98$, $SD=2.24$). More people received training (n=1344, 68.8 %) than not (n=609, 31.2 %). Among those trained, 82.4 % had employer-funded training, 74.6 % had online training, and 68.5 % earned a certificate.

For IT/computer skills, training also affected job satisfaction, $F(1, 1011)=4.45$, $p=.04$, $\eta^2_p=.004$. Those with IT training were more satisfied ($M=7.73$, $SD=2.05$) than those without ($M=7.36$, $SD=2.14$). Training in new software/machinery showed similar results, $F(1, 655)=4.67$, $p=.03$, $\eta^2_p=.007$, with higher satisfaction ($M=7.75$, $SD=2.08$) compared to those without training ($M=7.37$, $SD=2.09$).

There was no difference in job satisfaction between those who use computerised machines and those who do not ($p=.69$), or between those with or without computerised activity ($p=.67$). Job satisfaction was also similar for those perceiving a need to improve numeracy ($p=.40$), social ($p=.45$), or technical ($p=.20$) skills. However, more participants perceived a need to improve social skills (n=1034, 53.0 %) than those who did not (n=918, 47 %), while fewer participants felt the need to develop numeracy skills (n=796, 40.8 %) compared to those who did not (n=1157, 59.2 %). Most participants (67.7 %) perceived a need to improve technical job skills.

In sum, even controlling for the effect of covariates (education level, country, or occupation), workers employed in jobs and sectors compatible with the industrial ecosystem of ASD had their job satisfaction impacted by receiving training in general, and in computer/IT skills specifically, but their satisfaction does not change depending on specific use of machinery/software, or their need for skills development in different areas (numeric, social, technical), which is felt predominantly in terms of technical skills and social skills.

9.3.2 Associations with job satisfaction

The associations of most variables under analysis and job satisfaction are summarised in Table 20 (see Annex). Job satisfaction is positively associated with attitudes towards technology at work (i.e., the more positive the attitudes, the higher job satisfaction and vice-versa), $r(1951) = .29$, $p<.001$, and also positively correlated with the use of skills in the job, $r(1950) = .31$, $p<.001$. Contrarily, it is negatively correlated with the perceived likelihood to lose one's job, $r(1947) = -.25$, $p<.001$: the more likely to lose one's job, the lower the job satisfaction. Autonomous and dynamic work organisations are positively associated with problem-solving and social skills. Problem-solving skills correlate with the need to improve skills and digital intensity. The need to develop computer skills is linked to the likelihood of losing a job due to technology and lack of knowledge in new technologies, with stronger association for the latter ($r(1950) = .34$, $p<.001$) than the former ($r(1950) = .21$, $p<.001$). The need to improve skills is more associated with the fear of skills obsolescence than being replaced by technology. Both perceptions of job loss due to technology and lack of skills are positively correlated, but their association with actual job loss likelihood is weak.

The question remains whether these associations are influenced by covariates such as education level, especially regarding job satisfaction. Which factor would be the strongest predictor of job satisfaction when controlling for covariates? Would the need to develop skills still connect with the likelihood of job loss?

9.3.3 Predictors of job satisfaction

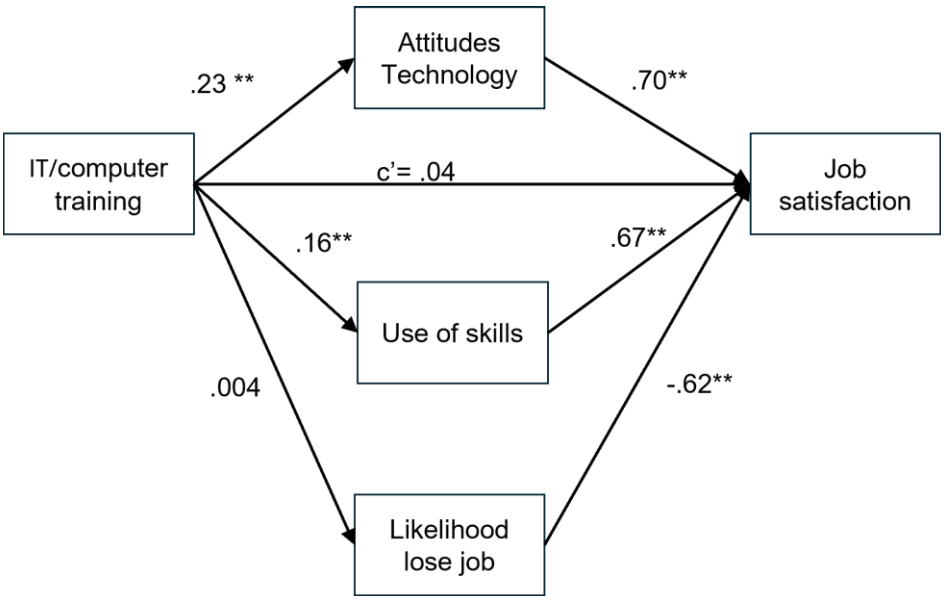
To answer the previous questions, hierarchical multiple regression is carried out, where the covariates are included in the first step and the variables correlating with job satisfaction as predictors in a second step. With job satisfaction as criterion variable, it is showed that, compared to the first step, the inclusion of the predictors increased variance significantly (F_{change} (3, 1481) =92.557, $p<.001$, r^2_{change}=.15). The overall model with the covariates and predictors was significant, $F(12, 1481)=29.38$, $p<.001$, and likelihood to lose job was the strongest predictor (and negative), $\beta=-.21$, $t(1481)=-8.52$, $p<.001$, followed by attitudes towards technology being a positive predictor, $\beta=.20$, $t(1481)=8.31$, $p<.001$, and use of skills appearing as the weaker predictor, $\beta=.20$, $t(1481)=8.18$, $p<.001$.

In the case of need to develop IT/computer skills, the inclusion of predictors increased variance compared with the covariates (F_{change} (2, 1483) = 107.39, $p<.001$, r^2_{change}=.12). The overall model with the covariates and predictors was significant, $F(11, 1483)=17.45$, $p<.001$, and likelihood of losing job due to lack of skills was a much stronger predictor, $\beta=.32$, $t(1482)=12.11$, $p<.001$, than due to technology replacing their work, $\beta=.05$, $t(1481)=2.05$, $p=.04$. A similar pattern was found for the overall need to develop skills (r^2_{change}=.10); the overall model is significant (p<.001, explaining 14 % of variance in need to improve skills) but in this case the likelihood of losing one's job due to replacement by technology was not a predictor (p=.06), whereas the likelihood of losing one's job due to lack of skills//knowledge was a significant predictor of the overall need to improve skills, β=.31, t(1482)=11.34, p<.001. These results suggest that workers in the ASD industrial ecosystem, regardless of education level, country, or occupation, are more motivated to upskill/reskill due to the fear of losing jobs from lacking necessary knowledge or skills, rather than the fear of being replaced by technology.

9.3.4 Mechanisms of job satisfaction

A joint model was proposed to analyze the role of digital training on job satisfaction among potential workers in the ASD industrial ecosystem. The model included job satisfaction as the outcome, IT/computer training as the main predictor, and attitudes towards technology, likelihood of losing job, and use of skills as parallel mediators, with covariates included (See Figure 20 for a graphical representation and main coefficients).

Figure 20. **Mediation model**



Source: Author's own elaboration.

The predictor's role on the mediators was significant for all three predictors (ps<.001), explaining 5 % of the variance in attitudes towards technology, 3 % in perceived likelihood of losing job, and 4 % in use of skills. Participants with IT/computer training showed more positive attitudes towards technology (β=.23, t(1482)=5.56, p<.001) and greater use of skills (β=.16, t(1482)=3.67, p<.001) compared to those without training, but training did not affect the perceived likelihood of losing the job (*p*=.92).

The mediators significantly explained 17 % of the variance in job satisfaction, with all three mediators being significant.

When mediators were included, training had no effect on job satisfaction (*p*=.79). Bootstrap estimates showed that attitudes towards technology (β=.23, *95 % CI* [.15, .39]) and use of skills (β=.11, *95 % CI* [.04, .18]) mediated the effect of IT training on job satisfaction, but perceived likelihood of losing jobs did not (β=-.003, *95 % CI* [-.05, .05]). This suggests that IT/computer training increased job satisfaction by improving attitudes towards technology and perceived use of skills, highlighting the importance of upskilling and reskilling beyond technical performance.

9.4 Summary and policy relevance

The present study explores the impact of training on job satisfaction, the relationship between job satisfaction and factors like attitudes towards technology, skill use, and perceived job security, and the need for various skills improvements. Additionally, it identifies key predictors of job satisfaction and proposes a model explaining how workers' participation in digital training influences job satisfaction through attitudes towards technology and skill utilisation. The ESJS2 variables provide a framework for identifying skill improvement needs, focusing on technical and digital skills, training methods, and readiness for workplace technology adoption. This approach aids comprehension of the current state of the workforce's skills, opening way for specific interventions and strategic planning in the domain of professional development considering the digital advances inherent to the ASD sector. Indeed, this paper aligns sectors with industrial ecosystems in the EU Pact for Skills, filtering the sample to address only those in jobs/sectors compatible with ASD.

Crossing ISCO and NACE codes for the 14 industrial ecosystems, despite limitations, can be a useful proxy. Although ASD is less prone to digital illiteracy, its high technological intensity makes it susceptible to digital skills obsolescence. This is relevant as perceptions often do not match actual skill levels, with highly skilled individuals feeling under-skilled. Analysing ESJS2 data for ASD can highlight workers in jobs with high or changing digital skill requirements, including lower-skilled workers in manufacturing (Bertoni et al., 2024). This paper focuses on these workers' perceptions related to socio-psychological indicators.

The sample consisted of highly educated and skilled workers, with a high rate of employment in SMEs, where in-house training is resource-demanding compared to larger corporations (European Union, 2024). Despite high employer investment in training, it is unclear if it focuses on technical or social skills, though it likely leans towards technical skills. This is puzzling, as over half the sample perceived a need to improve social skills. Surprisingly, there were no statistical associations between soft skills and job satisfaction. However, the perceived need to improve these skills suggests they relate to other organisational aspects not covered. Given the importance of communication and teamwork in the future (OECD, 2023), training in soft skills is crucial, especially for management and high-skilled jobs. Education-related policymaking should, therefore, invest in including soft-skills in the curricula for technical courses.

The results suggest that while the need to improve specific skills does not affect job satisfaction, receiving training does. This highlights the importance for employers to invest in employee training, leading to benefits like higher performance and lower turnover. Job satisfaction was linked to positive attitudes towards technology and the use of skills at work. Workers with IT training had better attitudes towards technology and used their skills more, which increased job satisfaction. However, job satisfaction was not related to the likelihood of losing a job. Higher payment did not significantly impact job satisfaction; instead, attitudes and skill use were more important. The data indicate that training improves job satisfaction through better attitudes and skill use, not through reducing job insecurity, which reinforces the importance of upskilling/reskilling mechanisms such as on-the-job training, and other opportunities to use acquired skills.

The data also show a gender imbalance, as females are under-represented in the ASD sector. Sociodemographic variables, particularly gender, offer important insights. Gender was a covariate in the main results and had a main effect on job satisfaction. Further analyses including gender as a factor would be interesting, but asymmetry in size (fewer women) made comparisons difficult in this paper. Gender in ASD may moderate some statistical effects, and further analyses could reveal stronger or weaker relations for women. Differentiating narrower sectors could better understand women's under-representation, as they are more represented in care-related engineering jobs (e.g., biotech, environmental, biomedical engineering) rather than male-dominated ASD jobs. Thus, focusing on engineering or manufacturing might be insufficient for understanding and acting on gender occupational segregation (Dieckman et al., 2015). Complementing with psychosocial accounts such as gender stereotypes could offer important cues for action, for instance showcasing how ASD jobs could fulfil communal goals.

The sample was balanced in terms of age, reflecting perspectives of young, old, and middle-aged workers, but contrary to some literature and societal consensus, age had no significant effects on relevant variables, except for a weak negative association with problem-solving (older workers engage less in problem-solving tasks). Society often expects older workers to make way for younger ones, while younger workers are expected to be tech-savvy (Schmitz et al., 2024). Cedefop data show that workers in ASD-compatible jobs can be upskilled/reskilled regardless of age. However, age stereotypes can impact upskilling and reskilling. If companies or older workers believe older individuals struggle with new learning, it may hinder lifelong learning and inclusion. Conversely, younger workers not meeting tech-savvy expectations may face career penalties, especially in technology-focused sectors like ASD. Again, psychosocial factors would be meaningful for both HR agents and policy makers.

Despite its contributions, the study has limitations. One is the tentative approximation to the ASD ecosystem, which cannot be guaranteed with the approach taken. Including a question or organizing information to better approximate the industrial ecosystems of the Pact for Skills could be beneficial in future ESJS waves. Another limitation is the survey's cross-sectional nature, meaning causal assumptions should be taken with caution. Additionally, data collection during the COVID-19 pandemic, with lockdowns in some countries, may affect the accuracy of appraisals.

Still, this study offers relevant avenues for both research and practice. By addressing technological change and providing continuous skill development, organisations can create a more engaged and stable workforce, especially in high-tech sectors like ASD. Large-scale skills partnerships aligned with European agenda goals can further bolster these efforts, fostering collaboration, innovation, and skill enhancement across industries. These commitments include promoting lifelong learning, digital and ICT skills development, micro-credentials, and certification (European Commission, 2020).

The study's findings emphasise the critical demand for digital and ICT skills development. Policymakers can use this data to advocate for targeted training programs, ensuring workers are equipped to thrive in their sectors while, at the same time, considering psychosocial variables and group-specific demands (for gender and age, for instance). Short-term, accredited training improves job satisfaction and performance, supporting robust accreditation processes. Additionally, the importance of diverse skill sets, including soft skills, enhances job satisfaction and retention. Policymakers can design comprehensive skills development initiatives to foster a versatile and adaptable workforce, able to navigate the constant transformations the ASD sector implies.

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Annex

Table 20. **Correlation matrix**

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Monotonous/repetitive work	2.65	0.76	--														
2 Dynamic/autonomous work	2.91	0.56	.079**	--													
3 Problem-solving skills	2.65	0.68	-.012	.485**	--												
4 Attitudes towards technology	4.01	0.66	.064**	.258**	.322**	--											
5 Job satisfaction	7.22	2.22	-.084**	.154**	.149**	.288**	--										
6 Use of skills	3.44	0.71	-.053*	.221**	.155**	.266**	.313**	--									
7 Need to develop computer skills	2.95	0.86	-.046*	.193**	.322**	.180**	.102**	.223**	--								
8 Perceived required education for job	6.09	1.73	-.189**	.127**	.217**	.078**	.091**	.103**	.130**	--							
9 Likelihood to lose job	1.53	0.63	.118**	-.031	.079**	-.066*	-.268**	-.143**	.111**	-.004	--						

	M	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
10 Social skills	2.30	0.65	.148**	.437**	.533**	.192**	.046*	.046**	.175**	.124**	.084**	--					
11 Level of education	6.28	1.75	-.149**	.092**	.203**	.114**	.066**	.074**	.116**	.708**	.049	.099**	--				
12 Likelihood of losing job due to replacement by technology	2.35	0.98	.183**	.033	.146**	.059**	-.083**	-.049*	.211**	-.025	.144**	.230**	-.006	--			
13 Likelihood of losing job due to tech skills	2.65	0.86	.046*	.129**	.194**	.097**	-.009	.054*	.341**	.056*	.124**	.137**	.056*	.421**	--		
14 Overall need to improve skills	2.98	0.79	.065**	.209**	.314**	.170**	.083**	.187**	.559**	.083**	.111**	.191**	.078**	.206**	.307**	--	
15 – DSI (digital intensity index)	2.44	0.81	-.132**	.127**	.365**	.160**	.105**	.081**	.322**	.187**	.056**	.218**	.160**	.134**	.188**	.183**	--

NB: **. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Associations with at least one ordinal variable are reported with a non-parametric correlation (Spearman's Rho)

Source: Cedefop second European skills and jobs survey

Chapter 10.
Setting Europe on course for a human digital transition in education

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10.1 Introduction

This study examines the uneven digital transition in EU primary and secondary education, where despite pandemic-driven technological adoption, systemic resistance persists due to teachers' central instructional role, skill gaps, and preferences for human interaction over mediated learning. The present study utilises Cedefop's 2021 European skills and jobs survey dataset, which encompasses responses from over 46 213 respondents across 29 countries (Cedefop, 2022). The objective is to analyse teachers' self-assessed digital competencies and training adequacy, while simultaneously mapping cross-national disparities in skill requirements. The paper progresses from a methodological framework to empirical results, concluding with policy implications for aligning digital transformation with human capital development in education. The findings reveal significant variations between countries in both perceived and actual digital readiness, suggesting that structural inequalities – rather than technological limitations – represent the primary barrier to equitable educational modernisation.

The advent of the pandemic precipitated a rapid adoption of digital technologies in education, thereby exposing both the transformative potential of artificial intelligence (AI) and the pervasive barriers to systemic integration. Digital tools hold great promise in enhancing learning outcomes, yet their adoption at primary and secondary levels remains uneven. This unevenness is constrained by three factors: teachers' central instructional role, attitudinal resistance, and insufficient training. The EU's progress in this regard is indicative of a fragmented transition. According to OECD data from 2023, a mere 56 % of lower-secondary teachers received ICT training during their initial education, with significant cross-national variation. This issue is further compounded by the fact that many teachers report low confidence in digital pedagogy. In particular, they cite training programs as being overly theoretical and disconnected from practical classroom demands. These disparities, further compounded by inherent inequalities between regions and institutions, underscore a pivotal misalignment between policy aspirations and pedagogical realities, thereby jeopardising the pursuit of equitable digital transformation (OECD, 2022).

These findings are corroborated by the *Digital Competences for Language Teachers* (DC4LT) report, which revealed that over two-thirds of surveyed educators expressed dissatisfaction with their current level of digital teaching proficiency. Furthermore, a resounding 95 % of respondents expressed the conviction that enhancing their pedagogical practices would be significantly facilitated by access to high-quality digital literacy training. These insights underscore the importance of structured, practice-oriented professional development that addresses not only technical skills but also pedagogical integration of digital technologies.

Developing a digitally competent teaching workforce is thus essential for leveraging the benefits of AI and other technologies in education. However, while frameworks for digital competence – such as the European Commission's DigCompEdu – provide clear standards, their implementation remains inconsistent across national contexts (Vuorikari et al., 2022). This inconsistency reflects broader systemic issues, including underinvestment in teacher training infrastructure and fragmented policy coordination.

While the COVID-19 pandemic has acted as a catalyst for digital adoption in education, particularly in higher education, primary and secondary institutions face enduring challenges. These include structural inequalities, teacher resistance, and insufficient support mechanisms. Bridging these gaps will require systemic reforms focused on professional development, investment in infrastructure, and the creation of inclusive digital strategies that reflect the realities of everyday teaching. This paper aims to contribute to this effort by examining cross-national differences in digital education and identifying pathways for more equitable and effective integration of digital competencies in teaching practice.

10.2 Data and empirical methodology

European teachers remain difficult to identify through surveys, as there are so many of them and analyses are often based on random samples taken directly from schools. The originality of the approach here lies in using the 2021 Cedefop general survey, which does not target teachers as such. This may yield objectively benchmarked results, as teachers are no longer subject to categorical logic but must define themselves in relation to broader professional practices that are comparable with those of other European workers. The study consists of exploiting microdata from the Cedefop European skills and jobs survey, refocused on respondents who declare themselves to be teachers. The aim of this approach is to break down barriers within the profession and facilitate comparisons.

The present study adopts a sequential analytical strategy to examine teachers' digital competencies across European education systems with greater specificity. The initial descriptive phase maps teachers' self-assessed digital skills, their anticipation of future skill demands, and current workplace technology usage, establishing a comprehensive baseline of digital proficiency levels.

The analytical sample comprises 1 630 primary and secondary teachers from 24 EU countries (excluding Cyprus, Malta, and Lithuania), selected from Cedefop microdata using ISCO-08 codes 23 (teaching professionals) and NACE educational sector classifications. In the given sample, Southern European countries show disproportionate representation (Italy n=170, Spain n=120). Parallel analyses of the general working population provide comparative benchmarks for interpreting teachers' digital competence patterns.

10.3 Main empirical findings: digital skills training for teachers

10.3.1 Pathways to digitisation in school systems

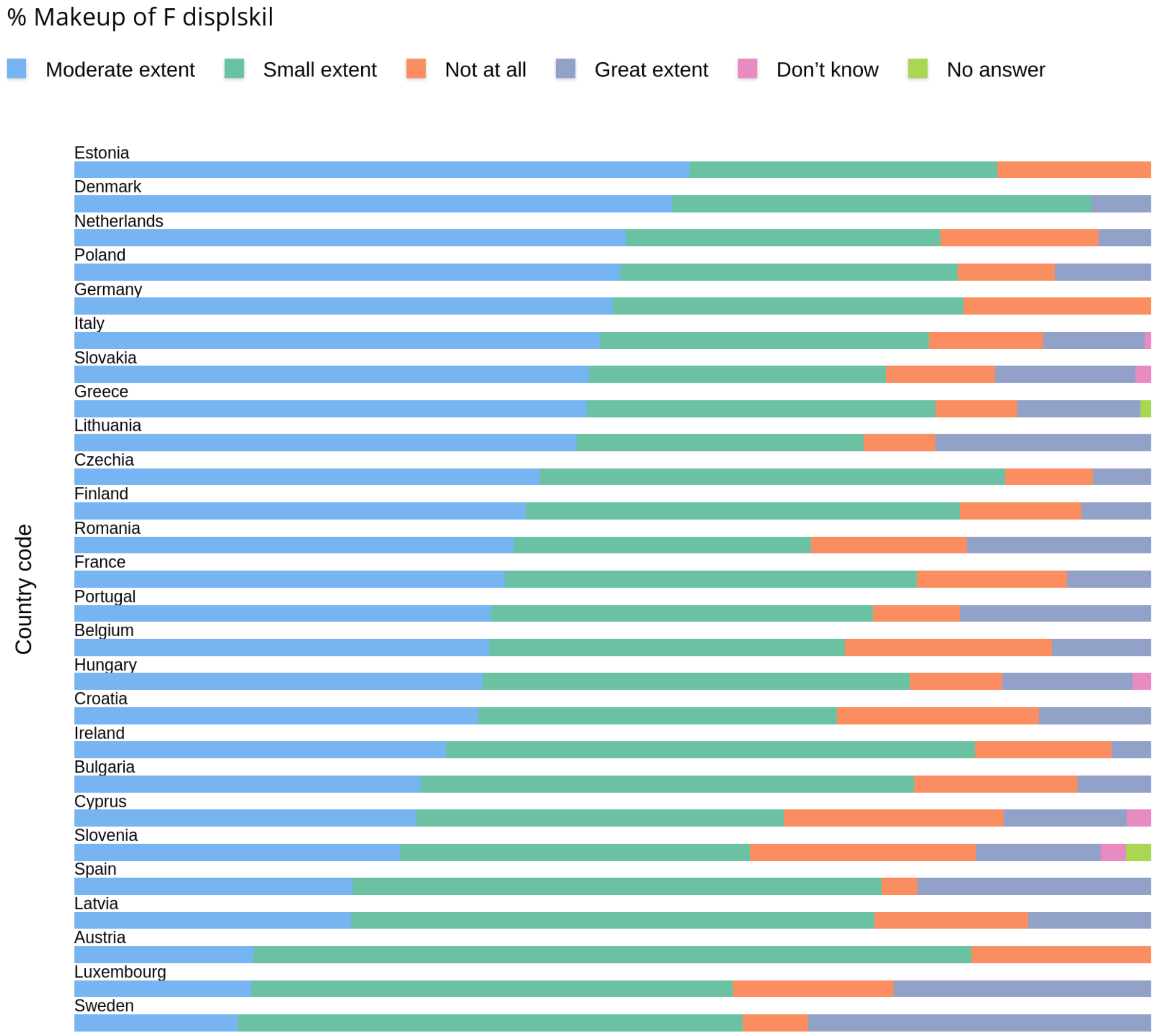
The development of AI technologies is regarded by some as a major revolution in the world of work, which should have a significant impact on job creation, to the extent that most jobs as we know them may disappear or be transformed. All jobs, from the most skilled to the least skilled, will be affected by the digital transformation. *A priori*, education is unlikely to escape this trend, with the use of digital technologies being essential from primary school onwards.

However, on average, 64 % of workers in the European Union (EU) express a fairly high level of confidence that new technologies would have a negligible impact on their work. Teachers have an even higher degree of confidence (65.89 %), with a resounding majority anticipating that new technologies are likely to have minimal impact on their future employment.

This phenomenon can be attributed to the inherent characteristics of the teaching profession, particularly in secondary schools (65.16 %) and even more so in primary schools (66.26 %), where teachers maintain a central role in mutual representations, akin to the conductor of an orchestra. In contrast, digital technologies are seen as merely tools that serve the pedagogy in these settings, in contrast to more exposed sectors in industry.

A closer analysis reveals significant variations between European countries. A distinction can be made between those with advanced technological and digital policies, where teachers are more confident in their added value and do not fear for the future of their profession. Such is the case, for instance, in the Baltic States (80 % of Lithuanian and even 100 % of Estonian teachers consider that digital technology will not do their job). Conversely, in Mediterranean countries such as Spain, where only 34 % of respondents believe that their jobs will be little or not at all affected by new technologies, there is a palpable sense of fear about how technology could potentially threaten their livelihoods.

Figure 21. **Distribution by country of need for new knowledge and skills because of new digital technology**



Source: Cedefop second European skills and jobs survey

European teachers do not expect, in general, a skills revolution. Teachers are aware of the need to acquire new digital skills to accompany this change, but to a moderate degree: 75.77 % believe that the need to develop new knowledge/skill is weak or moderate compared to what they already know. Only a few countries consider these needs to be significant: Sweden (31.82 %), Luxembourg (23.89 %) and Spain (21,67 %) are among the countries where teachers consider the need for new skills to be very significant. This is also the case of teachers with lower educational qualifications, who are aware of the fact that they need to further develop their skills.

10.3.2 COVID-19's ongoing effects on teachers' work

Teachers emerge as a particularly salient demographic in terms of maintaining employment stability during the crisis. In fact, a staggering 97.1 % of survey respondents in the teaching profession managed to retain their positions.

Conversely, teachers were working longer hours during the pandemic, contributing to elevated levels of fatigue in this profession. A mere 6.64 % of online respondents to the survey reported not working at all during this period (in comparison to an average of 10 % across all professional categories).

The transition to digital pedagogy during the COVID-19 period occurred along rapidly evolving and frequently improvised working conditions, with educators frequently required to transition from a predominantly in-person approach to a fully digital one. Digitalisation was not a novel concept in the field of education; however, the accelerated transition that commenced in February/March 2020 has precipitated a swift shift towards comprehensive digital pedagogy. This transformation has been so profound that it has been termed a 'digital shock', a term used to describe the profound and sudden impact of digital technology on various professions.

While about one in four European workers (39 %) have had to use new IT tools for their professional tasks, 75.15 % of those in primary and secondary education say they have had to do so. Geographical disparities are less marked, as most European teachers have had to teach online. However, the pace at which this change has taken place is contingent on the responses of national governments. Significantly high rates of migration to digital technologies have been observed in Slovenia (94.74 %) and Latvia (92.86 %), while the French rate of 43.33 % is particularly low, and this is even more pronounced in terms of the time devoted to e-learning (only 30 %).

While some colleagues were well prepared, many experienced significant difficulties, particularly in primary education, where these habits were somewhat less well established and teachers had to resort to them (72.5 %).

Consequently, the repercussions of the pandemic have led to a significant proportion of teachers (608 respondents, constituting 56.82 % of the survey participants who completed the survey online) asserting a decline in collaboration time with their colleagues (in contrast to the 39 % average).

10.3.3 Digital skill demands in primary and secondary educational settings

Whilst there is a certain degree of consensus on the need to furnish teachers with digital competencies that are both specific to their pedagogical practice and intended to be imparted, the scheduling and nature of these competencies prior to the conclusion of compulsory education remain relatively varied (Serodes, 2025). However, it should be noted that education recruitment competitions do not necessarily include digital tests. As these skills evolve beyond rudimentary competencies, approaches become more varied.

The integration of the internet into modern classroom and learning environments has become a necessity, akin to the fundamental utilities of power and heating. Teachers have become accustomed to using the internet and even among those who do not use digital devices at work, they still consider themselves to have a very good, above-average knowledge of fundamental office environments and software, including spreadsheets, which they utilise on a regular basis. Most teachers hence possess fundamental computer skills, which they can utilise on a daily basis in their job, whether by choice or because they are required to do so (for example, to exchange e-mails or enter grades). This utilisation rate is high, particularly when juxtaposed with that of other European workers.

However, it should be noted that there are some minor differences in digital usage. Teachers with lower levels of education demonstrate a lower frequency of utilisation of their current knowledge and skills in comparison to their more educated peers. Conversely, older teachers demonstrate a greater utilisation of their existing knowledge compared to their younger counterparts. For instance, all respondents aged over 59 (and up to 64) use a computer in the workplace. The equipment rate, defined as the percentage of basic digital tools used, is found to be a non-significant barrier to digitisation, with 98.22 % of respondents reporting the use of these tools. It is evident that computers, even in their most rudimentary form, have become a staple in all education systems, except for a few primary school teachers (23 out of 29 non-users), who still perceive their use as non-essential. A mere 29 out of 1630 respondents (1.78 %) categorically state that they have not utilised any electronic tools.

The analyses indicate that digital skill utilisation in education is shaped primarily by individual-level factors, particularly educational attainment and, to a lesser extent, teaching level. Unlike in other professions, country-specific variables and demographic traits exert only minimal influence.

Table 21. **Utilisation of computing devices by teachers**

Question	%	Number of respondents
Use the internet for browsing, sending emails or using social media for your work	96	1538
Write or edit text	94.98	1519
Prepare presentations of your work	81.57	1306
Use spreadsheets	69.89	1119
Work with any specialised, sector or occupation-specific software	41.16	659
Use the more advanced functions of spreadsheets, for instance macros or complex formulas	34.04	381
Manage and merge databases	16.3	261
Develop or maintain IT systems, hardware or software	12.05	193
Write programs or code using a computer language	11.12	178

Source: Cedefop second European skills and jobs survey

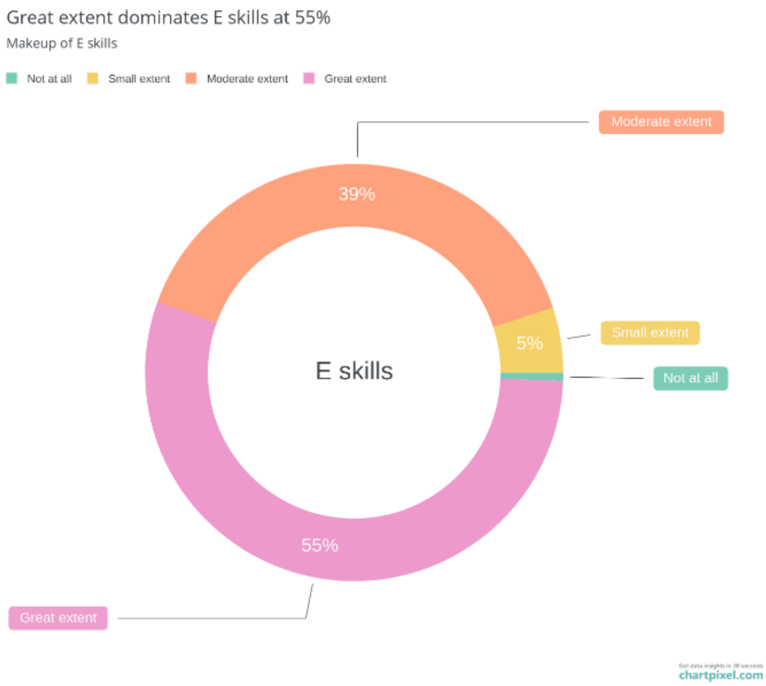
10.3.4 Understanding the importance of enhancing digital competencies

Teachers are aware of and willing to address any gaps in their general skills (78.32 %) and their digital skills, in particular (94.54 %). Despite being better equipped than average (with the majority of 50.86 % considering that they need additional digital skills to a moderate extent), teachers still require further development in this area.

Furthermore, most teachers feel that their skills and knowledge are well suited to the tasks at hand (587 out of 1,070, or 54.85 %). However, this assessment may be potentially misleading, as it may be indicative of either an absence of expectations regarding new skills (Romania tops the list with 74.55 %) or an overabundance of suitable qualifications (Estonia is at 71.43 % for the opposite reasons). It is noteworthy that horizontal mismatch is minimal, with only 113 respondents reporting such issues.

Within this predominantly female-dominated and egalitarian profession, issues concerning overqualification and underemployment among women are seemingly non-existent. Teachers (93.6 % of men; 94.67 % of women) expressed a strong sense of confidence in their ability to use their skills in their work to a significant extent, or even to a very great extent.

Figure 22. **Utilisation of current knowledge by teachers in the execution of their professional duties**



NB: ESJS2 variable E_SKILLU
Source: Cedefop second European skills and jobs survey

As with other workers who perceive needs for development according to their level of qualification, so do PhD teachers (29.27 % consider that they need even more skills). This perception merits closer examination. Is it a realistic and informed perception of the actual and proven skills deficit, or are PhDs caught in a spiral of infinite skills inflation in the digital field that never ends? Historically, the belief was that increasing the standards of professional entrance exams would guarantee a high level of competence, and politicians were able to elevate the profession (MA). More than half (50.98 %) of European teachers is required to have a Master's degree in order to practise the occupation. It is interesting to note that perceived needs to enhance IT skills seem to be primarily shaped by education level, sex and age.

10.3.5 Future training requirements for digital teachers

The time saved by commuting and some of the face-to-face lessons was utilised for training purposes during the 2020-21 period. Most teachers in the survey attended courses or workshops in the first year of the pandemic. This figure remains significantly higher (65.34 %) than the average for European workers. Most of these educational programmes incorporated an online component

(90.67 % of respondents). The integration of online teaching has effectively addressed the disparity in training opportunities between rural and urban schools, with no significant disparities in teacher perceptions of training quality (65 %) observed.

A significant proportion of this training was funded by the Member States as part of the educational continuum (66.52 % of respondents had their training paid for), except for 10 or so countries where the proportion not paid for may even be the majority (for Portugal 66.67 % of training was not covered and in Greece the respective percentage is 61.4 %). The cost and necessity of self-training in the absence of public facilities during the pandemic does not therefore seem to have prevented most teachers from taking training. Conversely, however, teachers did not always make full use of the courses and facilities made available by their employers.

It is challenging to quantify the nature and quality of the training received during a period characterised by unparalleled restrictions, which was addressed in divergent manners by each Member State. The content of these courses varied from one education policy to another. The training programmes have not been primarily focused on addressing the digital aspect. Two distinct groups can be identified: firstly, those where the majority have received at least some digital training (approximately twenty countries); and secondly, five countries where this training has been in the minority, including the Netherlands, Finland and Denmark. This disparity can be attributed to various factors, including the adoption of self-training opportunities that were not fully utilised, or the absence of a perceived necessity due to the perceived competence of teachers in the digital domain.

The predominant learning method for teachers has been a self-directed one (78.15 %), a figure significantly higher than the European average, with learning from colleagues (68.87 %) playing a less substantial role. The majority of respondents (51.35 %) reported spending more than a week on average to master the necessary IT tools. This finding lends further credence to the notion that many upskilling endeavours are modest in nature, often confined to acquiring fundamental digital software skills.

10.4 Summary and policy relevance: teaching in the digital age

10.4.1 Hesitation in schools: beyond technical and pedagogical barriers

In some European primary and secondary schools, there has been a delay in the implementation of digitisation. This can be explained by the reluctance of teachers to embrace new technology (Cheok et al., 2015). In addition to the technical challenges, numerous studies have highlighted the various pedagogical obstacles and the significant personal opposition to the digital revolution. The positive responses to the survey may be indicative of wishful thinking, resistance to technology, and a certain fear, as the teacher is humanly resistant to technological development.

The absence of 'digi-anxiety' among teachers concerning employment security suggests a persistent belief in the profession's inherent stability, bolstered by public-sector protections and its irreplaceable human dimensions. Nevertheless, this confidence may be an underestimation of the transformative risks posed by digital integration. While teachers are presumed to possess advanced digital competencies, critical uncertainties endure regarding the pedagogical implementation of new technologies, their empirical impact, and the lack of software capable of replicating the multifaceted nature of teaching – despite the expanding role of AI tutors, digital platforms, and automated educational resources.

The existence of regional disparities serves to emphasise this disparity. Teachers in Mediterranean nations, including Spain and Greece, demonstrate lower confidence in digital tools. This stance is not driven by baseless concern but by tangible labour market conditions. The increasing substitution of traditional teaching functions by conversational agents, influencer-produced educational content, and automated grading systems has been demonstrated to exacerbate existing unemployment challenges and accelerate the outflow of skilled educators. In contrast to countries such as Sweden and Luxembourg, where digital readiness corresponds with adaptive skill development, the scepticism observed in Spain and Greece reflects deeper socio-economic fragilities, framing digitalisation as an amplifier of professional instability rather than solely a technological shift.

10.4.2 Pandemic paradox: job security meets workplace tension

The resilience demonstrated by EU primary and secondary teachers during the pandemic suggests that higher qualification standards, which are now predominantly at bachelor's or master's level, may serve as a safeguard against labour market volatility. Nevertheless, this resilience remains exclusive to the education sector. While teachers develop transferable competencies in analytical reasoning, communication, and adaptive problem-solving, these skills are not widely recognised in broader labour markets, which limits their professional mobility. The teaching profession is frequently characterised as a vocational commitment rather than a strategic career path, offering limited returns on human capital investment – except for select cases such as Finland and Germany. This discrepancy between qualification levels and cross-sectoral employability highlights systemic inefficiencies in the valorisation of educational expertise within the European labour market.

The concept of professional status offers a more comprehensive explanation for the observed resilience. Teachers have been able to rely on one of the few remaining advantages, job protection, through a status that is on average quite protective. This notion was further reinforced by the social demand that intensified during the period of the pandemic, which brought to the fore the essential function of childcare and the alleviation of parents' responsibilities in terms of education, as is the case in other professions. Teachers thus played a leading role, a position that was valued in some countries, where, for a time, they were even considered ‘heroes’, since many teachers had to work face-to-face while others stayed at home. This feeling of privilege is particularly noticeable in countries where social policies have been fully implemented (Sweden), as opposed to countries with less protection (Italy, Spain).

The pandemic has presented schools with an unparalleled opportunity to embrace digital transformation. However, the significant variations in education policies across Member States complicate such comparisons. While some nations have prioritised health and transitioned fully to digital learning, others have placed greater emphasis on the 'human' aspect of the classroom. In France, the obligation imposed on teachers to return to face-to-face schooling has been the most active policy in this area in the European Union (a total of only 44 days of closure in French schools, compared with an OECD average of twice as many days (88)). However, the crisis has exposed deeper difficulties, as highlighted in the 2018 Talis survey by the OECD. This survey revealed that French teachers expressed a greater need and a lower supply compared to their counterparts (OECD, 2020).

The collation of these results took place at an early stage in the aftermath of the pandemic, when a considerable number of constraints were still in place. It is imperative that the more enduring repercussions of the pandemic on the utilisation of digital tools, digital training, face-to-face meetings and distance learning are measured. It remains uncertain whether this phenomenon will persist, a question that has yet to be answered for the other professions examined (Vargo et al., 2021). The return to the pre-pandemic era can be interpreted as a rejection of the past, which proved to be unsustainable. Consequently, the digital transition encountered significant challenges, often associated with an excessive reliance on digital technology. The valuable lessons imparted by sharing, discovering new tools and collaborating online were frequently disregarded.

The resurgence of face-to-face interactions also warrants consideration. It has been observed by some headteachers that, except for mandatory meetings, there has been a certain lack of interest in staff rooms. In 2021, the impact of digital technology on collaborative working had been particularly pronounced. Priority has now been given to more direct communication with students and families.

In the period examined, the ratio has been reversed, and members of the teaching profession may feel envious of other employees not for their status, but for their working conditions. This is due to the abrupt termination of the remote working experiment. While teleworking has become desirable in the longer term (Tessema et al., 2022), teachers are getting little or no flexibility.

10.4.3 Priority to strengthen and adapt existing skills (reskilling/upskilling) over introducing new ones

Empirical findings indicate that teachers exhibit relatively advanced digital competencies compared to other professions, though significant variations exist within the profession itself. Less-educated teachers demonstrate greater awareness of skill gaps and express stronger motivation for upskilling, while older educators show less urgency for digital adaptation. These patterns challenge prevailing narratives about inadequate teacher training, as 82 % of EU teachers regularly employ digital tools in their professional practice – exceeding usage rates among managers, technicians, and civil servants (Cedefop, 2021). The data suggests that equipment availability represents a lesser obstacle than previously assumed, with teachers frequently adapting personal devices for instructional use, though systematic provision for full student participation remains inconsistent. Notably, the impact of digitalisation appears less pronounced in certain Member States, implying that the primary barrier to effective digital integration lies not in technological access but in pedagogical implementation and systemic support structures. In this regard, Finnish or Swedish teachers are not inherently different from their Romanian or Greek counterparts, as is also observed in many other professional categories (Piasna, 2024). It is noteworthy that some teachers utilise specific software on a regular basis; however, the response to this question may be ambiguous, depending on whether it pertains to subject-specific software (e.g. Geogebra) or, more generally, to the digital workspaces that most teachers are more or less aware of using regularly. Finally, more specific and less advanced skills, such as data analysis or programming, are less well represented. Primary and secondary teachers do not really need them more than other professions (Centeno, 2022).

Many teachers have qualifications that go unused, particularly PhD holders whose skills in areas beyond science and IT receive no financial compensation or recognition. This skills mismatch is counterproductive, as training programmes often omit essential digital skills, leaving highly qualified educators unprepared. Digital skills are conceptualised as purely technical, overlooking crucial areas such as linguistics and data processing, which are particularly relevant for language-based AI applications. The increasing technicalisation of teaching in France and Italy is reducing generalist training, which is creating professional discouragement due to a lack of high-level opportunities rather than a lack of qualified staff.

Unlike in typical labour markets, educational competency requirements are shaped by programme filters rather than employment demands, enabling better alignment between curricula and CVs. However, this flexibility is not fully exploited by education managers. Rather than accumulating additional skills, adequate training should balance educators' potential competencies with practical pedagogical application. Current AI training programmes are ineffective and will likely become obsolete within a few years, a lack of holistic training on AI, confirmed by the findings of the Cedefop survey of European workers in general (Cedefop, 2025). Sustainable digital competencies such as formatting and analysis offer better prospects for aligning professional skills with educational needs.

10.4.4 Conclusion

In this contribution, an exploration was conducted into the digital transition among European teachers. A detailed examination was conducted into teachers' self-assessment of their digital competencies and the necessity for additional training. The findings revealed that the observed variations could not be attributed to conventional factors such as gender or geographical location. In terms of training, skills and needs, the traditional distinction between primary and secondary education appears to be less clear-cut. However, it is possible to better account for the specificity of the teaching world in primary and secondary education in the European Union by considering other more significant factors. The national policies adopted in this context exhibit significant variations in the emphasis placed on training, particularly in the digital domain, and the nature of this training. Additionally, there is a consideration of attitudes towards digital technology, which can be regarded as more or less useful educationally. A further question pertains to the role of the state in promoting this training, a particular aspect of which is the reliance on individual learning.

The results of the survey are of interest to the teaching profession, as they facilitate the identification of the genuine absence of digital competencies, in contrast to the occasionally idealised requirements. Moreover, they underscore the importance of maintaining manageable class schedules, as these educational programmes are uncomplicated.

The impact of the pandemic on educational settings has given rise to a series of challenges, prompting the conduct of surveys within a teaching environment that has undergone significant upheaval. This phenomenon has the potential to significantly distort several variables and observations. Firstly, some states have favoured face-to-face training over digital training. Secondly, digital training was often provided to organise video calls, but this proved less useful in the long term. Consequently, the long-term ramifications of the pandemic remain a subject of considerable debate. While the objective of promoting digitisation was indeed achieved through the introduction of certain software, its immediate reinvestment was constrained by the prioritisation accorded to face-to-face interactions. It is conceivable that the pandemic may ultimately engender an adverse effect, manifesting as pervasive forms of rejection once the transition to in-person instruction is fully reinstated. Consequently, it is uncertain that the expected digital transition was caused by the pandemic. This is further compounded by the emergence of more advanced technological trends, particularly those involving artificial intelligence, which may inadvertently lead to an unanticipated upsurge in the number of teachers pursuing training in the utilisation of these technologies.

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HUMAN-CENTRED DIGITAL TRANSITIONS AND SKILL MISMATCHES IN EUROPEAN WORKPLACES

New digital and artificial intelligence technologies are fast reshaping skill requirements in the EU labour market, fostering skill mismatches. There are marked concerns about the potentially adverse consequences of automation and AI on employment, as well as the lagging competitiveness of EU economies as individuals' upskilling or reskilling is failing to adapt.
To deepen understanding of how digitalisation is affecting the nature of work and skill mismatches in EU labour markets, Cedefop carried out the second wave of the European skills and jobs survey in 2021.
In this special edition of Cedefop's working paper series, ten original, short contributions have been drafted in which researchers explore in depth, for the first time, the ESJS2 microdata. The publication presents a wealth of focused and robust empirical analyses, covering a wide range of different issues on how the digital transition is affecting jobs, skills and training in Europe.

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