British Journal of Industrial Relations

WILEY

BJIR An International Journal of Employment Relations LSE

ORIGINAL ARTICLE OPEN ACCESS

When Jobs Change: Skills Mismatch and the Value of Training

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Received: 1 September 2025 | **Revised:** 27 May 2026 | **Accepted:** 3 June 2026

Keywords: mismatch | skills | training | vacancies

ABSTRACT

This article examines the impact of rapidly changing skill requirements on skills mismatch in Europe and the role of training in mitigating adverse effects. Using data on approximately 70 million online job vacancies, we estimate the extent to which occupational skill requirements changed between 2019 and 2023 across European Union (EU) countries plus Norway and the United Kingdom. STEM-related occupations saw the greatest degree of change, whereas lower skilled manual jobs saw the least. By linking job vacancies to survey data, we show that employees in fast-changing jobs are more likely to experience skills deficits. Training plays a role in mitigating these negative effects, and the type and intensity of training matters. Training seminars/workshops are most effective. Formal training courses and on-the-job training are less effective when used in isolation but can mitigate skills deficits when combined with other types of training. Our constructed dataset of occupational skill change is published as an accompanying data appendix. This should be of use for future research across a range of areas in labour economics and industrial relations.

1 | Introduction

The types of jobs that are available in the labour market and the skills that are required to do them are changing. Recent events such as the COVID-19 pandemic, the adoption of remote work and the diffusion of artificial intelligence (AI)-powered Generative Pretrained Transformers (GPTs) are among a range of factors that have altered the task content and skill requirements of jobs. These developments have implications for skill demand in the labour market, requiring workers to up- or re-skill to remain productive and, in turn, secure competitive wages. Digital technologies, in particular, are constantly evolving, requiring firms and employees to continuously acquire new skills to avail of the new capabilities brought about by technological change and innovation (Ciarli et al. 2021). The importance of training in mitigating skill deficits has been a key priority among European policymakers for many years.[1] However, with rapid technological change, this has become even more salient, as training provides workers with the necessary human capital to adapt to new technology (McGuinness et al. 2023; Acemoglu and Restrepo 2019).[2] Therefore, in the absence of sufficient training, workers and firms face the prospect of skills mismatch and sub-optimal productivity (Georgiadis and Pitelis 2016).

Changes in skill demand may affect workers in different ways. If new skills are introduced into the workplace over a relatively short period of time, and workers are not appropriately trained, then workers' competencies may become misaligned with the requirements of their job. In these situations, workers may exhibit a skill deficit (otherwise known in the literature as being 'underskilled').[3] On the other hand, if skills become obsolete in the workplace, and few new skills are introduced to replace them, workers may be left with competency in skills that are no longer relevant for their job, exhibiting a skill surplus (or being 'overskilled'). It is therefore important to assess both the magnitude and nature of skill change in the workplace over time and its relationship with skills mismatch and training. The evidence base in this area, however, is relatively underdeveloped.

In this article, we attempt to fill this gap in the literature by empirically evaluating the relationship between rapidly changing skill requirements and skills mismatch among European employees. Using data on approximately 70 million online job vacancies, we estimate a measure of occupational skill change between 2019 and 2023 for all occupations in each European Union (EU) country (plus Norway and the United Kingdom). This time period is relevant as it coincided with major events in the labour market that could lead to changes in the skills demanded by firms; for example, the COVID-19 pandemic and the increase in remote working in 2020, and the release of ChatGPT in 2022. Our data may, therefore, capture the early phase of Gen AI adoption, whose effects are becoming apparent in the labour market. Our job vacancy data reveal that between 2019 and 2023, the prevalence of 'AI' job titles in the EU grew by almost 50%. For the United States, McElheran et al. (2024) report that, by 2018, approximately 1 in 20 firms in the United States had adopted AI technology, with a much higher incidence when focusing on large firms and startups. Yotzov et al. (2026), using firm-level data for the United States, the United Kingdom, Germany and Australia, find that around 70% of firms actively use AI, whereas Chatterji et al. (2025) document the rapid expansion and broadening of ChatGPT use from 2022 to 2025. As it takes time to realise the full potential of new technologies (Brynjolfsson et al. 2021), the prevalence and impact of Gen AI may continue to increase in the coming years.

Our results show that, in general, high-tech jobs have exhibited significant changes to skill requirements in recent years, whereas lower skilled jobs have experienced fewer changes. By linking measures of occupational skill change with EU survey data, we show that workers in rapidly changing jobs are more likely to experience skills deficits. Our results also show that training plays an important role in mitigating these types of skill deficits. Training seminars emerge as the most effective type of training for insulating employees from adverse effects arising from changing skill requirements. When used in isolation, formal training courses and on-the-job (OTJ) training are the least effective types of training. However, when combined with other training forms, they have a greater impact on underskilling. Furthermore, employer-funded training appears to be more effective than non-employer-funded training.

An additional contribution of our work is the construction of a dataset on occupational skill change, which we make freely available to researchers. Having a measure that captures the extent to which skills are changing in each 3-digit ISCO occupation for each EU country (plus Norway and the United Kingdom) should be useful for future research in industrial relations and labour economics. A vast number of papers utilise survey data that contain occupational classifications to categorise a person's job—for example, ISCO or SOC occupational categories. Our measure of occupational skill change can be directly mapped to this type of survey data and is potentially useful as either an outcome variable or explanatory variable, depending on the context. To give a brief indication of its potential applicability, data containing established occupation classifications have been used to study related topics, including training (e.g., Greenhalgh and Mavrotas 1996; Nedelkoska and Quintini 2018), skills and educational mismatch (e.g., Maida and Tealdi 2021; Brun-Schammé and Rey 2021; McGuinness et al., 2018), wage inequality (e.g., Rabensteiner and Guschanski 2025; Fernández-Macías and Arranz-Muñoz 2020) and technological change (e.g., McGuinness et al. 2023; Goos et al. 2014).

Our measure of dynamic skill change is based on the methodology employed by Deming and Noray (2020). Using job vacancy data for the United States, they analyse the relationship between changing skill requirements and graduate earnings, with a specific focus on STEM graduates. They show that jobs with rapidly changing skill requirements exhibit declining wage premia over time due to rapid changes in tasks. Furthermore, STEM graduates tend to move out of jobs where skill requirements are changing, and this is done later in their careers. Others have used job vacancy data to look at skill requirements in the labour market, primarily focusing on the United States. Modestino et al. (2020) and Hershbein and Kahn (2018) show that employers' hiring requirements increased during the Great Recession, attributable to a greater supply of available workers and a restructuring of production towards routine-biased technologies. Acemoglu et al. (2022) show that from 2010 to 2018, AI roles have been increasing in the US labour market, concentrated in firms whose workers perform tasks compatible with AI. This resulted in changes to the skill requirements within these firms. However, although impacts are evident at the firm level, Acemoglu et al. (2022) note that AI-induced changes to the broader labour market were not detectable.

A related strand of literature focuses on skills mismatch. Several studies examine the outcomes associated with skills mismatch, and the results underscore the importance of developing our knowledge base in this area. For employees, skills mismatch can be associated with lower job satisfaction (Sloane and Mavromaras 2020; Vieira 2005) and an increased desire to quit their job (McGuinness and Wooden 2009). Overskilled employees also face a wage penalty compared to employees with similar skills in matched employment (Mavromaras et al. 2012; Green and Zhu 2010; Sánchez-Sánchez and McGuinness 2015). For employers, an underskilled workforce has been found to be associated with lower firm productivity and profitability (Kampelmann and Rycx 2012; Mahy et al. 2015; Kampelmann et al. 2020). Others have examined the causes of skills mismatch, typically focusing on barriers in the labour market that impede a worker's ability to find a suitably matched job. McGowan and Andrews (2015) suggest that policies that promote residential mobility, such as low property transaction costs and less stringent rental contracts, promote a greater degree of matching by allowing workers to move locations to find matched employment. Tani (2021) shows that occupational licensing was effective at reducing mismatch (specifically, overeducation) among skilled migrants in Australia. Other policies that facilitate spatial mobility of workers, such as better transportation networks, remote working and improved childcare provision, may also play an important role in reducing skills mismatch (Croce and Ghignoni 2015; Baran 2024; Santiago-Vela and Mergener 2022). Although the focus of existing work tends to be on labour market barriers, to our knowledge, we are the first to investigate rapidly changing skill requirements as a driver of skills mismatch.

The remainder of the article is structured as follows. Section 2 describes the two data sources that are used in the article—Lightcast online job vacancy data and the European Skills and Jobs Survey (ESJS). Section 3 outlines our measurement approach for estimating dynamic skill change. Section 4 empirically examines the relationship between occupational skill change and skills mismatch. Section 5 analyses the role of training, and Section 6 concludes.

2 | Data

2.1 | Online Job Vacancy Data

We use online job vacancy data from Lightcast (formerly Burning Glass Technologies) to estimate changing skill requirements in the EU plus Norway and the United Kingdom. Lightcast collects vacancy data from a wide variety of online job postings and websites and parses information into variables such as job title, occupation, industry, salary, location and date of the posting. It also contains information on education, experience and skill requirements. Lightcast analyses the raw job text of each online vacancy, identifying specific skills that are required for that vacancy and categorises them according to the European Skills, Competencies and Occupations (ESCO) skills taxonomy.[4] At the broadest level, skills can be grouped into six different subcategories: 'hard skills', 'application of knowledge', 'thinking', 'social interaction', 'attitudes and values', and 'language'. For the purpose of capturing occupation-specific skill change, we concentrate on 'hard skills', of which there are approximately 3000 different skills. We focus on 'hard skills' because they represent the most directly measurable aspects of job-specific capabilities that are tied to particular roles. 'Hard skills' generally refer to technical abilities or knowledge required to perform certain tasks or operate particular tools and technologies. In contrast, other categories, like 'application of knowledge', 'thinking', 'social interaction', 'languages', and 'attitudes and values', encompass more universal skills that are applicable across a wide range of occupations.[5] Although these are important for overall employability, they may not provide a focused view of the specific competencies that differentiate one occupation from another.

We estimate a measure of changing skill requirements for occupations across EU-27 (plus Norway and the United Kingdom) countries between two points in time. We focus on posted vacancies from the years 2019 and 2023. We choose these years for two reasons. First, 2019 is a pre-pandemic year, and 2023 is a post-pandemic year. By comparing 2019–2023, therefore, we should avoid the more pronounced short-run COVID-19 impacts that occurred in 2020 and 2021, while at the same time capturing more persistent labour market effects that remained in place following the pandemic. Second, Lightcast's algorithm for collecting vacancies has become more sophisticated over time, expanding its reach to include an increasing number of job portals. There is a trade-off involved with moving further back in time as the volume of job vacancies that are collected gets lower; the number of collected vacancies prior to 2019 is significantly lower than the post-2019 period. In total, we have approximately 70 million job vacancies in our data—20 million in 2019 and 50 million in 2023.[6] Although there are fewer observations in 2019 compared to 2023, our methodology (described below) ensures that we are looking at the same types of jobs in both years. Given the size of our dataset, the sample sizes within each country/occupation pairing are generally quite large. There are 124 ISCO 3-digit occupations. As there are 29 countries, this results in approximately 3500 occupation/country categories. However, there are some occupation/country categories containing relatively few job vacancies. We limit our analysis to occupation/country categories containing at least 100 observations in both years.[7]

Although 2019–2023 is a relatively short time frame, it is important to note that there have been rapid changes in labour market requirements even during this time period. For example, between 2019 and 2023, the prevalence of 'AI' job titles in the EU grew by almost 50%. Our research also highlights rapid changes associated with other skills, mainly in IT and technology-related jobs. Therefore, despite the short time period, our analysis captures a significant amount of skill change in the labour market.

In total, our data contain 2967 unique hard skills. Table 1 shows the top 20 skills demanded in 2019 and 2023 based on the proportion of job ads that the skill appears in.[8] These are predominantly made up of digital skills (e.g., 'have computer literacy', 'use microsoft office', 'business ICT systems') and some transversal skills (e.g., 'think proactively', 'communication', 'problem solving'). There is significant variation across occupations in the number of skills demanded by employers. This is shown in Figure 1 which graphs the top 20 most skill-intensive occupations, based on the 2023 data (i.e., those with the highest average number of skills per vacancy in 2023). On average, ICT and tech-related jobs require the most skills per vacancy; *database and network professionals* and *software developers* are the two most skill-intensive occupations. Figure 1 also shows the change over time in the average number of skills required in each occupation. *Database and network professionals* and *software developers* had similar skill requirements across both years. Other high-skilled occupations changed over time. For example, the average number of skills per vacancy for mathematicians and statisticians increased from nine in 2019 to 14 in 2023.[9]

2.2 | European Skills and Jobs Survey

In addition to Lightcast data, we use data from the 2021 ESJS. The ESJS is a representative survey of approximately 46,000 European employees, administered by Cedefop.[10] It contains questions relating to both socio-demographic characteristics, as well as a wide range of detailed questions relating to the respondents' employment. Of particular interest for our study are the questions that capture an employee's self-reported level of skill utilisation. We derive a measure of underskilling from the question '… to what extent do you need to further develop your overall level of knowledge and skills to do your main job even better?'. We consider a respondent to be underskilled if they respond 'great extent' or 'moderate extent' and zero if they respond 'small extent' or 'not at all'. This is modelled as a binary variable (i.e., equal to one if the respondent is underskilled, and zero if not). For overskilling, we use the question 'To what extent can you use your current knowledge and skills in your main

TABLE 1 | Top 20 'hard skills' in 2019 and 2023.

	2019		2023	
Rank	**Skill**	**%Vacancies**	**Skill**	**%Vacancies**
#1	have computer literacy	36.05	have computer literacy	33.84
#2	use microsoft office	22.96	use microsoft office	20.95
#3	problem solving	16.30	think proactively	18.69
#4	customer service	14.64	problem solving	16.18
#5	think proactively	14.47	communication	15.04
#6	office software	14.23	use office systems	14.65
#7	communication	13.37	customer service	13.17
#8	project management	12.69	office software	12.98
#9	use office systems	12.69	brainstorm ideas	12.46
#10	use spreadsheets software	10.19	project management	10.91
#11	communication/collaboration software	8.65	quality standards	10.62
#12	computer programming	7.94	use spreadsheets software	9.88
#13	brainstorm ideas	7.82	tolerate stress	8.22
#14	quality standards	7.71	think analytically	7.73
#15	excel	7.56	database	7.72
#16	office administration	7.32	proactivity	7.41
#17	sales activities	6.78	develop animations	7.06
#18	economics	6.05	customer relationship management	6.52
#19	business ICT systems	5.99	sales strategies	6.35
#20	sales strategies	5.84	office administration	6.19

Source: Lightcast Job Advertisement data. Authors' calculations.

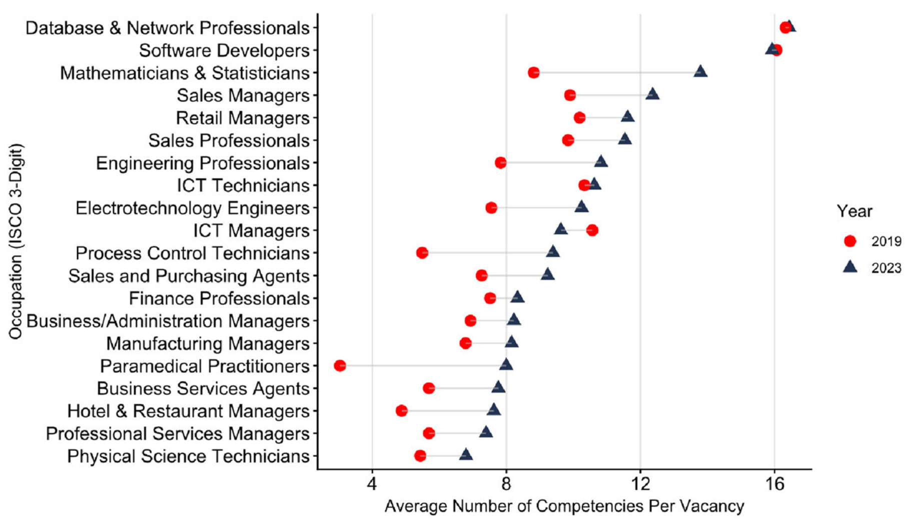

FIGURE 1 | Average skills per-vacancy (2019–2023, Top 20, 2023). *Source: Lightcast, authors' calculations.*

job?'. Respondents who answered 'small extent' or 'not at all' are considered overskilled.

It is important to acknowledge the limitations, as well as the advantages, of our approach for measuring overskilling and underskilling. As the measure is self-reported by workers, it is possible that some workers may misreport or inaccurately assess their skills against the actual requirements of their job. However, self-reported measures of skills deficits have the advantage of being specific to the employee. Other measures that take a broader approach, for example, by attempting to establish the skill or education requirements for a broadly defined occupation, fail to capture the variation in skill requirements that can emerge even within narrow occupation groups. Furthermore, although the underskilling question likely captures skills deficits, the overskilling question could be interpreted as relating to the relevance of an employee's skills as opposed to the relative level of their human capital. For example, an employee that we identify as overskilled using the ESJS questions could be highly skilled and working in a low-skilled job. On the other hand, it could capture employees that have low skills that may simply not be relevant for their jobs, with the job itself being either low- or high-skilled.

The ESJS captures information using a mixture of computer-assisted web interviews (CAWI) and computer-assisted telephone interviews (CATI). Although many of the questions in the dataset are administered to both the CAWI and CATI samples (including the underskilling question), the overskilling question is administered only to the CAWI sample. As a result, when it comes to our empirical strategy, the analysis relating to underskilling contains approximately 36,000 observations, compared to approximately 25,000 observations for the overskilling analysis. Finally, note that although the previous wave (2014) of the ESJS captured data for the United Kingdom, the 2021 wave does not. Therefore, although we calculate measures of occupational skill change for the United Kingdom using the Lightcast data (and publish the corresponding UK measures in our data appendix), our analysis that links the Lightcast data to the ESJS relates only to the EU-27 countries plus Norway.[11]

In Table 2, we report the 3-digit ISCO occupations with the highest incidence of underskilling and overskilling. Occupations with the highest rates of underskilling are often STEM-related: software developers; engineering professionals; database and network professionals. On the other hand, jobs with the highest rates of overskilling are often low-skilled and low-paid jobs such as cleaners, food preparation assistants and other elementary workers.

3 | Measuring Changing Skill Requirements

To estimate changing skill requirements within occupations, we use a measure that is based on previous work by Deming and Noray (2020) and is formalised in

$$\text{SkillChang } e_{o,c} = \sum_{s=1}^{S} \left\{ \text{Abs} \left[\left(\frac{\text{Skill}_{o,c}^{s}}{\text{Vacancies}_{o,c}} \right)_{2023} - \left(\frac{\text{Skill}_{o,c}^{s}}{\text{Vacancies}_{o,c}} \right)_{2019} \right] \right\} \quad (1)$$

$\text{Skill}_{o,c}^{s}$ denotes the number of times skill s appears in vacancies that are posted for ISCO 3-digit occupational category o in country c, and $\text{vacancies}_{o,c}$ denotes the total number of vacancies for that country/occupational category. Therefore, $\frac{\text{Skill}_{o,c}^{s}}{\text{Vacancies}_{o,c}}$ represents the prevalence of skill s in a given year, occupation and country. It is useful to take an illustrative example. Suppose there were 100 vacancies for Software Developers in country c in 2019, and 200 vacancies in 2023. If the skill 'Python' was present in 25 of the 100 vacancies in 2019 and present in 150 of the 200 vacancies in 2023, then this gives an absolute difference of $|0.75 - 0.25| = 0.5$. The same process is repeated for all skills within the occupation, and an absolute value is taken, giving us a measure of overall changes in skill requirements over time for occupation o in country c. As it is an absolute measure, high values of SkillChange indicate significant changes to skill requirements that could be due to increasing skill demand and/or falling skill demand over time. Low values of SkillChange represent jobs in which skills are not changing significantly over time.

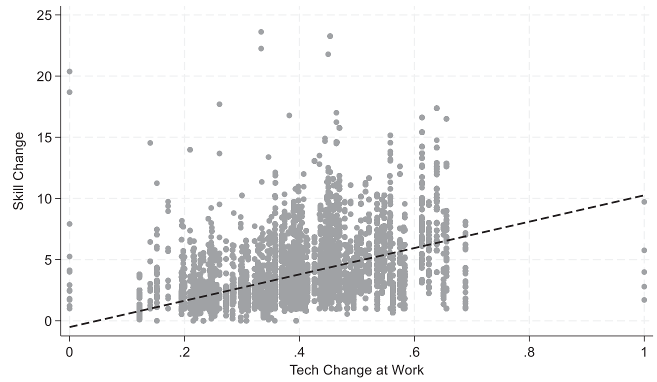

FIGURE 2 | Relationship between technological change at work and changing skill requirements. The *x* axis relates to the incidence of recent technological change at work, and the *y* axis measures changing skill requirements, both within 3-digit ISCO occupations. The dashed black line is a fitted regression line.

In Table 3, we show the occupations with the highest and lowest values of absolute SkillChange between 2019 and 2023. Note that SkillChange can take different values for the same occupation across different countries. The jobs that changed the most, in terms of skill requirements, tend to be STEM-related occupations—for example, software and applications developers and analysts and database and network professionals. The occupations that experienced little or no changes to their skill requirements (bottom panel of Table 3) are those that are generally considered to be more manual in nature, requiring fewer technical skills—for example, cleaners, labourers and drivers.

We can gain further insights into the relationship between STEM occupations and changing skill requirements by linking our measure of skill change to the ESJS survey data. Survey respondents are asked whether, in the last 12 months or since they started their job, they learned to use any new computer programmes, software or computerised machinery to do their job. Based on this question, we calculate the incidence of recent technological change within each ISCO 3-digit job. In Figure 2, we show the relationship between recent technological change and changing skill requirements. There is a positive and statistically significant relationship; occupations that experienced the greatest amount of skill change tend to contain the highest proportion of respondents that recently learned to use new technologies to do their job.

Although Figure 2 shows a positive relationship between technological change and occupational skill change, other factors, apart from changing technology, may play a role. For example, note that the most-changed job is paramedical practitioners in the United Kingdom. Although it may not be immediately apparent why this would be the case, there have been substantial changes to the requirements associated with this job. In 2023, the Health & Care Professions Council (HCPC) implemented a revised set of standards of proficiency, and those seeking to register with the HCPC must meet these revised standards.[12] Furthermore, there

TABLE 2 | Top 20 occupations with the highest rates of underskilling and overskilling (ESJS).

ISCO 3-digit category	Underskilled (%)
Medical doctors	79.3
Software and applications developers and analysts	77.5
Database and network professionals	77.1
Sales, marketing and public relations professionals	75.8
Primary school and early childhood teachers	75.7
Architects, planners, surveyors and designers	75.4
Librarians, archivists and curators	74.9
ICT service managers	74.6
Electrical equipment installers and repairers	74.5
Engineering professionals	73.8
Process control technicians	73.7
ICT operations and user support technicians	73.6
Managing directors and chief executives	72.9
Finance professionals	72.4
Sales, marketing and development managers	71.6
Life science professionals	71.2
Administration professionals	69.7
Secondary education teachers	69.5
Regulatory government associate professionals	69.3
Machinery mechanics and repairers	69.0
ISCO 3-digit category	**Overskilled (%)**
Domestic, hotel and office cleaners and helpers	40.5
Other elementary workers	26.6
Building and housekeeping supervisors	25.3
Manufacturing labourers	23.9
Food preparation assistants	22.8
Car, van and motorcycle drivers	21.5
Cashiers and ticket clerks	17.7
Transport and storage labourers	17.6
Cooks	16.4
Waiters and bartenders	16.0
Heavy truck and bus drivers	15.5
Protective service workers	15.3
Shop salespersons	15.1
Assemblers	14.6
Other sales workers	13.6
Mobile plant operators	12.8
Other craft and related workers	12.2
Other clerical support workers	12.0
Blacksmiths, toolmakers and related trades	12.0
Material-recording and transport clerks	11.9

Note: Occupation categories with fewer than 100 observations are excluded. ESJS survey weights for population representativeness are used to calculate the statistics. However, similar results are observed for unweighted statistics.
Source: ESJS2, authors' calculations.

TABLE 3 | Highest and lowest values of absolute SkillChange.

ISCO 3-digit category	Country	SkillChange
Highest values of SkillChange		
Paramedical practitioners	The United Kingdom	22.25
Veterinary technicians and assistants	The United Kingdom	17.70
Software and applications developers and analysts	Bulgaria	17.37
Legislators and senior officials	Ireland	17.00
Database and network professionals	Greece	16.61
Legislators and senior officials	The United Kingdom	16.23
Engineering professionals	Cyprus	15.77
Database and network professionals	Bulgaria	15.42
Mathematicians, actuaries and statisticians	Portugal	15.16
Mining and mineral processing plant operators	The United Kingdom	14.90
Mining and mineral processing plant operators	Ireland	14.68
Database and network professionals	Portugal	14.23
Software and applications developers and analysts	Cyprus	14.16
Refuse workers	Croatia	13.98
Database and network professionals	Spain	13.69
Mathematicians, actuaries and statisticians	Romania	13.62
Mixed crop and animal producers	The United Kingdom	13.50
Wood processing and papermaking plant operators	Croatia	13.38
Database and network professionals	Estonia	13.29
Mathematicians, actuaries and statisticians	Poland	13.20
Lowest values of SkillChange		
Agricultural, forestry and fishery labourers	Estonia	0.00
Rubber, plastic and paper products machine operators	Lithuania	0.16
Heavy truck and bus drivers	Slovakia	0.19
Transport and storage labourers	Slovakia	0.26
Building frame and related trades workers	Estonia	0.26
Domestic, hotel and office cleaners and helpers	Estonia	0.32
Transport and storage labourers	Finland	0.37
Domestic, hotel and office cleaners and helpers	Slovenia	0.37
Food and related products machine operators	Finland	0.39
Transport and storage labourers	Czechia	0.40
Heavy truck and bus drivers	Finland	0.41
Wood treaters, cabinet-makers and related trades workers	Austria	0.41
Mobile plant operators	Finland	0.42
Rubber, plastic and paper products machine operators	Czechia	0.48
Domestic, hotel and office cleaners and helpers	Denmark	0.55
Medical doctors	Slovenia	0.55
Transport and storage labourers	Lithuania	0.56
Transport and storage labourers	Latvia	0.58
Car, van and motorcycle drivers	Finland	0.59
Domestic, hotel and office cleaners and helpers	Austria	0.60

Source: Lightcast, authors' calculations.

was an additional change implemented in 2021, when the HCPC increased the required educational threshold (to degree level) for those wishing to join the register of occupations regulated by the HCPC.[13] This is largely a public sector occupation, and one could view these changes as 'regulation' type changes as opposed to market-driven, technology-related changes to skill demand. Irrespective of the underlying mechanism, the assumption that underpins much of our later analysis is that changes to skill requirements in job vacancies are reflected in actual changes to the skills required by workers in their jobs. If, in some instances, job vacancies show that skill requirements have changed, but this is not felt by workers in their jobs, then this could lead to an underestimate of the relationship between occupational skill change and skill deficits.

Although the measure described in Equation (1) relates to an absolute measure of skill change, we can capture the direction by using a measure of net skill change. This is equal to the sum of the difference in demand for each skill within an occupation (as opposed to an absolute value). Specifically, net skill change is given by

$$NetSkillChang\ e_{o,c} = \sum_{s=1}^{S} \left\{ \left[\left(\frac{\text{Skill}_{o,c}^{s}}{\text{Vacancies}_{o,c}} \right)_{2023} - \left(\frac{\text{Skill}_{o,c}^{s}}{\text{Vacancies}_{o,c}} \right)_{2019} \right] \right\} \quad (2)$$

In jobs where skill requirements are increasing over time, NetSkillChange will be greater than zero. In jobs where skill requirements are decreasing over time, NetSkillChange will be negative. Figure A3 shows the distribution of the NetSkillChange measure. Although many occupation-country combinations show a negative value for NetSkillChange, a positive value for NetSkillChange is more common.[14]

4 | Skills Mismatch and Changing Skill Requirements

We begin by examining whether absolute changes to skill requirements within an occupation are linked to underskilling. To do this, we merge our measures of within-occupation skill change (at the 3-digit ISCO level) with the ESJS survey data. Therefore, every respondent in the ESJS data is allocated a skill change measure based on their occupation-country category.[15] We then estimate the following probit model:

$$Pr(\text{Underskilled}_{i,o,c} = 1|X) = \Phi\left(\alpha + \delta\text{SkillChange}_{i,o,c} + Z'_{i,o,c}\beta_z + \sum_{\tau=2}^{28}\theta_\tau C_i^\tau\right) \quad (3)$$

where Underskilled is binary variable indicating whether an employee is underskilled or not. The continuous variable SkillChange captures the absolute measure of skill change based on the occupation and country that employee i works in. The main coefficient of interest is δ, which captures the relationship between SkillChange and the probability that an employee is underskilled. The vector Z' includes demographic control variables at the employee level; gender, sector (at the NACE 1 level), firm size, education level, part-time/full-time status and job tenure (in years). We also include country dummy variables, denoted C_i^τ. Although we control for these worker and firm characteristics, we refrain from making strong causal statements when interpreting the association between skill change and underskilling in Equation (3). There may be other unobserved characteristics, either at firm or employee level, that simultaneously impact the probability of experiencing skill change and underskilling. For example, if higher quality firms, with greater capacity to manage, retrain and reallocate staff, are also more likely to experience changing skill requirements, then this could bias the estimate downward.

The results from estimating Equation (3) are shown in Column (1) of Table 4. The marginal effect relating to the absolute measure of SkillChange is positive and statistically significant. This indicates that employees in occupations with rapidly changing skill requirements are more likely to be underskilled relative to employees with similar characteristics in jobs where skill requirements remain constant. Specifically, for each additional unit of absolute SkillChange, respondents are approximately 1.3 percentage points more likely to be underskilled. To put this into context, an additional unit of SkillChange within an occupation could arise in a situation where one new skill emerges in all job vacancies in 2023 that was not present in any vacancies in 2019. Conversely, as SkillChange is an absolute measure, it could arise due to a skill being present in 2019 but not in 2023.

Recall that the absolute measure of skill change can result from an increase and/or decrease in skill requirements. It may be that the impact of skill change on underskilling is more pronounced in jobs which experience a net increase in occupational skill requirements. In Column (2) of Table 4, we make this restriction, by focusing on occupations for which net skill change is positive. The estimated impact is slightly larger (1.4 percentage points vs. 1.3 percentage points for the baseline sample).

To further examine differences arising from the direction of skill change, Columns (3) and (4) use net skill change (instead of the absolute measure). The coefficient in Column (3) shows that an increase in skill requirements (i.e., a positive value of net skill change) is associated with a higher likelihood of underskilling.[16] The results in Column (4), however, suggest that employees in jobs for which skills are being eroded (a negative value of net skill change) are more likely to be left with surplus and potentially obsolete skills, which translates into a higher likelihood of overskilling.

4.1 | New vs. Existing Skills

It is possible that the impact of skill change on underskilling could vary depending on whether the changes in skill demand are characterised by the introduction of entirely new skills or changes in the prevalence of existing skills. For instance, if a firm begins requiring competency in an entirely new skill, the impacts on underskilling may be greater than if they began to require more of an existing skill. We can calculate a measure that captures the percentage of absolute occupational skill change that is attributable to new skills. As the absolute measure of skill change calculated in Equation (1) is a summation across all skills, we can simply calculate what percentage of this overall change, if any, comes from skills that were present in 2023 and not 2019. This continuous measure (from 0% to 100%) can then be

TABLE 4 | Skill change and skills mismatch (marginal effects).

Variables	(1) Underskilled	(2) Underskilled	(3) Underskilled	(4) Overskilled
SkillChange	**0.013*****	**0.014*****		
	(0.001)	**(0.002)**		
NetSkillChange			**0.005****	**−0.006*****
			(0.002)	**(0.002)**
Female	−0.028***	−0.026***	−0.030***	−0.001
	(0.006)	(0.007)	(0.006)	(0.004)
Tenure	−0.001***	−0.002***	−0.001***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size (Ref: 1–10)				
11–49 employees	0.020**	0.024**	0.021**	−0.021***
	(0.009)	(0.010)	(0.009)	(0.008)
50–249 employees	0.035***	0.039***	0.037***	−0.022**
	(0.010)	(0.010)	(0.010)	(0.009)
250 or more employees	0.036***	0.043***	0.040***	−0.015**
	(0.010)	(0.010)	(0.010)	(0.007)
Education (Ref: low education)				
Medium education	0.042***	0.043***	0.045***	−0.010
	(0.009)	(0.009)	(0.009)	(0.009)
High education	0.101***	0.092***	0.111***	−0.030***
	(0.010)	(0.009)	(0.009)	(0.009)
Part-time	−0.053***	−0.051***	−0.056***	0.046***
	(0.010)	(0.010)	(0.010)	(0.008)
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.05	0.06	0.05	0.06
Observations	36,346	26,380	36,346	24,977

Note: Low education is lower secondary or below. Medium education is upper secondary or post-secondary (non-tertiary), and high education is tertiary. Country clustered standard errors in parentheses.

***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

interacted with our Skill Change measure—that is, we can re-run the analysis that produces the results in Table 4 with the addition of the new skills measure and its interaction with the measure of absolute skill change. The results are shown in Table A7 and show that the impact of skill change on underskilling does not depend on the extent to which new skills are driving occupational skill change—neither the coefficient on the new skills variable, nor the coefficient of the interaction of new skills with the measure of absolute skill change is statistically significant.

4.2 | Importance of Skill Change in Predicting Underskilling—Machine Learning Classifier

Recent work indicates that machine learning algorithms can outperform probit models for predicting outcomes (see, e.g., Schonlau and Zou 2020; Couronné et al. 2018). Machine learning algorithms also offer insightful ways of ranking the relative predictive importance of each explanatory variable. Therefore, we implement a random forest machine learning algorithm for the purpose of ranking the relative importance of our explanatory variables for predicting the likelihood that an individual is underskilled.

A random forest uses results from multiple decision trees to make predictions. A decision tree is a simple predictive model that works through a series of 'yes or no' questions (e.g., 'Is the person's education level high?') and splits the data into branches based on the answers. This process continues until it reaches a final prediction (e.g., underskilled or not). Although decision trees are easy to interpret, they are prone to overfitting the data, meaning they might perform well on one particular dataset but have poor out-of-sample predictive properties. The random forest attempts to overcome this issue by building many decision

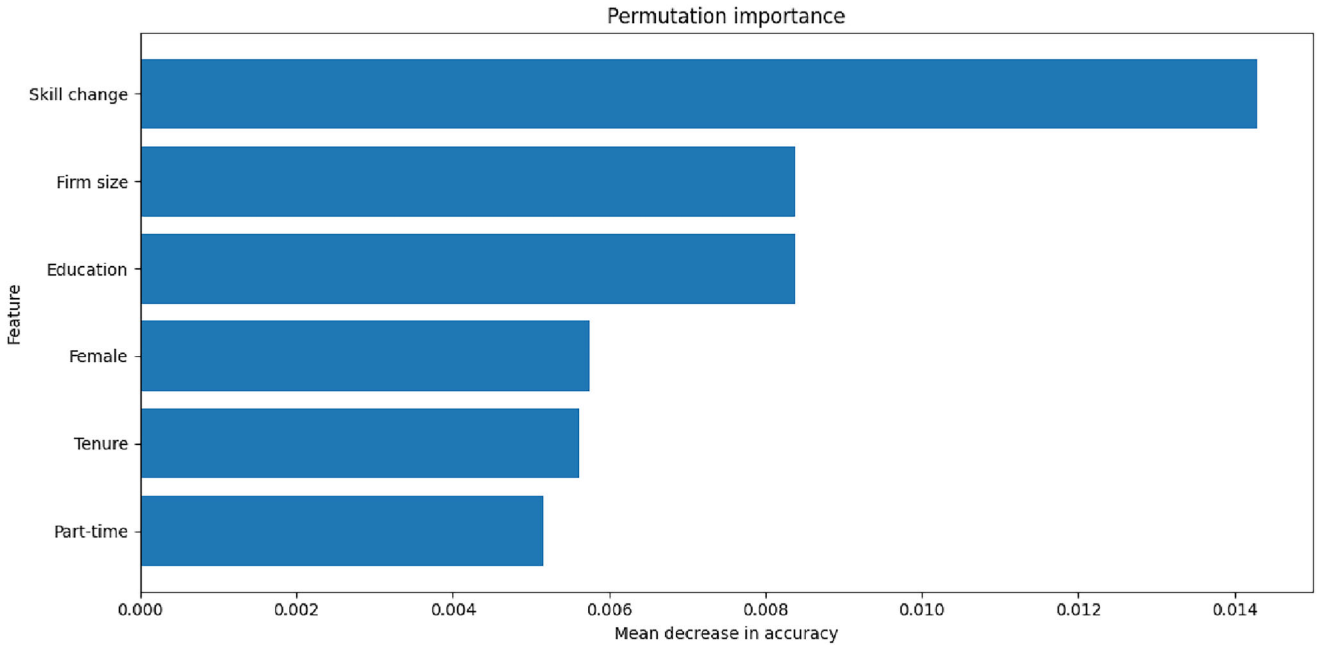

FIGURE 3 | Ranking the importance of variables for predicting underskilling. Variables are ordered in terms of their relative importance for predicting underskilling using a random forest machine learning algorithm.

trees, each trained on a slightly different subset of the data. Averaging predictions from all trees helps to mitigate overfitting (for further details, see Schonlau and Zou (2020)).[17] To rank the relative predictive importance of each explanatory variable, we can measure how much the random forest's predictive accuracy decreases when the values of that variable are permutated (randomly shuffled). The greater the decrease in predictive accuracy from permutating a variable, the more important that variable is for predicting the outcome. Using this approach, we show the relative importance of each variable in Figure 3.[18] This indicates that our measure of skill change is more important for predicting underskilling than firm size, education level, gender, tenure and part-time status.

5 | The Role of Training

It is possible that workers who receive training may be insulated from the effects of rapidly changing skill requirements. That is, when faced with similar rates of changing skill requirements, employees who receive timely, well-targeted training of sufficient quality may be less likely to experience underskilling than those who do not receive training. We capture training provision in two ways. The first is based on a question in the ESJS that asks respondents whether, in the last 12 months, they participated in training activities to learn new job-related skills, to which they answer yes or no. The second measure is based on a question in which respondents are asked whether their training needs are systematically reviewed by their employer, to which they respond yes or no. Although the first measure of training is asked to all respondents, the question relating to the systematic review of training is asked only to the CAWI subset of respondents (approximately 66% of the full sample). In Table 5, we re-estimate our baseline model (used in Column (1) of Table 4) separately for employees that received training and those that did not.

The first two columns in Table 5 show results based on the measure that captures whether an employee received training in the last 12 months. This suggests that the provision of training may mitigate skill deficits that arise due to changing skill requirements. For the group that did not receive training, a one unit increase in skill change is associated with a 1.6 percentage point increase in the probability of being underskilled. The results for the group that received training are also positive and statistically significant, but the magnitude effect is substantially lower (0.9 percentage points).[19] The results using the alternative measure based on whether an employee's training needs are systematically reviewed are shown in Columns (3) and (4). They are very similar to the estimates in Columns (1) and (2) and show that employees whose training needs are systematically reviewed have a lower probability of experiencing skill deficits in the face of changing skill requirements.

Our data also allow us to evaluate which type of training is most effective. Employees are specifically asked whether they completed any of the following types of training: (1) seminars/workshops; (2) courses; (3) OTJ training. Although courses denote more structured training programmes that typically result in some type of certification, seminars/workshops are considered less formal, more ad hoc and typically shorter in nature. OTJ training relates to training that is supported by, for example, a co-worker or supervisor. The three different training types are not mutually exclusive, meaning a respondent could indicate that they participated in more than one type of training. Therefore, to capture the potential effectiveness of different combinations of training types, we consider each possible training combination, of which there are eight (including no training of any type).

TABLE 5 | The role of training in mitigating underskilling (marginal effects).

Variables	No training Underskilled	Training Underskilled	Training needs not reviewed Underskilled	Training needs reviewed Underskilled
SkillChange	**0.016*****	**0.009*****	**0.019*****	**0.008*****
	(0.003)	**(0.001)**	**(0.003)**	**(0.002)**
Female	−0.007	−0.031***	−0.014	−0.021**
	(0.008)	(0.007)	(0.009)	(0.010)
Tenure	−0.001	−0.001***	−0.001	−0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
Firm size (Ref: 1–10)				
11–49 employees	0.007	0.004	0.008	0.000
	(0.017)	(0.010)	(0.015)	(0.012)
50–249 employees	0.015	0.015*	0.033**	0.013
	(0.020)	(0.009)	(0.017)	(0.011)
250 or more employees	0.018	0.012	0.020	0.001
	(0.015)	(0.010)	(0.015)	(0.011)
Education (Ref: Low education)				
Medium education	0.053***	0.021*	0.050***	−0.003
	(0.014)	(0.012)	(0.018)	(0.015)
High education	0.094***	0.058***	0.098***	0.042***
	(0.013)	(0.013)	(0.019)	(0.015)
Part-time	−0.070***	−0.032***	−0.078***	−0.032***
	(0.016)	(0.007)	(0.014)	(0.009)
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.05	0.05	0.06	0.05
Observations	13,188	23,158	12,656	12,300

Note: Low education is lower secondary or below. Medium education is upper secondary or post-secondary (non-tertiary), and high education is tertiary. Country clustered standard errors in parentheses.
***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

By interacting our measure of skill change with each training category (in our baseline model), we estimate the relative effectiveness of each training combination in mitigating skill deficits arising from changing skill requirements. We show the results in Figure 4. The least effective types of training are training courses and OTJ training (when used in isolation). However, when combined with other training forms, they have a greater impact on underskilling. Seminars emerge as the most effective type of training. Whether they are used in isolation, alongside courses or alongside both OTJ and courses, seminars appear to be the most effective type of training for insulating employees from adverse effects arising from changing skill requirements. The effectiveness of seminars may be explained by the changing nature of the work environment. Flexible, manageable and shorter learning options are required to adapt to changing skills needs and respond to emerging skill requirements (Ngoc Ha et al., 2025; Prior Filipe et al. 2020). Formal systems of education and training can lag behind the skill requirements of a rapidly changing labour market. This can lead to a misalignment in the perceived adequacy of technical and AI-related skills between educators and employers, which has been termed a 'digital-readiness paradox' (Nguyen 2026). Short, targeted seminars and workshops may be effective at addressing these types of skill gaps.[20] There is a growing emphasis on this type of learning among policymakers. For example, the European Commission recognises the importance of short, flexible training courses for lifelong learning and, as part of this, is working to develop a consistent European approach to micro-credentials.[21]

Finally, we examine whether the impact of training on underskilling differs depending on whether the training is funded by the employer. Employers are incentivised to fund training that is linked to the specific workplace needs of the employee. Employee-funded training, however, may be for reasons other than improving the skills required for the current job—for example, to improve prospects for finding another job. As such, employer-funded training may be more likely to alleviate job-specific underskilling than non-employer-funded training.[22] To

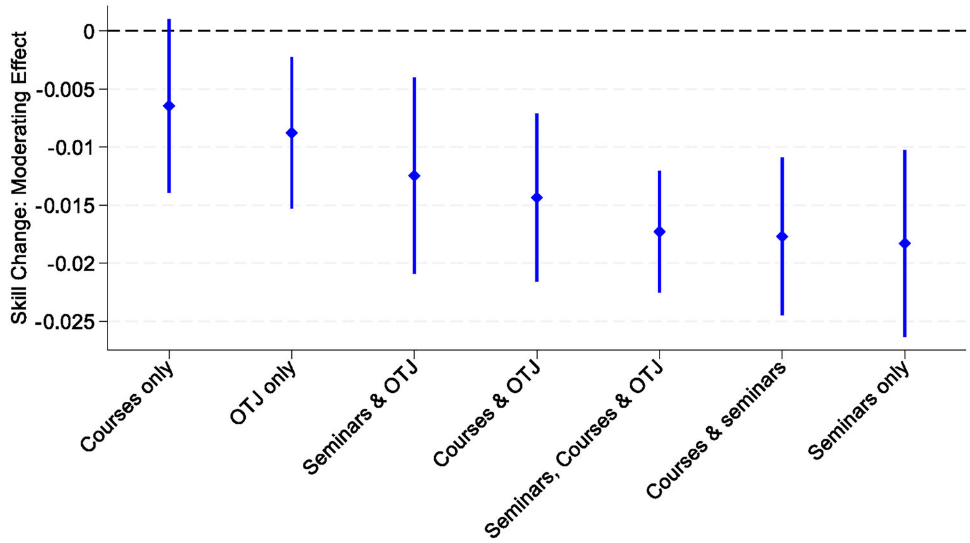

FIGURE 4 | The moderating effect of training type on underskilling. *Y* axis shows the estimated moderating effect of different training combinations on underskilling that arises from changing skill requirements. This is done by plotting the marginal effects from interacting each skill category with the measure of skill change in the baseline probit estimation. Overall, 95% confidence intervals are shown. OTJ, on-the-job.

investigate this, we utilise the following question that is asked to respondents in the ESJS that have participated in some form of training—'Was at least one of these education or training activities fully or partly paid by your current employer or done during paid working time'. Furthermore, employees are asked if they earned a certificate or an award for this training, thereby providing a proxy for training quality. This enables us to investigate the role of employer-funded (vs. non-employer-funded) training, and whether this varies depending on whether the training leads to a formal qualification or certificate. Note that these questions are only asked to the CAWI sample, meaning that the sample size of respondents (N = 11,239) is lower than our baseline estimates.

The results in Figure 5 show that employees that participated in employer-funded training that leads to a qualification are less likely to experience skill deficits associated with changing occupational skill requirements, compared to employees whose training was not funded by their employer. However, for training that does not lead to a qualification, there is no statistically significant impact.

5.1 | Robustness Analysis: Applying Skills Weights

It is likely that some skills are more important than others, and this can be reflected in different wage premiums attached to different skills (Stephany and Teutloff 2024). Our baseline analysis of changing skill requirements does not account for potential differences in the importance of skills. If an occupation displays changing skill requirements over time, then the implications of this change will likely differ depending on whether the occupation's essential skills have fundamentally changed, as opposed to changes in skills that are considered non-essential. Although it is difficult to accurately determine the relative value of different skills to employers, it is possible to ascertain a 'market return' for skills within occupations and countries. To do this, we pool both years of Lightcast data (2019 and 2023) and estimate the following regression,

$$Wage_i = \beta_0 + SkillCategory_i'\beta_1 + X_i'\beta_2 + \beta_3 Year_i + \varepsilon_i \qquad (4)$$

where Wage$_i$ denotes the real hourly wage posted in the job vacancy.[23] SkillCategory$_i$ is a vector of skill categories. We aggregate the initial set of approximately 3000 distinct skills into approximately 150 broader skill categories (e.g., 'software programming languages', 'graphical design software'). This aggregation allows for the inclusion of less frequently occurring skills by grouping them based on similarities, under the assumption that grouped skills have comparable impacts on salary. As such, the set of coefficients represented by β_1 denotes the salary returns to a job requiring a skill in a specific category (c). Using these coefficients, we determine the relative labour market value of each skill category, and weight the skills used in our calculation of SkillChange in accordance with their value, assigning higher weights to skills with higher salary returns and lower weights to skills with lower salary returns. Specifically, we calculate the skill category weights as

$$Weight_c = \frac{\beta_c + |\min(\beta_c)|}{\max(\beta_c) + |\min(\beta_c)|} \qquad (5)$$

This indexes the skill category coefficients between 0 and 1, providing us with weights for each skill depending on the category it falls under. We also include a range of vacancy-level control variables (X_i')—required education, required experience, country and ESCO skill categories. As we are pooling 2 years of data (2019 and 2023), we also include a dummy variable (Year$_i$) to control for year effects; this equals one if the vacancy appeared in 2023 and zero if in 2019.

The implicit assumption is that skills that carry a higher labour market premium are more important than skills with a lower premium, meaning changes in demand for those skills represent a more substantial change to the fundamental aspects of the job they are demanded in. Note that for certain skills, their relative

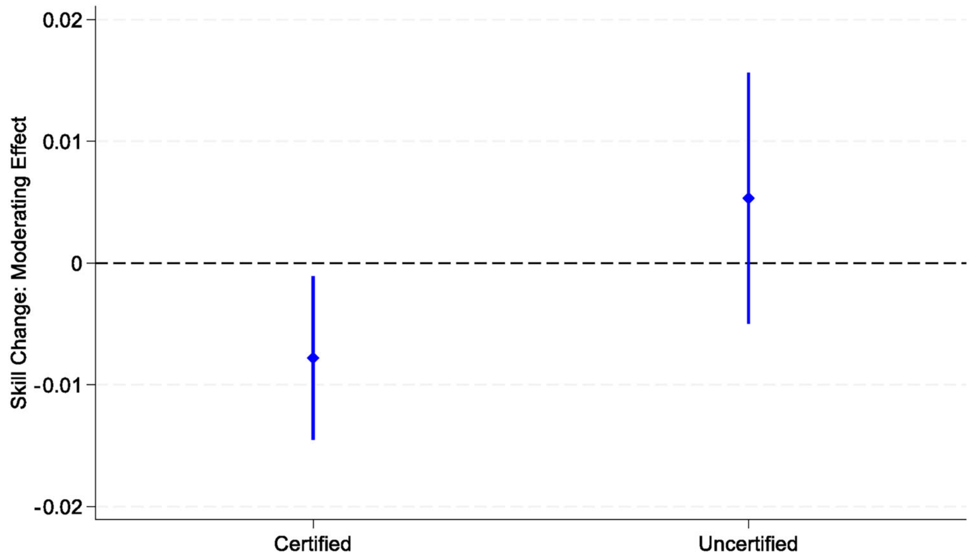

FIGURE 5 | The moderating effect of employer-funded training on underskilling. *Y* axis shows the estimated moderating effect of employer-funded training (relative to non-employer-funded training) on underskilling that arises from changing skill requirements. This is done by plotting the marginal effects from interacting an employer-funded training variable with the measure of skill change in the baseline estimation. This is done separately for training that leads to certification/qualification and training that does not. Overall, 95% confidence intervals are shown.

valuation may be endogenous to the measure of skill change. That is, some skills may have a higher value precisely because they are more sought after in 2023 relative to 2019. This could lead to a higher weighting for skills that appear in rapidly changing jobs compared to jobs with more constant skill requirements, provided the change in demand for those skills is reflected in higher wage returns. Nonetheless, our analysis represents a useful robustness test. Skill weights are a continuous measure. Therefore, even among skills whose value is driven by changing demand, there will be a continuum of relative values. Furthermore, some skills may be inherently more valuable in a way that has not changed over time. The aim of our weighted analysis is simply to evaluate whether our key findings hold when one takes account of the relative value of different skills, irrespective of the underlying mechanism driving skill value.

We re-estimate the models included in the previous section to determine whether weighting skill changes by the 'importance' of the skills influences our results. The corresponding tables with the reweighted skills change measure are shown inTables A8 and A9 andFigures A5 and A6. The results are in line with our baseline estimates; jobs that have seen additional skill requirements over time are associated with a higher likelihood of underskilling, and the impacts appear to be mitigated with training, especially seminars/workshops and employer-sponsored training.

6 | Conclusions

The skills that employees need to succeed in the labour market are constantly changing. This is often driven by technological and digital innovations. Recent trends in the labour market, such as the increase in remote work due to COVID-19 and the widespread adoption of AI-powered GPTs, are among a range of factors contributing to changing skill requirements. In this type of dynamic labour market, employees need to keep pace with changing skill requirements to ensure their skills match employer demands. This is a highly relevant policy area. Recently, the European Council adopted a set of recommendations on the key enabling factors for successful digital education and training. An emphasis was placed on the need to develop skills to keep pace with a rapidly changing labour market in order to avoid skills deficits. Our research directly addresses this issue by creating a measure of changing skill requirements at the occupation-country level and mapping this to survey data to analyse the relationship between changing skill requirements and skills deficits. In addition, we examine the role of training in mitigating skills deficits arising from occupational skill change.

Our approach involves linking data on approximately 70 million job vacancies in the EU with employee-level survey data. We begin by ranking the top skills that feature in job advertisements in both 2019 and 2023. In both years, skills relating to digital and computer literacy emerge as the top skills required by employers. This reflects the increasing importance of such skills in the labour market in recent decades. We then construct a measure of skill change at the country-occupation level to examine which jobs experienced the greatest changes to skill requirements over time. Our analysis shows that STEM-related jobs, such as software and applications developers and analysts, database and network professionals, and mathematicians, actuaries and statisticians, displayed the greatest degree of skill change. Conversely, occupations with little skill change over time are generally lower paid, manual-focused jobs, such as agricultural workers, machine operators, drivers and labourers. Using a machine-learning algorithm, we show that our measure of occupational skill change is one of the most important predictors of employee underskilling in the EU labour market.

Our findings also highlight the important role of training in alleviating skills mismatches in the EU. Although the importance of training is often mentioned in policy documents, there is a lack of evidence on the effectiveness of different types of training. We show that training, and in particular seminars and workshops, can be effective at insulating employees from some of the negative consequences associated with changing skill requirements. In a dynamic labour market, shorter and more flexible learning options are required to adapt to rapidly changing skills needs. This may explain why shorter and more flexible training options, such as seminars and workshops, emerge as being particularly effective in our analysis. The increasing importance of this type of training is also recognised by policymakers. For example, the European Commission is working to develop a consistent approach to micro-credentials in Europe.

Our analysis focuses on a period of time (2019–2023) during which global labour markets experienced dramatic changes—for example, the increase in remote working due to the COVID-19 pandemic and the adoption of generative AI tools. However, the implications derived from our analysis are likely to generalise beyond this time period. It is likely that technological change will continue to be a significant feature of labour markets. If automation and the adoption of Gen-AI continue to increase over time, skill requirements in the future may change at an even faster pace. Effective training, which is the focus of this article, is one potential policy lever to enable employees to adapt to this new technology. Acemoglu et al. (2026) highlight several other policy directions that could encourage 'pro-worker' AI, which would enhance as opposed to replace employees. This could include, for example, building AI expertise at a government level and increasing funding to pro-worker AI technology in sectors with the greatest AI potential, such as education and health. In addition, given the potential impact on workers, developing mechanisms to adequately capture worker input, such as through trade unions, would be useful. Finally, an important contribution of our work is that we make our measures of occupational skill change freely available to researchers (Supporting Information). Although we have demonstrated the importance of this measure in terms of its influence on skills mismatch, it is likely that occupational skill change will also have important implications for other labour market outcomes. It could, for example, potentially be used as an explanatory variable in future studies on automation, wages, employment, skills mismatch, job security and training, among others.

Funding

Funded by the European Union's Horizon Europe research and innovation programme under grant agreement no. 101132673.

Disclosure

Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or the Agency. Neither the European Union nor the granting authority can be held responsible for them.

Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in Cedefop at https://www.cedefop.europa.eu/en.

Endnotes

[1] See, for example, Cedefop (2010). More recently, the strategy outlined in the European Commission's Union of Skills, proposed in 2025, emphasises the importance of training and upskilling against the backdrop of a rapidly changing labour market.

[2] Skills, along with knowledge and other personal characteristics, make up an individual's productivity-enhancing human capital. For more details on the definition and measurement of human capital, see https://www.oecd.org/en/topics/sub-issues/human-capital-and-educational-policies.html.

[3] For a comprehensive review of the literature on skills mismatch, see McGuinness et al. (2018).

[4] See https://esco.ec.europa.eu/en/classification.

[5] The skill categorisations are derived from the European Skills, Competences, Qualifications and Occupations (ESCO) framework.

[6] Table A1 shows the number of vacancies by country for 2019 and 2023, and Table A2 shows the number of vacancies by 3-digit ISCO occupation for 2019 and 2023.

[7] As the vast majority have over 100 observations in both years, the inclusion or exclusion of these vacancies has no material bearing on the results.

[8] Figure A1 shows the 50 most prevalent hard skills in each year, ordered from highest to lowest by the share of vacancies in which each skill appears.

[9] Figure A2 shows the full distribution of skills per vacancy for 2019 and 2023.

[10] The data for the ESJS were collected between April and May of 2021. Although this may avoid the most severe labour market impacts that occurred in 2020, it is possible that some labour market effects persisted. In general, retail and accommodation and food workers were hardest hit by the public health restrictions due to COVID-19. However, a comparison of the sectoral distribution of the ESJS 2021 survey with the ESJS 2014 survey shows a similar percentage of employees in these two sectors over both periods (14%).

[11] Table A3 shows the number of observations by country in the ESJS data, and Table A4 shows the number of observations by ISCO 3-digit occupation.

[12] For more detail, see https://www.hcpc-uk.org/standards/standards-of-proficiency/paramedics/.

[13] For more detail, see https://www.hcpc-uk.org/news-and-events/blog/2021/hcpc-increase-set-1-degree-operating-department-practitioners/.

[14] Figure A4 shows the distribution of the absolute measure of skill change.

[15] Changing skill requirements may take time to materialise in the vacancy data. The first year of job vacancy data with a reasonable sample size occurs in 2019, and the last year of data we have is 2023. Therefore, we use these as the start and end points to allow enough time to pick up changing skill requirements. The assumption, then, is that occupations that we identify as having changing skill

requirements using the job vacancy data were also the occupations that were changing in 2021, which is the year that the employee data for the ESJS was collected.

[16] Table A5 shows results from a robustness test which drops ISCO 3-digit occupations that have fewer than 100 observations in the ESJS data. The results are virtually unchanged. Table A6 shows results from a robustness test which calculates a measure of skill change using Lightcast data from 2019 and 2021. For the baseline measure of absolute skill change, the results are virtually identical. For the measure of net skill change, the relationships work in the same direction (i.e., the coefficients have the same sign as the baseline estimates) but are not statistically significant.

[17] With a random forest classifier, each tree is trained independently and in parallel, using a different bootstrap sample of data. Final predictions are then based on a majority vote across trees. We implement this using the RandomForestClassifier class in Python's scikit-learn package.

[18] The mean decrease in accuracy approach is less useful for high-dimensional variables, like country and sector. Including such variables can lead to bias and overfitting, given the wide variety of possible combinations. Therefore, we focus the permutation importance on the six variables: skill change; firms size; education; female; tenure and part-time.

[19] The difference between the estimated impacts of 0.9 percentage points and 1.6 percentage points is statistically significant.

[20] For example, Google runs a short seminar on Python programming, and they make the materials from this seminar publicly available (Google's Python Class). Similarly, Anthropic provides a short online seminar on Claude Code (Claude Code: A Highly Agentic Coding Assistant).

[21] See https://education.ec.europa.eu/education-levels/higher-education/micro-credentials.

[22] The existing literature shows that employer-funded training can have positive effects on other outcomes such as wages, job satisfaction and job terminations (see, e.g., Ullah 2025; Kosteas 2023; Parent 2003).

[23] Hourly wages are not reported for all vacancies. However, salaries can be converted to hourly wages, and we convert all salary and wage postings to hourly wages as it represents a reasonable basis of comparison.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting File 1: bjir70067-supp-0001-SuppMat.docx

Appendix

TABLE A1 | Number of vacancies by country (2019, 2023, Lightcast).

Country	Vacancies (2019)	Vacancies (2023)
Austria	554,082	880,063
Belgium	616,329	2,335,776
Bulgaria	128,142	164,216
Croatia	45,277	168,676
Cyprus	10,988	12,527
Czechia	243,740	430,421
Denmark	52,132	587,259
Estonia	30,605	31,082
Finland	61,133	120,753
France	2,674,887	12,180,200
Germany	6,422,734	8,697,192
Greece	22,336	103,249
Hungary	79,322	422,787
Ireland	318,050	712,786
Italy	1,006,970	3,524,869
Latvia	50,838	64,901
Lithuania	63,605	67,897
Luxembourg	42,855	58,615
Malta	6264	23,376
The Netherlands	550,203	2,825,843
Norway	34,425	261,693
Poland	272,885	1,256,142
Portugal	129,331	582,423
Romania	185,621	384,233
Slovakia	93,100	90,451
Slovenia	28,229	66,486
Spain	943,873	1,289,748
Sweden	703,047	1,832,170
The United Kingdom	3,658,534	10,064,861
Total	**19,029,537**	**49,240,823**

TABLE A2 | Number of vacancies by ISCO 3-digit occupation (2019, 2023, Lightcast).

ISCO 3-digit category	Vacancies (2019)	Vacancies (2023)
Administration professionals	544,205	1,205,479
Administrative and specialised secretaries	535,805	1,174,302
Agricultural, forestry and fishery labourers	37,126	67,622
Animal producers	2222	2484
Architects, planners, surveyors and designers	177,362	320,305
Artistic, cultural and culinary associate professionals	213,288	463,152
Assemblers	208,758	523,133
Authors, journalists and linguists	65,192	135,566
Blacksmiths, toolmakers and related trades workers	208,331	559,698
Building and housekeeping supervisors	47,932	215,549
Building finishers and related trades workers	123,570	379,696
Building frame and related trades workers	61,079	254,262
Business services agents	497,035	921,490
Business services and administration managers	371,853	1,000,099
Car, van and motorcycle drivers	45,957	146,760
Cashiers and ticket clerks	78,343	251,446
Chemical and photographic products plant and machine operators	24,668	55,251
Child care workers and teachers' aides	121,038	630,361
Client information workers	425,053	1,140,780
Cooks	103,079	444,876
Creative and performing artists	33,458	73,370
Database and network professionals	266,280	534,591
Domestic, hotel and office cleaners and helpers	40,815	474,356
Electrical equipment installers and repairers	249,639	744,789
Electronics and telecommunications installers and repairers	127,455	244,596
Electrotechnology engineers	153,159	312,734
Engineering professionals (excluding electrotechnology)	954,858	2,218,994
Finance professionals	407,616	908,297
Financial and mathematical associate professionals	425,635	1,075,123
Fishery workers, hunters and trappers	17,083	1967
Food and related products machine operators	25,033	154,275
Food preparation assistants	58,512	331,740
Food processing and related trades workers	63,266	231,314
Forestry and related workers	965	2940
Garment and related trades workers	36,362	75,113
General office clerks	259,551	707,500
Hairdressers, beauticians and related workers	63,862	138,027
Handicraft workers	36,063	50,592
Heavy truck and bus drivers	135,379	570,479
Hotel and restaurant managers	68,235	103,380
Information and communications technology operations and user support technicians	349,447	486,757
Information and communications technology service managers	132,647	229,160

(Continues)

TABLE A2 | (Continued)

ISCO 3-digit category	Vacancies (2019)	Vacancies (2023)
Keyboard operators	24,172	49,090
Legal professionals	109,595	234,471
Legal, social and religious associate professionals	153,969	666,581
Legislators and senior officials	9521	15,652
Librarians, archivists and curators	14,966	40,445
Life science professionals	33,717	70,035
Life science technicians and related associate professionals	46,078	55,837
Locomotive engine drivers and related workers	9562	27,375
Machinery mechanics and repairers	270,383	774,650
Managing directors and chief executives	155,912	256,412
Manufacturing labourers	249,470	687,262
Manufacturing, mining, construction and distribution managers	188,884	542,343
Market gardeners and crop growers	20,320	86,310
Material-recording and transport clerks	218,966	651,844
Mathematicians, actuaries and statisticians	13,682	33,891
Medical and pharmaceutical technicians	64,424	193,144
Medical doctors	139,528	436,287
Metal processing and finishing plant operators	31,684	76,697
Mining and construction labourers	36,512	221,454
Mining and mineral processing plant operators	20,835	59,756
Mining, manufacturing and construction supervisors	175,430	471,908
Mixed crop and animal producers	6021	8059
Mobile plant operators	106,232	440,408
Numerical clerks	379,174	1,063,053
Nursing and midwifery associate professionals	90,339	346,588
Nursing and midwifery professionals	178,926	453,790
Other clerical support workers	329,441	954,802
Other craft and related workers	54,488	158,143
Other elementary workers	40,480	161,070
Other health associate professionals	162,412	479,242
Other health professionals	119,168	435,909
Other personal services workers	34,859	105,915
Other sales workers	307,377	892,933
Other services managers	10,077	36,479
Other stationary plant and machine operators	188,847	634,416
Other teaching professionals	127,439	395,775
Painters, building structure cleaners and related trades workers	81,907	170,681
Paramedical practitioners	473	2783
Personal care workers in health services	202,977	684,049
Physical and earth science professionals	21,135	52,850
Physical and engineering science technicians	813,199	1,846,830
Primary school and early childhood teachers	68,259	151,398

(Continues)

TABLE A2 | (Continued)

ISCO 3-digit category	Vacancies (2019)	Vacancies (2023)
Printing trades workers	22,611	44,447
Process control technicians	25,359	106,082
Production managers in agriculture, forestry and fisheries	185	872
Professional services managers	179,621	474,332
Protective services workers	60,381	279,856
Refuse workers	14,868	45,801
Regulatory government associate professionals	32,849	80,811
Retail and wholesale trade managers	235,752	524,754
Rubber, plastic and paper products machine operators	15,992	41,523
Sales and purchasing agents and brokers	573,515	1,093,742
Sales, marketing and development managers	594,372	1,719,416
Sales, marketing and public relations professionals	585,707	1,454,662
Secondary education teachers	42,533	138,936
Secretaries (general)	152,461	344,388
Sheet and structural metal workers, moulders and welders, and related workers	151,688	458,159
Ship and aircraft controllers and technicians	19,209	34,068
Ships' deck crews and related workers	1232	11,291
Shop salespersons	493,699	1,640,807
Social and religious professionals	208,415	628,100
Software and applications developers and analysts	1,604,032	2,622,277
Sports and fitness workers	50,296	171,707
Street and market salespersons	3130	6474
Street and related service workers	4206	9983
Street vendors (excluding food)	694	2096
Subsistence fishers, hunters, trappers and gatherers	0	52
Telecommunications and broadcasting technicians	22,503	44,290
Tellers, money collectors and related clerks	57,496	101,001
Textile, fur and leather products machine operators	94,025	65,829
Traditional and complementary medicine associate professionals	52	467
Traditional and complementary medicine professionals	138	662
Transport and storage labourers	194,296	979,363
Travel attendants, conductors and guides	42,448	104,713
University and higher education teachers	98,513	233,161
Vehicle, window, laundry and other hand-cleaning workers	25,016	154,651
Veterinarians	3578	16,552
Veterinary technicians and assistants	2315	12,210
Vocational education teachers	25,504	83,699
Waiters and bartenders	218,699	561,250
Wood processing and papermaking plant operators	38,408	124,600
Wood treaters, cabinet-makers and related trades workers	25,683	134,717
Total	**19,029,537**	**49,240,823**

TABLE A3 | Number of observations by country (ESJS data).

Country	Observations
Austria	1509
Belgium	1504
Bulgaria	1517
Croatia	975
Cyprus	754
Czechia	1562
Denmark	2946
Estonia	982
Finland	1264
France	2947
Germany	2946
Greece	1932
Hungary	1485
Ireland	1317
Italy	2956
Latvia	967
Lithuania	963
Luxembourg	927
Malta	753
The Netherlands	1493
Norway	908
Poland	3003
Portugal	1511
Romania	1989
Slovakia	964
Slovenia	958
Spain	2982
Sweden	1478

Source: European Skills and Jobs Survey.

TABLE A4 | Number of observations by ISCO 3-digit occupation (ESJS data).

ISCO 3-digit occupation	Observations
Commissioned armed forces officers	57
Non-commissioned armed forces officers	6
Armed forces occupations, other ranks	53
Legislators and senior officials	280
Managing directors and chief executives	287
Business services and administration managers	1077
Sales, marketing and development managers	736
Production managers in agriculture, forestry and fisheries	32
Manufacturing, mining, construction and distribution managers	940
Information and communications technology service managers	531
Professional services managers	675
Hotel and restaurant managers	176
Retail and wholesale trade managers	311
Other services managers	222
Physical and earth science professionals	108
Mathematicians, actuaries and statisticians	43
Life science professionals	340
Engineering professionals (excluding electrotechnology)	654
Electrotechnology engineers	192
Architects, planners, surveyors and designers	430
Medical doctors	383
Nursing and midwifery professionals	747
Traditional and complementary medicine professionals	1
Paramedical practitioners	15
Veterinarians	27
Other health professionals	366
University and higher education teachers	366
Vocational education teachers	160
Secondary education teachers	596
Primary school and early childhood teachers	1840
Other teaching professionals	650
Finance professionals	1349
Administration professionals	762
Sales, marketing and public relations professionals	557
Software and applications developers and analysts	1202
Database and network professionals	587
Legal professionals	326
Librarians, archivists and curators	215
Social and religious professionals	612
Authors, journalists and linguists	236
Creative and performing artists	131
Physical and engineering science technicians	442

(Continues)

TABLE A4 | (Continued)

ISCO 3-digit occupation	Observations
Mining, manufacturing and construction supervisors	256
Process control technicians	182
Life science technicians and related associate professionals	45
Ship and aircraft controllers and technicians	60
Medical and pharmaceutical technicians	200
Nursing and midwifery associate professionals	92
Traditional and complementary medicine associate professionals	3
Veterinary technicians and assistants	23
Other health associate professionals	412
Financial and mathematical associate professionals	611
Sales and purchasing agents and brokers	877
Business services agents	417
Administrative and specialised secretaries	1612
Regulatory government associate professionals	300
Legal, social and religious associate professionals	263
Sports and fitness workers	104
Artistic, cultural and culinary associate professionals	229
Information and communications technology operations and user support technicians	788
Telecommunications and broadcasting technicians	71
General office clerks	1431
Secretaries (general)	531
Keyboard operators	180
Tellers, money collectors and related clerks	329
Client information workers	1434
Numerical clerks	858
Material-recording and transport clerks	770
Other clerical support workers	688
Travel attendants, conductors and guides	113
Cooks	307
Waiters and bartenders	430
Hairdressers, beauticians and related workers	97
Building and housekeeping supervisors	237
Other personal services workers	112
Street and market salespersons	42
Shop salespersons	1391
Cashiers and ticket clerks	377
Other sales workers	422
Child care workers and teachers' aides	528
Personal care workers in health services	1107
Protective services workers	824
Market gardeners and crop growers	208

(Continues)

TABLE A4 | (Continued)

ISCO 3-digit occupation	Observations
Animal producers	57
Mixed crop and animal producers	23
Forestry and related workers	34
Fishery workers, hunters and trappers	35
Subsistence crop farmers	2
Building frame and related trades workers	416
Building finishers and related trades workers	174
Painters, building structure cleaners and related trades workers	118
Sheet and structural metal workers, moulders and welders, and related workers	163
Blacksmiths, toolmakers and related trades workers	296
Machinery mechanics and repairers	383
Handicraft workers	94
Printing trades workers	121
Electrical equipment installers and repairers	375
Electronics and telecommunications installers and repairers	271
Food processing and related trades workers	213
Wood treaters, cabinet-makers and related trades workers	61
Garment and related trades workers	91
Other craft and related workers	273
Mining and mineral processing plant operators	45
Metal processing and finishing plant operators	61
Chemical and photographic products plant and machine operators	74
Rubber, plastic and paper products machine operators	77
Textile, fur and leather products machine operators	69
Food and related products machine operators	95
Wood processing and papermaking plant operators	26
Other stationary plant and machine operators	186
Assemblers	327
Locomotive engine drivers and related workers	70
Car, van and motorcycle drivers	368
Heavy truck and bus drivers	498
Mobile plant operators	202
Ships' deck crews and related workers	23
Domestic, hotel and office cleaners and helpers	658
Vehicle, window, laundry and other hand-cleaning workers	79
Agricultural, forestry and fishery labourers	143
Mining and construction labourers	219
Manufacturing labourers	267
Transport and storage labourers	610
Food preparation assistants	237
Street and related service workers	20
Street vendors (excluding food)	2
Refuse workers	62
Other elementary workers	147

Source: European Skills and Jobs Survey.

TABLE A5 | Skill change and skills mismatch (marginal effects)—sample size restriction.

Panel A—Sample size restriction				
	(1)	**(2)**	**(3)**	**(4)**
Variables	**Underskilled**	**Underskilled**	**Underskilled**	**Overskilled**
SkillChange	**0.013*****	**0.014*****		
	(0.002)	**(0.002)**		
NetSkillChange			**0.004****	**−0.006****
			(0.002)	**(0.002)**
Observations	35,102	25,544	35,102	24,097
Panel B—Baseline estimates (from Table 4)				
	(1)	**(2)**	**(3)**	**(4)**
Variables	**Underskilled**	**Underskilled**	**Underskilled**	**Overskilled**
SkillChange	**0.013*****	**0.014*****		
	(0.001)	**(0.002)**		
NetSkillChange			**0.005****	**−0.006****
			(0.002)	**(0.002)**
Observations	36,346	26,380	36,346	24,977

Note: This table shows the results from estimating Equation (3) with the additional restriction of dropping ISCO 3-digit occupations with fewer than 100 observations in the ESJS data. Panel A shows the estimates with the sample size restriction, and, for comparability, Panel B restates the baseline estimates from Table 4).

TABLE A6 | Skill change and skills mismatch (marginal effects)—Lightcast Data from 2019 to 2021.

	(1)	**(2)**	**(3)**	**(4)**
Variables	**Underskilled**	**Underskilled**	**Underskilled**	**Overskilled**
SkillChange	**0.013*****	**0.013*****		
	(0.001)	**(0.003)**		
NetSkillChange			**0.001**	**−0.003**
			(0.002)	**(0.003)**
Observations	35,511	21,537	35,511	23,961

Note: This table shows the results from estimating Equation (3), using measures of skill change from Lightcast data for 2019 and 2021.
*** p < 0.01. ** p < 0.05. * p < 0.1.

TABLE A7 | Interacting measure of new skills (%) with skill change.

Variables	(1) Underskilled
SkillChange	0.011***
	(0.003)
New skill (%)	−0.043
	(0.041)
SkillChange × new skill (%)	−0.000
	(0.007)
Female	−0.029***
	(0.007)
Tenure	−0.001***
	(0.000)
Firm size (Ref: 1–10)	
11–49 employees	0.019*
	(0.009)
50–249 employees	0.032***
	(0.009)
250 or more employees	0.034***
	(0.010)
Constant	0.522***
	(0.0294)
Observations	34,524
R-squared	0.066

Note: A linear probability model, analogous to the probit model that produces results in Column (1) of Table 4, is implemented, with the addition of an interaction term between the measure of skill change and the percentage of this measure that is attributable to new skills. Low education is lower secondary or below. Medium education is upper secondary or post-secondary (non-tertiary), and high education is tertiary. Country clustered standard errors in parentheses.

***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

TABLE A8 | Weighted skill change and skills mismatch (marginal effects).

Variables	(1) Underskilled	(2) Underskilled	(3) Underskilled	(4) Overskilled
SkillChange	0.021***	0.0225***		
	(0.002)	(0.003)		
NetSkillChange			0.009***	−0.010***
			(0.003)	(0.003)
Female	−0.028***	−0.025***	−0.030***	−0.001
	(0.006)	(0.007)	(0.006)	(0.004)
Tenure	−0.001***	−0.002***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size (Ref: 1–10)				
11–49 employees	0.020**	0.024**	0.021**	−0.021***
	(0.009)	(0.010)	(0.009)	(0.008)
50–249 employees	0.035***	0.039***	0.037***	−0.022**
	(0.010)	(0.010)	(0.010)	(0.009)
250 or more employees	0.037***	0.043***	0.040***	−0.014**
	(0.010)	(0.010)	(0.010)	(0.007)
Education (Ref: Low education)				
Medium education	0.042***	0.043***	0.0448***	−0.010
	(0.009)	(0.009)	(0.009)	(0.009)
High education	0.101***	0.092***	0.111***	−0.030***
	(0.010)	(0.009)	(0.009)	(0.009)
Part-time	−0.053***	−0.051***	−0.056***	0.046***
	(0.010)	(0.010)	(0.010)	(0.008)
Industry FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.05	0.06	0.05	0.06
Observations	36,346	26,380	36,346	24,977

Note: Low education is lower secondary or below. Medium education is upper secondary or post-secondary (non-tertiary), and high education is tertiary. Table A1 corresponds to Table 4 in the main text. Country clustered standard errors in parentheses.
***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

TABLE A9 | The role of training in mitigating underskilling (using weighted skill change).

	No training	**Training**
Variables	Underskilled	Underskilled
SkillChange	0.026***	0.013***
	(0.004)	(0.002)
Female	−0.006	−0.031***
	(0.008)	(0.007)
Tenure	−0.001	−0.001***
	(0.001)	(0.000)
Firm size (Ref: 1–10)		
11–49 employees	0.007	0.004
	(0.017)	(0.010)
50–249 employees	0.016	0.015*
	(0.020)	(0.009)
250 or more employees	0.018	0.012
	(0.015)	(0.010)
Education (Ref: low education)		
Medium education	0.052***	0.021*
	(0.014)	(0.012)
High education	0.094***	0.058***
	(0.013)	(0.014)
Part-time	−0.070***	−0.032***
	(0.016)	(0.007)
Industry FE	Yes	Yes
Country FE	Yes	Yes
Pseudo R^2	0.05	0.05
Observations	13,188	23,158

Note: Low education is lower secondary or below. Medium education is upper secondary or post-secondary (non-tertiary), and high education is tertiary. Table A2 corresponds to Table 5 in the main text. Country clustered standard errors in parentheses.
***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

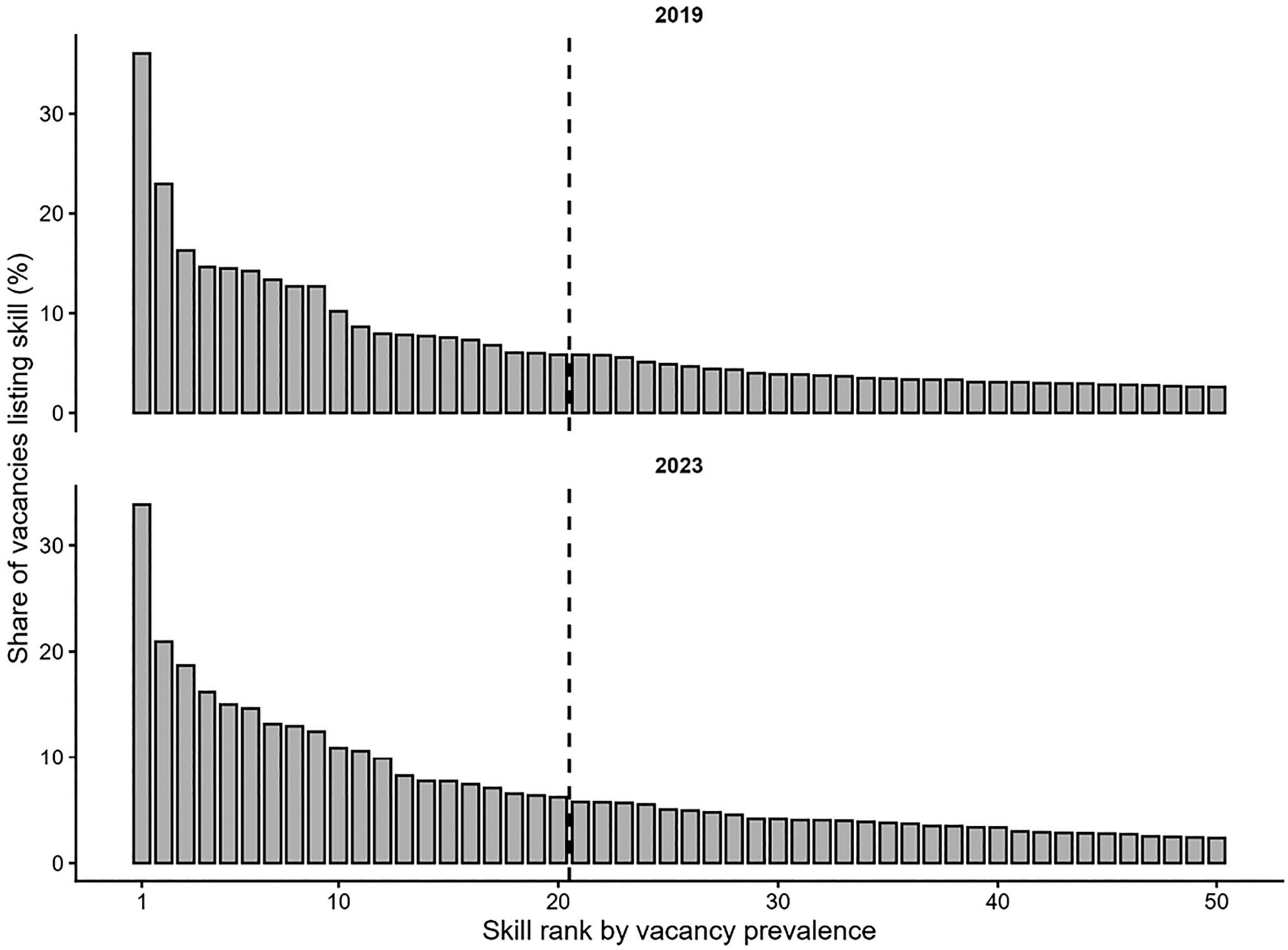

FIGURE A1 | Vacancy prevalence of the 50 most common hard skills, 2019 and 2023. The figure shows the 50 most prevalent hard skills in 2019 and 2023, ordered from highest to lowest by the share of vacancies in which each skill appears. Skill prevalence is calculated as the number of vacancies listing a given skill divided by the total number of vacancies in that year. The dashed vertical line marks the cut-off after the 20th-ranked skill, corresponding to the skills reported in Table 1.

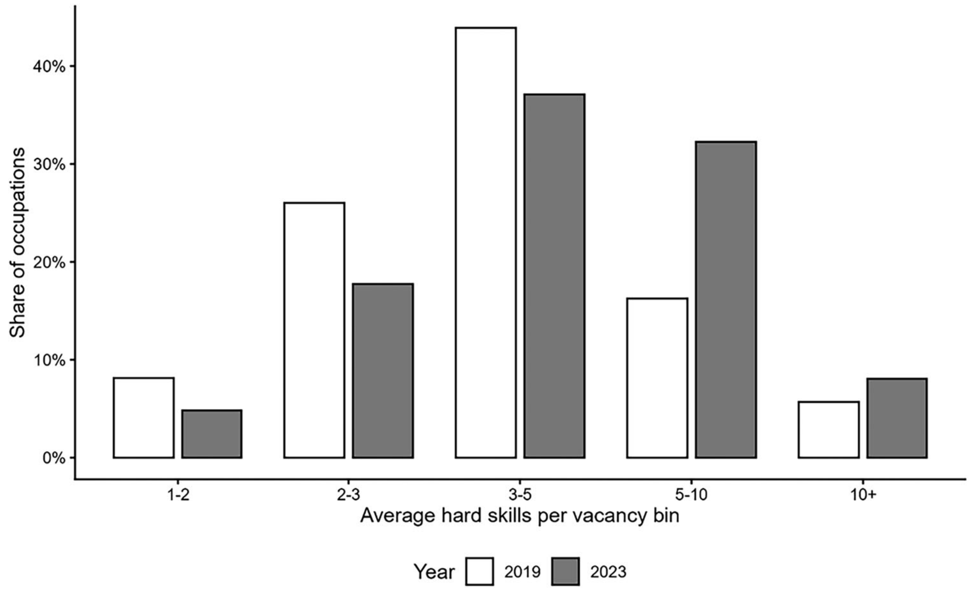

FIGURE A2 | Distribution of hard-skill intensity across ISCO 3-digit occupations, 2019 and 2023. The figure groups ISCO 3-digit occupations according to the average number of hard-skill mentions per vacancy. This measure is calculated as the total number of hard-skill mentions divided by the total number of vacancies within each occupation-year. The figure contextualises Figure 1 by showing the broader occupation distribution rather than only the top-ranked occupations.

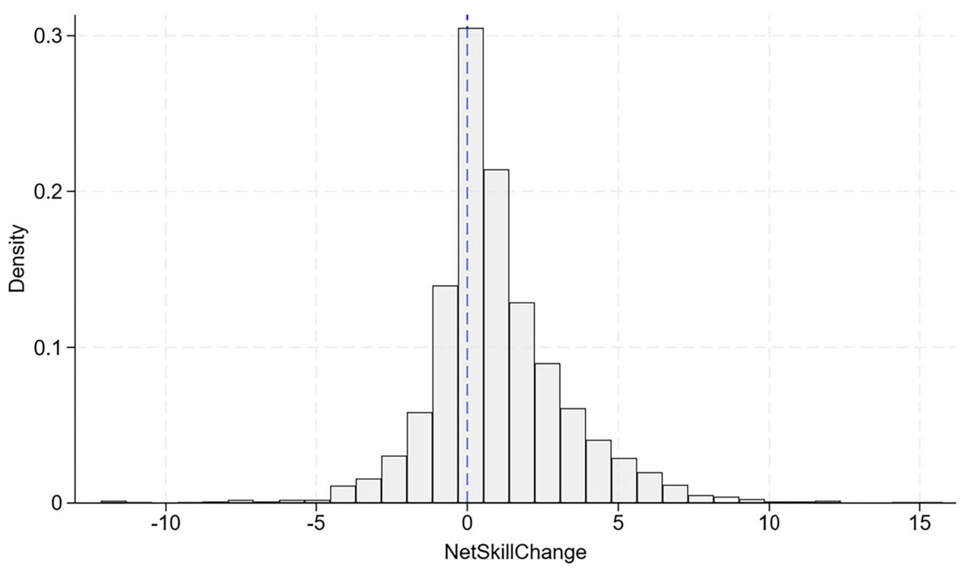

FIGURE A3 | Distribution of NetSkillChange values.

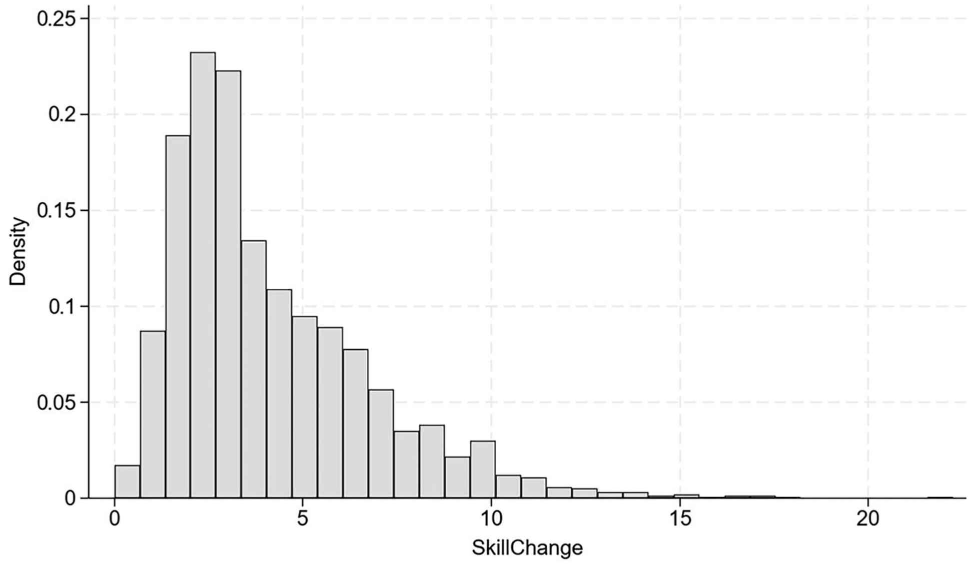

FIGURE A4 | Distribution of SkillChange values.

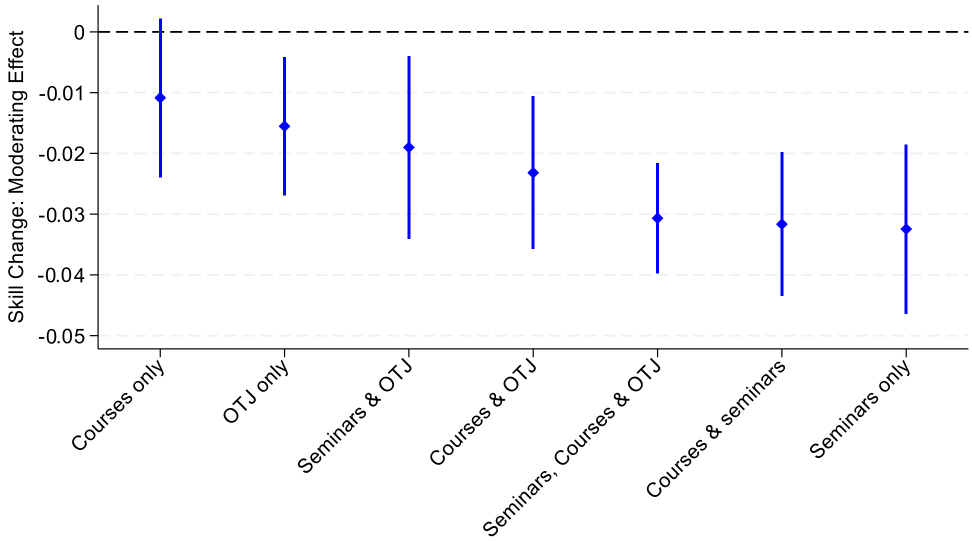

FIGURE A5 | The moderating effect of training type on underskilling using weighted skill change.

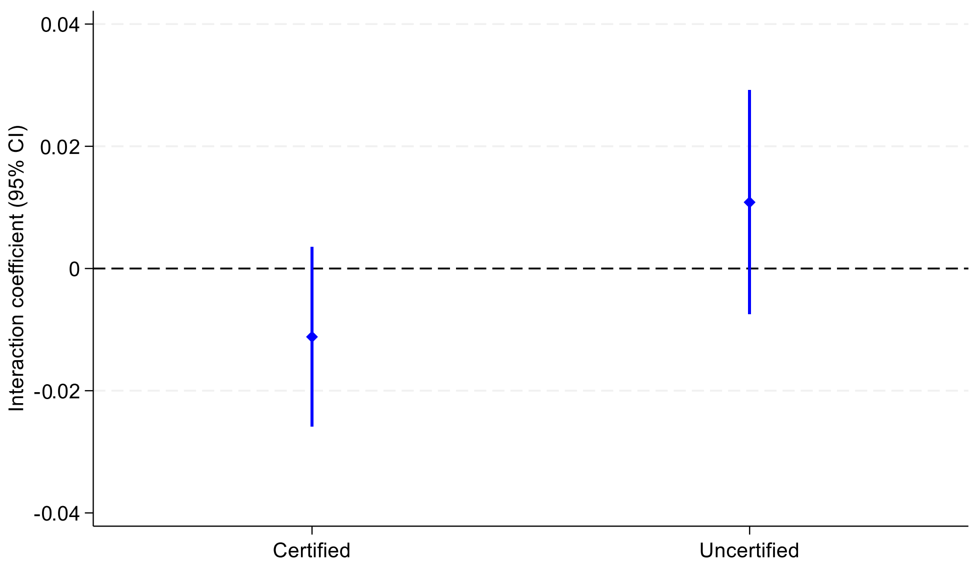

FIGURE A6 | The moderating effect of employer-funded training on underskilling using weighted skill change.