D5.2 – Report on employee skill obsolescence

[Analyse large international comparative studies to report on how employees' own perception about the obsolescence of their skills and likelihood of losing their job is related with participation in training and the effects of mismatch on individual well-being]

Skills2Capabilities Working Paper

April 2025

AUTHORS: LIISA MARTMA (TALLINN UNIVERSITY, IISS), PEPKA BOYADJIEVA, PETYA ILIEVA-TRICHKOVA, VENETA KRASTEVA, SVETLANA ALEXANDROVA (IPS-BAS)

ABSTRACT

This report uses data from the 2021 European Skills and Jobs Survey to analyse how skill utilisation, job complexity, and workplace changes influence training engagement. It further explores how employees' perceptions of skill obsolescence and job insecurity affect their participation in training and the effect on skills/educational mismatch on well-being. This deliverable defines subjective well-being as a multidimensional concept and develops a specialised index to analyse the relationship between skills mismatch and subjective well-being at work. The findings reveal that low skills utilisation reduces training engagement, whereas higher level of job complexity, workplace changes, and the risk of skill obsolescence increase it. Furthermore, the report finds that training participation is higher in larger firms and in the public or not-for-profit sectors. Our findings also demonstrate how various types of mismatch matter for subjective well-being at work. They provide evidence that the individual characteristics such as age, gender, level of education and occupational group moderate the effect of skills mismatch on subjective well-being at work differently, which should be considered in both analyses and policymaking.

ACKNOWLEDGEMENTS

Work Package 5 is coordinated by Tallinn University, led by Triin Roosalu and Eeva Kesküla. We extend our gratitude to Terence Hogarth (IER), Emily Erickson (IER), and to Joanna Kitsnik (TLU) for their insightful review on the draft of this report. We also acknowledge the significant contributions of Prof. Ellu Saar (TLU), whose involvement was integral to this project. Her commitment and dedication were invaluable, leaving a lasting impact on our work.

Skills2Capabilities, a Horizon Europe study, is about understanding how skills systems need to develop if they are to assist people to make labour market transitions – i.e. between jobs, employers or sectors – and thereby reduce the level of skill mismatch which might otherwise arise.

This Working Paper is part of the Skills2Capabilitiy Work Package WP5 entitled 'Drivers and effects of skills mismatch.'

For more information please visit skills2capabilities.eu

Funded by the European Union. 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.

Co-funded by the European Union

Contents

List of tables

List of figures

1 Introduction

The global landscape of work is evolving rapidly due to aging populations and accelerating economic changes, necessitating continuous skill development throughout individuals' lives (Cunha et al., 2006). Recognising this imperative, the European Union has set goals for lifelong learning to ensure individuals can continuously acquire and develop new skills, thereby enhancing their productivity (European Commission, 2010, 16). This emphasis on lifelong learning is crucial for firms grappling with dynamic skill demands and is essential for economic competitiveness and social cohesion (European Commission, 2000; World Economic Forum, 2014).

Despite the acknowledged importance of continuous skill development, access to further training remains uneven (Dieckhoff et al., 2007; Blossfeld et al., 2014). Empirical studies show that adults with lower levels of education are less likely to participate in job-related training compared to those with higher education (Bassanini et al., 2007; OECD, 2019a). However, recent research indicates that workplace and job characteristics have an even greater influence on participation (Schindler et al., 2011; Görlitz & Tamm, 2016; Saar & Räis, 2017; Ehlert, 2020; Hornberg et al., 2024). Ehlert (2020) highlights the role of job tasks in predicting training participation across various countries, revealing that employees engaged in routine tasks tend to receive less training[1]. This disparity is exacerbated for workers in jobs susceptible to automation, where the risk of job loss and limited training access intertwine (Görlitz and Tamm, 2016; Kleinert and Wölfel, 2018; OECD, 2019b). Consequently, individuals who are most in need of acquiring new skills receive presumably the least amount of training.

The term skills mismatch is very broad and is used to characterise various types of labour market imbalances, such as friction, vertical (educational and qualification) mismatch, horizontal (educational and qualification) mismatch, skill gaps, skill shortages, and skill obsolescence (Cedefop, 2010, 2018; McGuinness, Pouliakas, and Redmond, 2018). Skills mismatch has also been defined at different levels. Thus, at macro level, it 'refers to the gap between the (aggregate) supply and demand for skills, typically with reference to a specific geographical unit (region, country or country group), and to the fact that observed matches between available workers and available jobs offered by firms in terms of skills and/or qualifications are sub-optimal' whereas at the micro level, it captures situations 'when workers have a level of skills that is different from what is required for their job' (Brunello and Wruuck 2021, 1146).

[1] Ehlert (2020) found that routine tasks are significantly associated with the likelihood of training participation in approximately a quarter of the countries. However, there is substantial cross-national variation, with both negative and positive point estimates.

Skills2Capabilities

Co-funded by the European Union

In recent years, an expanding body of literature on skill mismatch has emerged (Desjardins and Rubenson, 2011; Green, 2013; Levels, van der Velden, and Allen, 2014; Felstead, Gallie, and Green, 2017; Livingstone, 2017), which has developed alongside the literature on adult training. However, there has been limited interaction between these fields.

Training can enhance the alignment between existing skills and those required for the rapid adoption of new technologies (Buchtemann and Soloff, 2003) and may be a crucial remedy for skill obsolescence (de Grip and van Loo, 2002). Desjardins (2014) examined the relationship between participation in employer-supported adult education and training, and skill supply and demand characteristics. Analysing data from the European Company Survey 2019, Russo (2024) has found that employers who rely on the following two organisational approaches to skills utilisation — an employment relationship balancing moderate requirements with moderate inducements, or an unbalanced employment relationship subsuming high requirements and moderate inducements — tend to provide training and on-the-job training to a wider fraction of employees than organisations with an employment relationship balancing low requirements and low inducements. Several studies have analysed the impact of education mismatch on training participation (van Smoorenburg and van der Velden, 2000; Büchel and Mertens, 2004; Verhaest and Omey, 2006; Korpi and Tåhlin, 2009; Verhaest et al., 2017). Additionally, Ferreira, Künn-Nelen, and de Grip (2017) have explored the heterogeneity in the relationship between training and workers' skill development relative to initial skill-job mismatch, focusing on how participation in different forms of work-related learning enhances skill levels. Despite a growing body of research, there is still limited understanding of factors such as skills utilisation at work, job complexity, workplace characteristics, but also perceptions about how job insecurity and skill obsolescence influence participation in job-related education and training.

The problem of skills mismatch looms large also because of its consequences for individual well-being and country's economic and social development. The greatest attention from both scholars and politicians has been paid to skills mismatch effects on individual job's economic rewards, firms' productivity and national economic development (Brunello and Wruuck, 2021). As far as subjective consequences from skills mismatch are concerned, the most studied is job satisfaction as a synthetic indicator of subjective well-being at work (e.g. McGuinness and Byrne, 2015; Urbanaviciute, Massoudi, and De Witte, 2024).

Against the above background, this deliverable[2] examines how employees' skills utilisation, job complexity, and workplace changes and characteristics influence their participation in training and shape opportunities for skills development, using data from the 2021 European Skills and Jobs Survey (ESJS). We also take into account how employees' perceptions of skill obsolescence and job insecurity relate to their participation in training. Finally, we define subjective well-being as a multidimensional construct and use a scale based on ESJS 2021 data (Cedefop, 2021) to study the influence of skills/educational mismatch on well-being at work.

[2] Based on Task 5.2, 5.3 and 5.5 of the Grant Agreement.

The structure of the report is as follows: Section 2 introduces the theoretical framework for understanding the impact of skills utilisation, job complexity, and technological change in job-related education and training participation and the association between skills mismatch and subjective well-being. It begins with a brief discussion of the use of human capital theory in studies on adult education. Then it outlines some alternative approaches, which are based on the political economy of skills and emphasise the demand side of the labour market. It also discusses skill obsolescence and argues that training and workplace learning are crucial to counteract it. The second section also develops an understanding of subjective well-being at work as a multidimensional phenomenon within the framework of the capability approach. Section 3 describes the data, variables, and research strategy used in the report. Section 4 presents the findings in two parts. The first part examines the effects of skill utilisation, workplace changes, skills obsolescence, job insecurity and job complexity on participation in job-related training. Additionally, it explores job-related training practices by workplace characteristics. The second part of Section 4 focuses on the association between five different types of skills/education-job mismatch (required education, vertical education mismatch, horizontal education mismatch, skills utilisation, skills obsolescence) and the subjective well-being at work. It also analyses if individual socio-demographic characteristics (age, gender, level of education, occupational group) moderate the effects of different types of skills/education-job mismatch on subjective well-being at work. Section 5 concludes the report, summarising and discussing the key findings and insights from the analysis and outlining some policy implications.

2 Theoretical framework and findings from previous research

2.1 The relationship of skills utilisation, job complexity, and technological change in job-related education and training participation

The prevailing theoretical framework in adult education is the human capital approach, introduced by Becker (1975). This theory suggests that individuals and employers invest in training based on the anticipated returns that exceed the costs. Human capital theory distinguishes between 'general' skills, which are transferable across different employers, and 'specific' skills, which are considered useful only to the current employer (Asplund, 2004). Based on the distinction between general and specific skills, the expectation is that employers would support only training that develops specific work-related skills, as they may be reluctant to invest in general skills due to the risk of employees leaving the firm after acquiring them. However, empirical evidence related to human capital theory indicates that companies are also willing to invest in the general knowledge and skills of their employees (Acemoglu and Pischke, 1999; Loewenstein and Spletzer, 1999; Bills and Hodson, 2007). Lazear's (2009) skill-weight approach argues that while many skills —such as knowledge of taxation, programming, and economics—may appear general when considered individually, their unique combination within a company's specific demands make them firm-specific. As a result, employers are also willing to bear the cost of training.

Job tasks are fundamental to the essence of performing a particular job (Autor and Handel, 2013). Effective job performance necessitates that workers possess the skills required for their jobs, implying that job task profiles significantly influence access to training opportunities (Schindler et al., 2011). Schindler et al. (2011) state that jobs involving complex tasks demand specific skills that are scarce in the labour market. Consequently, employees hired for these roles often lack the necessary skills and must undergo additional training to bridge the gap. Furthermore, some tasks require skills that quickly become outdated, making continuous training essential to maintain productivity. This dynamic is likely to result in increased participation in training, especially in occupations that involve the use of new technologies (Bresnahan et al., 2002).

The concept of human capital depreciation integrates human capital with technological change, highlighting training's critical role in restoring and replenishing human capital in the context of skill depreciation (Rosen, 1975; Mincer and Ofek, 1982). Acemoglu and Pischke (1999) argue that both firms and employees benefit from general and job-specific training, emphasising that new technologies make training essential, although labour market imperfections can result in suboptimal levels of workplace training.

The association between work-related learning and workers' skills mismatches has been still rarely analysed in empirical literature. A mismatch between employees' skills and job requirements can significantly influence participation in training for several reasons. Compared to workers in well-matched jobs, underskilled and overskilled workers are likely to have different motivations for engaging in job-related learning (Ferreira, Künn-Nelen, and de Grip, 2017). Underskilled workers typically need more training and learning to perform adequately in their jobs, while overskilled workers may seek training to keep their skills current or to prevent skill depreciation. Technological changes can reduce the utility of skills if they are underutilised in the job or increase the demand for further training if job skill requirements rise. Being underskilled may encourage further learning investments while being overskilled at job entry could discourage additional learning due to the potential deterioration of a worker's initial skill set from non-use.

In the 1990s, alternative approaches to human capital theory emerged, focusing on imperfect markets and grounded in the political economy of skills (Brown, Green, and Lauder, 2001). These approaches emphasise the demand side of the labour market. Critics of human capital theory argue that the decision to invest in human capital is influenced also by the structure of work settings at the meso-level and social and economic institutions at the macro-level (Brown et al., 2001; Bassanini et al., 2007). Recent research in adult education has sought to integrate and elaborate on the role of structural and institutional dimensions in shaping participation patterns (Blossfeld et al., 2014; Rubenson and Desjardins, 2009; Saar, Ure, and Desjardins, 2013). Desjardins and Rubenson (2011) suggest that this approach addresses a previous tendency to focus almost exclusively on the individual's decision to participate while overlooking the roles of employers and the broader institutional context. Existing theoretical and empirical work indicates that individual and structural characteristics of work, the economy, and society combine to influence participation in adult education (Rubenson and Desjardins, 2009; Nilsson and Rubenson, 2014). The decision to participate is not solely based on personal resources but also on workers' access to and position within the structure of work settings, as well as broader social structures.

Both the supply and the demand for skills shape opportunities for training participation (see also Roosmaa, 2021, for an overview). Research shows that individuals with higher levels of formal education and those in higher occupational positions are more likely to engage in training (Brunello & Medio, 2001; Bassanini et al., 2007; Dieckhoff, Jungblut & O'Connell, 2007). At the meso-level, workplace characteristics such as firm size and economic sector also play a significant role in training participation. Roosmaa (2021) found that participation in training is higher in the tertiary sector, particularly in public administration, healthcare, and education, where training is often state-financed (see also OECD, 2003; Cedefop, 2015; Desjardins, 2020). Additionally, participation rates differ between the public and private sectors, with greater skill-upgrading demands typically found in the public sector. Small and medium-sized enterprises (SMEs) tend to have lower participation rates compared to large firms, which generally possess more resources to support employee training. Larger companies, particularly in the public sector, are more likely to allocate specific training budgets[3], whereas smaller firms often face challenges such as financial constraints, staff shortages, and limited access to tailored training programs.

Technological advancements are reshaping the labour market by increasing the demand for certain skills while making others less relevant or obsolete (Deming, 2017; Deming & Noray, 2020). Regarding skill obsolescence, Cedefop's 2014 ESJS data revealed that 26% of adult employees in the European Union believed it was moderately likely, and 21% very likely, that several of their skills

[3] For example in Estonia, 77% of large firms allocate a specific budget to training, compared to only 16% of small enterprises (OECD, 2012, 66).

would become outdated within five years (Cedefop, 2018). Skill obsolescence poses significant risks, including increased job insecurity and challenges for workers to maintain adequate labour market participation, particularly due to rapidly evolving technologies.

Studies on skill-biased technological change (e.g., Card & DiNardo, 2002; DiPrete, 2005) show that advanced technology shifts the skill structure of employment, while other research highlights how technological change alters the relative demand for specific skills (Dickerson & Green, 2004). As a result, many existing skills become less relevant, replaced by new or previously less important ones (Welch & Ureta, 2002). For an overview of how technological change leads to skill obsolescence and its connection to lifelong learning, see also Allen and de Grip (2007), who found that workers experiencing skill obsolescence are more likely to engage in training.

Training and workplace learning are crucial to counteract skill obsolescence. Workplace learning is often intentional, with jobs designed to provide opportunities for skill development (Eraut, 2000). Jobs requiring new skills or facing rapidly changing requirements offer the highest learning potential (Rosen, 1972). In contrast, repetitive, hierarchical, and low-autonomy roles are expected to limit learning opportunities.

Based on the aforementioned theoretical framework this report will address the following **research questions** (RQs):

RQ_1: How do task complexity and changes in workplace/job characteristics affect participation in job-related training?

RQ_2: How employees' own perception about the obsolescence of their skills and likelihood of losing their job is related with participation in training?

RQ_3: How does the provision of job-related training practices vary by workplace characteristics (e.g. size and sector)?

2.2 Skills mismatch and subjective well-being at work from a capability approach perspective

Relying on the capability approach (Sen, 1992, Nussbaum, 2000), we view skills mismatch as a lack of correspondence between level of acquired skills/education/qualification, on the one hand, and the level of skills/education/qualification required for a job, which leads to capability deprivation with wider consequences for individual well-being than reduced economic benefits alone (see Boyadjieva et al., 2024).

Well-being is one of the central concepts in the capability approach (Nussbaum, 2011; Sen, 1999). Sen (1999) argues that the understanding of well-being should focus on what people can be and can do, rather than simply on what they have. He also emphasises the importance of the quality aspect of life in all its dimensions—family, health, employment, education, leisure, etc. According to Sen (1992), well-being has two aspects: freedom and achievement. Whereas well-being freedom is 'one's freedom to achieve those things that are constitutive of one's well-being' and 'is best reflected by a person's capability set' (Sen, 1992, 57), well-being achievements focus on the concept of functioning.

From the perspective of the capability approach, the level of satisfaction seems inadequate as a simple indicator of subjective well-being. Both Sen and Nussbaum have outlined that individuals – through the so-called "adaptive preferences" – may internalise external constraints and adjust to the circumstances in which they live, which influences their well-being. This process may result in paradoxical situations in which a poor and a rich person report the same levels of satisfaction. According to Robeyns (2017, 137): '[t]wo persons who find themselves in the same objective situation will have a very different subjective assessment, because one is happy with small amounts of 'objective goods', whereas the other is much more demanding.'

The above-reasoning indicates that in order to fully evaluate well-being from the capability approach, it is important to: 1) make 'an effort to take stock of and summarize the full range of elements that people value (e.g. their sense of purpose, the fulfilment of their goals and how they are perceived by others)' (Stiglitz, Sen, and Fitoussi, 2010, 65) and 2) take into consideration some objective information (e.g., the real opportunities that people have).

In this deliverable, we will limit our analysis to the subjective well-being in one specific and very important domain – work. As a rule, subjective well-being at work is related to and measured with job satisfaction and job distress as simple dimensions (Mavromaras et al., 2012; McGuinness and Byrne, 2015; Urbanaviciute, Massoudi, and De Witte, 2024). Many studies show that overeducation results in lower job and life satisfaction (see, e.g., Verhaest and Omey, 2006; Peiró et al., 2010; Diem, 2015; Piper, 2015; Congregado, et al. 2016). Some authors report more nuanced findings, arguing that this is only the case when overeducation is also accompanied by overskilling (see, e.g., Green and Zhu, 2010; Sloane and Mavromaras, 2020). According to Mavromaras et al. (2012) and McGuinness and Byrne (2015) overeducation is only associated with lower job satisfaction for females. Fleming and Kler (2014) further specify that "this effect is particularly strong for females without children at home" (McGuinness et al. 2018, 12).

Basing our understanding of the subjective well-being at work on the capability approach requires taking into account both its instrumental and intrinsic dimensions. Subjective well-being at work refers to the overall subjective state of an individual in relation to different aspects of work environment. We argue that from the capability perspective and having in mind the specificity of the contemporary highly dynamic and rapidly digitalised societies, subjective well-being at work should be defined as a multidimensional phenomenon, which – in addition to individuals' satisfaction with some instrumental dimensions, such as level of payment, working conditions, etc. – includes their attitudes to dimensions that capture intrinsic values: interest in the work, possibilities for continuous learning, acquiring of digital skills and professional growth, interpersonal relations. Taking into account the previous literature on skills mismatch, as well as previous work on well-being and job satisfaction within the capability approach (e.g. Boyadjieva and Ilieva-Trichkova, 2024; Leßmann and Bonvin, 2011), we believe that there is a need for further research on the link between skills mismatch and subjective well-being at work, which applies a more sophisticated understanding of the complexity of subjective well-being at work and pays attention to the moderating effects on this association of different factors at individual level.

More concretely, we will try to answer the following RQs:

RQ_4: How subjective well-being at work can be measured?

RQ_5: How different types of skills/education-job mismatch are associated with subjective well-being at work?

RQ_6: Do individual socio-demographic characteristics moderate the effects of different types of skills/education-job mismatch on subjective well-being at work?

3 Data, variables and research strategy

The analysis in this deliverable is divided into two parts: the first focuses on participation in job-related training, and the second examines the effects of mismatch on subjective well-being at work.

3.1 Data

The empirical basis of our study was individual-level data drawn from the second wave of the Cedefop (2021) Second European Skills and Jobs Survey[4] (ESJS), carried out via both telephone and online interviews. We have used this survey for two reasons: 1) The survey's focus on skill development, skill mismatches and initial and continuing learning of adult workers in the context of EU changing labour markets corresponds to the research questions of the present deliverable, and 2) The survey provides data which allow to apply our theoretical understanding of individual subjective well-being at work as a multidimensional phenomenon.

ESJS is a cross-national survey which targets all adults (aged 25–64) who are in wage and salary employment (i.e. paid employees, excluding those in self-employment and family workers). This group is also relevant to the European Commission's policy, and benchmarks in the field of education have been developed by monitoring the educational attainment of this age group (e.g. European Commission/EACEA/Eurydice 2021), although not specifically focusing on the employed adults. It is important to note that the second wave of ESJS was conducted in 2021, a period still affected by the COVID-19 pandemic. This context could have influenced both participation in job-related training and subjective well-being at work. Evidence suggests that the pandemic led to a significant decline in job-related training, especially among younger and less-educated individuals (Li, Valero, and Ventura, 2021). Furthermore, the pandemic brought about lasting changes in business practices, consumer behaviour, and working arrangements (Barrero, Bloom, and Davies, 2020), which could have altered the demand for certain skills, shaped employees' training opportunities and also affected their well-being.

3.2 Variables

3.2.1 Participation in job-related training

For the job-related training analyses, we used a sample of 28,834 employed adults from 27 countries. As the sample size varies between models, the exact numbers are provided in the Appendices.

The dependent variable used in the analysis is participation in job-related training is derived from the following survey question: "In the last 12 months, have you participated in any education or training activities to learn new job-related skills?" (E_TRAIND).

The analysis includes several independent variables to explore how different factors influence participation in job-related training.

[4] For more details see: Methodology | CEDEFOP (europa.eu)

Skills utilisation is measured based on the extent to which individuals apply their skills, as indicated by the following survey question: "To what extent can you use your current knowledge and skills in your main job?" (E_SKILLU). The original response scale was reversed for the analysis to: 1 “not at all or small extent”; 2 “moderate extent”; 3 “great extent”.

Job complexity is defined in terms of whether work is organised in a way that provides employees with scope for autonomy or requires breadth and depth of learning and generalised creativity and problem-solving capacities (Cedefop, 2022). The items for this index are derived from the question, "How often did you do any of the following activities as part of your main job in the last month?" The index is constructed using variables identified in the Cedefop (2022) report (Annex 3), which demonstrated high construct validity (α = 0.74). Each of these variables was normalised to a 0–1 scale before being combined into a composite index, where a score closer to 1 indicates higher job complexity.

Table 1. *Items used for the construction of job complexity index*

Index	Used ESJS items
Job complexity	Choosing the methods or tools of your work
	Planning your work activities
	Reacting to situations that could not be anticipated
	Working on varying assignments
	Learning new things
	Try to develop or create new or improved products or services
	Try to develop new or improved ways of doing your work

To measure the extent of workplace changes experienced by respondents, a composite variable, *level of workplace changes (scale 0–5)*, was created. This variable measures the cumulative number of specific changes that have occurred in the respondents’ across five dimensions. Each question was coded as 0 ("no") or 1 ("yes"). The composite variable was generated by summing the “yes” answers to the following questions regarding workplace changes in the last 12 months or since the respondents started working there:

1. New management methods (i.e. changes in how the work or pay is managed)
2. New working methods (i.e. changes in how the work is done)
3. New digital technologies (i.e. new computer systems/computer devices/computer programs)
4. New products or services
5. Part of the work done in your workplace was moved to another location or country

Skills obsolescence refers to a situation where a worker's skills become outdated. As McGuiness et al. (2025, p. 319) emphasise "skills can become obsolete due to ageing, which depreciates certain manual skills (physical obsolescence), through technological or economic change, which renders certain skills unnecessary (economic obsolescence), or through the underutilisation of skills (skills atrophy)".

In the ESJS 2014 questionnaire, the skill obsolescence question was formulated as: "Several of my skills will become outdated in the next five years" (rated on a 0–10 scale from "very unlikely" to "very likely". However, this question was excluded from the 2021 questionnaire. This is why, as a proxy for skill obsolescence, we use the following question from the ESJS 2021 data set: "To what extent do you think new digital or computer technologies in your company or organisation need or will need new knowledge and skills you currently do not have?". The response categories are: 1 "Great extent", 2 "Moderate extent", 3 "Small extent", 4 "Not at all". While this question primarily reflects the anticipated need for new knowledge and skills due to technological change, which as mentioned above is one of the relevant reasons for skills obsolescence, we interpret it as an indirect indicator of potential skill obsolescence. Although it does not measure skill obsolescence directly, it offers valuable insight into the perceived pressure to update skills, which can signal a broader risk of skill obsolescence.

To analyse *perceptions of job insecurity* the following variable was used "Do you think there is any change at all of you losing your main job in the next twelve months?". Responses to this variable has the following categories[5]: 1 "Yes, a very high chance", 2 "Yes, some chance", 3 "No chance at all".

The analysis includes several *control variables*: Gender (male, female), age group (25–39, 40–54, 55–65), highest educational level (lower secondary education or below (ISCED 0–2), upper secondary (ISCED 3), post-secondary non-tertiary (ISCED 4), and tertiary education (ISCED 5–8), occupational groups[6] (high-skilled white-collar, low-skilled white-collar, high-skilled blue-collar, low-skilled blue-collar), firm size (1–10, 11–49, 50–249, 250 and more), previous main activity (employed in another job, self-employed, in education and training, unemployed, inactive), tenure in the current company (years), sector[7], type of sector (public, private, not for profit, other sector), contract type (permanent, temporary, no contract) and work routinisation index[8].

---

[5] We excluded those who answered "don't know or no answer".
[6] The occupational groups are classified according to ISCO-08: high-skilled white-collar jobs (ISCO 1–3), low-skilled white-collar jobs (ISCO 4–5), high-skilled blue-collar jobs (ISCO 6–7), and low-skilled blue-collar jobs (ISCO 8–9).
[7] Sectors are classified based on NACE codes as follows: Sector 1 includes agriculture, forestry, and fishing; Sector 2 covers industry, construction, and transport; Sector 3 comprises wholesale and retail trade, accommodation, and food service activities; and Sector 4 includes professional, scientific, and technical activities, administrative and support service, public administration, defence, education, human health and social work activities, and other service activities.
[8] This index is constructed using variables identified in the Cedefop (2022) report using two items: task repetitiveness and following fixed procedures. Each of these variables was normalized to a 0–1 scale before being combined into a composite index, where a score closer to 1 indicates higher work routinisation.

3.2.2 Subjective well-being at work

For the subjective well-being at work analyses, after performing some list-wise deletion of the cases with missing values on one or more of the independent (except for the variables which measure different types of mismatch, control and dependent variables, we ended up with an analytical sample consisting of 30,585 employed adults nested within 27 countries. Still, this analytical sample differs in the models in which we have included different measures of mismatch. Details on the measurement issues are presented below.

In order to measure *subjective well-being at work*, we have developed an index with 10 items from the ESJS questionnaire from question Q64. 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?

Table 2. *Items used for the construction of subjective well-being at work index*

Index	Used ESJS items
Subjective well-being at work	Digital or computer technologies you use
	Job security
	Promotion/career prospects
	Pay and benefits
	Working conditions
	Interest in the work itself
	Work-life balance
	Training provided
	Relations with supervisor or manager
	Relations with colleagues

These items are very relevant as on the one hand, they complement the concept of job satisfaction with the concept of valuable work and allow for taking into account its multidimensionality (Leßmann and Bonvin, 2011), but on the other hand, items such as interest in work, training provided at the workplace as well as the digital or computer technologies are indispensable for understanding and evaluating jobs and working conditions in contemporary highly dynamic and digitalised world.

Thus, in accordance with the dimensions of the concept of subjective well-being at work, an index was developed from these 10 items, which was used as *dependent variable* in our analyses. All variables were standardized (converted into *z*-values) and then into z-scores which range between 0 and 100. The Index of subjective well-being at work was formed by averaging the comprising items. Its internal consistency, measured with Cronbach Alpha, was 0.95, Mean = 50, SD = 16.48. We have also tested the validity of this index by:

1) carrying out principal component analysis in which we have included these 10 items. It has shown that only one main component emerged from the analysis, having Eigenvalue above 1. In this case its value was 6.80.

2) testing if the developed new index is associated with other well-known and widely used measures of subjective well-being at work such as overall job satisfaction, which is available in the ESJS for the 27 studied countries. The correlation analysis, which we carried out, has shown that the index of subjective well-being at work is positively associated with the measure of overall job satisfaction, but still there is no full overlap between our index and this measure (Pearson's $r = 0.629$, $p < 0.001$). This suggests that with our index we grasp other important aspects of subjective well-being at work than the overall job satisfaction.

We have included two groups of *independent variables* in our analyses: a) the various forms of mismatch, available in the data, b) individual socio-demographic characteristics: gender, age, level of education, occupational status.

Acknowledging that so far, there is no uniform, undisputable typology or measurement framework regarding skills and education-job mismatch (see Quintini, 2011; ILO, 2014), in this deliverable to measure skills mismatch, we will use in the analysis the following independent variables:

1) *Level of education required for the job* in three categories: Q50. What is the level of education usually needed nowadays to do a job like your main job? 1) Lower secondary education or below (ISCED 0–2); 2) Upper secondary or post-secondary non-tertiary (ISCED 3–4) and 3) Tertiary education (ISCED 5–8).

2) *Education completed compared to education required by job* in three categories: 1) Higher level of education than job required; 2) Same level of education as job required; 3) Lower level of education than job required.

3) *Horizontal mismatch* in three categories: Q51. Considering your main subject or field of study at your highest level of education (business, engineering, health etc.), how relevant is it for doing your main job?: 1) No mismatch (in which we included the answers categories: "The job exclusively requires your field"; and "The job requires your field or a related field"); 2) The job mostly requires a different field and 3) The job does not require a specific field.

4) *Skills utilisation* in three categories: Q60. To what extent can you use your current knowledge and skills in your main job?: 1) Great extent; 2) Moderate extent 3) Small extent or not at all (we combined these answers in one category).

5) *Skills obsolescence* in three categories Q67b. To what extent do you think new digital or computer technologies in your company or organisation...? ...need or will need new knowledge and skills you currently do not have?: 1) Great extent; 2) Moderate extent 3) Small extent or not at all (we combined these answers in one category).

We include in the analyses the following socio-demographic variables at individual level: *gender* in two categories[9]: 1) Male; 2) Female; *age* (continuous); *level of education*[10] in three categories: 1) ISCED 0–2; 2) ISCED 3–4; 3) ISCED 5–8; and *occupational group*[11] in three categories: 1) ISCO 1–3 (refers to managers, professionals, technicians and associate professionals), 2) ISCO 4–6 (includes clerical support workers, service and sales workers and skilled agricultural, forestry and fishery workers) and 3) ISCO 7–9 (refers to craft and related trades workers, plant and machine operators, and assemblers and elementary occupations). As a *control variable* we use *place of living* in three categories: 1) Rural area or village; 2) Small or middle-sized town and 3) Large town or city.

3.3 Research strategy

The first part of the analysis focuses on participation in job-related training, employing multilevel modelling. Specifically, we used two-level logistic regression models to account for the nested structure of the data, with individuals (level 1) nested within 27 countries (level 2). We estimated several models to examine the factors associated with job-related training participation. Predicted probabilities of training participation were calculated based on these models and are presented in the figures in the result section (full models with estimates are available in the Appendices).

The second part of the analysis, focusing on the subjective well-being at work uses also multilevel modelling technique. More specifically, we have used two-level linear regression models. Usually, multilevel models are preferable in cases when the intraclass correlation (ICC) of the null model is 0.05 (Hox, 1998). However, the null model in our case is about 0.02, which means that there is not so much variation in the dependent variable (only 2%), which can be due to grouping of individuals in countries. So, we could also easily apply ordinary linear model, but still the estimates of these models are considered to be more precise than the estimates in linear regression models (e.g. Rabe-Hesketh and Skrondal, 2012). This is why, we have used them with fixed effects. Furthermore, the number of countries we have in the analyses is above 25, which is considered as the minimum number of groups that are sufficient for applying multilevel linear regression models (Bryan and Jenkins, 2016).

More specifically, we estimated seven multilevel linear models. Model 1 includes all independent variables and the control variable. In models 2–6 each of the five types of mismatch are included separately. In model 7 all five types of mismatch are included alongside the independent variables. We have also estimated four models with interaction effects between gender, age, level of education and occupational group and every of the five types of mismatch. For facilitation of the interpretation of the interactions, only the statistically significant ones are presented graphically.

---

[9] The questionnaire included one more category: None of the above/ Non-binary/ Do not recognise yourself in the above categories, but there were only 24 respondents which gave this answer, which is 0.08% of the analytical sample. No reliable analysis could be done and this is why we have deleted these cases from the analytical sample.

[10] The highest level of education completed is measured in the ESJS 2021 with the 2011 International Standard Classification of Education (ISCED).

[11] For distinguishing the occupational groups, we have applied the International Standard Classification of Occupations (ISCO) version 08, which was used in the ESJS 2021.

Skills2Capabilities

Co-funded by the European Union

4 Results

Descriptive analysis (see Appendix Figure A1) shows notable differences in participation rates in job-related training between European countries. The lowest participation is observed in France (50.7%), while the highest is in Ireland (73.6%).

The results highlight that participation in job-related training remains substantial across most countries, with several exceeding 60%. This variation suggests that country-specific factors—such as national policies, workplace practices, and sectoral composition—may influence the likelihood of employees engaging in training. While we acknowledge that participation patterns vary across countries due to institutional differences, this current deliverable uses pooled data and does not focus on country-specific or macro-level variations. However, these results present opportunities for future research to explore more specifically how institutional and policy differences influence training participation at the country level.

4.1 The association of skill utilisation, job complexity and workplace changes on participation in job-related training

The following subsection explores how the extent of skills utilisation and job complexity influence employees' likelihood of participation in training programs. Figure 1 reveals differences in job-related training participation across varying levels of skills utilisation. The analysis shows that workers who do not use their current knowledge and skills at all or only to a small extent in their main job are less inclined to participate in training programs compared to those who utilise their skills on a higher level. However, no significant difference in participation rates is observed between workers who utilise their skills moderately and those who do so to a great extent, as indicated by overlapping confidence intervals. The results in Figure 1 seem relatively weak. This could be due to the fact that the question, "To what extent can you use your current knowledge and skills in your main job?" is somewhat unprecise. This lack of precision may result in some individuals being unsure whether they fall into the 'moderate' or 'great' utilisation category. As a result, we may not observe a clear difference in training participation between these two categories.

These findings suggest that higher levels of skills utilisation encourage greater participation in job-related training. Workers who actively apply their knowledge and skills in their jobs are more likely to recognize the value and relevance of continuous learning, motivating them to engage in further training[12]. Additionally, employers may be more inclined to invest in training for employees who are already effectively leveraging their current skill sets, as the potential productivity gains from such investments may be more evident to them.

[12] However, it is also possible that the relationship may be bidirectional: workers who receive training might be more inclined to apply the knowledge they have acquired, thus utilising their skills on a higher extent.

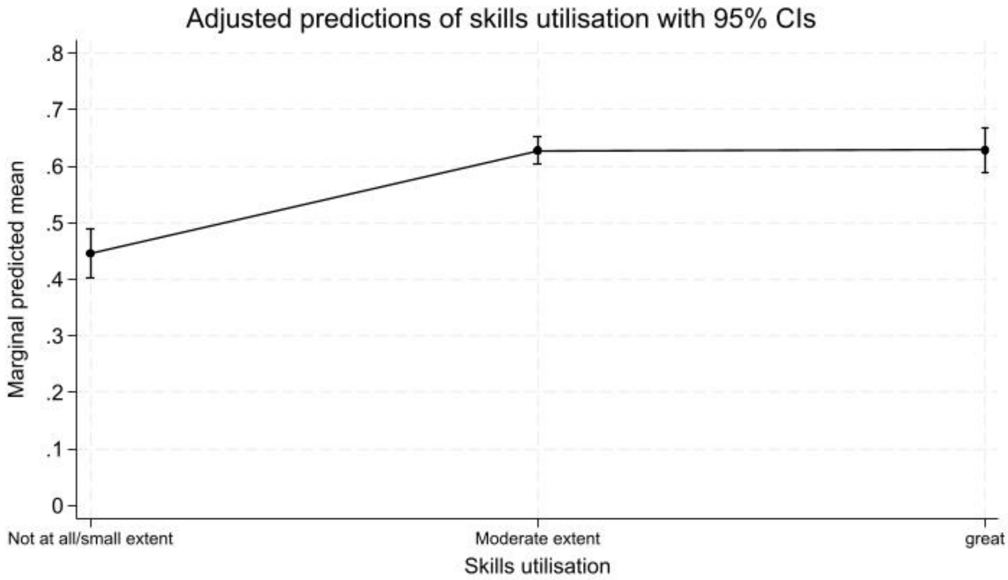

***Figure 1.** Predicted probabilities of job-related training participation at different levels of skills utilisation.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 1 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

Results from the multilevel regression model in Figure 2 reveal that higher job complexity significantly increases the likelihood of participating in job-related training. This finding aligns with the theoretical framework that emphasises the role of job tasks and their complexity in shaping training needs and opportunities (Schindler et al., 2011). Complex jobs often present challenges that require continuous skill development and adaptation, particularly in technology-driven fields where work environments are rapidly evolving (Bresnahan et al., 2002). Workers in these roles are more likely to engage in training to meet the demands of their dynamic job requirements, highlighting the strong connection between job complexity and training participation that we also see from the current analysis.

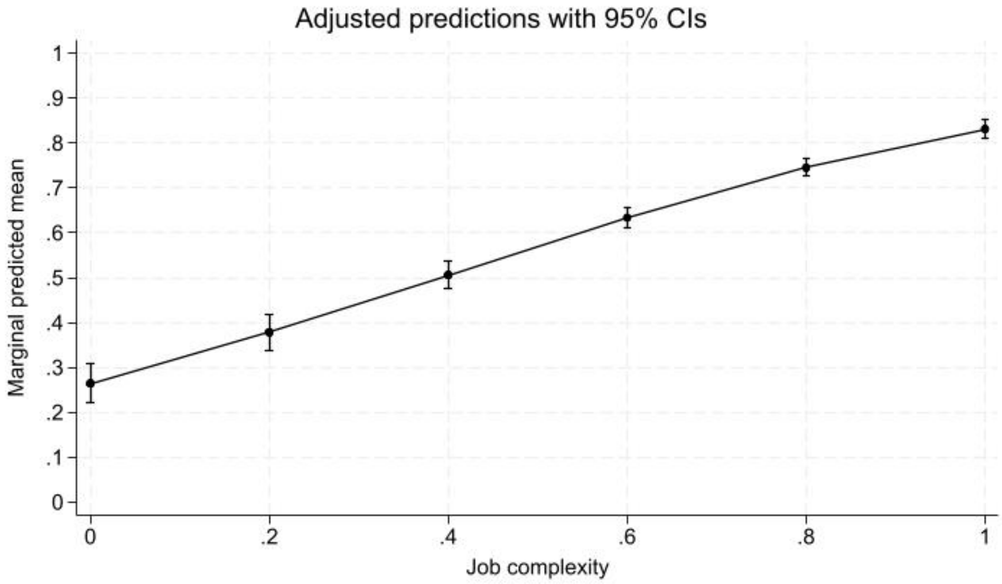

Figure 2. *Predicted probabilities of job-related training participation at different levels of job complexity.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 2 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

Workplace changes, such as the introduction of new management practices, working methods, digital technologies, new products or services, and workplace relocations, often require employees to acquire new skills to effectively adapt to these shifts. Figure 3 results indicate also a positive relationship between the extent of workplace changes and participation in job-related training. This suggests that for each additional workplace change experienced, the likelihood of participating in training increases. This can be explained by the circumstances that as organisations evolve, employees are more likely to engage in training to stay current with new processes and technologies, with employers also providing more training opportunities. This supports the idea that workplace changes act as a catalyst for training participation. These findings highlight the importance of a dynamic work environment in promoting continuous learning and adaptation to meet the demands of shifting job roles and responsibilities. This is consistent with Deming (2017) and Deming and Noray (2020), who argue that technological advancements are reshaping the labour market by increasing the demand for certain skills while making others less relevant or even obsolete, further reinforcing the notion that as workplace changes increase, so too does engagement in training.

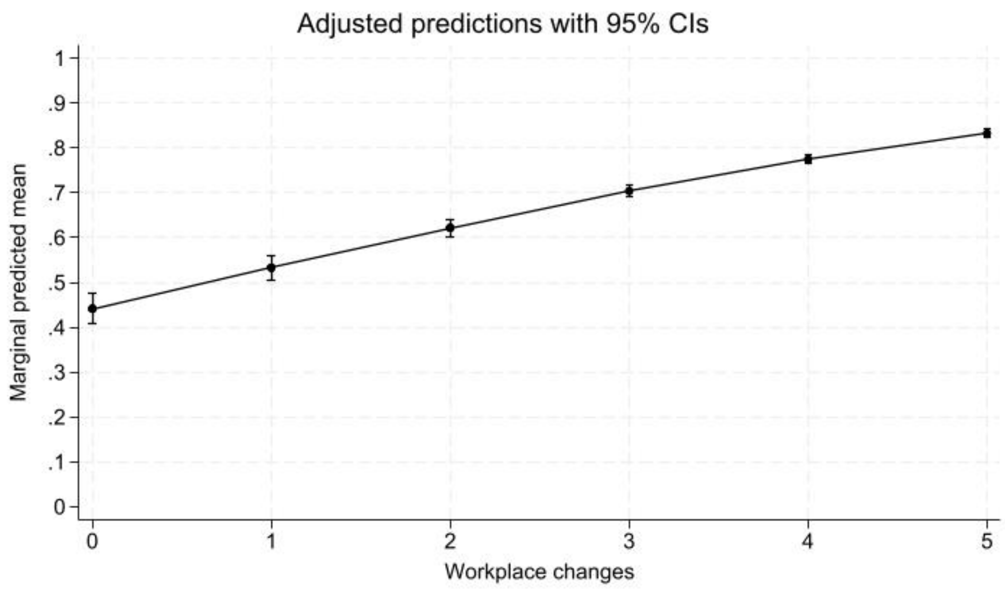

***Figure 3.** Predicted probabilities of job-related training participation at different levels of workplace changes.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 3 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

4.2 The relation of skills obsolescence and job insecurity on participation in job-related training

The results in Figure 4 reveal a clear relationship between perceived skill obsolescence[13] and participation in job-related training. Employees who believe that new digital or computer technologies will require new knowledge and skills to a great extent are the most likely to participate in training. This likelihood decreases as the perceived extent of (possible) skill obsolescence diminishes. Notably, the probability of participation for those who answered "moderate extent" and “small extent” does not differ significantly, suggesting similar levels of engagement between these groups.

It is important to clarify that while we use this variable as a proxy for skill obsolescence, the perceived need to acquire new skills does not necessarily imply that employees believe their current skills have become irrelevant or outdated. Instead, employees may see new skills as a complement to their existing skill set rather than replacement. Thus, their training participation may reflect both a proactive response to evolving job requirements and a desire to expand their competencies.

Overall, these findings suggest that employees who perceive a higher need for new knowledge and skills that they currently do not have are significantly more inclined to engage in training, while

[13] The following variable was used from the data set for skill obsolescence analysis: “To what extent do you think new digital or computer technologies in your company or organisation need or will need new knowledge and skills you currently do not have?”

those who believe their current skills are sufficient to adapt to these changes are the least likely to participate.

These results align with the theoretical framework on technological change and prior research on technological advancements in the labour market. As previous research has shown (Dickerson and Green, 2004; Deming, 2017; Deming and Noray, 2020), technological change reshapes the labour market by increasing demand for certain skills while making others obsolete. Consequently, many existing skills lose relevance and are replaced by new or previously less important ones (Welch and Ureta, 2002).

The findings of this study similarly indicate that individuals who perceive a greater extent that their skills are becoming obsolete – and recognise the need for new knowledge and skills – are significantly more likely to participate in training. This is consistent with the work of Allen and de Grip (2007), who found that employees facing skill obsolescence are more inclined to engage in training.

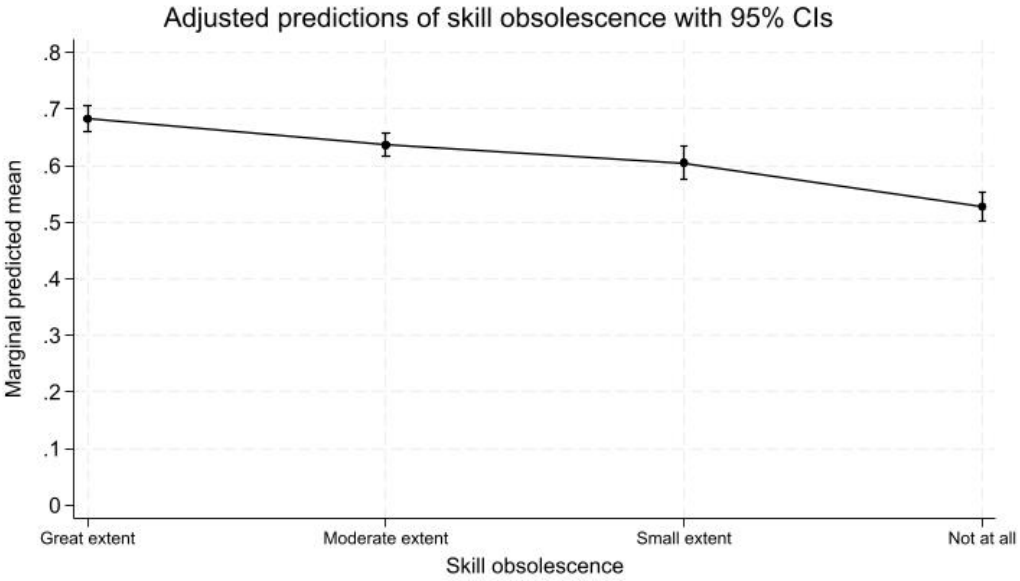

Figure 4. *Predicted probabilities of job-related training participation at different levels of perceived skill obsolescence.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 4 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

Figure 5 illustrates the relationship between perceptions of job insecurity and participation in job-related training. Employees who perceive a "very high chance" of losing their job within the next twelve months have a predicted probability of 59.9% of participating in training. This probability increases slightly to 62.1% for those who perceive "some chance" of job loss, and then slightly decreases to 60.8% for those who believe there is "no chance at all." While the probabilities show minor variation across categories, the overlapping confidence intervals suggest that these differences are not statistically significant. Therefore, participation in job-related training does not appear to vary significantly based on perceived job security risk.

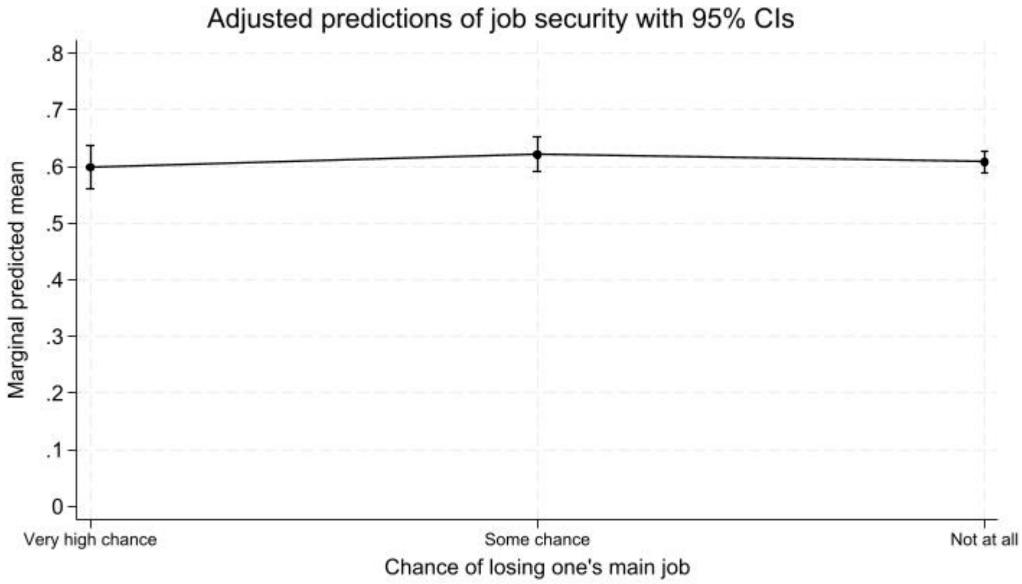

Figure 5. *Predicted probabilities of job-related training participation at different levels of perceived chance of losing one's job.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 5 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

4.3 Job-related training practices by workplace characteristics

Workplace characteristics play a crucial role in shaping opportunities for participation in job-related training. The results in Figure 6 reveal that firm size is associated with the likelihood of participating in training. Employees in small firms (1–10 employees) have a notably lower likelihood of participating in job-related training compared to those in somewhat larger and significantly larger firms.

These findings are overall consistent with previous research showing that larger firms generally offer more training opportunities due to their specific training budgets and more formalised training structures (OECD, 2012). For employees in larger firms (11–49, 50–249, and 250+ employees), the predicted probabilities are higher, ranging from 0.61 to 0.64. However, the overlapping confidence intervals suggest that these groups do not differ significantly from each other in terms of training participation. This indicates that while training participation is lower in small firms (1–10 employees) compared to larger companies, the results do not show a consistent increase in training participation as company size grows.

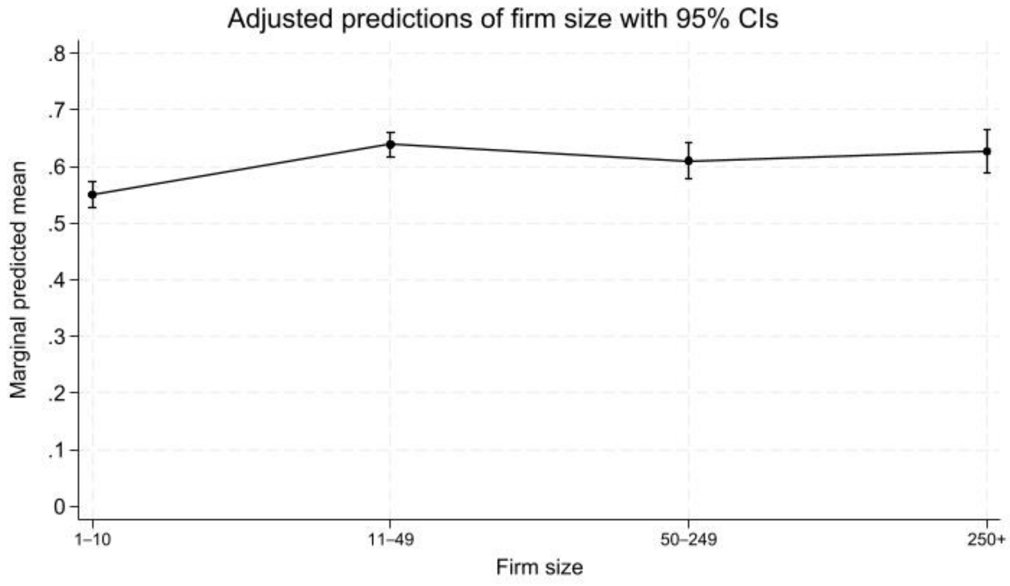

Figure 6. *Predicted probabilities of job-related training participation by firm size.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 5 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

There are also differences in participation in job-related training across sectors[14] as classified by NACE. Employees in Sector 4 have the highest probability of participation. This finding aligns with previous research showing that these sectors often benefit from well-developed training infrastructures and state-financed programs (OECD, 2003; Cedefop, 2015; Roosmaa, 2021; Desjardins, 2020). While Sector 4 stands out with the highest participation likelihood, the overlapping confidence intervals for Sectors 1, 2, and 3 suggest that participation rates among the other sectors do not differ.

[14] Sectors are classified based on NACE codes as follows: Sector 1 includes "Agriculture, forestry, and fishing"; Sector 2 covers "Industry, construction, and transport"; Sector 3 comprises "Wholesale and retail trade, accommodation, and food service activities"; and Sector 4 includes "Professional, scientific, and technical activities, administrative and support service, public administration, defence, education, human health and social work activities, and other service activities".

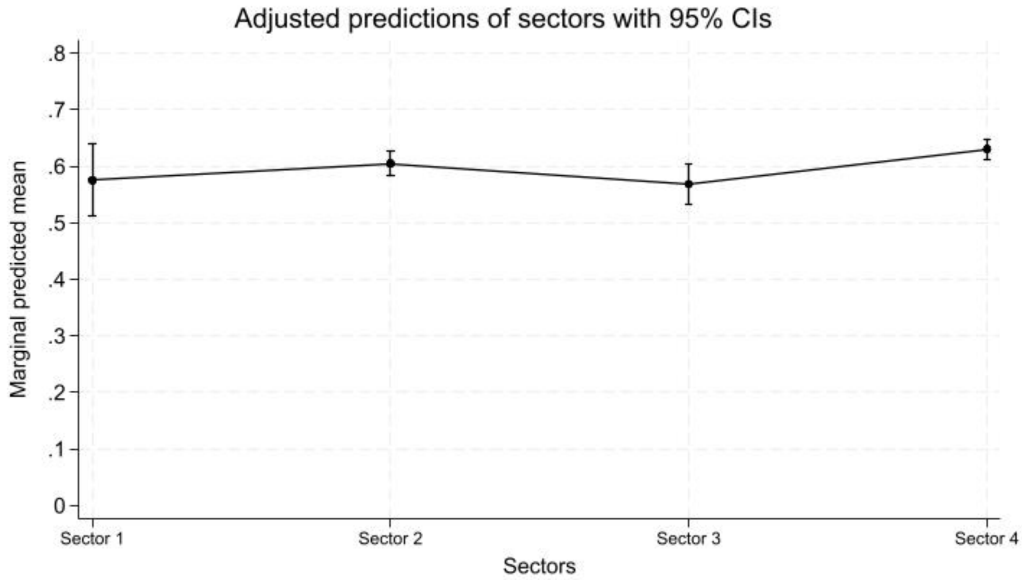

Figure 7. *Predicted probabilities of job-related training participation by sectors.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 5 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

Furthermore, participation in job-related training varies across different sector categories, such as public, private, not-for-profit, and other. Employees in the not-for-profit sector have the highest predicted probability of engaging in training, followed closely by the public sector, which suggests that training opportunities are widely available and encouraged in these types of sectors. This result is consistent also with previous research showing that public sector jobs generally offer structured training programs and have greater demands for continuous skill upgrading (Roosmaa, 2021; Desjardins, 2020). Although, the wide confidence intervals for the not-for-profit sector indicate some uncertainty of the estimates, likely due to a smaller sample size.

In contrast, employees in the private sector have a lower probability of participation in training, reflecting fewer training opportunities compared to the public and not-for-profit sectors. This finding confirms the results of earlier studies indicating that training participation is generally lower in the private sector due to greater reliance on on-the-job learning and fewer state-financed training initiatives. The "other" sector category shows a predicted probability of 0.64, which is lower than that of the not-for-profit sector (0.70) but higher than the private sector (0.58). However, since its confidence intervals overlap with those of the public sector (0.67), the probability of participation in training does not differ significantly between these two categories. The wider confidence intervals for the "other" sector suggest some variability, likely due to a smaller sample size, which limits the precision of this estimate.

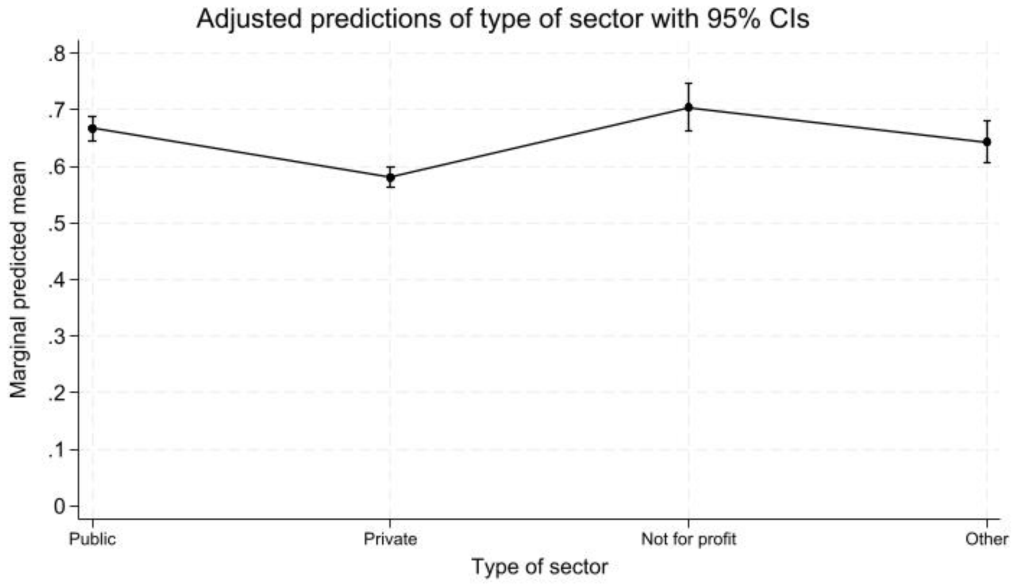

Figure 8. *Predicted probabilities of job-related training participation by type of sectors.*

Source: ESJS 2021, own calculations based on mixed-effects logistic regression Model 5 in Table A1 (see Appendix). All other covariates in the model were set to their respective means for these predictions.

4.4 Skills mismatch and subjective well-being at work

Descriptive analysis (see Appendix Figure A2) shows the average scores of the index of subjective well-being at work, which we have constructed according in 27 European countries. Overall, our calculations show that there are not major country variation between the scores of the index of subjective well-being among the employed adults. The lowest score of the index is in Italy (46.3) and highest in Iceland (54.5). The results also show that there is a huge scope for improvement of the subjective well-being at work for all studied countries, as in any of them there are no scores close to 100.

The summarised results of the analyses of the first set of models (Models 1–7) are presented in Table 3. More specifically, Model 1 demonstrates that the higher the level of education, the higher the employed adults' level of subjective well-being at work given the other covariates (see the variables used in the analysis here).

The estimates also reveal that the occupational group matters for the subjective well-being at work. More specifically, those adults who are employed in occupations, which can be classified in ISCO 4–6 categories, and especially those working in occupations which fall into some of the ISCO 1–3 occupations[15] have higher level of subjective well-being at work compared to those working in occupations which can be classified in ISCO 7–9 categories. Model 1 also shows that the employed adults who are living in large town or city report on average 0.707 higher scores of subjective well-being at work than those living in rural area or village. These findings highlight the importance of the acquired level of education and occupation for subjective well-being at work. The higher level of

[15] In this category are those occupations, which usually require tertiary qualifications.

subjective well-being at work in occupations such as managers and professionals, compared to service and sales workers or plant and machine operators indicate that they provide better working conditions in terms of payment, career opportunities and working environment. We suggest that the lower level of subjective well-being at work for people living in rural areas reflects the fact that, as a rule, these people are employed in occupations classified in lower ISCO categories.

Regarding the other individual level characteristics, being female is associated with lower level of subjective well-being at work in comparison to that of being male. This is in line with other studies (Mavromaras et al., 2012; McGuinness and Byrne, 2015) which reveal that overeducation is associated with lower job satisfaction for females.

In models 2–6, we include all five forms of mismatch separately. The analysis shows that each of them matters for subjective well-being at work, holding all above-mentioned covariates constant. More specifically, the higher is the level of education required for the job, the higher is the subjective well-being at work (Model 2). Interestingly, Model 3's estimates show that those adults who are employed in jobs where the same or lower level of education for the job is required than the level completed by them, they have reported significantly higher level of subjective well-being at work than those who are employed in jobs which require higher level of education than the one completed by them (respectively with 2.542 and 2.845 scores higher).

Model 4 shows that the presence of horizontal mismatch is associated with lower level of subjective well-being at work. In this model, the number of cases has considerably reduced as this variable refers only to those who reported their field of study (ISCED 3 and above). The analysis reveals that those who are having jobs which mostly require a different field report lower level of subjective well-being at work in comparison to those who are employed in jobs which match their field of study. The difference in the subjective well-being at work of about -3.839 scores. In the case of those adults who are employed in a job which does not require a specific field, their level of subjective well-being at work is about 4.578 scores lower than that of adults who are employed in jobs which match their field of study. The above results reveal that both vertical and horizontal mismatch matter for subjective well-being at work but in different way.

The estimates also show that the lower is the level of reported skills' utilisation in work, the lower is the subjective well-being at work (Model 5). Thus, those adults who say that use their skills at moderate extent report on average 6.431 scores lower in comparison to those who mentioned that they did so to a great extent. In the case of adults who report that they used their skills to small extent or not at all the difference is even more considerable. On average, these adults report -12.839 lower scores of subjective well-being at work in comparison with the reference category (those who said that they used their skills to a great extent). This finding suggests that in order to increase the employees' subjective well-being at work employers should take care of the way employees' skills are utilised.

In the case of model 6 where we added a proxy of skills obsolescence, the analyses show that the lesser is the extent to which employed adults assess that new digital or computer technologies in their company or organisation would need new knowledge and skills they currently do not have, the lower is the subjective well-being at work.

***Table 3.** Results of multilevel linear models showing associations between subjective well-being at work and different forms of mismatch, regression coefficients*

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Level of education (ref ISCED 0-2)							
ISCED 3-4	2.951***	.864*	3.312***	(base)	2.601***	2.977***	(base)
ISCED 5-8	4.201***	.231	5.193***	.684*	3.897***	4.246***	-.256
Age	.007	.003	.005	-.029*	-.031***	.008	-.068***
Gender (ref male)							
Female	-.549**	-.054**	-.488**	-.954***	-.625***	-.559**	-1.221***
Place of living (ref rural area or village)							
Small or middle-sized town	.152	.072	.100	-.237	.123	.152	-.189
Large town or city	.707**	.578*	.661*	.378	.603*	.688**	.297
Occupational group (ref ISCO 7–9)							
ISCO 4–6	2.24***	1.422***	1.982***	3.588***	1.219***	2.274***	2.108***
ISCO 1–3	5.001***	3.512***	4.415***	5.698***	2.724***	5.02***	3.114***
Level of education required for the job (ref ISCED 0–2)							
ISCED 3–4		3.607***					2.91***
ISCED 5–8		6.39***					4.598***
Education completed compared to education required by job (ref higher level of education than job required)							
Same level of education as job required			2.542***				-0.258
Lower level of education than job required			2.845***				-1.467**
Horizontal mismatch (ref no mismatch)							
The job mostly requires a different field				-3.839***			-1.99***
The job does not require a specific field				-4.578***			-1.427***
Skills utilisation (ref great extent)							
Moderate extent					-6.431***		-6.345***
Small extent or not at all					-12.839***		-12.1***
Skills obsolescence (ref great extent)							
Moderate extent						-2.72***	-1.535***
Small extent or not at all						-1.692***	-0.359
Constant	43.26***	42.99***	41.26***	49.17***	50.86***	45.07***	53.76***
ICC	0.021	0.021	0.020	0.019	0.022	0.021	0.022
Number of cases	30,560	30,546	30,539	19,132	30,560	30,540	19,106

Source: Own calculations based on the ESJS 2021 for employed adults 25–64, using multilevel linear regression modelling. * p<0.05; ** p<0.01; *** p<0.001.

In model 7 all variables which measure different types of mismatch studied are included. The estimates are lower, but still statistically significant for all categories of mismatch, except for adults who reported same level of education as job required, there was no statistically significant difference with those who reported that they higher level of education than job required which served as a reference category in our analyses and for those who reported small extent or not at all on the question about the extent to which they think new digital or computer technologies in their company or organization will need or will need new knowledge and skills they currently do not have in comparison to those who answered great extent on this question.

At a next stage we tested if there are individual level interaction terms between various individual level socio-demographic characteristics and the five types of mismatch studied. To facilitate the interpretation, we have plotted only the significant interaction terms (Figures 9–12).

Figure 9 shows that having ISCED 3–4 is associated with higher level of subjective well-being at work in comparison with those adults who are with low levels of education (ISCED 0–2). As regards to those who reported ISCED 5–8 as level of education which is required for their job this is associated with higher levels of subjective well-being at work for both those adults who have reported either ISCED 3–4 or ISCED 5–8 as their highest level of education than those who are with low levels of education (ISCED 0–2).

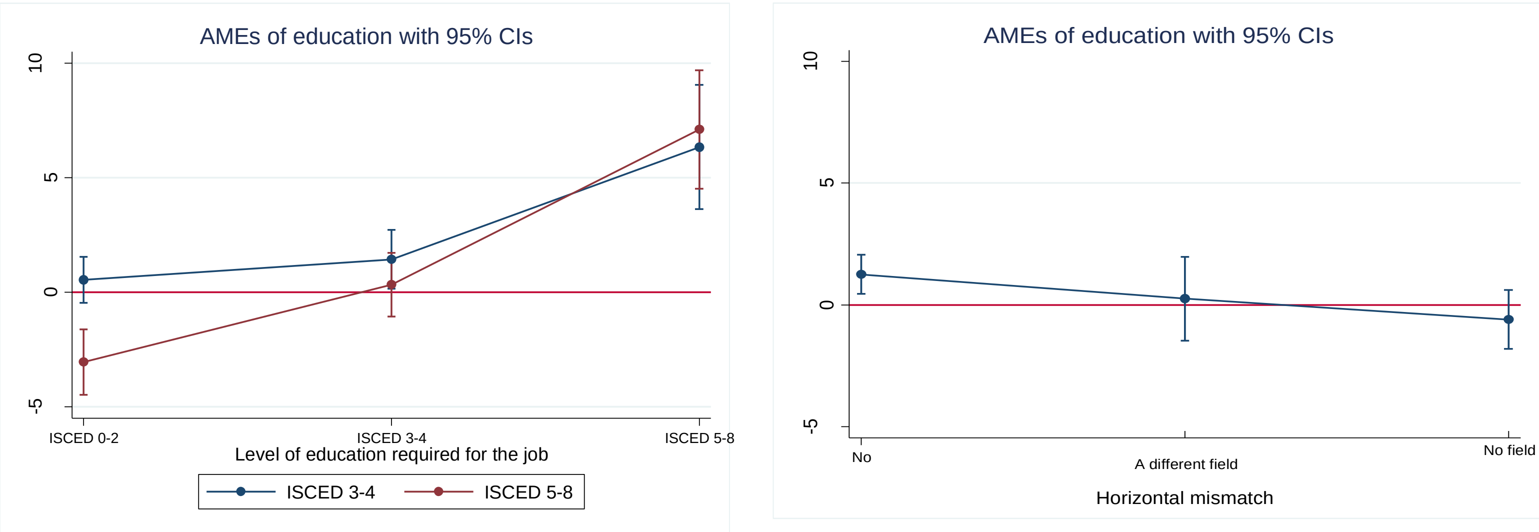

Figure 9. *Average marginal effects (AMEs) of significant individual level interaction terms between education and different types of mismatch on subjective well-being at work (SWBW).*

Source: Own calculations based on the ESJS 2021 for employed adults 25–64, using multilevel linear regression modelling (the full models' estimates are available at request).

In the case of the horizontal mismatch a significant interaction term was found only between adults having a tertiary degree and those who reported that their job does not require specific field. This term is negative. If higher education graduates reported that their job does not require any specific field their level of subjective well-being at work is lower in comparison to that of adults who have ISCED 3–4 and who also reported that their job does not require specific field.

Figure 10 illustrates the significant individual level interaction terms between age and different forms of mismatch on subjective well-being at work. In the case of the level of education required, this term is negative, indicating that higher level of education required for the job is associated with lower levels of subjective well-being at work for those who are older. In the case of educational-job mismatch, there is a positive interaction term between age and reporting that the education completed was lower compared to the education required for the job regarding the level of subjective well-being at work. In the case of the skills obsolescence, there is a positive interaction term with age for employed adults who reported that they think that new digital or computer technologies in their company or organisation will need new knowledge and skills that they currently did not have to small extent or not at all.

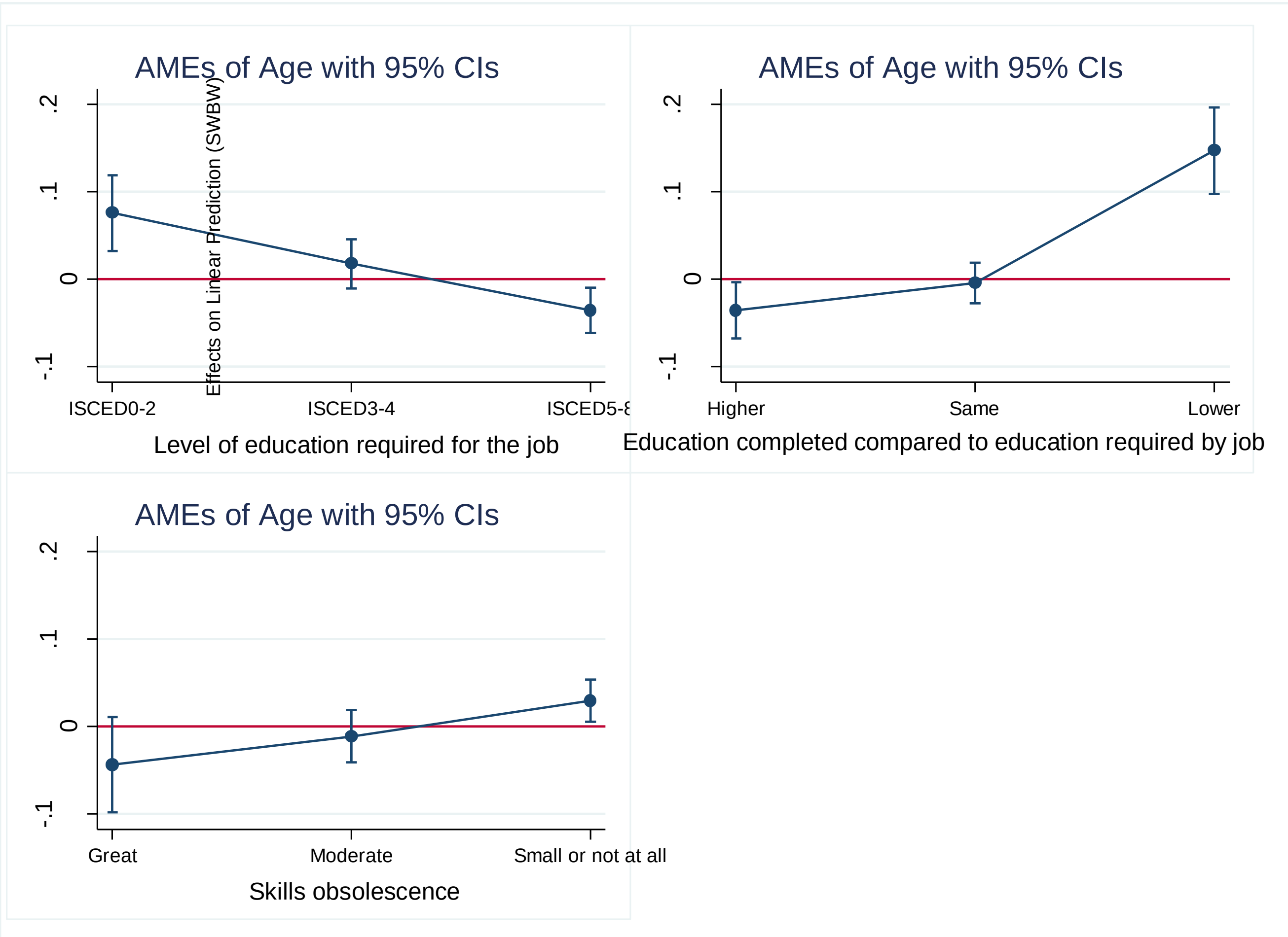

Figure 10. *Average marginal effects (AMEs) of significant individual level interaction terms between age and different types of mismatch on subjective well-being at work (SWBW).*

Source: Own calculations based on the ESJS 2021 for employed adults 25–64, using multilevel linear regression modelling (the full models' estimates are available at request).

In the case of the interaction between gender and different types of mismatch on individual subjective well-being at work, the significant terms are presented in Figure 11. The analysis shows that employed adults with female gender have higher level of subjective well-being at work than males in the case when the job requires a different field or does not require a specific field. Female employees also had higher level of subjective well-being at work in cases when they reported that they had used their skills to moderate or to small extent or when they think that new digital or computer technologies in their company or organisation will need new knowledge and skills that they currently did not have to small extent or not at all.

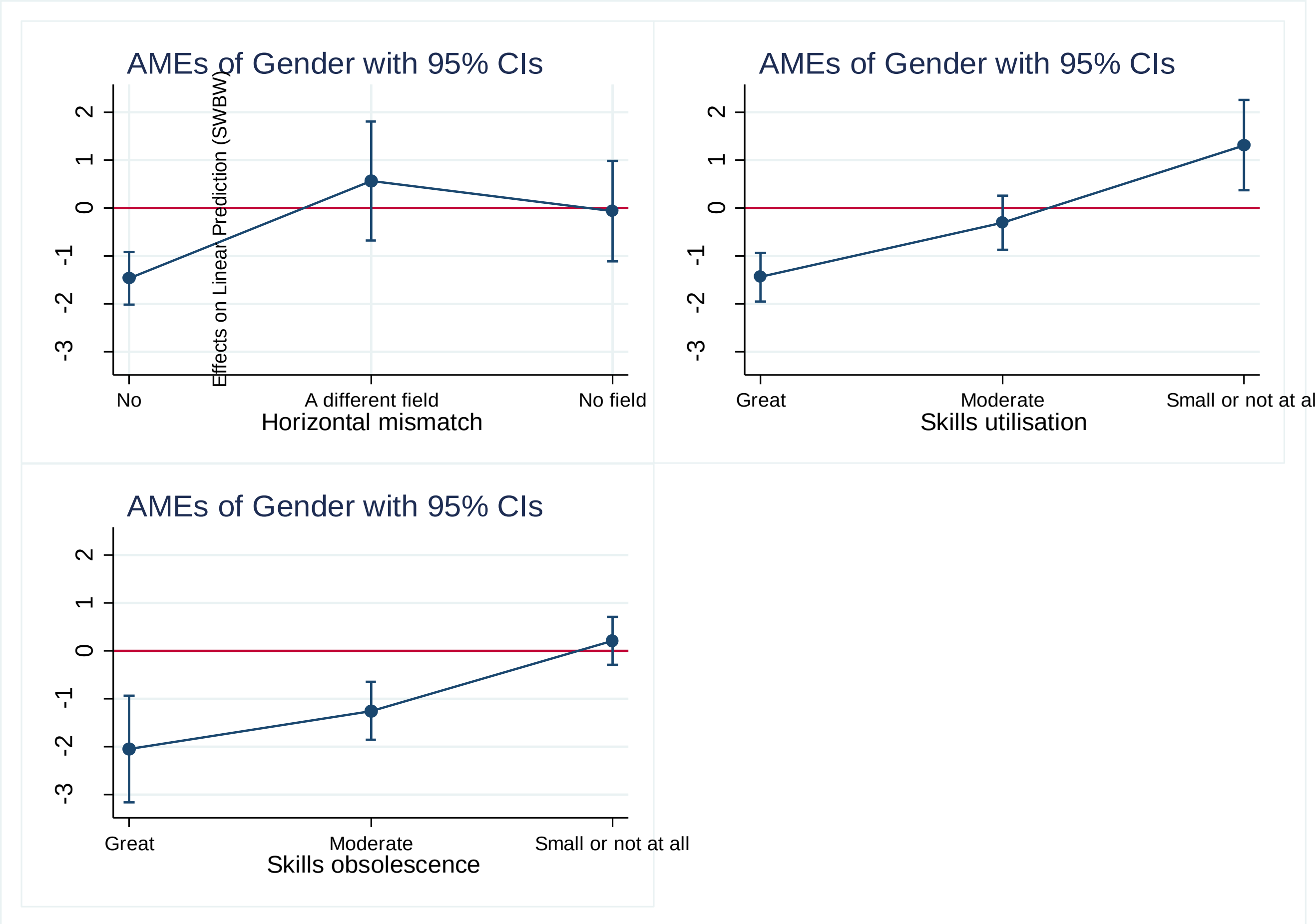

Figure 11. *Average marginal effects (AMEs) of significant individual level interaction terms between gender and different types of mismatch on subjective well-being at work (SWBW).*

Source: Own calculations based on the ESJS 2021 for employed adults 25–64, using multilevel linear regression modelling (the full models' estimates are available at request).

As regards the interactions between occupational groups and different types of mismatch on subjective well-being at work, the significant interaction terms are presented in Figure 12. The analysis shows that only in the case of adults who reported that ISCED 5–8 of education is required for their job, those who are with occupations ISCO 4–6 have significantly higher level of subjective well-being at work in comparison to those who are with occupations which can be classified in some of the ISCO 7–9 categories. At the same time, adults who are employed in occupations in ISCO 1–3 categories report significantly higher levels of subjective well-being at work in comparison with those who have occupations from ISCO 7–9 categories in the cases when ISCED 3–4 and especially when ISCED 5–8 is required for their job.

The analysis further shows that although adults with ISCO 1–3 occupations have significantly higher levels of subjective well-being at work than that reported by adults who are employed in ISCO 7–9 occupations when they are employed in jobs which require same or lower levels of education by their job the difference in subjective well-being at work between these two occupational groups become smaller.

Regarding the level of skills utilisation, we observe that although adults having occupations which fall into ISCO 1–3 categories report a higher level of subjective well-being at work than those who are employed in ISCO 7–9 occupations, when they use their skills in work to a small extent or not at all their level of subjective well-being at work is significantly lower. This suggests that people who are employed in more complex and advanced occupations (managers, professionals) are more sensitive towards any loss and underuse of their skills.

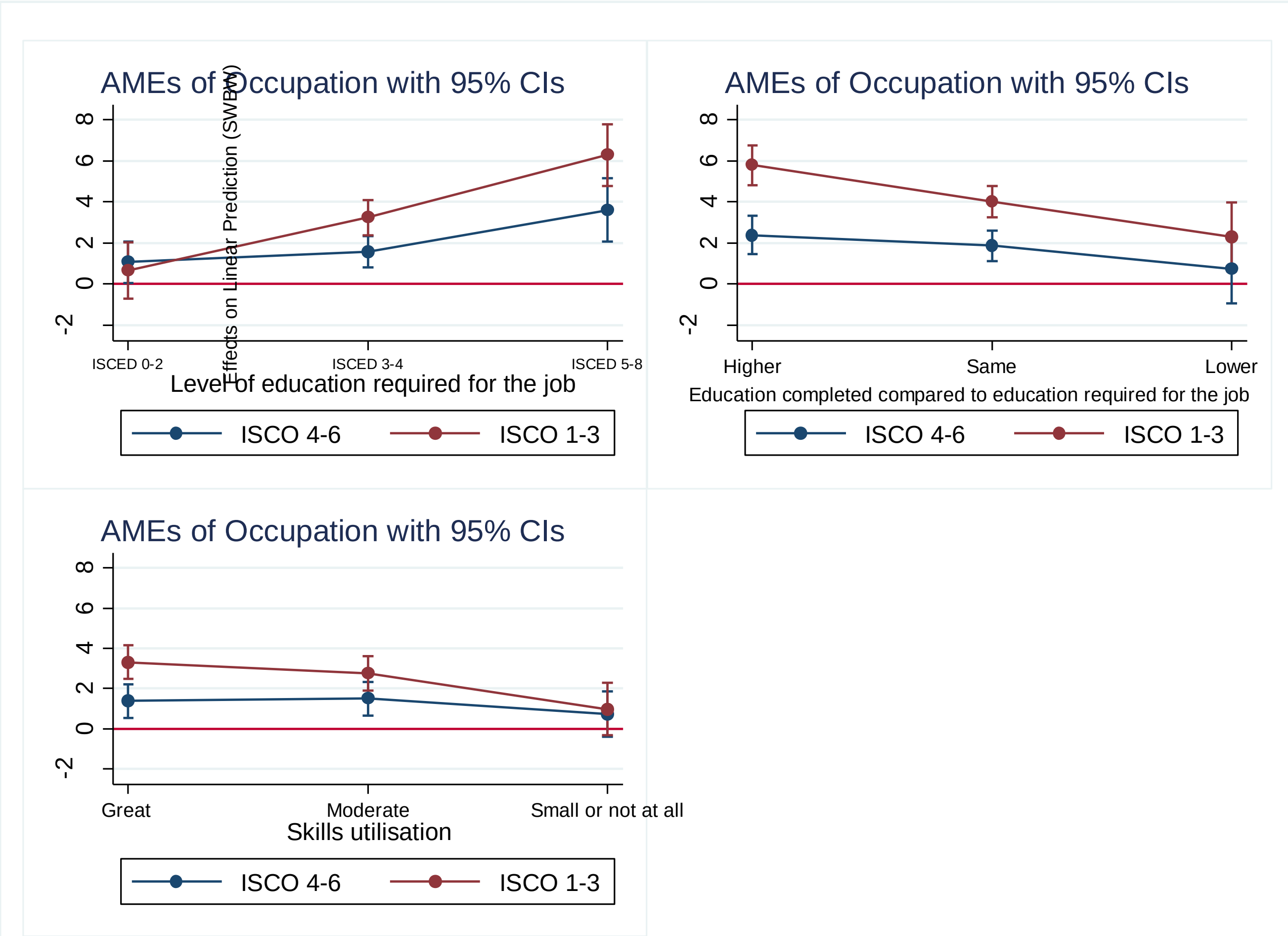

Figure 12. *Average marginal effects (AMEs) of significant individual level interaction terms between occupation and different types of mismatch on subjective well-being at work (SWBW).*

Source: Own calculations based on the ESJS 2021 for employed adults 25–64, using multilevel linear regression modelling (the full models' estimates are available at request).

5 Discussion and conclusions

The evolving global work landscape, shaped by demographic shifts, technological advancements, and rapid economic changes, highlights the growing importance of continuous skill development throughout individuals' careers. Understanding the factors that influence participation in training is essential for helping individuals and organisations adapt to these changing conditions, particularly in the context of increasing automation, shifting job requirements, and the need for upskilling or reskilling. It is also very important to understand how skills mismatch, as one of the main characteristics of the contemporary rapidly changing work landscape, affects subjective well-being at work, paying attention not only to employees' job satisfaction but also to the complexity of its instrumental and intrinsic dimensions.

This deliverable uses data from the second wave (2021) of the Cedefop European Skills and Jobs Survey and consists of two parts. The first one examines job-related training participation, focusing on how factors like skills utilisation, task complexity, and changes in workplace characteristics (RQ1) influence engagement. Furthermore, it also explores how employees' perceptions of skill obsolescence and job insecurity impact employees' involvement in training (RQ2), and how training practices vary across workplaces based on different characteristics such as firm size and types of sectors (RQ3). The second part revolves around subjective well-being at work, analysing how different types of skills and education mismatch—such as vertical and horizontal mismatches, skills underutilisation and skills obsolescence—affect employees' well-being (RQ4, RQ5), while considering the moderating role of socio-demographic factors (RQ6).

Regarding RQ1, the results show that workers who do not use their skills at all or only to a small extent are less likely to engage in job-related training compared to those with moderate or high skills utilisation. This aligns with the notion that higher skills utilisation is linked to greater training engagement. The analysis also indicates that higher job complexity increases the likelihood of training participation, which is consistent with the theoretical framework suggesting that complex job roles necessitate continuous skill development to keep pace with evolving demands (Schindler et al., 2011; Bresnahan et al., 2002). The results also revealed a significant positive relationship between workplace changes and job-related training participation. As organisations undergo changes, such as new management practices, technologies, or product introductions, employees are more likely to engage in training to stay updated. This supports the idea that workplace changes drive training participation, emphasising the need for continuous learning in a dynamic work environment. These findings align with Deming (2017) and Deming and Noray (2020), who highlight how technological advancements and shifting workplace demands increase the need for skill development.

The findings related to RQ2 reveal a link between employees' perceived skill obsolescence and participation in job-related training. Employees who believe that new digital or computer technologies in their company or organisation will require new skills are more likely to engage in training than those who perceive a lower need for new skills. This suggests that employees anticipating the need for new skills due to digital or technological changes may also recognise the potential obsolescence of their existing skills, which could motivate them to participate in training.

Alternatively, it may indicate that these employees acknowledge the rapid pace of technological advancements and make a conscious choice to learn and develop in workplace. Their participation in training likely reflects both a proactive response to evolving job requirements and a broader desire to enhance their competencies. The research on technological change (Dickerson and Green, 2004; Deming, 2017; Deming and Noray, 2020) states that technological advancements reshape the labour market by increasing demand for new skills while making others obsolete. Consistent with Allen and de Grip (2007), this study confirms that employees who anticipate possible skill obsolescence are more proactive in pursuing training. However, while previous literature has stated that preventing skill atrophy was the reason for participating in training for people who are underutilising their skills, due to the lack of relevant data, here we are unable to state the reasons why people with different skills utilisation levels are participating in training: this needs some further research with some other data (if available). The second research question also explored the relationship between job insecurity and participation in job-related training. The findings indicate minor variations in predicted probabilities based on perceived job insecurity and the overlapping confidence intervals suggest that these differences are not statistically significant. Employees' likelihood of participating in training appears largely unaffected by their perception of job loss risk, implying that job insecurity may not be a strong motivator for training engagement. Furthermore, while the results show a link between training participation and perceived skill obsolescence, training participation is more strongly associated with job complexity and workplace changes. This suggests that the nature of job tasks and recent workplace developments are stronger predictors of training participation than the perceived need for new skills and the potential risk of skill obsolescence.

The findings related to RQ3 reveal that job-related training participation varies significantly based on workplace characteristics, particularly firm size and different types of sectors. Employees in larger firms are more likely to participate in training compared to those in small firms (1–10 employees), reflecting the greater availability of formal training structures and dedicated budgets in larger organisations (OECD, 2012). Also, the results showed that employees in the public and not-for-profit sectors, have the highest likelihood of engaging in training, likely due to well-developed training infrastructures and state-financed programs (Cedefop, 2015; Roosmaa, 2021). In contrast, employees in the private sector show lower participation, consistent with prior research linking private-sector training to more informal, on-the-job learning and fewer external training opportunities. These findings highlight the role of workplace characteristics in shaping access to training.

We regard subjective well-being at work as a multidimensional phenomenon which refers to different dimensions of work, both instrumental (income benefits, working conditions, security, work-life balance) and intrinsic (interest in the work, opportunities for personal growth, social relations). This understanding goes beyond the widespread focus on instrumental and economic effects of skills mismatch and affirms the importance of subjective well-being and intrinsic values for people's flourishing. It is in line with Stiglitz, Sen, and Fitoussi (2010, 65)'s thesis that 'the subjective dimensions of quality of life encompass several aspects.' Data from the second wave of the Cedefop European Skills and Jobs Survey allows to apply this understanding of subjective well-being at work and instead of using one indicator to develop a scale for measuring it (RQ4).

Regarding RQ5, the analyses reveal that each of the types of skills mismatch studied – required education, vertical education mismatch, horizontal education mismatch, skills utilisation and skills obsolescence – matters for subjective well-being at work. It is very important to emphasise that our findings demonstrate that various types/forms of mismatch influence subjective well-being at work in different ways. Thus, for example, horizontal mismatch and the lower level of reported skills' utilisation in work are associated with lower level of subjective well-being at work. In case of mismatch that refers to education completed to education required by job, however, adults who are employed in jobs where the same or lower level of education for the job is required than the level completed by them, have reported a significantly higher level of subjective well-being at work than those who are employed in jobs where a higher level of education than theirs is required. Regarding skills obsolescence, the analysis shows that higher assessments that new digital technologies would need new knowledge and skills positively influence the subjective well-being at work. This creates an optimistic expectation that employees will be ready to participate in retraining as this will not be at the price of lower subjective well-being at work. In turn, employers can motivate employees to be involved in training to acquire new skills, highlighting that this will also increase their subjective well-being at work (economic benefits, but interest in the work and career opportunities as well). Based on these results we argue that skills mismatch should always be studied as a multidimensional phenomenon and that its different types have to be examined separately in general, but also specifically in relation to the subjective well-being at work.

In relation to RQ6, the report provides evidence that individual characteristics moderate the effect of skills mismatch on subjective well-being at work differently, which should be considered in both analyses and policymaking. Thus, for example, we reveal that horizontal mismatch matters less for females' subjective well-being at work, as they show a higher level of subjective well-being at work than males in the case they report a form of horizontal mismatch. We suggest that because of their greater family responsibilities, women might be more inclined to accept a job that does not correspond to their field of study if it met other criteria (e.g. close to home or a more convenient working time). The analysis also shows that higher education graduates are more sensitive when they experience a horizontal mismatch – if they report that their job does not require any specific field, their level of subjective well-being at work is lower in comparison to that of adults with secondary education and who report that their job does not require specific field. Our plausible explanation is that because graduates invest more resources (not just economic) in obtaining their degrees than people with a lower level of education, they value more the opportunity to work in line with their specialty.

There are several directions for future research, which we think that are worth pursuing. First, it is important to further make a comparative analysis between countries. Second, there is a need to find better indicators of skills obsolescence that not only capture the perceived need for new skills but also directly assess whether employees believe their current skills will become outdated in the near future. Third, more control variables should be included in the analyses, such as ethnicity and history of migration for participation in job-related training and sector and firm size for subjective well-being at work. Lastly, future research should examine the relationship between participation in job-related training and well-being at work. Employees with fewer opportunities to participate in training or further develop (or maintain) their skills may also experience lower well-being at work, which could have significant implications for both employees and the companies.

The findings suggest several important policy implications to promote training engagement, skill development and well-being at work. First of all, workplace policy should be based on the acknowledgment of the complex nature of work and on the understanding that it is a crucial factor in people's lives, not only for its economic and instrumental value, but also for its intrinsic importance in fostering a meaningful, interesting and personal growth-related life. While participation in job-related training may not always result in immediate economic benefits—given that many courses are short and salaries do not necessarily rise after each one—there may be long-term advantages. Attending training helps individuals learn new skills, adapt to changes, and become more effective in their roles. It may also boost their sense of job security and career advancement. In this regard, employers can encourage employees to engage in training by emphasising that it not only enhances their skillset but also contributes to their overall well-being at work, including (long-term) economic benefits, greater job satisfaction, and career growth opportunities.

Policymakers should encourage workplaces to design job roles that foster active skill use and create opportunities for growth. Even within roles designed to meet specific task requirements, there is scope to promote continuous learning and skill enhancement (e.g. by rotating responsibilities inside a team or by mentorship and peer learning). Supporting continuous learning in dynamic work environments is equally critical, given the positive relationship between workplace changes and training participation. Policies should prioritise programs that help employees adapt to organisational and technological transformations, particularly in rapidly evolving industries. Raising awareness about the importance of reskilling and upskilling is also essential – targeted training can encourage proactive skill development and increase the employability and productivity of the employees. Government-sponsored reskilling programs are also worth promoting, especially thinking that when some groups are not able to follow all the technological changes then later on it will be also costly for the state when they would be laid back because of this and unemployed.

Additionally, the difference in training participation between small and large firms highlights the need for targeted support for small companies, which often lack resources for formal training. Policies offering financial incentives, grants, or partnerships with external training providers can help make training more accessible for small firms. Sector-specific training initiatives are also important, especially in replicating the well-developed training structures of public and not-for-profit sectors in private sectors with lower participation rates.

6 References

Acemoglu, D., & Pischke, J. (1999). The structure of wages and investment in general training. *Journal of Political Economy, 107*(3), 539–572.

Allen, J. P., & de Grip, A. (2007). Skill obsolescence, lifelong learning and labor market participation. *ROA Research Memoranda*, No. 006. Retrieved from https://doi.org/10.26481/umaror.2007006 (accessed on 18 July 2024).

Asplund, R. (2004). The provision and effects of company training: A brief review of the literature. *ETLA Discussion Paper No. 907*. Helsinki: The Research Institute of the Finnish Economy.

Autor, D. H., & Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. Journal of Labor Economics, *31*(S1), S59–S96.

Barrero, J. M., Bloom, N., & Davis, S. J. (2020). *COVID-19 is also a reallocation shock* (Becker Friedman Institute for Economics Working Paper No. 2020-59). University of Chicago. Retrieved from https://www.nber.org/system/files/working_papers/w27137/w27137.pdf (accessed on 28 January 2025).

Bassanini, A., Booth, A., Brunello, G., De Paola, M., & Leuven, E. (2007). Workplace training in Europe. In G. Brunello, P. Garibaldi, & E. Wasmer (Eds.), *Education and Training in Europe* (pp. 143–309). Oxford: Oxford University Press.

Becker, G. (1975). *Human Capital* (2nd ed.). New York, NY: Columbia University.

Bills, D. B and Hodson, R. (2007). Worker training: A review, critique, and extension. Research in Social Stratification and Mobility, *25*, 258–272.

Blossfeld, H. P., Kilpi-Jakonen, E., Vono de Vilhena, D., & Buchholz, S. (Eds.). (2014). *Adult Learning in Modern Societies: An International Comparison from a Life-course Perspective*. Cheltenham: Edward Elgar Publishing.

Boyadjieva, P., & Ilieva-Trichkova, P. (2024). Does participation in non-formal adult education matter for individual subjective well-being as a multidimensional functioning? *European Educational Research Journal*, *23*(1), 125–144.

Boyadjieva, P., & Ilieva-Trichkova, P., Krasteva, V., Alexandrova, S. (2024). Skills2Capabilities Project. Deliverable 5.3: Effects of mismatch on inclusive growth and social justice report. Available: working_papers_d5-3_deliverable.pdf

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics, 117*, 339–376.

Brown, P., Green, A., & Lauder, H. (2001). *High Skills: Globalisation, Competitiveness and Skill Formation*. Oxford: Oxford University Press.

Brunello, G., & Medio, A. (2001). An explanation of international differences in education and workplace training. *European Economic Review, 45*(2), 307–322.

Brunello, G., & Wruuck, P. (2021). Skill shortages and skill mismatch: A review of the literature. *Journal of Economic Surveys*, 35(4), 1145–1167.

Bryan, M.L., & Jenkins, S.P. (2016). Multilevel Modelling of Country Effects: A Cautionary Tale. *European Sociological Review,* 32(1), 3–22.

Buchtemann, C. F., & Soloff, D. J. (2003). Education, training and the economy. *Vocational Training: European Journal, 13*, 9–21.

Büchel, F., & Mertens, A. (2004). Overeducation, undereducation, and the theory of career mobility. *Applied Economics, 36*(8), 803–816.

Card, D., & DiNardo, J. E. (2002). Skill-biased technological change and rising wage inequality: Some problems and puzzles. *Journal of Labor Economics, 20*(4), 733–783.

Cedefop (2010). Skill Mismatch in Europe Europe's Challenge is not just to Improve Skill Levels, but to Match People with the Right Skills to the Right Jobs. *Briefing Note*, Thessaloniki.

Cedefop. (2018). *Insights into skill shortages and skill mismatch: Learning from Cedefop's European skills and jobs survey*. Cedefop reference series, vol. 106, Luxembourg: Publications Office of the European Union.

Cedefop (2021). *Cedefop second European skills and jobs survey* (1st edition) [data set], https://www.cedefop.europa.eu/en/projects/european-skills-and-jobs-survey-esjs (accessed on 5 February 2024).

Cedefop (2022). *Setting Europe on course for a human digital transition: new evidence from Cedefop's second European skills and jobs survey.* Cedefop reference series, No 123, Luxembourg: Publications Office. Retrieved from http://data.europa.eu/doi/10.2801/253954 (accessed on 20 September 2024).

Congregado, E., Iglesias, J., MiAllán, J.M., & Román, C. (2016). Incidence, effects, dynamics and routes out of overqualification in Europe: A comprehensive analysis distinguishing by employment status. *Applied Economics*, *48*(5), 411–445.

Cunha, F., Heckman, J. J., Lochner, L., & Masterov, D. V. (2006). Interpreting the evidence on life cycle skill formation. In E. A. Hanushek & F. Welch (Eds.), *Handbook of the Economics of Education* (pp. 698–812). Amsterdam: North-Holland.

De Grip, A., & van Loo, J. (2002). The economics of skills obsolescence: A review. In A. de Grip, J. van Loo, & K. Mayhew (Eds.), *The Economics of Skills Obsolescence: Theoretical Innovations and Empirical Applications* (pp. 1–26). Amsterdam: Elsevier Science.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics, 132*(4), 1593–1640.

Deming, D. J., & Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. *The Quarterly Journal of Economics, 135*(4), 1965–2005.

Desjardins, R. (2014). *Rewards to skill supply, skill demand and skill-mismatch. Studies using the Adult Literacy and Lifeskills Survey*. Lund Economic Studies, no 176. Lund: Lund University.

Desjardins, R., & Rubenson, K. (2011). An analysis of skill mismatch using direct measures of skills. *OECD Education Working Papers 63*. Paris: OECD Publishing.

Dickerson, A., & Green, F. (2004). The growth and valuation of computing and other generic skills. *Oxford Economic Papers, 56*(3), 371–406.

Dieckhoff, M., Jungblut, J. M., & O'Connell, P. J. (2007). Job-related training in Europe. In D. Gallie (Ed.), Employment regimes and the quality of work (pp. 77–104). Oxford University Press.

Diem, A. (2015). Overeducation among graduates from universities of applied sciences: Determinants and consequences. *Journal of Economic and Financial Studies, 3*, 63–77.

DiPrete, T. A. (2005). Labor markets, inequality, and change: A European perspective. *Work and Occupations, 30*(2), 119–139.

Eraut, M. (2000). Non-formal learning and tacit knowledge in professional work. *British Journal of Educational Psychology, 70*(1), 113–136.

European Commission. (2000). Communication from the Commission to the Council, the European Parliament, the Economic and Social Committee and the Committee of Regions: Social Policy Agenda. Brussels, Belgium: Commission of the European Communities.

European Commission. (2010). *Europe 2020: A strategy for smart, sustainable and inclusive growth*. Brussels: European Commission.

Felstead, A., Gallie, D., & Green, F. (2017). Measuring skills stock, job skills, and skills mismatch. In C. Warhurst, K. Mayhew, D. Finegold, & J. Buchanan (Eds.), *The Oxford Handbook of Skills and Training* (pp. 321–342). Oxford: Oxford University Press.

Ferreira, M., Künn-Nelen, A., & de Grip, A. (2017). Work-related learning and skill development in Europe: Does initial skill mismatch matter? In W. Solomon, K. Polachek, K. Pouliakas, G. Russo, & K. Tatsiramos (Eds.), *Skill Mismatch in Labor Markets* (pp. 345–407). Emerald Publishing Limited.

Fleming, Ch. M., & Kler, P. (2014). Female overeducation, job satisfaction and the impact of children at home in Australia. *Economic Analysis and Policy, 44*(2), 143–155.

Green, F. (2013). *Skills and skilled work – An economic and social analysis*. Oxford: Oxford University Press.

Green, F., & Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers, 62*(4), 740–763.

Görlitz, K., & Tamm, M. (2016). Revisiting the complementarity between education and training—the role of job tasks and firm effects. *Education Economics, 24*, 261–279.

Hornberg, C., Heisig, J. P., & Solga, H. (2024). Explaining the training disadvantage of less-educated workers: the role of labor market allocation in international comparison. *Socio-Economic Review, 22* (1), 195–222.

Hox, J. (1998). Multilevel modeling: When and why. In I. Balderjahn, R. Mathar & M. Schader (Eds), *Classification, Data Analysis, and Data Highways* (pp. 147–154). Berlin and Heidelberg: Springer.

ILO. (2014). *Skills Mismatch in Europe: Statistics Brief*. Geneva: International Labour Office, Department of Statistics.

Kleinert, C., & Wölfel, O. (2018). Technologischer Wandel und Weiterbildungsteilnahme. *BWP – Berufsbildung in Wissenschaft und Praxis, 1*/2018, 11–15.

Korpi, T., & Tåhlin, M. (2009). Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974–2000. *Labour Economics, 16*(2), 183–193.

Lazear, E.P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of Political Economy*, *117*(5) 914–940.

Leßmann, O., & Bonvin, J.-M. (2011). Job-satisfaction in the broader framework of the capability approach. *Management Revue, 22*(1), 84–99.

Levels, M., van der Velden, R., & Allen, J. (2014). Educational mismatches and skill mismatches: New empirical tests of old hypotheses. *Oxford Economic Papers, 66*(4), 959–982.

Li, J., Valero, A., & Ventura, G. (2020). *Trends in job-related training and policies for building future skills into the recovery* (Discussion Paper No. 033). Centre for Vocational Education Research. Retrieved from https://cver.lse.ac.uk/textonly/cver/pubs/cverdp033.pdf (accessed on 5 February 2024).

Livingstone, D. W. (2017). Skill under-utilization. In C. Warhurst, K. Mayhew, D. Finegold, & J. Buchanan (Eds.), *The Oxford Handbook of Skills and Training* (pp. 281–300). Oxford: Oxford University Press.

Loewenstein, M. A., & Spletzer, J. R. (1999). General and Specific Training: Evidence and Implications. *Journal of Human Resources*, *34*, 710–733.

Mavromaras, K., Mahuteau, S., Sloane, P., & Wei, Zh. (2012). *The Effect of Overskilling Dynamics on Wages*. IZA Discussion Paper No. 6985. Retrieved from http://ftp.iza.org/dp6985.pdf (accessed on 17 July 2024).

McGuinness, S., & Byrne, D. (2015). Born abroad and educated here: Examining the impacts of education and skill mismatch among immigrant graduates in Europe. *IZA Journal of Migration,* 4, 17.

McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills mismatch: Concepts, measurement and policy approaches. *Journal of Economic Surveys, 32*(4), 985–1015.

McGuinness, S., Redmond, P., Staffa, E., Devlin, A., & Whelan, A. (2025). Skills mismatch: what do we already know and what do we need to know? In M. H.J. Wolbers & D. Verhaest (Eds.), *Handbook of Education and Work* (pp. 318–339). Cheltenham, UK: Edward Elgar Publishing.

Mincer, J., & Ofek, H. (1982). Interrupted work careers: Depreciation and restoration of human capital. *Journal of Human Resources, 17*(1), 3–24.

Nilsson, S., & Rubenson, K. (2014). On the determinants of employment-related organized education and informal learning. *Studies in Continuing Education, 36*(3), 304–321.

Nussbaum, M. (2000). *Women and Human Development*. Cambridge: Cambridge University Press.

Nussbaum, M. (2011). *Creating Capabilities. The Human Development Approach*. Cambridge and London: The Belknap Press of Harvard University Press.

OECD. (2012). *OECD economic surveys: Estonia 2012*. OECD Publishing. Retrieved from https://doi.org/10.1787/eco_surveys-est-2012-en (accessed on 13 January 2025).

OECD. (2019a). *Education at a glance 2019: OECD indicators*. Paris: OECD Publishing.

OECD. (2019b). *OECD Employment Outlook 2019: The Future of Work*. Paris: OECD Publishing.

Peiró, J. M., Agut, S., & Grau, R. (2010). The relationship between overeducation and job satisfaction among young Spanish workers: The role of salary, contract of employment, and work experience. *Journal of Applied Social Psychology*, *40*(3), 666–689.

Piper, A. (2015). Heaven knows I'm miserable now: Overeducation and reduced life satisfaction. *Education Economics, 23*(6), 677–692.

Quintini, G. (2011). *Over-Qualified or Under-Skilled: A Review of Existing Literature*. OECD Social, Employment and Migration. Working Papers No. 121. Paris: OECD Publishing.

Rabe-Hesketh, S., & Skrondal, A. (2012). *Multilevel and Longitudinal Modeling Using Stata*, 3rd ed. College Station: Stata Press, vols. 1 and 2.

Robeyns, I. (2017). *Wellbeing, Freedom and Social Justice. The Capability Approach Re-Examined*. Cambridge: Open Book Publishers.

Roosmaa, E.-L. (2021). *Adult education and training: A comparative perspective of participation patterns across Europe*. Tallinn: Tallinna Ülikool.

Rosen, S. (1975). Measuring the obsolescence of knowledge. In F. T. Juster (Ed.), *Education, Income and Human Behavior* (pp. 199–232). New York: McGraw-Hill.

Rubenson, K., & Desjardins, R. (2009). The impact of welfare state regimes on barriers to participation in adult education: A bounded agency model. *Adult Education Quarterly, 59*(2), 187–207.

Russo, G. (2024). *Human capital utilisation, quiet quitting and employee retention*. Publications Office of the European Union. Cedefop working paper, 23. http://data.europa.eu/doi/10.2801/229379

Saar, E., & Räis, M. L. (2017). Participation in job-related training in European countries: The impact of skill supply and demand characteristics. *Journal of Education and Work, 30*, 531–551.

Saar, E., Ure, O. B., & Desjardins, R. (2013). The role of diverse institutions in framing adult learning systems. *European Journal of Education, 48*(2), 213–232.

Schindler, S., Weiss, F., & Hubert, T. (2011). Explaining the class gap in training: The role of employment relations and job characteristics. *International Journal of Lifelong Education, 30*, 213–232.

Sen, A. (1992). *Inequality Reexamined*. Oxford: Oxford University Press.

Sen, A. (1999). *Development as Freedom*. Oxford: Oxford University Press.

Sloane, P. J., & Mavromaras, K. (2020). Overeducation, skill mismatches, and labor market outcomes for college graduates. Retrieved from https://wol.iza.org/articles/overeducation-skill-mismatches-and-labor-market-outcomes-for-college-graduates/long (accessed on 17 July 2024).

Stiglitz J.E., Sen, A., & Fitoussi, J.-P. (2010). *Mismeasuring Our Lives. Why GDP Doesn't Add Up? The Report by the Commission on the Measurement of Economic Performance and Social Progress*. New York, NY; London: The New Press.

Urbanaviciute, I., Massoudi, K., & De Witte, H. (2024). Job insecurity and (un)sustainable well-being: unravelling the dynamics of work, career, and life outcomes from a within-person perspective. *European Journal of Work and Organizational Psychology*, *33*(5), 658–670.

Van Smoorenburg, M. S., & van der Velden, R. K. (2000). The training of school-leavers: Complementarity or substitution? *Economics of Education Review, 19*(2), 207–217.

Verhaest, D., & Omey, E. (2006). The impact of over-education and its measurement. *Social Indicators Research, 77*, 419–448.

Verhaest, D., Sellami, S., & van der Velden, R. (2017). Differences in horizontal and vertical mismatches across countries and fields of study. *International Labour Review, 156*(1), 2–23.

Welch, F., & Ureta, M. (2002). The obsolescence of skill. In A. de Grip, J. van Loo, & K. Mayhew (Eds.), *The economics of skills obsolescence: Theoretical innovations and empirical applications* (Research in Labor Economics, Vol. 21, pp. 51–81). Emerald Group Publishing.

World Economic Forum. (2014). *Matching skills and labour market needs: Building social partnerships for better skills and better jobs*. Geneva: Global Agenda Council on Employment.

Appendix

Table A1. Participation in job-related training, regression coefficients

	Model 1	Model 2	Model 3	Model 4	Model 5
Gender (ref male)					
Female	-.201***	-.192***	-.133***	-.110***	-.108***
Age (ref 24–39)					
40–54	-.362***	-.277***	-.157***	-.149***	-.151***
55–64	-.593***	-.475***	-.303***	-.277***	-.276***
Highest ed (ref tertiary)					
Lower secondary or below	-.300**	-.276**	-.269*	-.267*	-.269*
Upper secondary	-.355***	-.299***	-.276***	-.269***	-.269***
Post-secondary	-.152**	-.144***	-.118*	-.121**	-.122**
Occupation group (ref high-skilled white-collar)					
Low-skilled white-collar	-.319***	-.112*	-.114	-.121	-.121
High-skilled blue-collar	-.369***	-.239***	-.145*	-.119*	-.120*
Low-skilled blue-collar	-.554***	-.291***	-.229***	-.210***	-.210***
Last activity (employed in another job)					
Self-employed	.191***	.149	.036	.034	.034
In education and training	.280***	.265***	.233***	.221***	.221***
Unemployed	-.273***	-.169*	-.152	-.167*	-.164
Inactive	-.267***	-.213***	-.183*	-.176*	-.175*
Firm size (ref 1–10)					
11–49	.439***	.460***	.367***	.370***	.372***
50–249	.422***	.441***	.261***	.246***	.249***
250 and more	.522***	.554***	.339***	.315***	.320***
Tenure (years)	-.009**	-.010***	-.011***	-.012***	-.012***
Sector (ref professional, scientific and technical activities, administrative and support service etc.					
Agriculture, forestry and fishing	-.194	-.211	-.219	-.237	-.234
Industry, construction and transport	-.093*	-.099*	-.106***	-.107***	-.109***
Whosesale and retail trade, accommodation and food service	-.190**	-.210***	-.276***	-.263***	-.261***
Type of sector (ref other)					
Public	-.357***	-.328***	-.359***	-.368***	-.373***
Private	-.268***	.199**	.166*	.185*	.177*
Not-for-profit	-.013	-.019	-.089	-.100	-.103
Contract (ref permanent)					
Temporary	.125**	.154***	.189***	.183***	.176***
No contract	-.444***	-.419**	-.341*	-.325*	-.321*
Work routinisation	.493***	.214**	.027	.038	.040
Skills utilisation (ref great extent)					
Not at all/small extent	-.752***	-.468***	-.481***	-.445***	-.450***
Moderate extent	-.003	.118	.059	.038	.033

Job complexity		2.65***	1.89***	1.77***	1.78***
Workplace changes			.370***	.354***	.353***
Skills obsolescence (ref not at all)					
Great extent				.661***	.663***
Moderate extent				.453***	.450***
Small extent				.320***	.316***
Job insecurity (ref not at all)					
Very high change of losing the job					-.040
Some chance of losing the job					.056
Constant	.979***	-.647***	-.702***	-.949***	-.961***
Number of countries	27	27	27	27	27
N	28,916	28,887	28,887	28,870	28,834

Source: Own calculations based on the ESJS 2021 for employed adults 25–64, using mixed-effects logistic regression modelling. * p<0.05; ** p<0.01; *** p<0.001.

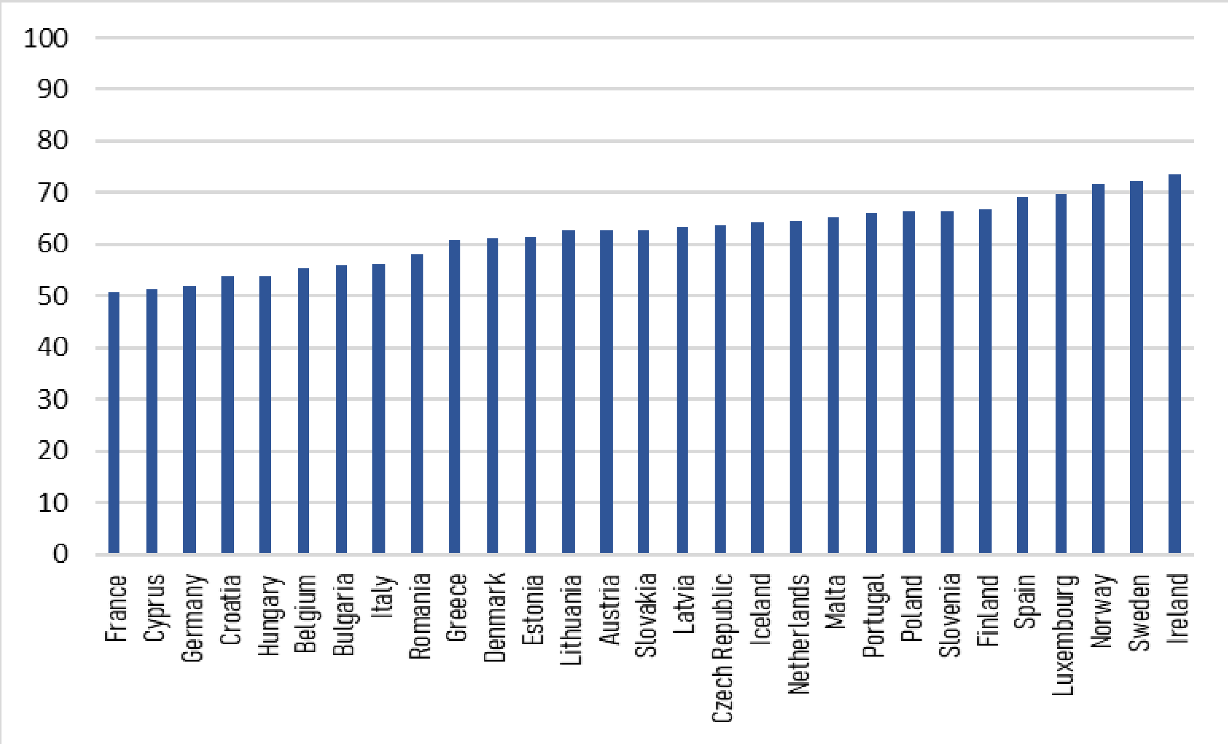

Figure A1. *Variation in participation rates in job-related training across European countries.*
Source: Own calculations based on the ESJS 2021 for employed adults 25–64.

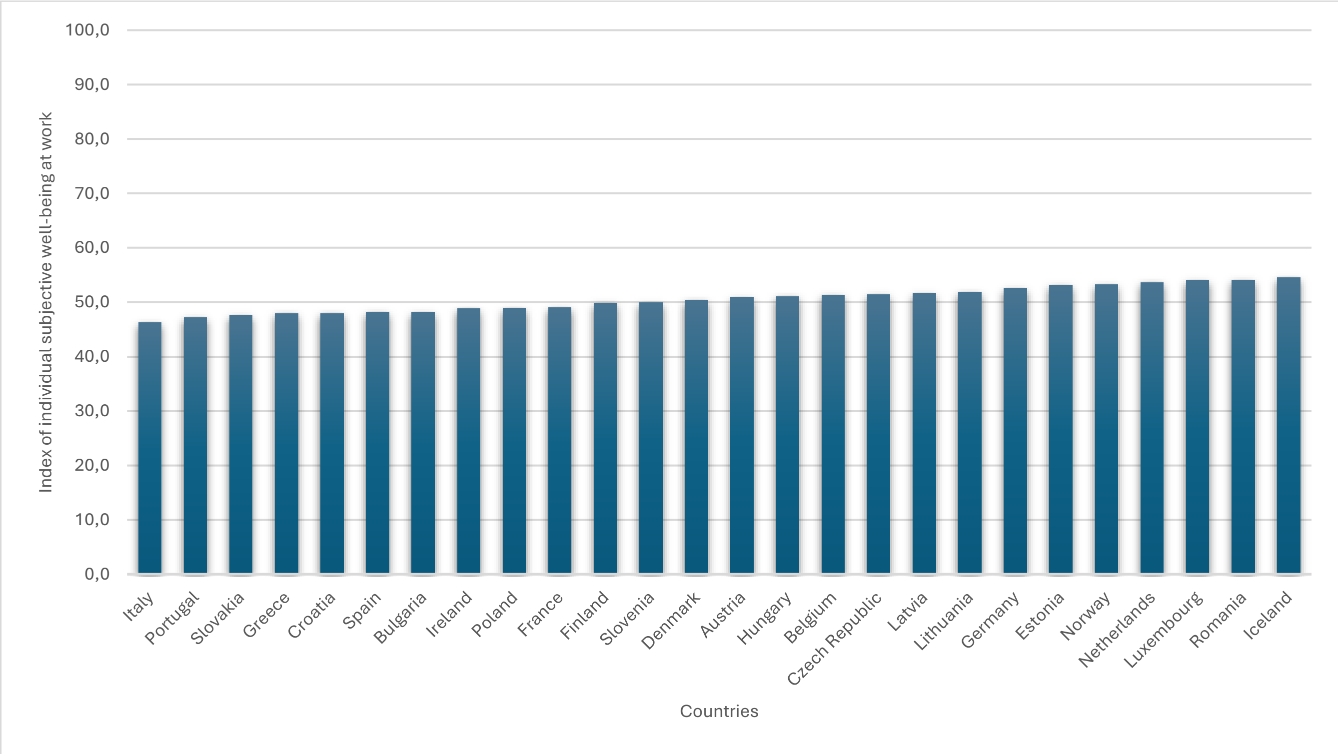

Figure A2. *Index of subjective well-being at work in 27 European countries.*
Source: Own calculations based on the ESJS 2021 for employed adults 25–64.

This working paper "Report on employee skill obsolescence" [Analyse large international comparative studies to report on how employees' own perception about the obsolescence of their skills and likelihood of losing their job is related with participation in training and the effects of mismatch on individual well-being] was authored for Skills2Capabilities by Liisa Martma (Tallinn University, Institute of International Social Studies), Pepka Boyadjieva, Petya Ilieva-Trichkova, Veneta Krasteva and Svetlana Alexandrova (IPS-BAS). This paper is a deliverable from the work package 5 entitled "Drivers and effects of skills mismatch", led by Triin Roosalu and Eeva Kesküla (Tallinn University).

This D5.2 working paper represents the views of the authors based on the available research. It is not intended to represent the views of all Skills2Capabilities affiliates.

www.skills2capabilities.eu

Skills2Capabilities Partner Institutions: