NEETs in the digital age

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Abstract

The rapid digital transformation of the labour market has increased the demand for cognitive skills, posing challenges for vulnerable groups such as NEETs (Not in Education, Employment, or Training). Using the Labor Force Survey ad hoc module on job skills, we investigate skill utilisation at a workplace between NEETs with prior work experience and employed individuals, the role of upskilling, and the impact of training on NEET outcomes. We identify significant skill utilisation gaps between NEETs and their employed peers. NEETs more often worked in repetitive, physically oriented jobs and less often used digital, numerical, and social skills in the workplace. Through counterfactual analysis, we show that while digital upskilling programs may reduce NEET rates, their effects vary in different characteristics. Notably, we find the largest positive effect among highly educated NEETs with low digital skills, as they may possess the necessary human capital. Our findings suggest that addressing NEET challenges requires more than just training, including early interventions and multi-component programs that address the educational and socio-economic disadvantages NEETs face.

Keywords: digitalisation, NEETs, skills, unemployment

1. Introduction

The digital transition in the labour market shifts tasks from workers to machines and software, leading to increased labour productivity in developed economies (Bloom et al., 2015; Lewandowski et al., 2022). Still, compared to previous rounds of automation, the increased pace of digitalisation leaves little time for vulnerable groups to adapt to new conditions, characterized by higher demand for cognitive skills. Therefore, digitalisation creates the risk that workers with little access to training might involuntarily leave the labour market. At the same time, young people entering the labour market are expected to have sufficient skills to thrive in the digital age, as they are often described as digital natives. Still, more and more research shows that despite being born in a digitally rich environment, youth do not possess skills that allow them to use digital tools critically (Calvani et al., 2012). Therefore, understanding where young people fall behind the most could help policymakers adjust education offers and other complementary policies more effectively.

In this report, we analyse the skills of young people in the NEET group (Not in Education, Employment, or Training), a particularly vulnerable demographic group in the working-age population. NEETs account for approximately 11% of individuals aged 15–29 in the European Union; however, the proportion varies across member states, ranging from 5% in the Netherlands to 19% in Romania (Eurostat, 2023). To mitigate the risk of long-term unemployment or inactivity, which could hinder their future labour market prospects (Schmillen & Umkehrer, 2017), the European Union has recently implemented various initiatives to improve employment outcomes. The Youth Guarantee, introduced in 2013 and reinforced in 2020, is a cornerstone of these efforts. These initiatives focus on providing NEETs with quality employment or educational opportunities, fostering skills development, and offering effective active labour market policies (ALMP). With the increasing risk of Artificial Intelligence exposure, upskilling and reskilling initiatives could potentially enhance the situation of NEETs in the labour market.

In our study, we focus on NEETs with prior work experience as we analyse skill utilisation in the workplace. Using the Labor Force Survey ad hoc module on job skills, we investigate (i) the key differences in skill utilisation between NEETs and employed individuals, (ii) the role of upskilling in reducing the NEET rate, and (iii) the predictive power of training activities in determining the likelihood of falling into the NEET category. Our findings suggest that while there are significant differences in skills between NEETs with prior work experience and employed individuals, the role of training is limited in predicting the NEET status, calling for further research into the causes of inactivity or unemployment among young people.

We make two major contributions to the literature. Our first contribution relates to the literature on the skills levels and NEET status (Barth, Keute, Schøne, von Simson, et al., 2021; Dickerson et al., 2023; Lundetræ et al., 2010). On average, NEET rates in OECD countries are three times higher among individuals with a lower-secondary education and 1.5 times higher among those with an upper-secondary education, compared to individuals with tertiary degrees (OECD, 2016). Basic skills in numeracy and literacy predict youth unemployment (Lundetræ et al., 2010; Rodrigues, 2020) and contribute to bearing a NEET status (OECD, 2016), but mainly in an indirect manner, through low education, which poses a negative signal in the labour market (Jongbloed & Giret, 2023). Barth et al. (2021) showed that school education itself can be more predictive of NEET status, rather than adult skills. Similarly, Gladwell et al. (2022) showed that general cognitive skills are among the most important predictors of NEET status. However, these results may not be informative for the policymakers in terms of what support should be provided for NEETs.

Secondly, we contribute to the literature on the role of training in closing the skill gaps and effectiveness of Active Labour Market Policies (ALMPs) (e.g. Alzúa et al., 2016; Groh et al., 2016; Ibarrarán et al., 2019). Despite the existing skill disadvantage, some studies show that stand-alone training programmes are not effective. Card et al. (2011) showed that the effect of the training programme in the Dominican Republic was low and statistically insignificant in terms of both wages and employment. While previous meta-analyses have reported mixed findings regarding the impact of ALMPs on the labour market outcomes of unemployed youth (Caliendo & Schmidl, 2016), more recent systematic reviews indicate a positive effect of such programs, including those involving classroom-based and vocational training (International Labour Organization & World Bank, 2024; Kluve et al., 2019; Mawn et al., 2017; Stöterau et al., 2022).

While most existing studies on skills have relied on data from the Program for International Student Assessment (PISA) and the Programme for the International Assessment of Adult Competencies (PIAAC), our research focuses on skills utilisation in the workplace, drawing on recent Eurostat data to provide a new perspective on this topic.

Our findings show that NEETs tend to have work experience in highly repetitive and physically oriented occupations. They also lag behind their peers of similar age in using digital, numerical, and social skills in the workplace. We use a counterfactual analysis to assess whether upskilling NEETs could reduce NEET rates. Our findings suggest that, while upskilling could close the skill gap, the largest benefits concern the NEET group with higher and middle education, while for the low-educated, the effects of the intervention are small.

The paper is structured as follows: Section 2 outlines the data, sample, and methods. Section 3 presents results on skill utilisation in the workplace. Section 4 examines the role of training in mitigating NEET status. Finally, Section 5 concludes and provides policy implications.

2. Methodology

2.1. Data

We use the 2022 Labour Force Survey's ad hoc module on job skills, which offers insights into the skills used at work and their respective time allocations. The module examines various skills, such as using digital devices, involvement in physically demanding activities, tasks requiring finger dexterity, performing calculations, and reading job-related documents. The question about skills used at work is addressed to both employed individuals and not employed (unemployed or inactive) individuals who left employment in the last two years before the LFS survey. Employed individuals provide information about their current workplace, while non-working individuals refer to their last workplace[1].

The module records the subjective perception of the respondents about the time allocated to various skills at work. Respondents rate their time allocations on a 5-point Likert scale, ranging from "none of the working time" to "all or most of the working time'. Additionally, the module collects information about the degree of job autonomy (on a 9-point Likert scale ranging from 'little or no autonomy' to 'large or very large autonomy'), task repetitiveness and procedures (on a 5-point Likert scale ranging from 'to no extent' to 'to a very large extent'). Table 11 in the Appendix provides an overview of skills and the nature of tasks covered by the ad hoc module[2].

[1] The skills studied in this study reflect the utilisation of skills rather than the possible skill stock. Our results may overestimate the skills level of NEETs because, during unemployment and inactivity, their skills may potentially deteriorate. In particular, NEETs who did not secure a position in the labour market in the past could be significantly more under-skilled compared to NEETs with prior work experience.

[2] In the survey respondents were asked about skills used in their current or most recent jobs. It does not need to mean that workers do not have given skill. Still, within this report, we use interchangeably the skill level and skills utilisation.

Our analysis includes 20 EU countries due to limited data on skills utilisation in the remaining EU states[3]. We focus on the skills of young people aged 15–34[4], comparing NEETs with prior work experience with employed individuals. Following Eurostat's definition, we consider a person to belong to the NEET group if they are non-working (either unemployed or outside the labour force) and did not receive any education or training during the four weeks preceding the survey. Using LFS variables, we classify an individual as NEET if they meet all of the following criteria[5]:

1. Is not in employment
2. Did not receive any form of education and training within the last 4 weeks
3. Is between the ages of 15 and 34

The analysis of skill utilisation focuses on NEETs with job experience who left their employment within two years prior to the LFS survey. This specific subgroup represents approximately one-third of all NEETs in our sample[6]. These individuals are older, better educated, and more active in the labour market than NEETs without job experience. Over half (56%) of NEETs in this subgroup left employment within six months, and 76% left within one year before the LFS survey (see Tables 12 - 13 in the Appendix). Therefore, when generalizing the results, one should refer to NEETs with prior job experience rather than the general NEET population.

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[3] Austria, Belgium, Bulgaria, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Italy, Latvia, Lithuania, Luxembourg, Poland, Portugal, Romania, Sweden, Slovenia

[4] While most research focuses on the 15–29 age group, Eurostat often provides data for the 15–34 age group as well. In our analysis, we extend the age bracket to increase the sample size, especially since older NEETs are more likely to have job experience.

[5] Individuals interested in replicating in our results should pay attention to variables ILOSTAT, EDUC4WEEKS and AGE in EU-LFS.

[6] The share of NEETs with job experience obtained within the two years preceding the LFS survey varies across countries, ranging from 9% in Romania to 51% in both Estonia and Austria (Table 11 in the Appendix).

We also used the classification developed by Matysiak et al. (2024), which captures the differences in occupations' required skills. The authors utilised the European Skills/Competencies Qualifications and Occupations (ESCO) database by aggregating the skills essential for the profession. The interpretation of the measure relates to increased skill utilisation compared to other professions in the EU as of 2018. We use this measure to test the differences in the task structure of occupations between NEETs and employed individuals.

2.2. Empirical strategy

Our analysis takes three major steps. First, we estimate the probit regression to estimate the skill difference between NEETs and their employed peers. We further use the model for employees only to make out-of-sample predictions for NEET skills. Next, we run probit regression, using real and counterfactual skills, explaining individual NEET status and assessing the possible role of upskilling in changing the NEET status in the labour market. Lastly, we use a novel machine learning algorithm to evaluate the role of skills in training in predicting the NEET status.

2.2.1. Skills differences between NEETs and employed individuals

We estimate the following equation to compare the skill level between NEETs and employed:

$$P(S_i = 1 \mid X) = \Phi(\beta_0 + \beta_n\, NEET_i + \alpha_{country} + \gamma_{gender} + \eta_{ISCO} + \kappa_{edu} + \rho_{age} + X_i + \epsilon_i) \quad (1)$$

where S indicates skill or job characteristic reported as taking place often (or at least sometimes) for individual i. During the analysis, we focus on the marginal effects of selected variables on the probability that an individual uses a skill often (or at least sometimes)[7]. We report only the marginal effects for NEET status to illustrate the probability difference between NEETs and employed. For the comparison, we control for country- ($\alpha_{country}$), gender- (γ_{gender}), occupation- (η_{ISCO}), education- (κ_{edu}) and age (ρ_{age}) fixed effects. X_i is a vector of other characteristics included in the analysis (e.g. degree of urbanisation, general health self-assessment).

2.2.2. Simulation of the effects of upskilling

Using the skill-gap model, we show the possible role of upskilling in decreasing the NEET rate. We estimate the equation explaining the k-th skill level for employees only:

$$S_{k,i} = \alpha_{country} + \gamma_{gender} + \eta_{ISCO} + \kappa_{edu} + \rho_{age} + \epsilon_i \ (2)$$

We proceed with equation (2) using OLS instead of probit, because we want to capture full variation in the skill levels. We further conduct out-of-sample prediction for NEETs, which allows us to see what would be the skill level of NEETs conditional on no skill gap. We plug this data into the model predicting the NEET status:

$$P(NEET_i = 1 \mid X) = \Phi(\sum_{k=1}^{n} \widehat{S_{ki}} + \alpha_{country} + \gamma_{gender} + \eta_{ISCO} + \kappa_{edu} + \rho_{age} + X_i + \epsilon_i) \ (3)$$

where $\widehat{S_{ki}}$, is the out-of-sample predicted k-type skill. We estimate the same model using data with skill-gap and compare the predictions.

[7] Due to the selective nature of the data used, we do not leverage causal effects, but rather show associations since the selection to employment and the NEET status may depend on unobservable characteristics such as motivation, academic achievement and social network (Chowa et al., 2023; Rodwell et al., 2018). Consequently, the research questions raised within this report are of an exploratory nature. We show the differences between NEETs that are associated with their individual characteristics and the local labour market.

2.2.3. Variable importance in predicting NEET Status

We further explore the role of training and skills in predicting the NEET status. For this purpose, we use the random forest algorithm. Machine learning methods have recently built their importance within methods used in economic research.[8] These methods are especially useful when it comes to the prediction problem – how close are the model estimates to the real data. In our case, we want to understand if recent participation in training, significantly improves the model fit to the data. List et al. (2024) show that using machine learning methods, especially in settings with scarce data, can improve the power of the analysis, and thanks to the automatic nature of the algorithmic methods, the risk of data-snooping is reduced. Accordingly, machine learning can improve our analysis compared to the standard econometric toolset applied otherwise.

Random Forest is a variation of the decision tree algorithm. Decision Trees can be viewed as a generalisation of the so-called fixed effects models, where the fixed effect depends on the split or division based on the covariates used for prediction (Bajari et al., 2015). Random forest, compared to a standard decision tree, introduces randomness when splitting the tree, as for each tree, only a selection of predictors is used. These results are further averaged, reducing the possible bias. In the context of our study, we focus on the post-analysis often used with random forests – variable importance analysis. Variable (or permutation) importance involves randomly shuffling each predictor in our data and recording the change in the evaluation metrics. By repeating the process for each variable, we obtain the score for each measure.

[8] See Mullainathan & Spiess (2017) for a summary of the machine learning methods and their applicability to economic research.

Therefore, high importance of skill measures and upskilling would indicate large differences in these characteristics between NEETs and non-NEETs, determining the prediction.

3. Gaps in skill utilisation

First, we examine whether NEETs differ from employed individuals in terms of occupations. Table 1 shows that approximately half of NEETs were previously employed in sales (29.2%) and elementary occupations (21.0%), compared to about one-fourth (18.7% and 8.3% respectively) of employed individuals in these occupational groups. In contrast, nearly half of employed individuals worked as professionals, technicians, or associate professionals, whereas these categories accounted for only about one-fifth of NEETs' work experience. Additionally, we find that the work experience of NEETs is more concentrated in fewer occupations. Studying the more detailed ISCO-08-unit groups, we find the top five occupations among NEETs represent nearly 30% of the total group, while for employed individuals, these top occupations account for only about 15% (see Table 15 in the Appendix).

Table 1. The occupational structure of NEETs with prior job experience and employed individuals aged 15-34, ISCO-08 major groups

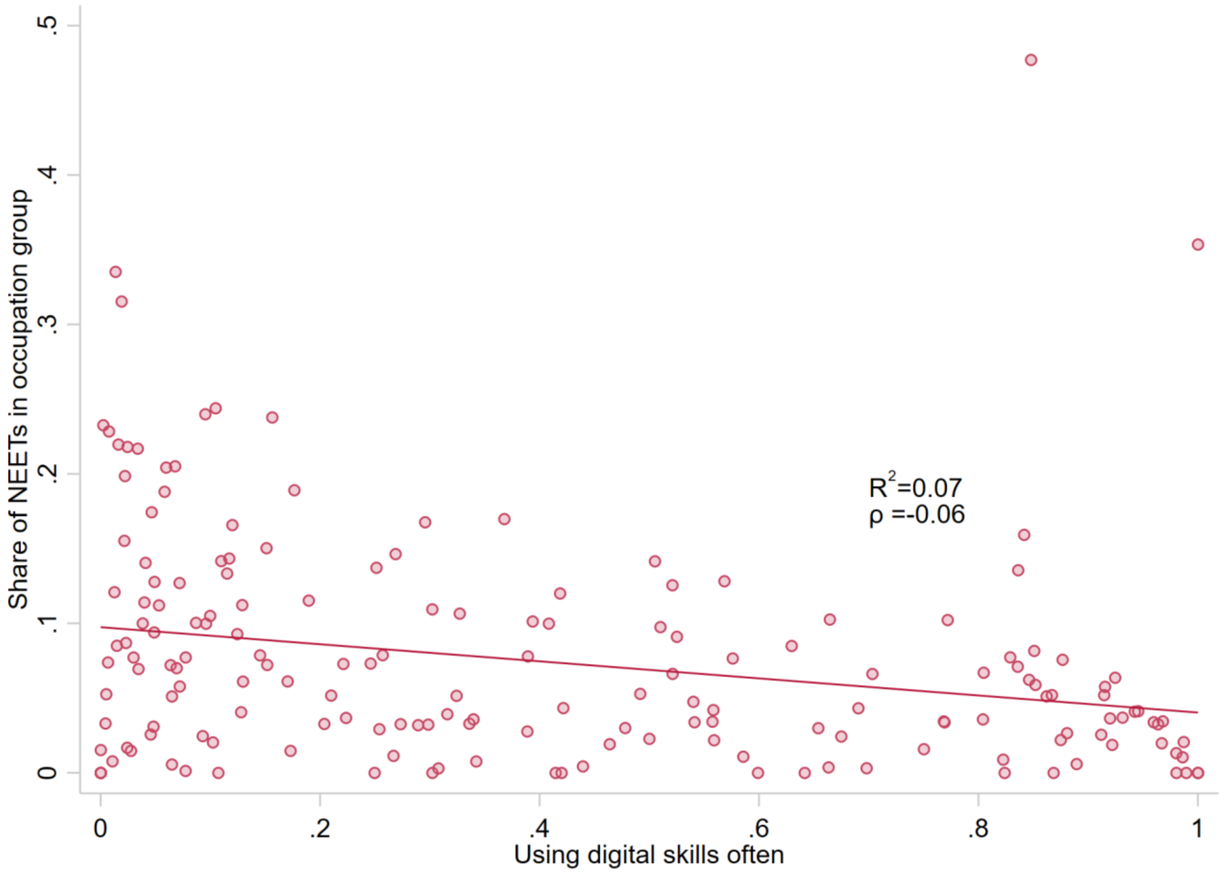
	Employed (%)	NEETs (%)
Armed Forces Occupations	0.8	0.3
Managers	2.6	1.1
Professionals	22.0	9.8
Technicians and Associate Professionals	16.9	10.4
Clerical Support Workers	9.9	9.7
Service and Sales Workers	18.9	29.2
Skilled Agricultural, Forestry and Fishery Workers	2.4	1.3
Craft and Related Trades Workers	11.9	9.8
Plant and Machine Operators, and Assemblers	6.3	7.4
Elementary Occupations	8.3	21.0

Source: own elaboration based on EU-LFS 2022 data

We also plot the share of NEETs in a given occupation in relation to the share of respondents stating they used digital skills often (Figure 1). We find a significant negative relationship ($p < 0.01$), suggesting that

NEETs worked in occupations requiring fewer digital skills than employed individuals. Visually, we observe a difference in variation depending on the digital skills level reported. Therefore, in the main part of the analysis, we account for the potential heteroskedasticity, using standard errors robust to heteroskedasticity.

Figure 1. **Share of NEETs in occupation in relation to the share of respondents using digital skills often**



Source: own elaboration based on EU-LFS 2022

Table 2 shows the proportion of individuals who use various skills for at least half of their working time. Employed individuals demonstrate higher utilisation rates of digital, reading, and calculation skills and more often provide guidance or supervise others. The largest gap is observed in digital skills, which are utilised by 42.9% of employed individuals compared to 26.0% of NEETs, a difference of 16.9 percentage points. Social skills and dexterity are used with similar frequency (with a difference of up to 1 percentage point). In contrast, physical skills are used more frequently by NEETs (42.9%) than by employed individuals (30.1%).

Table 2. Share of employed and NEETs aged 15-34 declaring often use of skills at work

Skill (Used often)	Employed (%)	NEET (%)	Difference between Employed and NEETs (p.p.)
Digital	42.9	26.0	16.9***
Reading	17.6	11.7	5.9***
Calculations	11.7	7.2	4.5***
Guidance	17.8	14.7	3.1***
Social: within company interaction	45.5	46.1	-0.6***
Social: outside company interaction	38.6	39.5	-0.9***
Finger dexterity	19.7	20.7	-1.0***
Physical	30.1	42.9	-12.8***

Note: We define that one used a given skill often if he or she used it at least half of the time in his or her current or most recent occupation. Column 4 reports the percentage point difference between Employed and NEETs (sorted by difference in skill utilisation). Column 4 reports the result of the McNemar's test. (*) (**) (***) indicate significance at the (5%) (1%) (0.1%) level.
Source: own elaboration based on EU-LFS 2022.

We also examine job autonomy and the nature of tasks (Table 3). First, NEETs report having less influence over the order and content of their tasks, with a difference of 14.7 percentage points compared to their employed peers. They also more frequently report performing repetitive tasks (60.5% among NEETs and 49.9% among employed individuals). Surprisingly, despite reporting lower autonomy and higher task repetitiveness, NEETs indicate slightly less often that they had to follow strictly defined procedures in their work (38.2% among NEETs and 41.1% among employed individuals). This may be because they more often work in sales and elementary occupations, which may require greater levels of discretion from workers. In the next step, we employ probit regression to assess whether NEET status is associated with skill utilisation or task performance, controlling for socio-demographic and job-related factors. We report marginal effects while accounting for the country, education (low, middle, high), age (15-19, 20-24, 25-29, 30-34), gender, health, disability status, local unemployment rate, quarter of the interview, and ISCO-3D occupation fixed effects (Tables 4 and 5).

Table 3. Share of employed and NEETs aged 15-34 by current/most recent work characteristics

Tasks characteristic	Employed (%)	NEET (%)	Difference (p.p.)
Job Autonomy	51.8	37.1	14.7***
Strict procedure	41.1	38.2	2.9***
Task repetitiveness	49.9	60.5	-10.6***

Note: For job autonomy, we define that one has high job autonomy if he or she reported at least some autonomy on both the order and content of the job. For procedures and task repetitiveness, we report that one has strict procedures or his/her job was repetitive if they reported it at least "to a large extent". Column 4 reports the percentage point difference between Employed and NEETs (sorted by difference in task characteristics). Column 4 reports the result of the McNemar's test. (*) (**) (***) indicate significance at the (5%) (1%) (0.1%) level.
Source: own elaboration based on EU-LFS 2022.

The first panel of Tables 4 and 5 shows the likelihood of using specific skills for most of the working time or engaging in tasks characterized as highly repetitive, autonomous, or defined by strict procedures. The table largely confirms the descriptive data. After controlling socio-economic, job-related and local labour market characteristics, the differences are smaller, yet in most cases significant. NEETs are less likely to use calculation, social, and reading skills, with the largest gap observed in utilisation of the digital skills. NEETs are almost 6 percentage points less likely to use digital skills most of the working time. They are also less likely to work in autonomous settings, more likely to perform repetitive tasks, and less likely to work according to strict procedures. However, they are more likely to use physical skills at work.

The second panel of Tables 4 and 5 explore the association between NEET status and the probability of using specific skills for at least half of the working time. Here, the observed differences between NEETs and employed individuals are, in most cases, even larger (except for physical skills and repetitive tasks). The results suggest that NEETs are less likely to engage in cognitively demanding skills, such as proficiency in digital and calculation tasks.

Table 4. Probit Marginal Effects – association between skills used at (most recent) work and NEET status

	Digital	Calculations	Physical	Job Autonomy	Repetitive tasks	Procedure
Often						
NEET status	-0.058***	-0.019**	0.028***	-0.081***	0.028**	-0.020*
	(0.008)	(0.006)	(0.008)	(0.010)	(0.010)	(0.010)
Sometimes and Often						
NEET status	-0.068***	-0.045***	0.14	-0.083***	0.003	-0.022*
	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.010)
Personal Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes	Yes	Yes
Work experience	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome (Often)	0.43	0.12	0.31	0.52	0.50	0.41
Mean Outcome (Sometimes and often)	0.58	0.26	0.43	0.71	0.76	0.63
Observations	78563	77173	78107	76855	77499	76409

Note: F.E. stands for fixed effects. Standard errors are in parentheses. * (**) ((***)) indicates significance at the 5% (1%) ((0.1%)) level. Robust standard errors adjusted for heteroskedasticity. Weighted estimation. Personal characteristics include age group, gender, education, disability status, general health. Local Labour Market characteristics include youth unemployment rate in 2022, quarter of the interview and degree of urbanisation. Work experience includes information on current or most recent occupation. Share of NEETs equal to .137. The dependent variable is a binary variable indicating whether an individual uses a skill ‘Often’ (or ‘Sometimes and Often’) (coded as 1) or not (coded as 0). Estimated models differ in number of observations due to missing data on specific skill utilisation.

Source: own elaboration based on EU-LFS 2022.

Table 5. Probit Marginal Effects – association between skills used at (most recent) work and NEET status (continued)

	Social within	Social outside	Finger Dexterity	Reading	Guidance
Often					
NEET status	-0.022*	-0.020*	-0.004	-0.016*	-0.017*
	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)
Sometimes and Often					
NEET status	-0.030***	-0.036***	-0.005	-0.030**	-0.033***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
Personal Characteristics	Yes	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes	Yes
Mean Outcome (Employees)	0.46	0.38	0.20	0.18	0.18
Mean Outcome (Sometimes and often)	0.72	0.57	0.30	0.39	0.35
Observations	77726	77432	77992	77547	79726

Note: F.E. stands for fixed effects. Standard errors are in parentheses. * (**) ((***)) indicates significance at the 5% (1%) ((0.1%)) level. Robust standard errors adjusted for heteroskedasticity. Weighted estimation. Personal characteristics include age group, gender, education, disability status, general health. Local Labour Market characteristics include youth unemployment rate in 2022, quarter of the interview and degree of urbanisation. Work experience includes information on current or most recent occupation. Share of NEETs equal to .137. The dependent variable is a binary variable indicating whether an individual uses a skill 'Often' (or 'Sometimes and Often') (coded as 1) or not (coded as 0). Estimated models differ in number of observations due to missing data on specific skill utilisation.

Source: own elaboration based on EU-LFS 2022.

We conduct the same analysis with a broader focus on NEETs only. We want to investigate if NEETs who are unemployed differ from NEETs who are outside of the labour force (inactive). For this purpose, we exclude employed individuals from the sample. These groups, while both classified as NEETs, often face distinct challenges and barriers to labour market integration. Unemployed NEETs are actively seeking work and are more closely connected to the labour market, while inactive NEETs are disengaged, often due to caregiving responsibilities, health issues, or discouragement. Inactive NEETs are also more difficult for public employment services to reach, reducing their opportunities to access ALMPs that could facilitate their return to the workforce. These distinctions have significant implications for policy design, as the support required for re-entering the labour market varies between the groups.

Tables 6 and 7 present the marginal effects, presenting differences between unemployed and inactive NEETs. In most cases, we find no significant differences in skill levels between the two groups. These findings suggest that being actively engaged in job searching, while NEET, is not directly associated with skill levels.

EU-LFS ad hoc module is characterised by a high share of missing information about NEETs skills used in most recent work. Therefore, we match the data on NEETs and other employees most recent occupation to skill intensity data (Matysiak et al., 2024). The measure used in this part refers to the task content. The indicator was initially used to inform about the skills required in a given occupation. As compared to the analysis presented above, the individuals were matched according to their most recent/current occupation.

Table 6. Probit Marginal Effects – association between skills used at most recent workplace and the NEET type

	Digital	Calculations	Physical	Job Autonomy	Repetitive job	Procedure
Often						
Inactive	0.013	-0.005	-0.025	0.044*	0.005	-0.004
	(0.013)	(0.010)	(0.017)	(0.018)	(0.018)	(0.019)
Sometimes and Often						
Inactive	-0.016	-0.004	-0.012	0.047*	0.004	-0.016
	(0.014)	(0.014)	(0.016)	(0.019)	(0.015)	(0.019)
Personal Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5499	4868	5670	5718	5843	5748

Note: F.E. stands for fixed effects. Standard errors are in parentheses. * (**) ((***)) indicates significance at the 5% (1%) ((0.1%)) level. Robust standard errors adjusted for heteroskedasticity. Weighted estimation. Personal characteristics include age group, gender, education, disability status, general health. Local Labour Market characteristics include youth unemployment rate in 2022, quarter of the interview and degree of urbanisation. Work experience includes information on current or most recent occupation. Share of NEETs equal to .137. The dependent variable is a binary variable indicating whether an individual uses a skill 'Often' (or 'Sometimes and Often') (coded as 1) or not (coded as 0). Estimated models differ in number of observations due to missing data on specific skill utilisation.

Source: own elaboration based on EU-LFS 2022.

Table 7. Probit Marginal Effects - association between skills used at most recent workplace and the NEET type(continued)

	Social within	Social outside	Finger Dexterity	Reading	Guidance
Often					
Inactive	0.014	0.018	-0.003	0.008	0.007
	(0.018)	(0.017)	(0.014)	(0.012)	(0.014)
Sometimes and Often					
Inactive	-0.008	0.046	0.007	-0.019	0.024
	(0.017)	(0.016)	(0.016)	(0.014)	(0.016)
Personal Characteristics	Yes	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes	Yes
Observations	5818	5603	5707	5072	5269

Note: F.E. stands for fixed effects. Standard errors are in parentheses. * (**) ((***)) indicates significance at the 5% (1%) ((0.1%)) level. Robust standard errors adjusted for heteroskedasticity. Weighted estimation. Personal characteristics include age group, gender, education, disability status, general health. Local Labour Market characteristics include youth unemployment rate in 2022, quarter of the interview and degree of urbanisation. Work experience includes information on current or most recent occupation. Share of NEETs equal to .137. The dependent variable is a binary variable indicating whether an individual uses a skill 'Often' (or 'Sometimes and Often') (coded as 1) or not (coded as 0). Estimated models differ in number of observations due to missing data on specific skill utilisation.

Source: own elaboration based on EU-LFS 2022.

Table 8 presents the results based on the classification of skills intensity in different occupations (Matysiak et al., 2024). The variation of the skill is at the occupation level, compared to previous tables, where skills differed between workers. Therefore, one should interpret the results below whether NEETs have the necessary skills to take up a given job. We find that NEETs worked in occupations requiring less analytical and social tasks. At the same time, they were more likely to work with manual and routine tasks. Therefore, digitalisation and higher demand for cognitive and digital skills could potentially play a role in displacing young workers.

Table 8. Probit Marginal Effects NEET Status vs Skills required for occupations

	NEET Status	NEET Status	NEET Status	NEET Status
Analytical Tasks	-0.303**			
	(0.058)			
Social Tasks		-1.463***		
		(0.280)		
Manual Tasks			0.203***	
			(0.039)	
Routine Tasks				0.185***
				(0.035)
Personal Characteristics	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes
Local Labour Market	Yes	Yes	Yes	Yes
Observations	219512	219512	219512	219512

Note: F.E. stands for fixed effects. Standard errors are in parentheses. (*) (**) (***) indicates significance at the (5%) (1%) (0.1%) level. Robust standard errors adjusted for heteroskedasticity. Weighted estimation. Share of NEETs equal to .137. The dependent variable is a binary variable indicating whether an individual was regarded as NEET (with prior work experience) (coded as 1) or not (coded as 0).
Source: own elaboration based on EU-LFS 2022.

4. The role of training in reducing NEET status

Knowing the observed association between NEET status and skills used at work, policymakers could be interested if providing training could make a significant difference among NEETs. Therefore, we conduct a counterfactual analysis, involving an increase in skills of NEETs. We model the skills of employees, based on their characteristics. We use the model from column 1 in Table 4 to predict the digital skills of the employees. We later do out-of-sample prediction of skills for NEETs, assuming that employees and NEETs could share the skill level, conditional on their observed characteristics. We refer to this scenario using the upskilling programme, as these policies could potentially close the gap between NEETs and employees In the next step, we run the probit model explaining the probability of NEET status, based on two sets of skills – observed and predicted from the model. We make predictions on NEETs status and assess the share of individuals that could benefit from training digital skills. We further cluster NEET groups based on the comparison between predicted and real skills. We disaggregate the estimated effect by several dimensions, including, gender, country and age.

We start with the analysis of the residuals coming from equation (2). We cluster the residuals using k-means clustering to detect NEETs groups which differ from the model prediction (Tables 9 and 10). We find four major clusters – (1) low-skilled NEETs, (2) average-skilled NEETs, (3) low-skilled NEETs with high-skilled predicted, (4) high-skilled NEETs. We find that almost 60% of NEETs have very low digital skills (groups 1 and 3), while only 22% used their digital skills often. We find no large differences between the groups based on the dimension of labour market status, age and health status. The first group – the low-skilled – includes more males, with low education, who are less often in urban areas. This group has mainly work experience in occupations involving physical and manual tasks. The third group was characterised by high residuals – the model predicted higher skills than were observed. This is associated with several characteristics in line with skill utilisation – a relatively high share of individuals with higher education living in urban areas.

Table 9. NEETs Clustering based on predicted vs real digital skills

	(1)	(2)	(3)	(4)
		Digital Skills: Time spent on working on digital devices		
All or most of the working time	0%	0%	0	79.1%
Half of the working time or slightly more	0%	20.4%	0	17.5%
Some of the working time	0.%	45.7%	5.6%	3.4%
Little of the working time	11.2%	33.9%	14.2%	0.0%
None of the working time	89.0%	0%	80.2%	0.0%
		Sex		
Male	54.7%	47.2%	45.3%	43.2%
Female	45.3%	52.8%	54.7%	56.8%
		Status		
Unemployed	58.3%	57.1%	57%	57.3%
Inactive	41.7%	42.9%	43%	42.7%
		Education		
Higher	9.7%	34.3%	36.5%	49.8%
Middle	46.7%	48.4%	49.1%	37.1%
Lower	43.4%	17.1%	13.4%	13.1%
		Training (Last 12 months)		
Yes	26.1%	36.0%	36%	38.6%
No	73.9%	64.0%	64%	61.4%
		Skills		
Best skill	Physical (57.1%)	Social inside (47.1%)	Social inside (46%)	Digital (97%)
Worst Skill	Digital (0%)	Calculations (5.9%)	Digital (0%)	Calculations (19.9%)
Number of observations	2664 (41.5%)	1148 (17.9%)	1190 (18.5%)	1417 (22.1%)

Source: own elaboration based on EU-LFS 2022

Table 10. NEETs Clustering based on predicted vs real digital skills (conitnued)

	(1)	(2)	(3)	(4)
		Age		
15-19	8.8%	3.5%	3.8%	2.1%
20-24	29.4%	27.6%	28.7%	21.4%
25-29	30.0%	33.2%	35.6%	40.0%
30-34	31.8%	35.6%	31.9%	36.4%
		General Health		
Very good	45.3%	47.4%	47.8%	50.0%
Good	40.1%	38.1%	37.2%	38.2%
Neither good nor bad	11.1%	10.8%	10.0%	8.9%
Bad	3.9%	2.9%	4.3%	2.6%
Very bad	0.0%	1%	0.5%	0.2%
		Degree of urbanisation		
City	39.9 %	51.9%	54.4%	56.9%
Towns and suburbs	33.5%	25.6%	29.0%	26.5%
Rural areas	26.6	22.5%	17.1%	16.7%
		Local labour market		
Youth unemployment rate	17.4%	15.9%	15.9%	16.2%
Observations	2664 (41.5%)	1148 (17.9%)	1190 (18.5%)	1417 (22.1%)

Source: own elaboration based on EU-LFS 2022

Still, most of these individuals rarely used any digital skills in their most recent jobs. The fourth group presents a relatively high utilisation of digital skills, even higher than among employees. It is unclear why a group with high utilisation of digital and other skills, accompanied by higher education, is of NEET status. The distinguished groups do not differ in terms of regional youth unemployment rates. The highly educated and skilled group may lack motivation, experience a temporary career break due to family reasons, caregiving responsibilities, or other factors.

We plot the estimated NEETs rate with included several dimensions of heterogeneity – country (Figure 2), age (Figure 3), education (Figure 4), gender (Figure 5) and skill group (Figure 6). As expected, the largest effects of the possible impact of upskilling of the policy are visible in countries where the skill gap was initially the largest. We find that, in general, the upskilling could lead to lower NEETs rates, especially among the group with low utilisation of digital skills despite slightly better education. In the dimensions of age, education and gender, we find consistent reductions in the NEET rate. For each age group older than 19 years old, the upskilling policy reduces the probability of NEET status. The same result can be observed for education. Interestingly, the effect is especially observed for the group with higher education, but little digital skills. The effect is larger than for the group (1) with very low digital skills and a higher share of low-educated. This may be a result of a lack of general human capital that needs to be accumulated before participation in training. The first group of NEETs may benefit more from general training[9], rather than specific upskilling programme. In comparison, group (3), with a relatively high share of highly educated workers, can benefit significantly from the upskilling programme.

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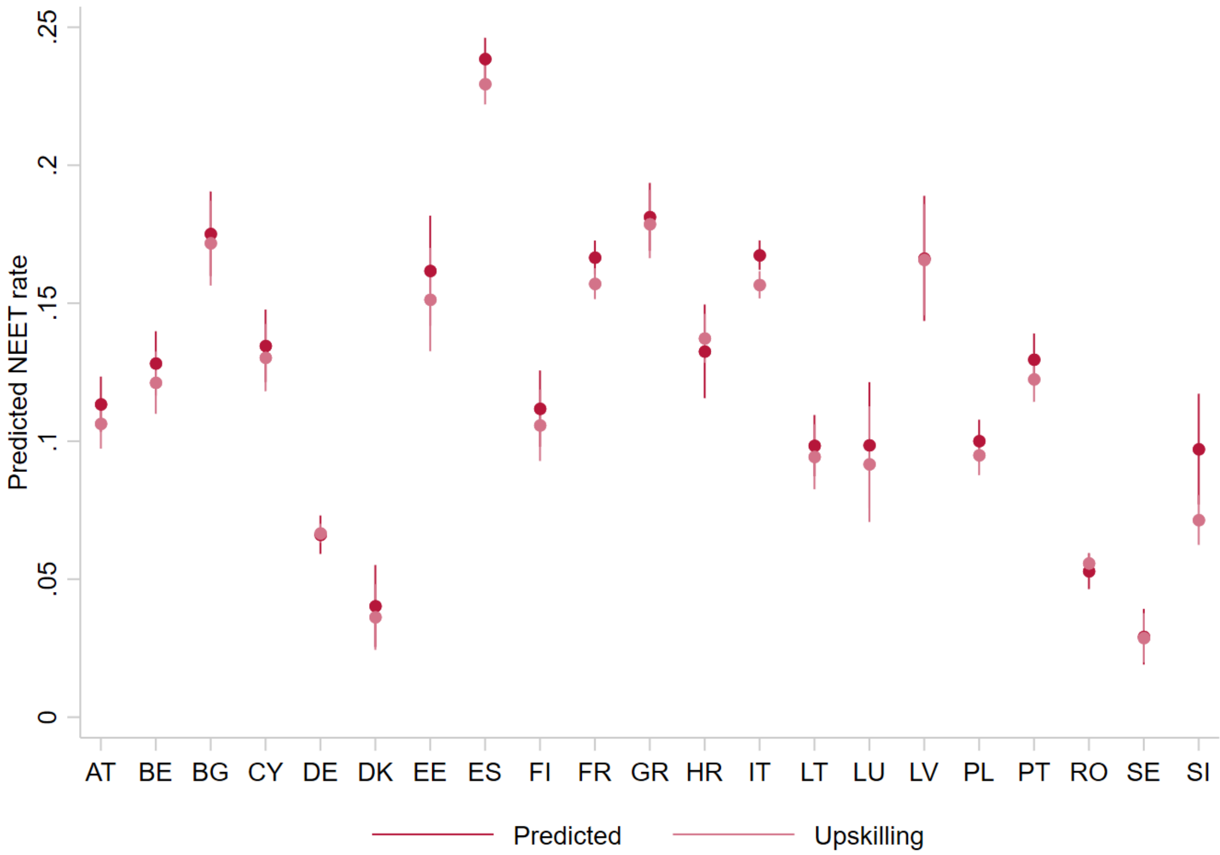
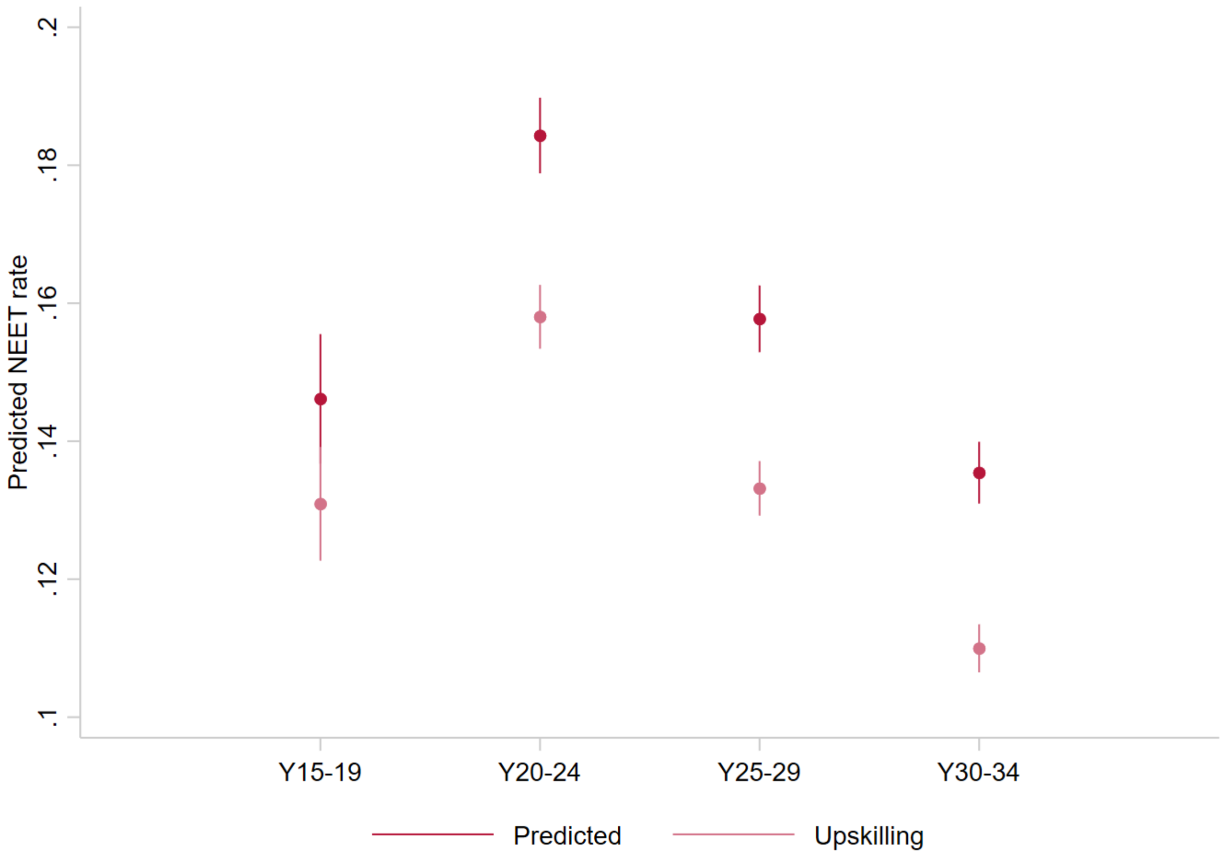
[9] For further discussion between investments in specific or general training see Acemoglu & Pischke (1999).

Figure 2. **Predicted vs simulated NEET rate, by country**



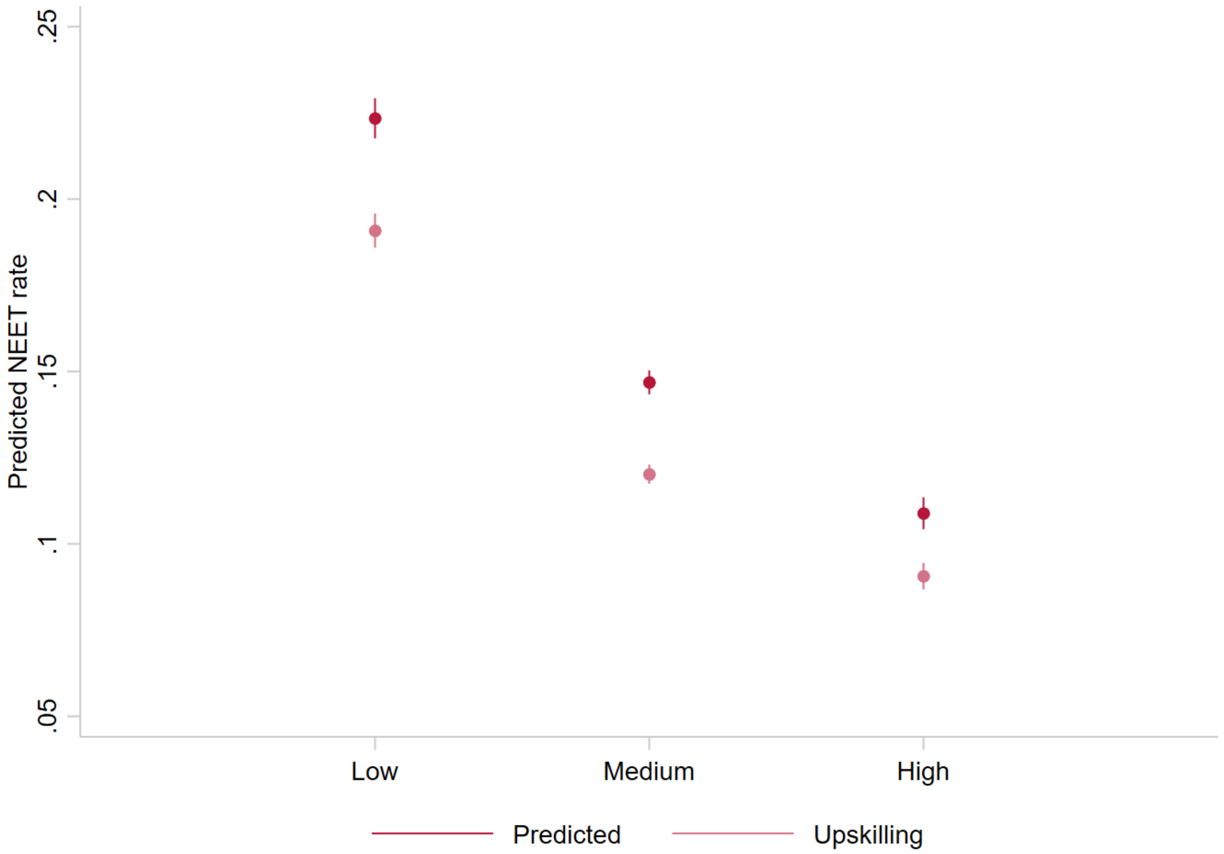
Source: own elaboration based on EU-LFS 2022. 95% CI displayed.

Figure 3. **Predicted vs simulated NEET rate, by age**



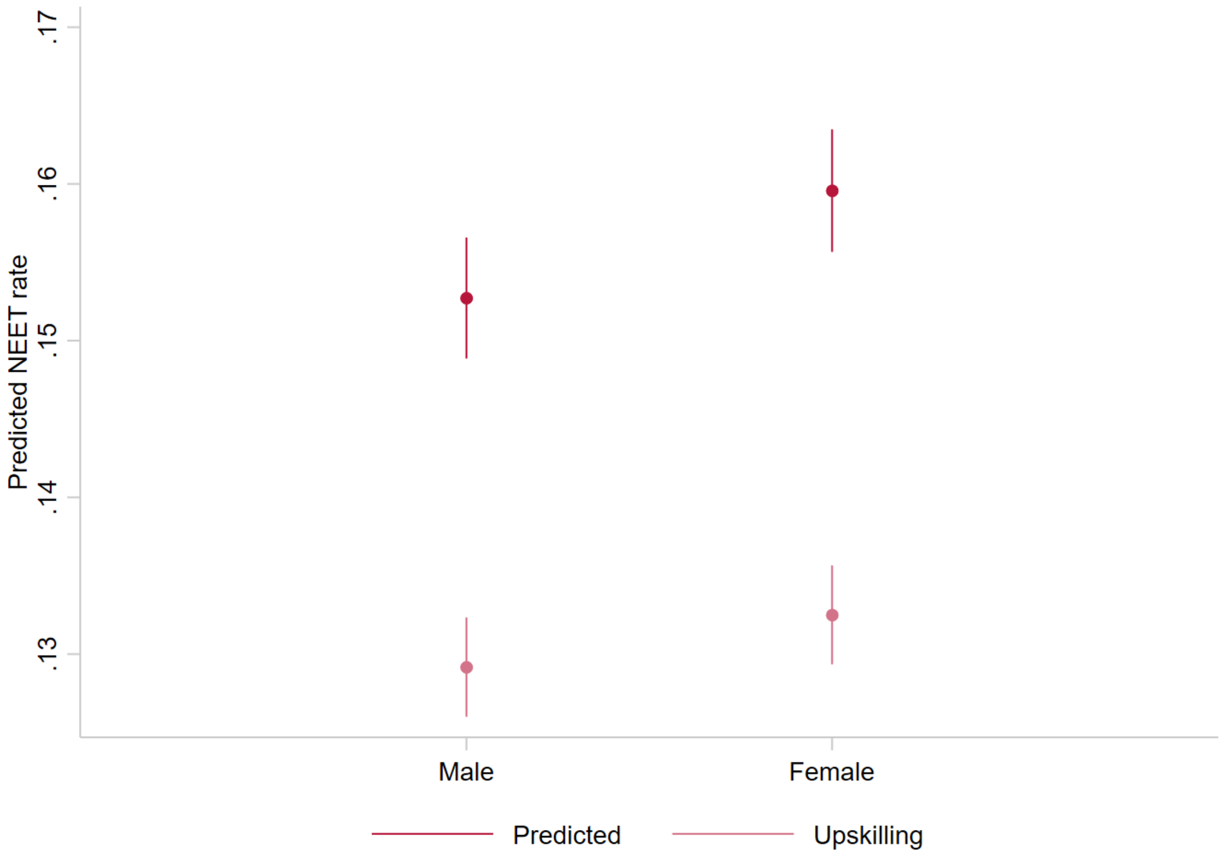
Source: own elaboration based on EU-LFS 2022. 95% CI displayed.

Figure 4. **Predicted vs simulated NEET rate, by education**



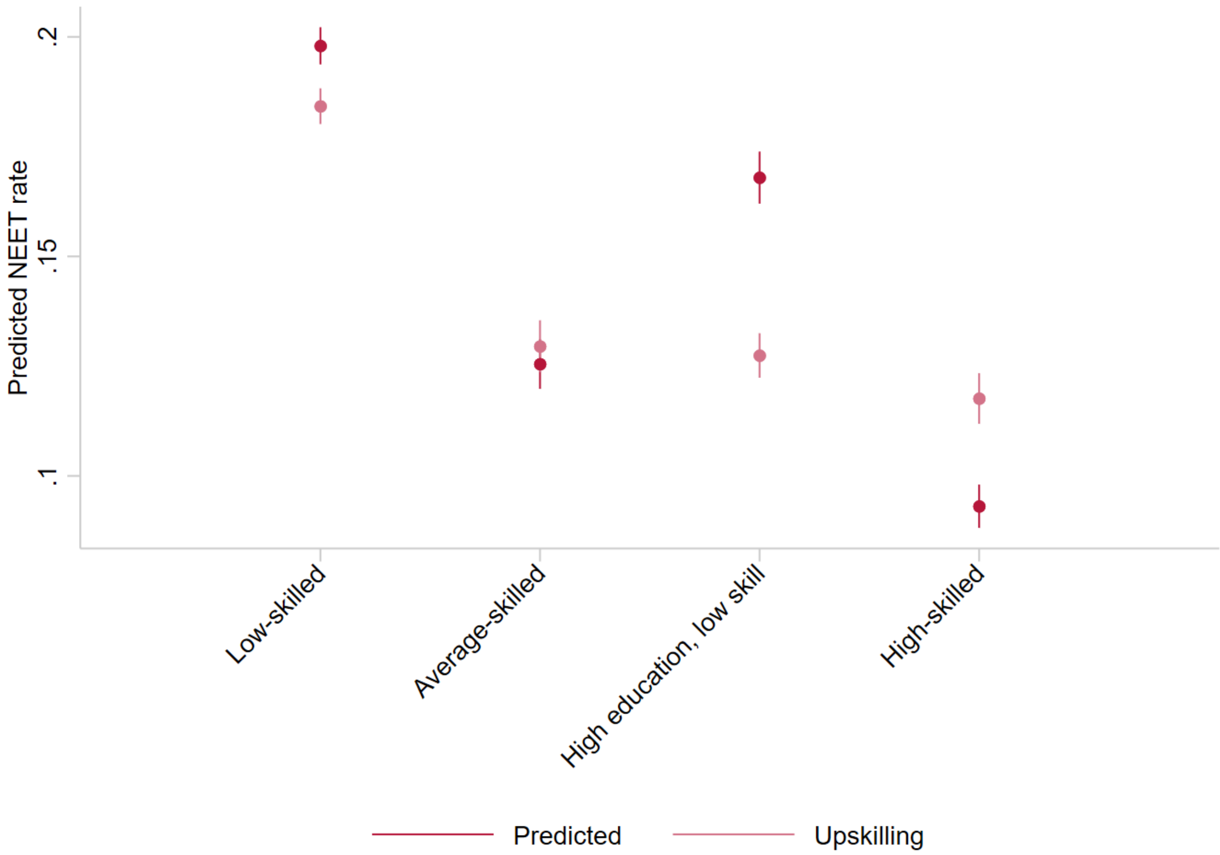
Source: own elaboration based on EU-LFS 2022. 95% CI displayed.

Figure 5. **Predicted vs simulated NEET rate, by gender**



Source: own elaboration based on EU-LFS 2022. 95% CI displayed.

Figure 6. **Predicted vs simulated NEET rate, by skill group**



Source: own elaboration based on EU-LFS 2022. 95% CI displayed.

We further use the random forest to test if participation in training within the last 12 months predicts NEET status. In this case, we do not leverage closing the skill gap, but analyse whether recent participation in training reduces the likelihood of falling within NEET category. Therefore, we do not make any assumption about training effectiveness.

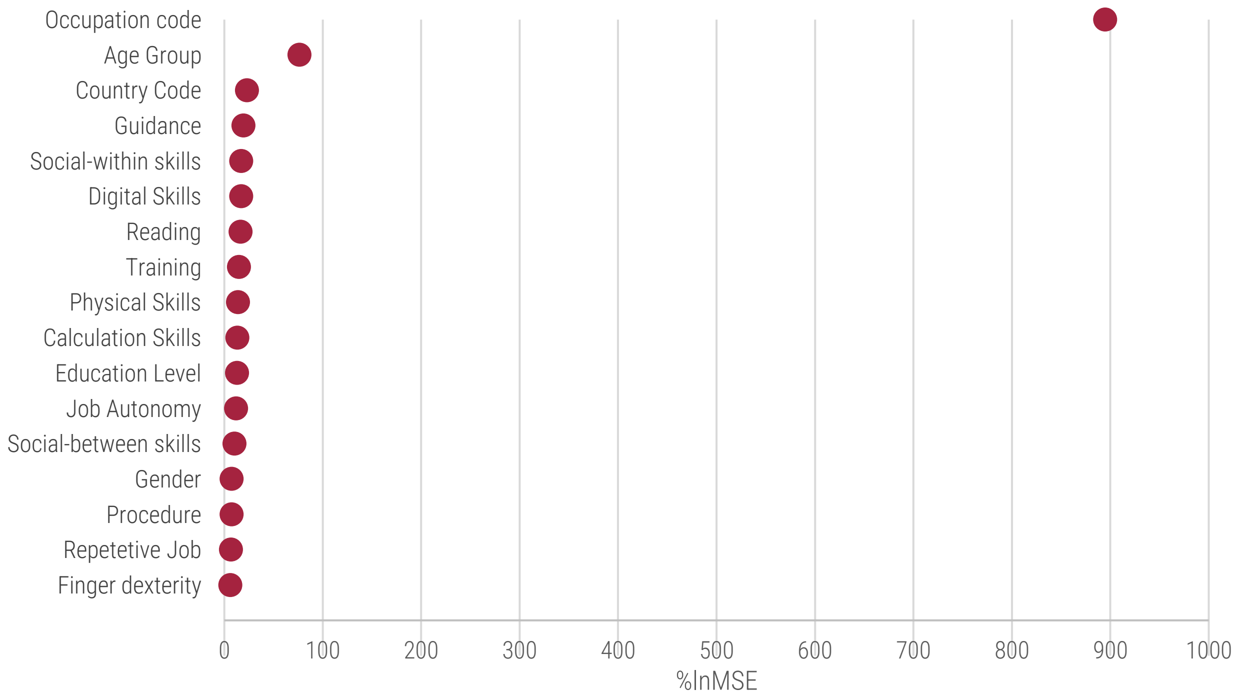
Since this relationship between participation in training and NEET status can be mechanical due to the NEET definition, we made some adjustments to our data. We exclude employees who received training within the last 4 weeks from our sample. As a result, we ended up with a group of individuals who could have received training only within 12 months. We also check if assignment to training was correlated with skills used at work. Table 16 (in the Appendix) shows the results of probit regression where the outcome was whether NEET participated in training last 12 months. We find that participation in training was only significantly associated with higher physical skills utilisation.

The first results show that ISCO-3d occupation codes are responsible for almost all accuracy. (Figure 7, panel (a)). We check the sensitivity of the obtained results by excluding the ISCO occupation code. Panel (b) of Figure 7 presents the variable importance of each variable used in the final model. We find that country, digital, social and reading skills play a key role in predicting NEET status. However, training, repetitive job experience, and age group contribute little to the prediction of NEET status. Still, when controlling for work experience, the contribution of skills and previous training experience does not significantly improve the predictive power of the model. These results suggest that training may not be the most effective tool in protecting employment, calling for further research[10].

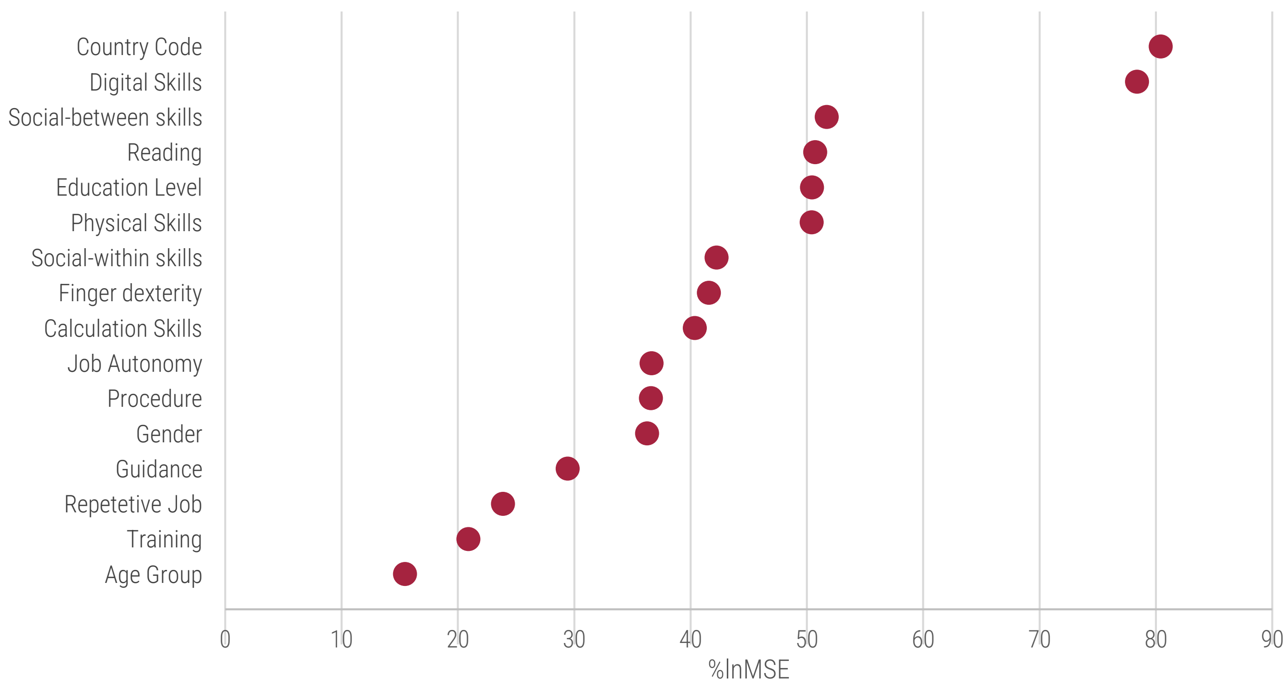
[10] This may also suggest that current training offer does not serve the purpose of closing the skill gap between NEETs and employees.

Figure 7. **Random Forest Variable Importance**

(a) occupation code included



(b) occupation code excluded



Source: own elaboration based on EU-LFS 2022

5. Conclusions and discussion

Using data from the 2022 Labor Force Survey ad hoc module on job skills, we compare occupations and skill utilisation at work between NEETs with prior work experience and employed individuals aged 15–34. We show that NEETs less often work in occupations requiring analytical and social tasks and more often work in occupations involving manual and routine tasks. They also demonstrate lower utilisation of digital skills, cognitive skills (e.g., reading and calculating), and social skills (e.g., communication within and outside the organization). Instead, NEETs with prior work experience rely more on physical tasks, such as lifting, pushing, pulling, or carrying objects. They also tend to have lower levels of autonomy in the tasks they perform. We observe that the largest skill gap lies in the use of digital skills, with NEETs being nearly six percentage points less likely to utilise these skills than their employed peers.

We find that nearly 60% of NEETs possess very low digital skills. These individuals can be divided into two subgroups. The first, comprising about two-thirds, is characterized by lower education levels, physically oriented occupations, and a higher proportion of men. The second group, comprising one-third, also has poor digital skills but is relatively well-educated, includes a higher proportion of women, and works in occupations primarily requiring social skills.

We also show that, in general, training and digital upskilling can lead to a lower NEET rate, though the differences are moderate across various socio-demographic groups. However, we find the strongest positive effect among highly educated individuals with low digital skills. This group potentially can benefit the most from specific upskilling programme, as they have already acquired general human capital. As argued by (Tobback et al., 2024) the effects of learning can be driven by the fact that individuals with vocational education have already obtained skills useful for their education profile, while they may lack general human capital, fundamental for developing other skills.

Our findings align with existing literature, which highlights the associations between skills and NEET status (Attanasio et al., 2011; Warburton et al., 2024). The modest impact of training, however, should be interpreted within a broader context. The literature on the effectiveness of ALMPs emphasizes several key points that are crucial when discussing support measures for youth unemployment or NEETs, including training programs. First, given the heterogeneous nature of the NEET group, support should be tailored to address the specific needs and challenges faced by its various subgroups (Eurofound, 2016; European Commission, 2018). Second, recent studies indicate that the design and implementation are more important than the type of intervention. (Kluve et al., 2019; Stöterau et al., 2022). Third, for the most disadvantaged groups, such as NEETs, interventions should address multiple barriers, including low motivation, as well as social and health-related challenges. Multi-component programs that combine elements such as mentoring, social support, and health considerations have shown promising results (Caliendo & Schmidl, 2016; Mawn et al., 2017; Kluve et al., 2019; International Labour Organization & World Bank, 2024). Fourth, when supporting young people, it is crucial to weigh the potential drawbacks of training programs against formal education. Short-term programs focus on addressing minor skill deficits, whereas long-term programs aim to tackle more structural deficiencies, such as gaps in education. However, long-term training programs may compete with formal education. Additionally, employers may not perceive training programs as equivalent to formal education, which could result in negative stigmatization effects for participants (Caliendo & Schmidl, 2016).

Moreover, the training system does not need to help NEETs as they may already have skills demanded in the labour market, but may fall behind employees in other categories (e.g. location) (Cammeraat et al., 2022; Jongbloed & Giret, 2023). Policy cohesion may be more effective — training policies must be combined with policies focused on poverty and the inclusion of the education system and labour markets (Berigel et al., 2023). NEETs may also sort themselves into poorer education, which makes it more difficult for the training to be effectively provided. Since the risk of NEET is already visible in primary education and is closely associated with special education needs and social deprivation, early intervention could be more beneficial than training for some groups (Warburton et al., 2024).

These factors underscore the need for carefully designed, context-sensitive and multi-component policies that address various challenges faced by NEETs. Our study highlights that NEETs with poor digital skills represent a diverse population, including low-educated individuals working in occupations requiring physical strength, as well as highly educated individuals in occupations requiring social skills. The first group may benefit more from early intervention programs focused on improving educational outcomes, reducing school dropouts, and building human capital. This is primarily the role of educational institutions and social assistance organizations for individuals from vulnerable backgrounds, with PES playing a supportive role in collaboration with these institutions at the early stages. The second group may benefit from upskilling training programs, which can be more easily provided by PES. Effective profiling of NEETs in terms of digital skill shortages upon registration seems to be an essential first step, which has recently been introduced by some countries (European Commission, 2024).

Our study has some limitations. First, due to the ad hoc module design, NEETs' responses may be slightly biased as they refer to their last employment, which they may not remember accurately. However, given that most NEETs in our sample are short-term NEETs, we believe this is unlikely to significantly affect the results. Second, we may not observe some characteristics (e.g. related to motivation) that may predict employment status, the NEET status, or selection to the training. To reduce the selection bias, we control for various socio-demographic, job-related and regional factors that may improve the accuracy of our regression models and counterfactual analysis.

Third, we focus on NEETs with prior job experience. Individuals in this group may face temporary setbacks (e.g., layoffs) rather than structural barriers. It is unclear if the training programme could significantly increase the employability of NEETs without prior job experience as they may face various educational and socio-economic disadvantages. Therefore, rather than drawing conclusions on the general population of NEETs, our results relate primarily to policies reducing short-term unemployment and inactivity among young people.

Finaly, our approach is of comparative statics only. We analyse only the possible change in the NEET status conditional on bridging the skill-gap. The applied skill-gap model has some limitations. Our first results indicate positive relationship between training participation and employment probability[11]. This does not have to hold, as some training offers may offer education not suitable for the current labour demand. Our analysis also does not explore possible horizontal job mismatch, which could relate to lack of opportunities in line with individual interest.

[11] Importantly, some of the high-skilled NEET group already have better qualifications, compared to the average employee. Therefore, closing the skill gap for this group means mechanically lowering their skill level, leading towards a higher NEET rate after upskilling. This group despite high-skill level report neither in employment nor education or training. It is unclear if further upskilling policy could potentially increase their employability, as they are already qualified for the position.

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Appendix

Table 11. Skills and tasks included in the Labour Force Survey ad hoc module on job skills

Skills	Definition	Scale
Digital	Time spent on working on digital devices in main or last job	1 – All or most of the working time 2 –Half of the working time or slightly more 3 – Some of the working time 4 – Little of the working time 5 – None of the working time
Calculations	Time spent on doing relatively complex calculations in main or last job	
Reading	Time spent on reading work-related manuals and technical documents in main or last job	
Physical	Time spent on doing hard physical work in main or last job	
Dexterity	Time spent on tasks involving finger dexterity in main or last job	
Social - interactions within organisation	Time spent on interacting with people from the same enterprise or organisation in main or last job	
Social - interactions outside organisation	Time spent on interacting with people from outside the enterprise or organisation in main or last job	
Guidance	Time spent on advising, training or teaching other people in main or last job	
Task characteristic	**Definition**	**Scale**
Job autonomy on tasks[12]	Degree of autonomy on tasks in main or last job	11 – Large or very large autonomy on both order and content 12 – Large or very large autonomy on order and some autonomy on content 13 – Large or very large autonomy on order and

[12] Note that this question does not follow standard Lickert scale. We used answers 11, 12, 21 and 22 to define high level of job autonomy.

		little or no autonomy on content 21 – Some autonomy on order and large or very large autonomy on content 22 – Some autonomy on both order and content 23 – Some autonomy on order and little or no autonomy on content 31 – Little or no autonomy on order and large or very large autonomy on content 32 – Little or no autonomy on order and some autonomy on content 33 – Little or no autonomy on both order and content
Task repetitiveness	Repetitiveness of tasks in main or last job	
Strict procedures	Tasks precisely described by strict procedures in main or last job	

Source: own elaboration based on EU-LFS 2022 and the "Explanatory notes for the variables on 'Job Skills'".

Table 12. NEET rates, and the share of NEETs with job experience among NEETs in the EU countries, individuals aged 15-34 y.o.

	NEET rate (%)	Share of NEETs with job experience among NEETs (%)
Italy	20.81	24.7
Romania	20.34	9.2
Greece	17.77	34.6
Bulgaria	16.33	26.4
Croatia	14.43	33.0
Cyprus	14.36	41.6
Spain	13.04	51.4
France	12.55	48.4
Latvia	12.52	49.0
Poland	11.66	25.6
Belgium	10.99	31.9
Lithuania	10.69	35.8
Finland	10.6	37.5
Estonia	10.49	46.6
Germany	10	33.9
Portugal	9.9	42.6
Austria	9.67	51.3
Denmark	8.82	45.0
Slovenia	8.72	28.4
Sweden	5.82	23.4
Luxembourg	5.36	28.5
Total	13.17	34.2

Source: own elaboration based on the LFS data

Table 13. The structure of NEETs and employed individuals aged 15-34 y.o.

	NEETs without job experience (%)	NEETs with job experience (%)	Employed (%)
Sex			
Male	38.7	48.2	54.2
Female	61.3	51.8	45.8
Age group			
15-19	13.5	4.9	5.6
20-24	23.8	26.1	21.5
25-29	29.1	33.5	33.0
30-34	33.6	35.5	39.9
Education level			
Third level	12.3	23.0	37.6
Upper secondary	45.7	27.9	15.6
Lower secondary	42.0	49.1	46.9
Labor market status			
Unemployed	25.4	51.8	-
Inactive	74.6	48.2	-

Source: own elaboration based on the LFS data

Table 14. Time since last worked among NEETs with job experience gained up to two years prior to the LFS survey

	%	Cum. %
0-3 months	38.0	38.0
4-6 months	18.3	56.3
7-9 months	11.1	67.4
10-12 months	8.6	76.0
13-15 months	7.4	83.4
16-19 months	6.1	89.6
20-21 months	5.0	94.6
22-24 months	5.4	100.0

Source: own elaboration based on the LFS survey

Table 15. Most popular occupations, by group, ISCO-08-unit groups

NEETs (%)		Employed (%)	
Shop Salespersons	8.3	Shop Salespersons	6.3
Waiters and Bartenders	7.1	Software and Applications Developers and Analysts	2.4
Domestic, Hotel and Office Cleaners and Helpers	4.9	Machinery Mechanics and Repairers	2.3
Transport and Storage Labourers	3.5	General Office Clerks	2.3
Agricultural, Forestry and Fishery Labourers	3.2	Material Recording and Transport Clerks	2.3

Source: own elaboration based on EU-LFS 2022 data

Table 16. Within-NEET sorting into training

	Receive Education 12 months before
	Probit
Digital Skills often	0.0148
	(0.0151)
Calculations used often	-0.0197
	(0.0249)
Physical skills used often	0.0337**
	(0.0129)
Job Autonomy	0.0209
	(0.0149)
Repetitive job	0.0124
	(0.0121)
Country F.E.	Yes
Gender F.E.	Yes
Education	Yes
Age group F.E.	Yes
Occupation 3d-iSCO F.E.	Yes
Observations	15870

Source: own elaboration based on EU-LFS 2022

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WeLaR is Horizon Europe research project examining the impact of digitalisation, globalisation, climate change and demographic shifts on labour markets and welfare states in Europe. It aims to improve the understanding of the individual and combined effects of these trends and to develop policy proposals fostering economic growth that is distributed fairly across society and generates opportunities for all.

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