

Digitalisation of jobs and gender-age segregation in digital tasks:

Cross-country evidence based on ESJS2 data

Sebastian Leitner and Stella Zilian



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SEBASTIAN LEITNER

STELLA ZILIAN

Sebastian Leitner and Stella Zilian are Economists at The Vienna Institute for International Economic Studies (wiiw).

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Abstract

This paper addresses the disproportional effects of digitalisation across age by investigating: (i) within-job age segregation in tasks by digital intensity; (ii) within-job age disparities in digital upskilling; (iii) age inequalities in wage returns to digital job tasks; and (iv) the role of gender in this age segregation and inequalities. The analysis is based on data of Cedefop's second wave of the European Skills and Jobs Survey (ESJS2), conducted in 2021. First results of the analysis show that even when controlling for occupation-industry job pairs apart from using other explanatory variables, age segregation and gender gaps are prevalent in the case of digital skill intensity of tasks performed in the jobs of employees, though not in the case of digital upskilling via training measures. Applying the same appropriate controls, we also find that higher within-job digital skill intensity is associated with higher hourly wages. Gender wage gaps are sizable across all skill intensity categories in addition to widening in older age groups.

Keywords: Age inequalities, earnings, gender gaps, job segregation, digital skills, tasks

JEL classification: J01, J08, J14, J16, J24, J31

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1. Introduction

1.1. BACKGROUND AND CONTRIBUTION

The world of work is changing rapidly, and the EU is exposed not only to labour shortages, but also to skill shortages. Labour shortages are a pressing issue owing to the demographic challenges affecting most EU countries (Astrov et al. 2021; Leitner and Stehrer 2019). Specifically, the working-age population of the EU is shrinking, and this trend is likely to accelerate over the current decade. Moreover, in the 2015-2020 period, the 65+ age group recorded the fastest increase in labour-market participation. However, fewer young people have entered the labour market, and the expectation is that youth participation rates will decline (Bertelsmann Stiftung and wiiw 2023).

Changes on the supply side are coupled with important developments on the labour demand side. Automation and digital technologies are transforming the world of work, and reskilling and upskilling are crucial if we are to successfully adapt to these changes (World Economic Forum 2021). However, not all workers are equipped with the skills and abilities needed to adjust to the ongoing shift in job tasks and expanding digitalisation. Specifically, in the EU, every third person at work lacks the proper digital skills, resulting in major skill shortages and widening inequalities as labour market returns to skills – particularly digital skills – steadily increase (Falck et al. 2021; Frey 2019; DiMaggio and Bonikowski 2008).

However, as the demographic shift is coupled with rapid digitalisation, the job skill requirements and the rising importance of digital skills may appear challenging to older workers, who often experience a sharp digital divide both at work and in everyday life (Blažič and Blažič 2020). Members of older generations tend to have lower digital literacy and, consequently, less experience with digital devices and computerised machinery (Falck et al. 2021; Bejaković and Mrnjavac 2020). Indisputably, older workers possess other invaluable skills and competencies, largely stemming from their long labour-market experience. Yet, increasing digitalisation and automation change the content and organisation of work, with most job tasks inevitably being affected and requiring some degree of digital skills. As a result, especially older workers – who are now staying in the labour market for longer and who possess, on average, lower digital skills – need to engage in upskilling and reskilling given the extra difficulties they face in adapting to technological change (European Commission 2021).

A widening age gap in digital skills will inevitably amplify age segregation in job tasks that require digital skills as older workers opt out of these because of their lack of digital skills. They may also be reluctant to engage in additional training given the smaller life-long returns to be gained from acquiring digital skills (Peng et al. 2017). Age segregation in jobs has long been documented in the literature, and substantial entry barriers to occupations with steep wage profiles, pension benefits and computer usage have been among the major factors driving age segregation (Biagi et al. 2011; Hirsch et al. 2000). However, rapid automation and digitalisation, which have further accelerated in the wake of the COVID-19 pandemic, may result in even more persistent job-task selection patterns across older and

younger workers, largely driven by differential digital skill profiles.¹ Furthermore, opting out of digital tasks can be even more pronounced among older women, as the persistent gender gap in digital skills and the use of digital skills may reinforce age segregation with regard to digital tasks in the case of older women (Siddiq and Scherer 2019). Given the increasing wage returns to digital skills, this could widen the gender wage gap even further.

To date, there has been limited internationally comparable evidence on within-job age selection in digital tasks, on selection into digital upskilling, and on age gaps in the wage returns to digital job tasks. This is largely due to a lack of international surveys of workers that would enable researchers to derive harmonised and comparative measures of digitalisation at the job-task level and of workers' engagement in digital training/upskilling. Our analysis makes some contributions in this respect to the existing literature. It provides some of the first comprehensive evidence on age selection into digital tasks within similar jobs in the EU context by harnessing the very detailed measures of digital tasks of the second European Skills and Jobs Survey (ESJS2) of the European Centre for the Development of Vocational Training (Cedefop), conducted in 2021. Aiming to investigate how older workers are adjusting to the shift in work tasks towards greater digital intensity, it answers the following research questions:

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

1.2. LITERATURE REVIEW

Early research in economics on the effect of technology on older workers is rooted in standard human capital theory and the notion of skill-biased technological change, meaning that new technologies increase the relative productivity of the highly skilled (college-educated), leading to rising wage disparities between different skill groups (see Acemoglu and Autor 2011). Older workers are assumed to lack the kinds of skills needed to enable them to keep up with rapid technological change, which reduces their competitiveness in the labour market and may lead to early retirement, unemployment or relative wage loss (Biagi et al. 2011). Moreover, older workers may be subject to ageist hiring practices because of prevailing stereotypes about age and technology (Losh 2013).

Auber et al. (2006) provide some empirical evidence for the detrimental effect of new technologies on older workers' labour market outcomes. Based on French firm-level data, they find that new technologies and innovation activities negatively affect older workers by decreasing hiring opportunities as well as reducing the relative wage-bill share of older workers compared to younger workers. This negative wage bias can be observed across genders and within occupational groups, indicating that skills may not

¹ It is worth mentioning that digital skill gaps between age groups may also shrink over time as overall technology adoption increases and because the current young generation is the old generation of the future. Zilian and Zilian (2020) find mixed results for Austria using Eurostat data from 2015 and 2019: while the gap between older and younger adults with advanced digital skills has decreased over time, the gap has widened for those with low and basic digital skills.

entirely protect workers from adverse age-related effects. Another strand of literature studies whether the use of information and communications technology (ICT) and computer literacy delays retirement of older workers, but the results are mixed. For example, Bartel and Sicherman (1993) show that older workers in industries experiencing rapid technological advancement tend to delay retirement, but if these advancements cause an unexpected rapid depreciation of their skills, it leads to earlier retirement. Similarly, Friedberg (2003) indicates that US workers who use personal computers (PCs) tend to postpone retirement, whereas Schleife (2006) finds no significant relationship between computer use and retirement of older workers in Germany. Finally, Biagi et al. (2011) find that while computer literacy and PC usage alone do not significantly impact retirement probability, the combination of these two factors significantly decreases the likelihood of retirement among older workers. This indicates that computer-specific skills can extend labour market participation of older workers if they have jobs in which they can apply these skills.

With the availability of new international comparable micro-data on skills and tasks used at work – such as the OECD’s Programme for the International Assessment of Adult Skills and Competencies (PIAAC) and Cedefop’s European Jobs and Skills Survey (EJSS) – a growing body of research investigates both the distribution of digital skills and the use of ICT at work. One important finding regarding the former is that older adults, women and people with lower levels of educational attainment tend to have lower digital problem-solving skills compared to younger adults, as measured by the computer-based assessment administered by the PIAAC (Ertl et al. 2020; Zilian and Zilian 2020; Drabowicz 2021; Non et al. 2021; Falck et al. 2022). These findings are in line with the vast body of literature on digital inequality, which studies the causes and consequences of unequal access to and utilisation of digital technologies across society and shows that digital divides reflect patterns of offline social inequalities (see DiMaggio et al. 2004; Zillien and Hargittai 2009; van Deursen and van Dijk 2011; van Deursen et al. 2011; Robinson et al. 2015). Although there is less research on digital inequality *among* older adults, Hargittai and Dobransky (2017) reveal significant differences based on US survey data on internet access and use from 2009. Specifically, they find that within the 55-and-older age group, respondents of higher socioeconomic status (i.e. higher educational attainment and higher income) have better internet skills in addition to engaging in more varied and beneficial (‘capital-enhancing’) online activities.

The consequences of these digital divides are far-reaching, particularly in the labour market. The role of cognitive skills in general and digital skills in particular for individual workers is highlighted in various national and cross-country studies based on PIAAC data, which typically find that greater digital problem-solving proficiency is associated with better labour market outcomes, such as higher wages (Hanushek et al. 2015; Hampf et al. 2017; Falck et al. 2021). The positive relationship with wages is also persistent over time, as shown by Non et al. (2021), who link Dutch PIAAC data to register data to allow for an analysis of individual careers from 2012 to 2019. Apart from a persistent positive relationship between digital problem-solving skills and wages, the authors also find that individuals with at least basic digital skills are 10% more likely to be employed than respondents who failed the basic computer test (Non et al. 2021). A recent study for the US further shows that higher digital problem-solving skills are associated with a lower risk of automation (Yamashita et al. 2024), highlighting the important role that digital skills play in the face of ongoing advancements in the realm of generative artificial intelligence (AI).

While most studies on skills and labour market performance typically use age as a control variable, Falck et al. (2022) specifically address the age dimension of digital skills and labour market outcomes across 27 OECD countries. The authors focus on the prevalence of basic digital skills and show that the

share of individuals with at least basic digital skills is always highest in the youngest age group (25-44) and always lowest in the oldest age group (55-64), although the skill gaps between the oldest and the youngest groups vary considerably across countries, with smaller gaps in Western Europe and Scandinavia compared to Eastern and Southeastern Europe. Falck et al. (2022) find this to be mostly due to cross-country differences in the shares of elderly workers with basic digital skills. Whereas the share of workers aged 55-64 with basic digital skills amounts to less than 20% in Turkey and Poland, it exceeds 75% in countries like Sweden, the Netherlands and Denmark. The authors further explore how digital skills relate to labour market outcomes among older workers (55-64) and find that digital skills are associated with better employment prospects, higher wages and a higher share of abstract tasks.

Switching perspective from skills to tasks carried out at work, Fernandez-de-Alava et al. (2017) use Spanish PIAAC data to compare how different generations use ICT at work. They categorise individuals based on their age and respective exposure to digital technology: 'digital natives' (born 1980-1996), 'digital immigrants' (born 1967-1979), and 'pre-digital immigrants' (born 1947-1966). Digital natives grew up with digital technology from a young age; digital immigrants experienced the introduction and rapid expansion of digital technology during their formative years and early adulthood; and pre-digital immigrants had to adapt to digital technologies later in life. They find that digital immigrants use ICT significantly more than the other two groups, while pre-digital immigrants use ICT the least. Data from the ESJS2 also highlight that older workers tend to be less exposed to digital technologies at work, but this varies by educational attainment and occupation, which may be related to labour market segmentation patterns (Cedefop 2022).

The issue of digital labour market segmentation is further studied in Calderón-Gómez et al. (2020). Based on online survey data collected in 2016 from a representative sample of Spanish internet users, they use cluster analysis to identify three groups among people using ICT for work. The first group, labelled the 'emerging digital precariat' (10% of the sample), encompasses younger, predominantly female and often less educated workers in precarious economic conditions. This group uses the internet linked to mobile devices and for communication tasks. The second group, identified as 'traditional digital labour' (around 27% of the sample), is characterised by older workers using the internet for productive rather than communication tasks on fixed PCs in the office. The third group, called the 'innovative class' (around 26% of the sample), combines digital communication with productive tasks, reflecting the incorporation of new organisation trends in their work. This group tends to be young, male and highly educated. Finally, Vasilescu et al. (2020) also use cluster analysis and combine different aspects associated with the impact of digitalisation to identify a 'digital vulnerable' group that is most likely to be negatively affected by the digital transformation. Based on data from the 2017 Eurobarometer 87.1, the authors identify members of the digital vulnerable group as respondents with low levels of self-reported digital skills, limited use of digital technologies, and pronounced fears about robots and AI taking people's jobs. People in this group tend to be older and female, to have lower educational attainment, to be manual workers or unemployed, and to suffer from financial stress.

While research consistently points towards the digital vulnerability of older adults, results of the ESJS2 show that a substantial share of older workers invest in digital skill development. Moreover, they tend to direct their training activities more often at digital skill development compared to younger workers (Cedefop 2022). Research in the field of human-computer interaction also shows that even though older adults are interested in learning digital skills, they still face significant challenges in using technology effectively, and that many older adults still experience digital exclusion because they often lack confidence in using

computers, the internet and other communication technologies (Hill et al. 2015). Other challenges identified in the literature include: age-related barriers, such as cognitive (e.g. reduced speed of learning) or physical issues (e.g. muscle weakness); problems associated with the design of technologies (e.g. touchscreens, user interface); negative social attitudes, such as stereotypes about older adults' (in)ability to learn how to use new technologies; and inadequate training materials (Hill et al. 2015).

In summary, there is clear evidence that older workers are disadvantaged in terms of digital skills and that they tend to be less engaged in digitally intensive work compared to younger workers. However, research further shows that older workers are not homogenous and that socioeconomic inequalities in terms of skills, ICT use and the associated labour market outcomes also prevail within this age group. Reskilling programs for older adults need to take into account these inequalities as well as the particular challenges that older adults encounter when learning how to use new technologies.

2. Data and descriptive analysis

2.1. DATASET AND SAMPLE SELECTION

The data used in this analysis stems from the Cedefop's second European Skills and Jobs Survey (ESJS2), which was conducted in 2021. The data enable us to look at how skills needs are changing as a consequence of digitalisation and technological progress as well as at how workers are adapting their skills to respond to such transformations. The ESJS2 covers all EU27 countries, Iceland and Norway, and it has a sample of over 45,000 adult employees. It provides comprehensive information on the socio-demographic characteristics of respondents (e.g. age, gender, education, urbanisation) and detailed job profiles (e.g. industry, occupation, employment tenure, firm size, type of contract, work hours, earnings, job satisfaction).

Most importantly, the survey maps the task structure of jobs and uses this mapping to proxy job-skill requirements in labour markets. The second wave of the ESJS places the digital demands of jobs in the spotlight. As a result, it makes it possible to capture the wider use of digital skills and the greater digital demands of jobs across a broad range of occupations by collecting data on: (i) on-the-job use of various digital devices; (ii) the performance of diverse job tasks requiring digital skills and the use of digital devices; and (iii) operation of various types of computerised machinery. This is a major advantage of the ESJS2 survey, as it measures the use of digital skills at work very comprehensively, covering multiple applications and numerous devices that require digital competence. The ESJS2 data include a broad range of 10 digital job tasks² performed by employees, from simple tasks (e.g. using the internet) to complex tasks (e.g. advanced programming for AI).

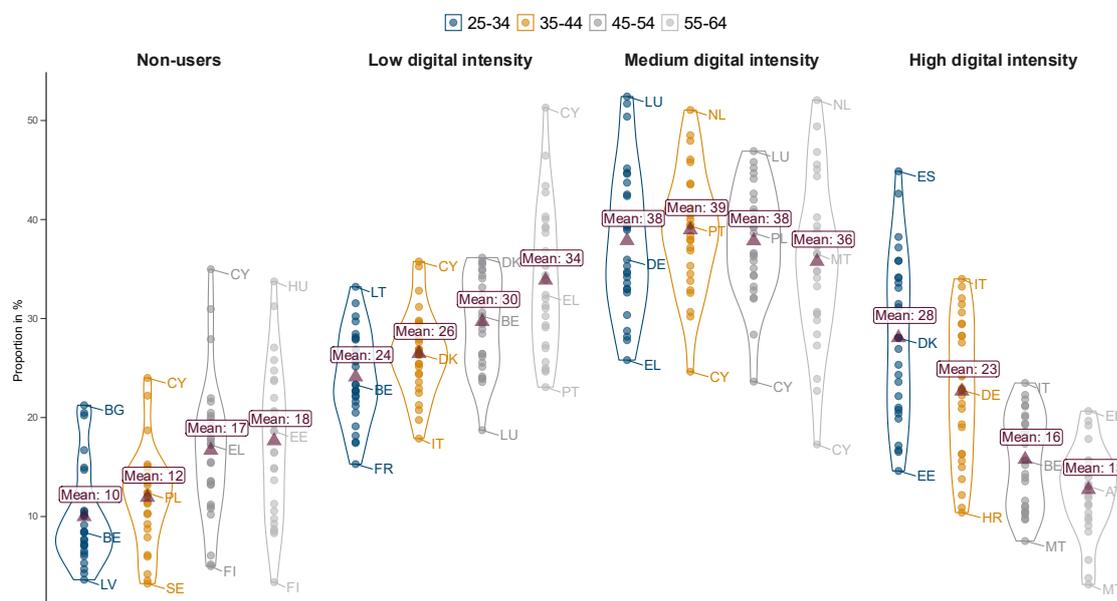
Based on the information collected on digital tasks within jobs, the Cedefop digital skills intensity (DSI) index is derived. This index relies on a composite-indicator approach to characterise jobs in terms of the intensity of on-the-job use of digital technology (non-users as well as low-, medium-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

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

2.2. DESCRIPTIVE ANALYSIS

In this section, we present the employment patterns across the four categories of digital skills intensity (non-users as well as low-, medium- and high-intensity users) in EU countries. Figure 1 shows the employment distribution for each age group using violin plots. Countries with the highest, median and lowest values are labelled. Additionally, the simple means within each DSI category and digital generation are reported. The width of each violin shows the density of the distribution of employment shares. In other words, the wider the section, the more countries have employment shares around these values, highlighting the extent of cross-country variation.

Figure 1 / Employment distribution by digital generation across different categories of digital skills intensity



Note: The observations labelled are the countries with the highest, median and lowest values. Mean refers to the simple mean within each DSI category and age group. The width of each violin shows the distribution density of the employment share within each group (i.e. the wider the section, the more countries have employment shares around these values). The employment shares within each generation sum to 100% across the four DSI categories.

Source: ESJS2 (2021); own calculations.

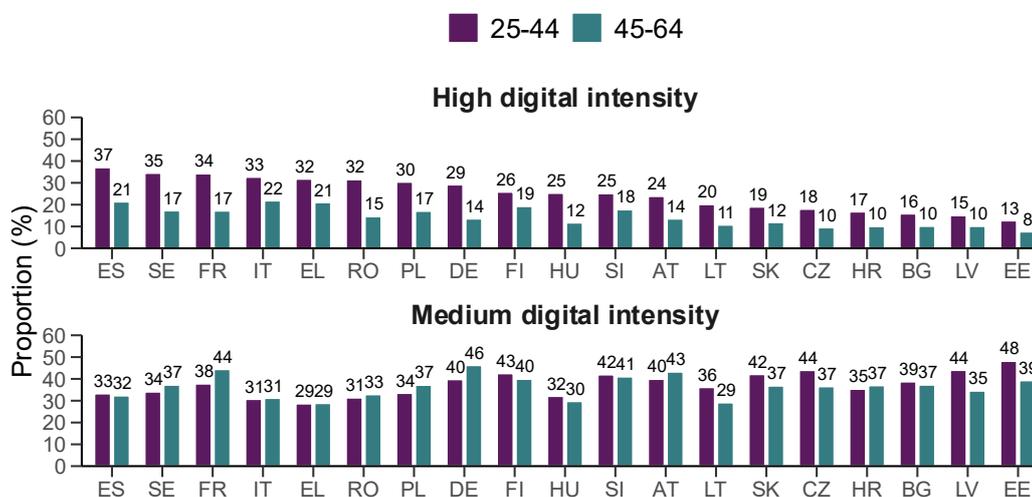
The figure reveals clear age differences in how digital tools are used at work:

- › On average, the employment share is highest in the medium DSI category for all age groups: 38% of those aged 25-34, 39% of those aged 35-44, 38% of those aged 45-54, and 36% of the oldest age cohort (aged 55-64) perform activities of medium DSI. However, there is considerable cross-country variation, especially among the oldest age group: 17% perform medium DSI activities in Cyprus, compared to 52% in the Netherlands.
- › Younger employees are more concentrated in the high DSI category: on average, 28% are engaged in high DSI activities, compared to 23% of those aged 35-44 and only 16% and 13% of those aged 45-54 and 55-64, respectively. Cross-country variation is most pronounced among the youngest age group, ranging from about 15% in Estonia to 45% in Spain.

- › Members of older generations are more concentrated in the low DSI category: on average, 34% of the oldest age group perform low DSI activities, compared to 30% of those aged 45-54, 26% of those aged 35-55, and 24% of the youngest age group (aged 25-34). However, there is substantial cross-country variation for those aged 55-64, with shares ranging from around 23% in Portugal to around 51% in Cyprus.
- › Members of older generations are also more likely than digital natives to be non-users: the employment shares are, on average, 18% for the oldest age group (aged 55-64) and 17% for those aged 45-54, while employment shares are, on average, 12% for those aged 35-44 and 10% for the youngest age group (aged 25-34). Again, there is considerable cross-country variation, especially for the two older age groups, with shares of non-users ranging from about 5% in Finland to 35% in Cyprus for those aged 45-54 and from about 3% in Finland to 33% in Hungary for the oldest age group (aged 55-64).

Figure 2 takes a closer look at cross-country differences, showing the employment shares in the high and medium DSI categories in 19 selected countries, where the two younger and older age groups are aggregated into two distinct age categories. The countries are ordered by the share of the younger age group (25-44) in the high DSI category.

Figure 2 / Employment distribution by age group across high and medium digital skills intensity categories in selected countries



Note: Employment shares within each age group sum to 100% across the four DSI categories (low digital intensity and non-users not shown). Countries are ordered according to the proportion of those aged 35-35 in the high DSI category (from highest to lowest).

Source: ESJS2; own calculations, weights applied

The upper panel of Figure 2 highlights the generational divide in high DSI employment, as the share of those aged 45-64 in high DSI roles is consistently lower than that of the younger age group across all countries. However, some notable country differences in the share of employees performing activities of high and medium DSI can be observed:

- › Looking at younger employees (aged 25-44), Spain emerges at the top, with 37% of younger employees engaged in high DSI tasks, followed by Sweden and France (35% and 34%, respectively).

These shares are substantially above those seen in Finland (26%), which roughly marks the median among the selected countries. At the other end of the spectrum, only 13% of younger workers in Estonia and 15-16% in Latvia and Bulgaria are employed in high DSI activities. This suggests that even among the younger workforce, there are substantial disparities regarding the engagement with high DSI tasks at work.

- › Similar patterns are observable for the older age group: while around 21% of older employees in Spain are engaged in high DSI tasks, this figure drops to just 8-10% in the Baltic states, Bulgaria, Croatia and Czechia, underlining the limited integration of older workers into work requiring high DSI tasks in some countries, especially those in Central and Eastern Europe (EU-CEE).
- › Among the EU-CEE countries, Romania and Poland stand out with relatively high shares of younger employees working in high DSI tasks (30-32%), which are higher than those in Germany (29%), Finland (26%) and Austria (24%). However, the lower panel reveals that Romania and Poland show somewhat smaller shares in medium DSI employment. This suggests that a significant share of workers in these countries may perform low DSI tasks or be non-users, indicating a potential gap in the overall digital integration of the workforces.
- › The older age group is better represented in medium DSI roles across all countries, and age gaps are less pronounced across all countries. This suggests that jobs requiring medium digital skills are more accessible to older workers. However, in certain countries (e.g. Cyprus, Estonia, Latvia and Malta), the share of those aged 25-44 in medium DSI roles exceeds that of older generations by around 9-10 percentage points (pp). This pattern indicates that in these countries, younger workers tend to dominate both high and medium DSI roles, while older employees are more often left behind.

In summary, the figures illustrate how employment across DSI categories varies by age group and country. Medium DSI roles dominate for all ages, though with wide cross-country differences. Younger workers are more engaged in high DSI tasks, especially in Spain, Sweden and France, while older workers are more concentrated in low DSI and non-user categories. In general, the share of employees involved in high DSI activities tends to be lower in EU-CEE countries compared to other EU countries, which suggests a slower integration of more advanced digital work.

3. Methodological approach

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

$$P\{y_i = \{0,1,2,3\} | A_{ij}, G_{ij}, Job_{ij}, X_{ij}^n\} = \alpha + \beta A_{ij} + \mu G_{ij} + \rho Job_{ij} + \gamma_n X_{ij}^n + \varepsilon_{ij} \quad (3.1)$$

$$P\{y_i = \{0,1,2,3\} | A_{ij}, G_{ij}, Job_{ij}, X_{ij}^n\} = \alpha + \beta A_{ij} + \mu G_{ij} + \sigma A_{ij} \times G_{ij} + \rho Job_{ij} + \gamma_n X_{ij}^n + \varepsilon_{ij} \quad (3.2)$$

In specifications (3.1) and (3.2), the dependent variable $y_i \in \{DSI_{ij}\}$ refers to the digital complexity of tasks performed on the job by individual i in country j . Respondent age A_{ij} is a categorical variable with 10-year age categories, G_{ij} stands for gender, Job_{ij} implies industry-occupation pairs, and the vector X_{ij}^n includes a broad range of demographic (e.g. educational attainment and urbanisation) and employment controls (e.g. employment tenure, firm size, type of contract, and work hours). Specification (3.2) adds an interaction term between age and gender, allowing us to investigate gender disparities in age segregation in digitalised tasks.

In the second part of the analysis, we will analyse age disparities in digital upskilling. As measure of upskilling, we employ whether an individual has learned how to use new computer programs or software to do her or his main job within the last year (or since the start of employment). In this case, we will employ specifications similar to (3.1) and (3.2), but with the upskilling variable $y_i \in \{ICT\ Training_{ij}\}$ as the dependent variable. We will estimate the models using weighted logistic regression based on ESJS2 data.

In the third part, we investigate differentials in within-job wage returns to digital tasks across older and younger workers by gender. We employ weighted linear regressions of the following form applying the ESJS2 data:

$$\ln W_{ij} = \alpha + \beta A_{ij} + G_{ij} + \omega DSI_{ij} + \rho Job_{ij} + \gamma_n X_{ij}^n + \varepsilon_{ij}, \quad (3.3)$$

$$\ln W_{ij} = \alpha + \beta A_{ij} + G_{ij} + \phi A_{ij} \times G_{ij} + \omega DSI_{ij} + \rho Job_{ij} + \gamma_n X_{ij}^n + \varepsilon_{ij}, \quad (3.4)$$

We regress the logarithm of the hourly wage W_{ij} of individual i in country j on age (A_{ij}); gender (G_{ij}); the digital skills intensity index of the job (DSI_{ij}), derived within ESJS2; industry-job pair (Job_{ij}); and a set of the same demographic and employment controls X_{ij}^n , as in specifications (3.1) and (3.2).

Specification (3.4) adds an interaction term between age and gender to identify potential gender differences of within-job age related disparities in wage returns.

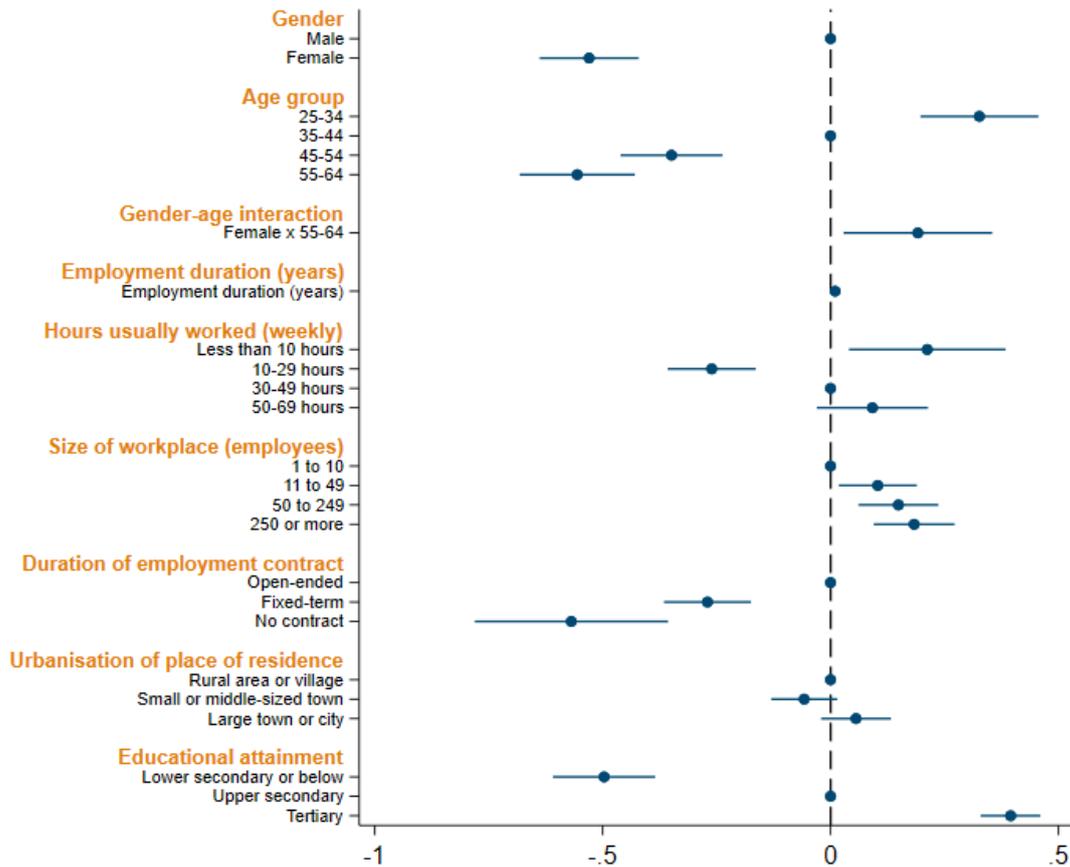
4. Results and discussion

4.1. AGE SEGREGATION OF DIGITAL SKILLS INTENSITY OF JOBS

In this section, we present the main results of the analysis on age segregation in digital skill intensity (DSI) in jobs performed by employees. We apply ordered logistic regressions and use survey weights, as described in Section 3 by Eq. (3.1) and Eq. (3.2). The dependent variable is the categorical variable of the DSI index, which comprises non-user of digital devices as well as low, medium and high levels of DSI of the tasks in the main job. Since we present raw coefficients, we can only observe whether an explanatory variable is associated with a higher probability of being in a higher DSI category significantly, but not by how much. The detailed regression results are presented in Table A.1 in the Appendix. In regression model [1], in addition to the explanatory variables,³ we also control for countries. In model [2], we also control for occupations (ISCO one-digit) and sectors (NACE one-digit) individually. In model [3], we also control for jobs (i.e. occupation-industry pairs), as also described in Section 3 by Eq. (3.1). Lastly, in regression model [4], which corresponds to Eq. (3.2) in Section 3, we also apply an interaction term between age groups and gender. Comparing the results of model [1] and model [4], we can observe that the coefficients and their significance do change, but only slightly. Thus, we present below (in Figure 3) the raw coefficients of our preferred regression specification [4]. Marginal effects will be presented further below in Figure 4.

The raw coefficients show that women are less likely than men to fulfil tasks of a higher DSI category within jobs. We can also observe the expected age differences, where higher age is associated with a lower likelihood of falling into a higher DSI category. The interaction term between age groups and gender shows that the prevalent gender gap of DSI within jobs decreases with rising age, but significantly only for the 55-64 age group. Thus, in Figure 3, we only show this category and not those with insignificant coefficients. The probability of a higher DSI category increases with having worked more years in the same enterprise. Moreover, it is higher for those working on average, full-time (30-49 hours per week) or even more (50-69 hours) in comparison to part-time (10-29), while those in the group of employees with fewer than 10 working hours per week seem to have rather different characteristics and are also more likely to perform more complex digital tasks. The likelihood of a higher DSI category increases with more employees working in an enterprise, but it does not differ by degrees of urbanisation of the employee's place of residence. Employees with open-ended contracts are more likely to have a higher DSI index than those with fixed-term or no contracts at all. In addition, those employees that have tertiary education and those with upper secondary education show a higher probability compared to those with education below the upper secondary level.

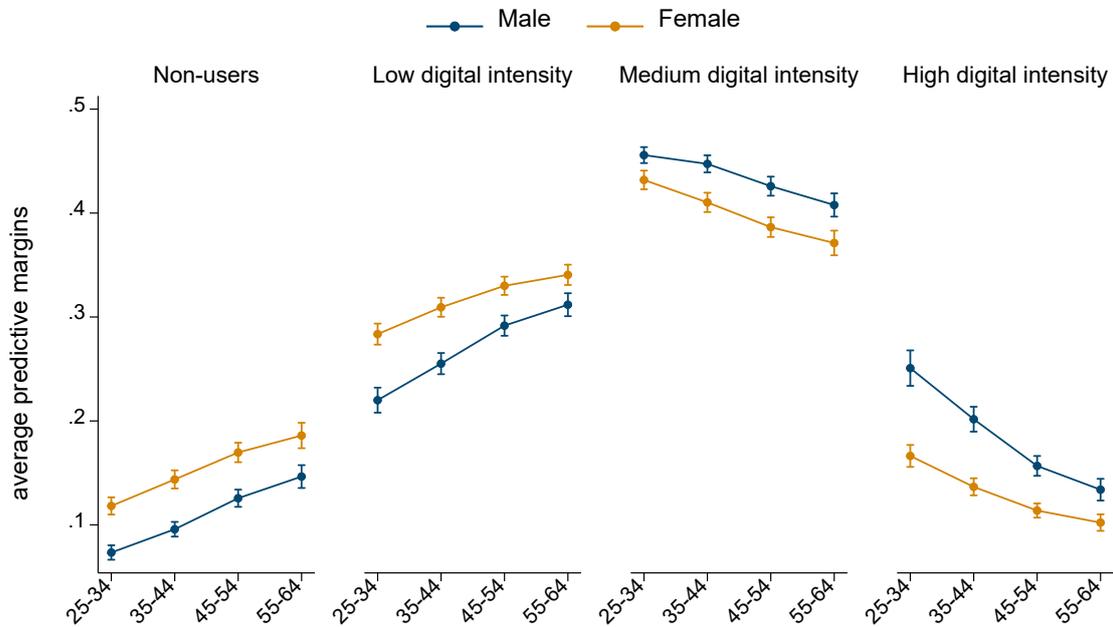
³ Most of the explanatory variables include, in addition to the presented categories, a category for 'Don't know' and another for 'No answer', which we included in our regressions. However, we suppressed these categories in the presentation of the results.

Figure 3 / Digital skills intensity of jobs: raw coefficients of ordered logit regression

Source: ESJS2; own calculations; robust standard errors; weights: Pan_Country_weight_v2.

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

Figure 4 / Digital skills intensity of jobs: average predicted probabilities by age group and gender



Source: ESJS2; own calculations; robust standard errors; weights: Pan_Country_weight_v2.

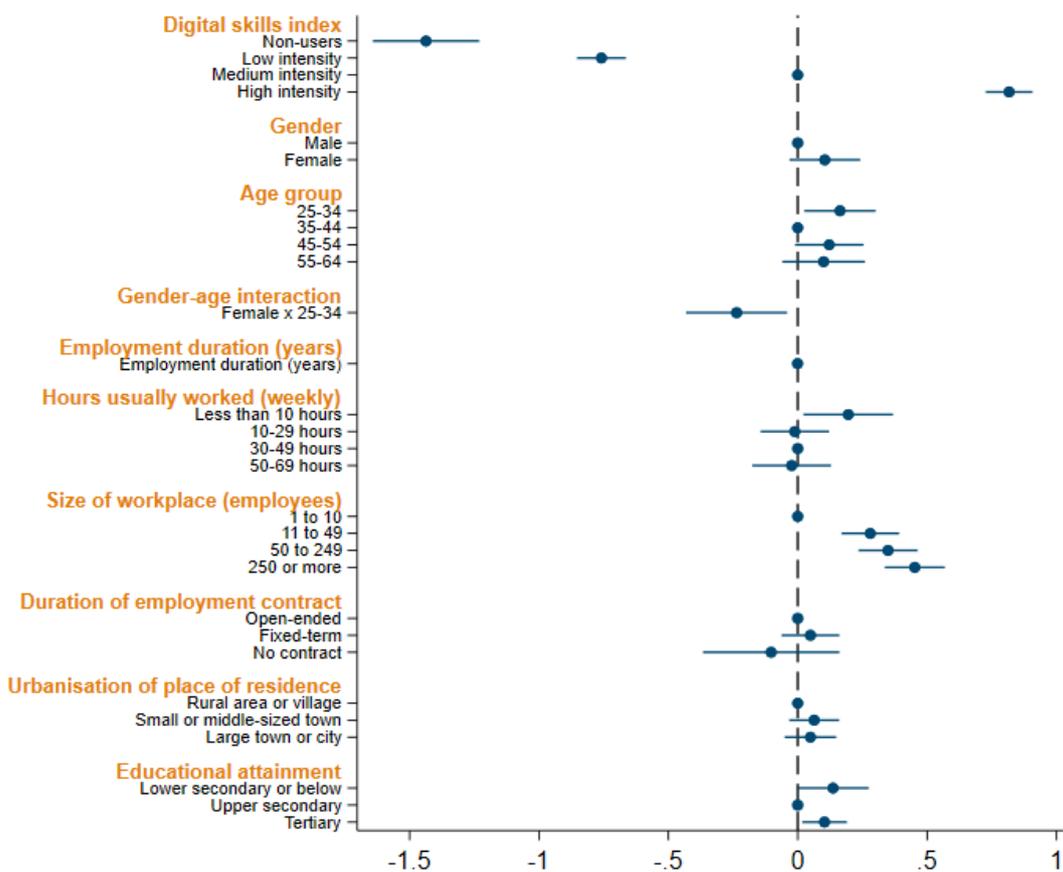
4.2. AGE SEGREGATION OF IT TRAINING PARTICIPATION

In the following, we present the results of the analysis on the participation of employees in IT training. We apply logistic regression using survey weights similar to Eq. (3.1) and Eq. (3.2), as described in Section 3. The dependent variable indicates whether the employee took part in something related to IT training (e.g. a course, a workshop, on the job training) in the past 12 months in which she or he could enhance her or his digital skills. In regression model [5] (see detailed regression results in Table A.2 in the Appendix), in addition to the explanatory variables presented in the table, we also control for countries (EU27 as well as Iceland and Norway); in model [6], additionally for occupations (ISCO one-digit) and sectors (NACE one-digit) individually; and, in model [7], for occupation-industry pairs. In regression model [8], we apply an interaction term between age groups and gender, while in model [9] we add the categories of the DSI index. Comparing the results of model [9] and the previous ones, we can observe that some coefficients – particularly the one for gender – change considerably given that the probability of participating in training depends a lot on the specific DSI category of the job performed. Again, we first present raw coefficients of our preferred regression specification [9] in Figure 5. Thus, we can only observe whether an explanatory variable is associated with a higher probability of having participated in an IT training measure. Marginal effects will be presented further below in Figure 6.

As expected, employees in jobs of higher DSI categories obtain more IT training, while when controlling for those categories, we see that women show a higher probability of participating in digital skills training measures, although this result is not statistically significant. We do not find a pronounced pattern of age segregation, as only the youngest age group (25-34) is more likely to receive IT training. However, the interaction between age group and gender shows that young women participate less frequently in IT

training (the other interaction terms are not statistically significant and are thus omitted from Figure 5 for the sake of conciseness). The likelihood of participating in IT training increases with more employees working in an enterprise, while the differences are not statistically significant between individuals living in more urbanised areas as well as between those with open-ended, fixed-term or no contracts. Employees with tertiary education show a higher probability compared to those with education below the upper secondary level, while no difference is found between those with tertiary education and those with lower secondary education. Longer employment duration in a company is also not associated with a difference in the likelihood of participating in training.

Figure 5 / IT training participation by digital skills intensity of jobs: raw coefficients

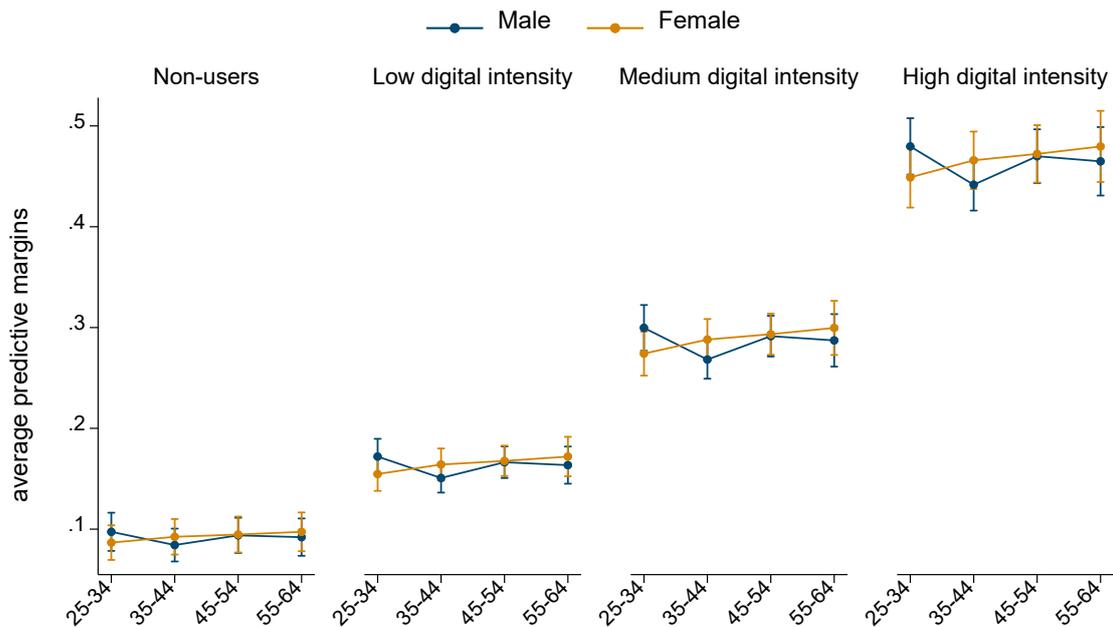


Source: ESJS2; own calculations; robust standard errors; weights: Pan_Country_weight_v2.

Figure 6 illustrates how the likelihood of participating in IT training diverges between jobs of different task categories of DSI (all other covariates being held constant). We plot the average adjusted predictions (y-axis) of any given individual falling into each of the four DSI categories for the four age groups (x-axis), differentiated by gender (blue represents men, orange women). In jobs of higher DSI categories, IT training is of course a permanently built-in process. Employees in the high-digital-intensity group have a 40-50% chance of participating in training, and there are not any significant differences between genders and age. Surprisingly, IT training probability differs a lot between DSI categories but hardly at all between age groups. There are not any significant gender training gaps if we apply the rich set of control variables in our

regression analysis. This, however, also indicates that a narrowing of the gender DSI gap is not likely to take place given the non-existence of preferential training measures in the workplace.

Figure 6 / IT training participation by digital skills intensity of jobs: average predicted probabilities by age groups and gender



Source: ESJS2; own calculations; robust standard errors; weights: Pan_Country_weight_v2.

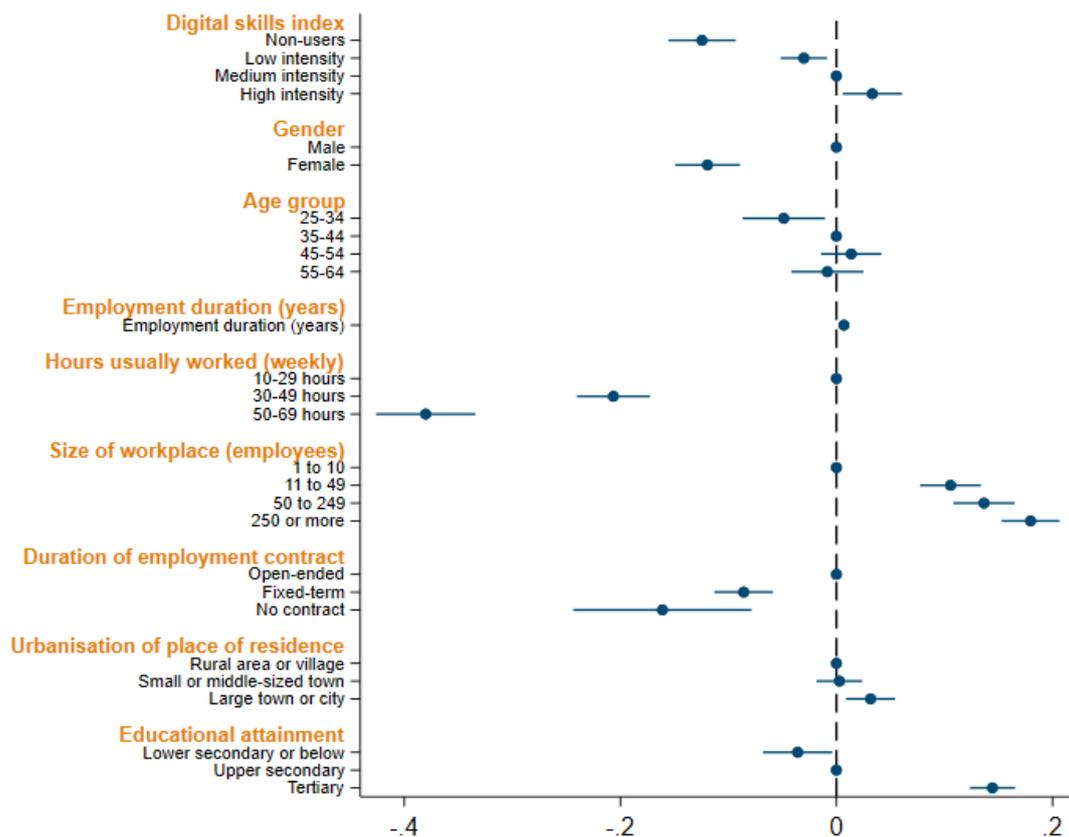
4.3. AGE SEGREGATION OF WITHIN-JOB WAGE RETURNS TO DIGITAL TASKS

The next part of our analysis covers age differentials in within-job wage returns to digital tasks by applying linear regressions and using survey weights, as described in Section 3 by Eq. (3.3) and Eq. (3.4). The dependent variable is the logarithm of the hourly wage of employees. The coefficients describe percent change in wage associated with a one-unit change in the respective explanatory variables. In all regression models (see [10]-[12] in Table A.3 in the Appendix), in addition to the explanatory variables presented in the table, we also control for countries (EU27 as well as Iceland and Norway) and for occupation-industry pairs. In regression models [11] and [12], we additionally apply an interaction term between age groups and gender. First, we present the coefficients of our preferred regression specification [11] in Figure 7. Marginal effects will be presented further below in Figure 8.

The results show that wages rise as the DSI of jobs becomes higher. As expected, we also find a gender wage gap in the ESJS2 data after controlling for several important explanatory variables. Hourly wages increase up to the age group 45-54 but decrease thereafter; however, these differences are not statistically significant. Thus, no significant differences can be detected among the age groups 35-44, 45-54 and 55-64. The more hours employees work per week, the lower their hourly wage (possibly due to unpaid overtime). Higher wages are more likely in firms with more employees and for individuals living in large towns and cities. Employees with open-ended contracts earn higher hourly wages than those with fixed-term or no contracts. In addition, individuals with upper secondary and tertiary education earn

higher wages compared to those with education below the upper secondary level. We also include an interaction term between gender and age group. However, we do not find any significant differences in wages across age groups by gender. In model [11] (see Table A.3 in the Appendix), we additionally include the variable indicating whether the employee took part in IT training. We find that training participation is associated significantly with a 4.7% higher wage.

Figure 7 / Within-job wage returns by digital skills intensity: raw coefficients

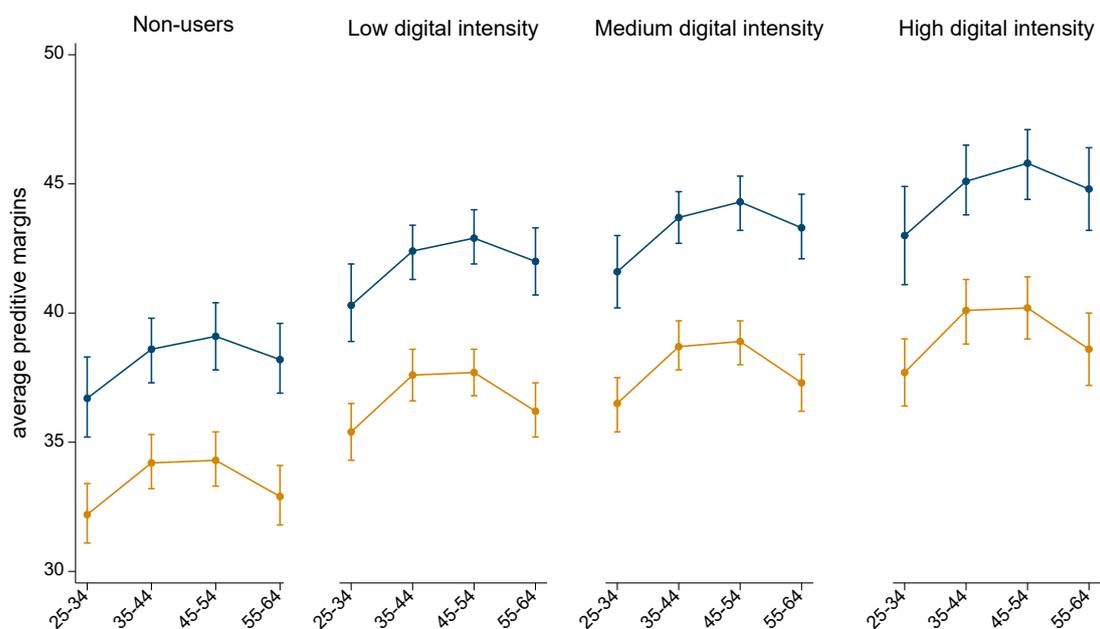


Source: ESJS2; own calculations; robust standard errors; weights: Pan_Country_weight_v2.

Figure 8 illustrates how hourly wages diverge within jobs (i.e. for occupation-industry pairs) by task categories of different digital skill content (i.e. by different DSI index groups), with all other covariates being held constant, as well as how those outcomes are associated with gender and age group. We plot the average adjusted predictions (y-axis) of any given individual falling into each of the four DSI categories for the four age groups (x-axis), differentiated by gender (blue represents men, orange women). Obviously, a large part of wage differences between jobs of the four DSI categories are already eliminated when applying the set of control variables, particularly occupation categories and NACE sectors. Moreover, part of the age differences is also captured by the variable documenting the duration of employment in a specific company. Nevertheless, jobs with tasks of higher DSI categories show a more generous hourly remuneration. In jobs of all DSI categories, hourly wages increase with age, but decrease again for the 55-64 age group, with this decrease being even more pronounced for women than for men. Of course, employees do not experience a decline in wage in their job in an enterprise over their career. However, as

shown by Charni and Bazen (2017), who compared wage developments using cross-sectional and panel data, younger cohorts still experience faster wage growth, whereas older cohorts no longer do. On average, the younger generation also surpasses the previous one in terms of wage levels. Moreover, for younger workers, job changes and periods of unemployment generally lead to wage increases rather than declines, while for older workers such events are more likely to result in wage losses. Figure 8 also shows an enormous gender wage gap across all DSI categories. While these wage gaps become somewhat smaller in the 35-44 age group compared to the youngest group (25-34), they increase again for the older age groups (particularly 55-64). This is likely also due to the reasons described above for the kink in the wage curve by age. The steeper decline observed among women may be because more women than men in the 55-64 age group have already retired.

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



Note: Estimation results are presented in EUR, not logs.

Source: ESJS2; own calculations; robust standard errors; weights: Pan_Country_weight_v2.

5. Conclusions

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

Our descriptive analysis of employment patterns across digital skills categories of jobs shows that younger workers are more engaged in high digital skill intensity (DSI) tasks, especially in Spain, Sweden and France, while older workers are more concentrated in low DSI and non-user categories. In general, the share of employees involved in high DSI activities tends to be lower in EU-CEE countries compared to other EU countries, which suggests a slower integration of more advanced digital work

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

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

In the second part of the analysis, we investigate age disparities in digital upskilling. We apply a weighted logistic regression with participation in ICT training in the past 12 months as the dependent variable, using the same explanatory variables as in the previous specification, but also including the DSI index categories as an independent variable. Our main result is that, when controlling for a large set of job characteristics:

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

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

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

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

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Appendix

Table A1 / Regression results: age segregation of digital skills intensity of tasks

Regression types: Ordered logit regression; Dependent variable: Digital skill index category; Survey weights applied; Coefficient output: raw coefficients (no marginal effects)

Regression models	[1]	[2]	[3]	[4]
Women	-0.401*** (0.029)	-0.483*** (0.031)	-0.475*** (0.032)	-0.530*** (0.055)
Age group (reference group: 35-44)				
25-34 years	0.304*** (0.041)	0.281*** (0.042)	0.291*** (0.042)	0.326*** (0.066)
45-54 years	-0.284*** (0.037)	-0.271*** (0.038)	-0.289*** (0.038)	-0.349*** (0.057)
55-64 years	-0.442*** (0.044)	-0.441*** (0.045)	-0.461*** (0.045)	-0.556*** (0.064)
Gender-age interaction				
Men # 25-34 years				0.000 (0.000)
Men # 35-44 years				0.000 (0.000)
Men # 45-54 years				0.000 (0.000)
Men # 55-64 years				0.000 (0.000)
Women # 25-34 years				-0.066 (0.083)
Women # 35-44 years				0.000 (0.000)
Women # 45-54 years				0.117 (0.074)
Women # 55-64 years				0.191** (0.083)
Duration of employment in company	0.012*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.010*** (0.002)
Hours usually worked (reference: 10-29)				
< 10	0.134 (0.087)	0.189** (0.086)	0.218** (0.088)	0.212** (0.088)
30-49	-0.392*** (0.049)	-0.282*** (0.049)	-0.254*** (0.049)	-0.261*** (0.049)
50-69	-0.061 (0.060)	0.079 (0.062)	0.094 (0.062)	0.092 (0.062)
Size of workplace (reference: 1-10)				
11-49	0.107** (0.043)	0.123*** (0.043)	0.106** (0.044)	0.104** (0.044)
50-249	0.169*** (0.044)	0.167*** (0.044)	0.152*** (0.045)	0.149*** (0.045)
250 or more	0.273*** (0.044)	0.201*** (0.045)	0.184*** (0.045)	0.183*** (0.045)

contd.

Table A1 / Continued

Regression models	[1]	[2]	[3]	[4]
Duration of employment contract (reference: open-ended)				
Fixed-term	-0.393*** (0.047)	-0.285*** (0.049)	-0.276*** (0.049)	-0.270*** (0.049)
No contract	-0.691*** (0.106)	-0.581*** (0.106)	-0.567*** (0.108)	-0.569*** (0.108)
Urbanisation of place of residence (reference: rural area or village)				
Small or middle-sized town	-0.021 (0.036)	-0.059 (0.037)	-0.059 (0.037)	-0.058 (0.037)
Large town or city	0.183*** (0.038)	0.064* (0.039)	0.055 (0.039)	0.056 (0.039)
Highest education completed (reference: upper secondary)				
Lower secondary education or below	-0.795*** (0.056)	-0.519*** (0.057)	-0.498*** (0.057)	-0.497*** (0.057)
Tertiary	0.715*** (0.030)	0.399*** (0.033)	0.390*** (0.033)	0.395*** (0.033)
/cut1	-2.081*** (0.077)	-3.008*** (0.096)	-2.783*** (0.161)	-2.815*** (0.164)
/cut2	-0.334*** (0.074)	-1.101*** (0.092)	-0.838*** (0.160)	-0.870*** (0.162)
/cut3	1.864*** (0.076)	1.269*** (0.093)	1.570*** (0.160)	1.539*** (0.163)
Observations	45,623	45,623	45,623	45,623
Pseudo R-squared	0.058	0.104	0.115	0.115
Controls for:				
Countries	YES	YES	YES	YES
ISCED/ISCO one-digit	NO	YES	NO	NO
Industry-occupation pairs	NO	NO	YES	YES

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; weights applied: Pan_Country_weight_v2

Source: Cedefop ESJS2; own calculations

Table A2 / Regression results: age segregation of IT training participation

Regression types: Logit regression; Dependent variable: IT training; Survey weights applied; Coefficient output raw coefficients (no marginal effects)

Regression models	[5]	[6]	[7]	[8]	[9]
Digital skills index (reference: medium intensity)					
Non-users					-1.437*** (0.105)
Low intensity					-0.759*** (0.048)
High intensity					0.817*** (0.046)
Women	-0.094*** (0.036)	-0.136*** (0.038)	-0.131*** (0.039)	-0.061 (0.067)	0.104 (0.070)
Age group (reference group: 35-44)					
25-34 years	0.121** (0.049)	0.120** (0.049)	0.127** (0.050)	0.244*** (0.069)	0.163** (0.070)
45-54 years	-0.029 (0.047)	-0.015 (0.047)	-0.019 (0.047)	0.003 (0.066)	0.122* (0.068)
55-64 years	-0.077 (0.058)	-0.064 (0.059)	-0.069 (0.059)	-0.078 (0.079)	0.100 (0.081)
Gender-age interaction					
Men # 25-34 years				0.000 (0.000)	0.000 (0.000)
Men # 35-44 years				0.000 (0.000)	0.000 (0.000)
Men # 45-54 years				0.000 (0.000)	0.000 (0.000)
Men # 55-64 years				0.000 (0.000)	0.000 (0.000)
Women # 25-34 years				-0.242** (0.097)	-0.236** (0.100)
Women # 35-44 years				0.000 (0.000)	0.000 (0.000)
Women # 45-54 years				-0.047 (0.092)	-0.095 (0.095)
Women # 55-64 years				0.023 (0.108)	-0.041 (0.111)
Duration of employment in company	0.005** (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	-0.001 (0.002)
Hours usually worked (reference: 10-29)					
< 10	0.238*** (0.082)	0.282*** (0.084)	0.276*** (0.084)	0.270*** (0.084)	0.195** (0.088)
30-49	-0.080 (0.064)	-0.075 (0.065)	-0.074 (0.066)	-0.084 (0.066)	-0.012 (0.068)
50-69	-0.059 (0.074)	-0.003 (0.077)	0.001 (0.078)	-0.002 (0.077)	-0.024 (0.078)

contd.

Table A2 / Continued

Regression models	[5]	[6]	[7]	[8]	[9]
Size of workplace (reference: 1-10)					
11-49	0.347*** (0.054)	0.298*** (0.055)	0.294*** (0.055)	0.292*** (0.055)	0.280*** (0.057)
50-249	0.439*** (0.054)	0.370*** (0.056)	0.373*** (0.056)	0.370*** (0.056)	0.349*** (0.058)
250 or more	0.532*** (0.055)	0.464*** (0.057)	0.474*** (0.057)	0.473*** (0.057)	0.452*** (0.059)
Duration of employment contract (reference: open-ended)					
Fixed-term	-0.080 (0.054)	-0.042 (0.055)	-0.027 (0.055)	-0.020 (0.055)	0.049 (0.057)
No contract	-0.326** (0.131)	-0.256* (0.132)	-0.269** (0.132)	-0.268** (0.132)	-0.103 (0.135)
Urbanisation of place of residence (reference: rural area or village)					
Small or middle-sized town	0.064 (0.047)	0.043 (0.048)	0.047 (0.048)	0.047 (0.048)	0.064 (0.049)
Large town or city	0.125*** (0.048)	0.064 (0.049)	0.067 (0.049)	0.067 (0.049)	0.049 (0.051)
Highest education completed (reference: upper secondary)					
Lower secondary education or below	-0.179*** (0.067)	-0.005 (0.068)	0.012 (0.069)	0.011 (0.069)	0.136* (0.071)
Tertiary	0.487*** (0.038)	0.201*** (0.043)	0.196*** (0.043)	0.200*** (0.043)	0.104** (0.044)
Constant	-1.356*** (0.094)	-1.075*** (0.119)	-1.387*** (0.230)	-1.423*** (0.233)	-1.425*** (0.245)
Observations	45,623	45,623	45,557	45,557	45,557
Pseudo R-squared	0.033	0.057	0.064	0.065	0.114
Controls for:					
Countries	YES	YES	YES	YES	YES
ISCED/ISCO one-digit	NO	YES	NO	NO	NO
Industry-occupation pairs	NO	NO	YES	YES	YES

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; weights applied: Pan_Country_weight_v2
Source: Cedefop ESJS2; own calculations.

Table A3 / Regression results: age segregation of within-job wage returns to digital tasks

Regression types: OLS regression; Dependent variable: Ln wage per hour; Survey weights applied

Regression models	[10]	[11]	[12]
Digital skills index (reference: medium intensity)			
Non-users	-0.125*** (0.016)	-0.124*** (0.016)	-0.116*** (0.016)
Low intensity	-0.030*** (0.011)	-0.030*** (0.011)	-0.024** (0.011)
High intensity	0.033** (0.014)	0.033** (0.014)	0.024* (0.014)
Women	-0.130*** (0.010)	-0.119*** (0.015)	-0.120*** (0.015)
Age group (reference group: 35-44)			
25-34 years	-0.054*** (0.013)	-0.049** (0.019)	-0.049** (0.019)
45-54 years	0.009 (0.010)	0.014 (0.014)	0.013 (0.014)
55-64 years	-0.022* (0.012)	-0.008 (0.017)	-0.009 (0.017)
Gender-age interaction			
Men # 25-34 years		0.000 (0.000)	0.000 (0.000)
Men # 35-44 years		0.000 (0.000)	0.000 (0.000)
Men # 45-54 years		0.000 (0.000)	0.000 (0.000)
Men # 55-64 years		0.000 (0.000)	0.000 (0.000)
Women # 25-34 years		-0.012 (0.026)	-0.011 (0.026)
Women # 35-44 years		0.000 (0.000)	0.000 (0.000)
Women # 45-54 years		-0.010 (0.020)	-0.010 (0.020)
Women # 55-64 years		-0.029 (0.024)	-0.029 (0.024)
Duration of employment in company	0.007*** (0.000)	0.007*** (0.000)	0.007*** (0.000)
Hours usually worked (reference: 10-29)			
< 10	1.153*** (0.046)	1.153*** (0.046)	1.152*** (0.046)
30-49	-0.206*** (0.017)	-0.206*** (0.017)	-0.207*** (0.017)
50-69	-0.380*** (0.024)	-0.380*** (0.024)	-0.380*** (0.024)
Size of workplace (reference: 1-10)			
11-49	0.106*** (0.014)	0.106*** (0.014)	0.104*** (0.014)
50-249	0.137*** (0.015)	0.137*** (0.015)	0.134*** (0.014)
250 or more	0.180*** (0.014)	0.180*** (0.014)	0.176*** (0.014)

contd.

Table A3 / Continued

Regression models	[10]	[11]	[12]
Duration of employment contract (reference: open-ended)			
Fixed-term	-0.086*** (0.014)	-0.086*** (0.014)	-0.086*** (0.014)
No contract	-0.161*** (0.042)	-0.161*** (0.042)	-0.160*** (0.042)
Urbanisation of place of residence (reference: rural area or village)			
Small or middle-sized town	0.003 (0.011)	0.003 (0.011)	0.002 (0.011)
Large town or city	0.032*** (0.012)	0.032*** (0.012)	0.031*** (0.012)
Highest education completed (reference: upper secondary)			
Lower secondary education or below	-0.036** (0.016)	-0.036** (0.016)	-0.037** (0.016)
Tertiary	0.145*** (0.011)	0.144*** (0.011)	0.144*** (0.011)
IT training participation			0.047*** (0.011)
Constant	4.124*** (0.062)	4.118*** (0.063)	4.106*** (0.063)
Observations	33,364	33,364	33,364
Pseudo R-squared	0.542	0.542	0.542
Controls for:			
Countries	YES	YES	YES
ISCED/ISCO one-digit	NO	YES	NO
Industry-occupation pairs	NO	NO	YES

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; weights applied: Pan_Country_weight_v2
Source: Cedefop ESJS2; own calculations.

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Postanschrift: A 1060 Wien, Rahlgasse 3, Tel: [+431] 533 66 10, Telefax: [+431] 533 66 10 50
Internet Homepage: www.wiiw.ac.at

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