WeLaR

Effects of technological progress on the decision to retire early. Evidence for Europe

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Abstract

We provide one of the first analyses, in an EU-wide setting, of the implications of digitalisation and automation on employment and the decision to retire. The analyses are based on several European databases. The first set of analyses rely on the EU-LFS data to explore if digitalisation has affected older workers employment prospects. The second analysis uses the Survey of Health, Ageing and Retirement in Europe to examine to what extent digital skills impact early retirement for workers aged 50 and above, using an instrumental variable strategy. The third analysis, utilising the EU-SILC dataset, extends the inquiry into the influence of automation on the retirement choices of older workers across 11 European countries. The analyses suggest that digitalisation and automation has not reduced employment of older workers, and occupational-level automation potential is negatively related to the likelihood of early retirement. We find the subjective self-assessed level of digital skills to have a negative effect early retirement propensity for women, but not for men. Other variables affecting the probability of entering early retirement are age, gender, educational background and job status also matter. Moreover, older workers in non-routine cognitive tasks tend to delay early retirement, while men with high digital skills show a positive impact on early retirement likelihood.

Keywords: retirement, early retirement, employment, technological change, digital skills, automation, robotisation, ICT, Europe

1. Introduction

European societies are ageing fast. Increasing the length of working lives by reducing early retirement options and increasing statutory retirement ages (OECD, 2021) combined with an improvement in productivity through digitalisation and automation are important ways to address the challenge of a smaller physical workforce relative to the size of the non-working population. Related literature has identified various factors that affect early retirement, including individual attributes, occupational conditions, job characteristics, health status, financial stability, and macroeconomic and institutional elements such as political structures and social security systems. However, the introduction of new technology may also affect the decision of older workers to retire early (Hudomiet & Willis, 2022; Martin, 2018).

Digitalisation, automation and artificial intelligence in the workplace create new tasks, change the way other tasks are carried out and replaces some tasks altogether. This process may affect the employability of older workers who tend to have skills related to old tasks, and lower formal levels of education. On the other hand, automation and digitalisation may make some tasks easier by performing very physically or cognitively demanding tasks, thereby increasing the employability of older workers (Damman, 2016). As an example, the introduction of handheld calculators into the workplace (Fitzgerald, 1988) or collaborative robot (cobot) use in manufacturing systems (Calzavara *et al.*, 2020).

Several studies have shown that older workers are lagging younger workers in digital skills (OECD, 2015; Hecker *et al.*, 2021), and the share of people reporting that they lack computer skills to do their jobs well or that that their chances of career progress have been impacted by a lack of computer skills are increasing with age (Polder, 2015). However, differences between younger and older workers in active usage of digital skills at the workplace may not be large. Hudomiet and Willis (2022) report that in the US while younger workers were initially more exposed to digitalisation, by 2017 older workers had essentially caught up with younger cohorts. Barslund (2022) found that the digital skills usage intensity of older workers in the EU is around 20% lower compared to younger workers. It is well-documented that older workers receive less training in comparison with younger workers (Leuven, 2005), and may face barriers to assessing online training (Hecker *et al.*, 2021; Asia, 2023). However, Messe *et al.* (2014) analysed French data to investigate how technical advancements and in-job training influence intentions to retire. Their research suggests that as technology evolves, older individuals are more inclined to extend their work duration in jobs with a high probability of skill upgrading.

These differences between older and younger workers in digital abilities and usage are important but are - for the reasons noted above - not in themselves informative of the impact in terms of employment outcomes or to assess whether digitalisation and automation work as push factors into early retirement. Our study assesses the impact of digitalisation and automation on (relative) employment outcomes for older workers with particular attention to the impact on the propensity to retire early. For this purpose, we use three different datasets: (1) The European Labour Force Survey (EU-LFS), (2) the Survey of Health, Ageing and Retirement in Europe (SHARE) and (3) the European Union Statistics on Income and Living Conditions (EU-SILC).[1] We focus on outcomes in the EU, but also detail some country-specific results, paying particular attention to the heterogeneity of the effects depending on demographic characteristics, e.g., gender and age. Digitalisation, automation at the occupation-level and self-perceived digital skills are separately investigated. Out of the three empirical analyses conducted in this study, only the one based on SHARE data explicitly addresses the endogeneity problem between automation technologies and the decision to retire early. The empirical analyses based on EU-LFS and EU-SILC are of descriptive and explorative nature.

In the first set of analyses, we rely on the EU-LFS to look at occupational-level changes in the employment of older workers as a function of the digital capital stock per worker within the occupation. In the second set of analyses, we define an occupational-level employment rate and relate the change in employment rate gaps between workers aged 60-64 years old and workers in the same occupation aged 50-54 years old to indicators of occupation risk of automation, AI exposure and ICT capital. In the third analysis, we look at 5-year occupational retention rates of 55-59 year olds and relate changes in these rates to exposure to ICT capital (at age 55-59). These three analyses, combined provide an understanding of how technological change has influenced the employment dynamics of older workers within the specified timeframe.

Then we investigate the causal effect of subjective digital skills on the decision to retire early for older workers aged 50 and older, using a large-scale multi-country setting using SHARE. Identifying the effects of technology on retirement is challenging due to its endogenous nature. In this analysis based on SHARE data, we seek to fil these gaps by handling the reverse causality potential and presenting nuanced evidence of the multifaceted impacts of digital skills on effective early retirement.

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[1] The proposal initially focused on measuring technological progress using data from the EIB Group Survey on Investment and Investment Finance (EIBIS) and the International Federation of Robotics (IFR). However, the EIBIS data is limited to specific sectors and countries, and access issues arose with the IFR dataset. In response, we integrated alternative datasets to measure technological progress, including automation data derived from the PIAAC survey at the occupational level, artificial intelligence data from Tolan et al. (2021), and self-perceived digital skills data measured at the individual level from the SHARE survey. The proposal also highlights the use of Employment Protection Legislation (EPL) data. However, we decided to use other macroeconomic indicators from Eurostat and OECD to control for country fixed effects due to the lack of variability over time of EPL data. In addition, we originally intended to use EU-LFS (2006, 2012) and SHARE (2013 to 2017). However, we have now extended our analysis to include EU-SILC data from 2016 to 2019. This expansion was not part of the initial proposal, but it provides a more up-to-date assessment of the impact of technological changes. By combining these datasets, we can offer a clear and comprehensive understanding of how technological advancements have influenced society over this extended period.

We adopt an instrumental variable strategy based on digitalisation's exposure at the sector level to provide estimates of the causal effect of digital skills on early retirement. Employing an instrumental variable strategy based on the sector-level digitalisation exposures, the research provides nuanced insights beyond existing correlational studies. Key findings include gender-specific effects, where women with higher digital skills are less likely to retire early, especially those women with higher education and those who are self-employed. We also show an age-specific effect, suggesting that digital skills are more advantageous for older workers than younger ones, as they can help them to stay longer in the labour market. Finally, older workers in occupations intensive in non-routine cognitive tasks tended to postpone early retirement while men with high digital skills exhibited a notably positive impact on the likelihood of early retirement.

Finally, we conduct an analysis based on EU-SILC data spanning the years 2016-2019, for investigating the implications of the share of workers with high automation potential in specific occupation on the estimation of early retirement decisions. In this exploration, early retirement is defined as individuals who transitioned out of the workforce to retirement during the specified period. The analysis unveils a robust and statistically significant negative correlation between the share of workers immersed in highly automated occupations and the propensity for early retirement. This signifies that those engaged in occupations with heightened automation potential are notably less prone to pursue early retirement, accentuating the discernible impact of technological dynamics on retirement choices. The positive influences of educational attainment, self-perceived general health, age, and the number of years worked further contribute to shaping retirement trajectories in this evolving occupational landscape.

The rest of the study is organised as follows. Section 2 provides the theoretical framework. Section 3 provides the description of the data sources we draw on. Section 4 presents our results. We end with a discussion of the results and their implications for older workers' employment opportunities.

2. Theoretical framework

2.1. Determinants of early retirement

An extensive literature has identified several determinants of early retirement such as personal characteristics, work conditions, social norms, the nature of work, health, financial well-being or broader macroeconomic and institutional factors like political regimes and the generosity of social security systems.

Personal characteristics: Wilson *et al.* (2020) use a meta-analysis to investigate contemporary early retirement factors, identifying several factors impacting early retirement such as health considerations, workplace issues, ageism, pension requirement criteria or societal norms.

Among those factors, health considerations stand out as the most consistently analysed and prominent factor influencing retirement decisions. However, the impact of health varies across studies and remain inconclusive. On one hand, numerous studies have identified a correlation between poor health and an inclination towards early retirement (Wilson *et al.*, 2020). This result is also highlighted across various studies, such as those conducted in the Netherlands (de Wind *et al.*, 2017) and a broader Europe-based investigation (Axelrad, 2018). Additionally, a Canadian study by Scott *et al.* (2018) consistently highlights that workers experiencing injuries and enduring permanent physical impairments are more inclined to take early retirement. Some others show that individuals in good health and positive work prospects are less inclined to consider early retirement and show a greater willingness to work up to 65 or even longer (Sousa-Ribeiro *et al.*, 2021). Some analyses, however, fail to provide a distinct relationship between poor health and the intention to retire early (Schreurs *et al.*, 2011; Du Prel *et al.*, 2019). There are also studies suggesting that good health can sometimes be associated with early retirement, particularly among those who have the financial means to do so (Pond *et al.*, 2010). These heterogeneous results highlight the complexity of choices related to early retirement from the labour market. Early retirement can also be influenced by mental health issues. Several studies show a significant impact on early retirement among individuals taking prescribed psychiatric medications for diagnosed mental illnesses (Jensen *et al.*, 2017), among those with poor physical health and mental functioning (von Bonsdorff *et al.*, 2016), or among those with early childhood adversity, such as abuse or neglect.

Other studies establish connections between early retirement decisions and factors such as grandparenthood (Hochman & Lewin-Epstein, 2013; Backhaus & Barslund, 2021), a nutritious diet (Celidoni *et al.*, 2020), social relationships (Comi *et al.*, 2020), or self-employment (Axelrad & TurSinai, 2021).

Working conditions: Empirical literature has extensively focused on the impact of the work environment. Sundstrup *et al.* (2021) show that high physical work demands and poor psychosocial working conditions are factors that can push older workers out of the labour market prematurely. Hermansen (2015) investigates the effect of working hours on early-retirement choice in Norway, showing that being employed in a company that provides reduced working hours for older workers does not influence the relative risk of a 61- or 62-year-old individual opting for early retirement. Using the SHARE survey, Siegrist *et al.* (2007) provide evidence of the link between a poor psychosocial work environment and the inclination for early retirement among older employees in Europe. Sejbaek *et al.* (2012) also highlight the association between high physical strain and high early retirement intention. Elovainio *et al.* (2005) show that high job demands and job control are predictors of early retirement.

Macroeconomic and institutional factors: Baumann and Madero-Cabib (2021) explore the impact of welfare regimes and health conditions on retirement trajectories in countries with flexible retirement policies using longitudinal methods and harmonised panel data from social-democratic (Sweden and Denmark) and liberal welfare regimes (Chile and the United States). They reveal a higher frequency of early retirement in social-democratic regimes compared to liberal welfare regimes. They also uncover varying health conditions among early retirees in these distinct political contexts. Schils (2008) investigates whether early retirement patterns vary between countries with distinct early retirement systems. Using longitudinal data from the United Kingdom and Germany, the results suggest that pursuing a shift from public to private early retirement schemes can lower the incidence of early retirement. Several papers also investigate the effects of financial incentives on the timing of retirement, providing mixed results. Andersen *et al.* (2021) examined the effects on early retirement of a reform of the Norwegian early retirement program aiming at removing a strict retirement earnings test. They show that the reform leads to a considerable increase in labour supply of older workers above the threshold age for early retirement. Vestad (2013) studies the Norwegian reform consisting of a reduction in the lower age limit for early retirement, showing that if the age threshold had been set at 64 instead of 62, over two-thirds of retirees would remain employed at the age of 63. On the contrary, Baker and Benjamin (1999) find that early retirement reforms in Canada had only little effect on labour supply.

Social norms (Radl, 2012) and age discrimination are institutional factors that positively affect the propensity to exit the labour market or retire early.

2.2. Technological change and early retirement

2.2.1. Digital skills

Only a few recent papers have focused on digitalisation and older workers' employment situation. Hudomiet and Willis (2022) show - using data for the US for the period 1984-2017 - that older workers started using computers later than younger workers, and that this led to an initial knowledge gap and increased retirement. Also based on US data, Barth *et al.* (2023) show that firm-level investment in software capital leads to higher wages and lower exit rates, but that these effects were absent for older workers (close to 65 years old), suggesting a shift in demand towards middle-aged workers relative to older workers. Solem *et al.* (2023) explored whether digital challenges were associated with the preference of workers to retire early. The authors used the survey Norwegian Senior Policy Barometer which collected data on workers above the age of 50 to show that workplace conditions are more important than individual characteristics in their impact on early retirement behaviour. They suggest that reducing digital difficulties at the workplace could prevent early retirement.

Recently, Lakomý (2023) investigates the effects of self-assessed digital skills on older workers' early retirement intention. He finds mixed results as to whether digital skills are associated with a wish to work longer. Yashiro *et al.* (2022) show that older workers - employed in the private sector in Finland - who are more exposed to digital technologies face a higher risk of exiting employment in comparison to the workers less exposed to technological changes. In particular for those who are eligible for an extension of unemployment benefits until the earliest age for drawing old age pension. They argue that those involved in routine tasks have a higher risk of being replaced by automation. This, combined with generous unemployment and disability benefits for older citizens, could push older workers to retire early.

Conversely, other studies show positive effects of technological change. Nagarajan and Sixsmith (2021, 2019) highlight the potential of technology to help create an age-friendly work environment. They argue that digital technologies may serve as a lifeline for older workers, diminishing the physical rigour associated with certain jobs and providing tools to better monitor and manage their health.

Earlier literature includes Schøne (2009), who studies personal computer usage in Norwegian data from 1997 and 2003 and finds a bias against older workers in the cross-sectional sample, but it disappears with the introduction of firm-level fixed effect in a panel estimation.

2.2.2. Automation and artificial intelligence

Casas and Román (2023) focus on how automation at the occupation level pushes older workers to retire early. They show that current technological change is playing a significant role in the transition from work to retirement, although it affects heterogeneously certain groups in the sample. Using German data for the period 1993-2012, Battisti *et al.* (2023) show that technological and organisational change increases the risk that older workers withdraw from the labour market. Bessen *et al.* (2023) find that older workers are more severely impacted when firms automate. Albinowski and Lewandowski (2022) look at the impact of ICT and automation (robots) on the relative labour market performance of different demographic groups for 14 EU countries in the period 2010-2018. They find a negative effect for women above the age of 60 years old. According to the authors, exposure to ICT and robots reduces employment for older women by 4.7 and 5.3 percentage points, respectively.

Other studies have asked (older) workers directly about the impact of new technology in the workplace. A Danish survey-based study asked workers aged 50+ (N=10,300) in 2018 if new technology had been implemented at their workplace within the past 2 years[2] (Sundstrup *et al.*, 2022). Using administrative data their employment status was assessed in 2020. The study looked at associations

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[2] Question was 'Has new technology been introduced into your work within the last 2 years?' with yes/no answer categories.

between new technology and subsequent loss of employment. Overall, the introduction of new technology was less like to lead to subsequent loss of paid employment, however, sub-group analysis revealed that people working with ‘with people, service, care’ were 22% more likely to have lost their job in the two-year period under study. In a systemic review of the literature on the impact of ICT on stress, burnout and mental health (Berg-Beckhoff *et al.*, 2017), no evidence was found that older workers are more likely to be affected by the use of ICT.

3. Data sources

To address our research question, we use a range of EU-wide data sources: the EU Labour Force Survey (EU-LFS), the Survey of Health, Ageing, and Retirement in Europe (SHARE), the EU data for analysis of capital, labour, energy, material and services input (EU-KLEMS) and the European Union Statistics on Income and Living Conditions (EU-SILC). Each one of them is described in detail below.

3.1. EU-LFS

The EU-LFS provides harmonised and comparable data on the labour market situation across the European Union and its member states, covering a wide array of topics including employment, unemployment, education, training, income, and working conditions. The EU-LFS adheres to the International Labour Organisation (ILO) definition of employment, capturing individuals aged 16 years and over who have engaged in at least one hour of paid work in the reference week or were temporarily away from their job.

One of the significant strengths of the EU-LFS is its wide coverage and the inclusion of various forms of employment. The EU-LFS encompasses all forms of employment including the self-employed, unpaid family workers, and individuals on government training schemes among others. Moreover, the data collected through the EU-LFS is harmonised across the EU Member States, ensuring consistency and comparability of the data, thereby facilitating cross-country analyses and policy evaluations.

For our purposes, the EU-LFS has two major advantages. First, from 2011 and onwards it provides a detailed 3-digit ISCO classification of occupations. Second, the ISCO classification is provided for both people in employment and for the last job for people not in employment. This enables us to calculate what we term ISCO employment rates, the share of people in each five-year age cohort who had their current or most recent job in a specific ISCO category.[3]

Due to the change in ISCO classification (with 2011 being the first year that ISCO-08 is used), we look at the period from 2011-2021 (2021 being the latest year currently available).

3.2. SHARE

The SHARE survey covers data from 18 European Union countries and includes Israel. The primary objective of the SHARE initiative is to provide a comprehensive view of the ageing landscape in Europe, encompassing health, socio-economic conditions, and the complex dynamics of social and familial ties. Within this framework, individuals over the age of 50 were interviewed using computer-aided personal interviewing methods (CAPI). The survey's first wave was initiated in 2004/2005 and was followed by subsequent waves until 2023.

Given our research interest in early retirement, we used waves 5, 6, and 7, which were carried out in 2013, 2015, and 2017, respectively. We first merged the data from wave 5 with wave 6, taking into account only individuals who were working during wave 5 and, in wave 6, narrowed it down to only those who either continued working or had entered retirement. A similar procedure was employed independently for waves 6 and 7. The final dataset was obtained by pooling these two cross-sectional datasets, resulting in 6,135 observations. Of these, 4,331 were derived from the merge of waves 5 and 6, while the remaining 1,958 observations were from the merge of waves 6 and 7. The final sample covers 14 countries: Austria, Germany, Sweden, Spain, Italy, France, Denmark, Greece, Belgium, Czech Republic, Luxembourg, Slovenia, Estonia and Croatia.

Effective early retirement is a binary variable. For the dataset derived from the merge of waves 5 and 6, it takes the value 0 if the individual worked in 2013 (wave 5) and continued working in 2015 (wave 6). For the dataset from the merge of waves 6 and 7, it takes the value 0 if the individual worked in 2015 (wave 6) and continued working in 2017 (wave 7). In both datasets, the variable will take the value 1 if the individual transitioned into retirement before reaching the official retirement age (OECD) of their respective country in the subsequent wave.

The literature has highlighted alternative explanations for the evolution of early retirement. Therefore, we introduced additional controls and explanatory variables in the regression models, including age,

[3] The EU-LFS data also contains two so-called ad-hoc modules conducted in 2006 and 2012. These additional surveys had a special focus on retirement and early retirement. However, a main limitation is that the ISCO classification system changed between the two modules (from ISCO-88 to ISCO-08). The 2006 module contains an ISCO-88 classification, whereas the 2012 module is coded in ISCO-08. There is a reasonably accurate conversion table at ISCO 4-digit level (88 and 08) but not at ISCO 3-digit, which is available in the ad-hoc modules. Constructing a 3-digit conversion table based on the 4-digit conversion table, leads to too many ad-hoc choices. Moreover, sample sizes were not much larger than can be obtained from the standard EU-LFS by pooling two or more years.

gender, job status (private employees, civil servants, and self-employed workers), worked hours, job contract, income, subjective health status (poor, fair, good, very good, excellent). Additionally, we incorporated controls for cognitive abilities, assessed through a word recall test where older individuals are presented with a list of ten words and asked to recall them immediately and after a five-minute delay. Education is categorised based on ISCED level: secondary (ISCED=0, 1, 2), post-secondary non-tertiary (ISCED=3, 4), and tertiary (ISCED=5,6). Occupations are classified into four task groups: non-routine cognitive, routine cognitive, routine manual, and non-routine manual (Maciej & Lewandowski, 2022) (see Appendix 1).

To account for the broader economic context, we use real GDP growth (World Bank) and the standardised unemployment rate (OECD) as macroeconomic indicators to control for the labour market situation. We also include old pensions measured in Purchasing Power Standards per resident (Eurostat) to control for the impact of financial generosity on early retirement (Baumann & Madero-Cabib, 2021).

3.3. EU-SILC

The EU-SILC is a valuable resource for analysing the impact of digitalisation on the early retirement decision within the European Union (EU). Similar to the EU Labour Force Survey (EU-LFS), EU-SILC provides comprehensive and harmonised data that can shed light on how digitalisation influences retirement trends.

EU-SILC is an annual survey conducted by the EU to collect data on income, poverty, social exclusion, and living conditions of individuals and households in all EU Member States and several non-EU countries. The survey employs standardised questionnaires adapted to each country's specific circumstances, conducting interviews and using administrative data sources.

This survey is a rich repository of socio-economic information, encompassing not only data on income and living conditions but also vital occupational data, which includes a 2-digit ISCO (International Standard Classification of Occupations) classification. Importantly, EU-SILC gathers occupation-related information for individuals who are currently employed and for those whose last job was in an occupation, which is especially relevant for retirees. This unique feature enables a comparison of early retirement rates across various occupations and an assessment of whether disparities exist in occupations more susceptible to automation versus those with lower risk.

In addition to occupation data, EU-SILC provides an array of demographic, living conditions, social inclusion, and educational attainment data. This allows for the examination of the broader socio-economic factors that underpin early retirement decisions in the era of digitalisation. Demographic information can help analyse how age, gender, health, and family composition affect these decisions, while data on living conditions offers insights into the overall well-being of retirees. Social inclusion and educational attainment data contribute to a nuanced understanding of the socio-economic context in which individuals make early retirement choices. All these variables are to be used as the control variables in the analysis of the impact of automation on the decision to retire early. There is no automation-specific data in the EU-SILC dataset. Therefore, in the analysis, this survey is combined with other data sources, using 2-digit ISCO classification.

3.4. Technological progress

3.4.1. Self-perceived digital skills

This indicator is derived from the question 'How would you rate your computer skills?' in the SHARE survey. Responses are ranked on a Likert scale ranging from 'Never used a computer' to 'Excellent'.

3.4.2. EU-KLEMS

The EU KLEMS database is an important resource for analysing growth and productivity at an industry level across the European Union (EU) member states. One of the key strengths of the EU KLEMS database is its granularity, facilitating analysis beneath the aggregate economy level, thus providing a more detailed understanding of economic dynamics across different sectors and countries. Additionally, the database's rich dataset allows for industry-by-industry estimations, thereby offering a comprehensive cross-section panel dimension for the analyses.

Our interest centres around the EU KLEMS estimates for digital capital at the industry level (NACE 2-digit) in each country. Digital capital consists of the three categories of computer equipment, communications equipment, and computer software and databases.

3.4.3. Automation

Arntz *et al.* (2017) used the detailed task data from the PIAAC to account for the range of tasks within occupations. Their measure of automation potential is thus assessed at the occupational level, while incorporating the job-level variation in automation exposure derived from the PIAAC data. They also used an imputation method to derive a weighted occupational risk of automation that varies across individuals according to their characteristics. The automation data are merged with the EU-LFS and EU-SILC at the occupation and country levels.

3.4.4. Artificial intelligence

To measure AI, we used data from the paper of Tolan *et al.* (2020). The explicit focus on AI distinguishes this analysis from studies on robotisation (Acemoglu & Restrepo, 2018), digitalisation and online platforms (Agrawal *et al.*, 2015), and the general occupational impact of technological progress and automation (Autor, 2015). That is, automation through technologies that do not require AI, e.g., self-checkout machines that replace human cashiers in supermarkets, is not considered in this framework.

These AI-related metrics reflect the intensity of current research and development in different AI techniques. The authors acknowledge that the ‘research intensity’ indicator is not necessarily a good proxy of future AI progress, since breakthroughs do not always appear where more research effort is spent, and there may be dead ends that are not obvious yet. But future AI progress is hardly difficult to predict and this indicator aims to identify which occupations and types of task contents are more directly related to pre-chatGPT developments in AI research. The present analysis is limited to the technical potential of AI (i.e., the things that AI could potentially do at work). The AI data are merged with the EU-LFS and EU-SILC at the occupation and country levels.

4. Results

4.1. Analysis based on EU-LFS

This section focuses on the relationship between employment and digitalisation for the group of 60-64-year-olds (‘older workers’) from 2011-2020. This age group is most susceptible to early retirement, whether indirectly, voluntarily and involuntarily, via unemployment schemes, or directly through early retirement schemes.

We assess the impact of digitalisation by analysing the occupation-specific employment retention rates of older workers the EU-27 countries (AT, BE, BG, CY, CZ, DE, DK, EE, EL, ES, FI, FR, HR, HU, IE, IT, LT, LU, LV, MT, NL, PL, PT, RO, SE, SI and SK). Specifically, we examine the 5-year occupational retention rates of 50-54 and 55-59-year olds and relate them to their exposure to ICT capital (at ages 50-54 and 55-59). The analysis provides some understanding of how technological change has influenced the employment dynamics of older workers within the specified timeframe.

ICT capital per worker

ICT capital is drawn from EU-KLEMS Capital accounts database. The ICT capital stock is expressed in chained linked volumes (2015) in millions of national currencies and is available by NACE (Rev. 1, one-digit level), year (1995-2020) and country. The indicator consists of three subcategories:

(1) Computing equipment, (2) Communications equipment and (3) Computer software and databases. In our analyses, we use total ICT capital (sum of the subcategories).[4]

To calculate the average ICT capital per worker by ISCO, year and country, we apply three transformations to the dataset. First, we calculate the average ICT capital per worker by NACE, year and country using the EU-KLEMS National accounts. This involves dividing the ICT capital stock (expressed in millions of national currencies) by the number of persons employed for each specific subgroup by NACE Rev. 1 (one-digit level), year and country (expressed in thousands of workers). Second, we merge the average ICT capital per worker (now expressed in thousands of national currencies per worker) with the LFS microdata. Third, we aggregate the ICT capital information by computing the means across ISCO, year, and country groups, utilising weighting variables provided by LFS. This third step results in the average ICT capital per worker by ISCO, year and country. We keep the occupation (ISCO) within NACE structure fixed at 2011 values such that changes over time in ICT capital per occupation do not reflect within occupation reallocation of workers towards NACE industries with higher ICT capital per worker. Given that ICT capital is available up until 2020 and the LFS adopts the detailed ISCO-08 categorisation from 2011 onwards, we use all LFS survey years from 2011 to 2020.

4.1.1. Retention rate of older workers

We relate the 5-year occupation-level older worker retention rate to occupation-specific ICT capital exposure. We define the retention rate of older workers as the ratio of the number of older workers (60-64- and 55–59-year-olds) in an occupation at time t to the number of workers in the age group 55-59, respectively 50-54, year olds in the same occupation at time $t-5$ *(5 years earlier)*. Equation (Eq. 4.1) takes the following form for the retention of 55–59-year-olds:

$$\boldsymbol{Eq. 4.1}: Retention\ of\ older\ workers_{ISCO,c,y} =$$

$$\frac{Number\ of\ workers\ aged\ 60{-}64\ at\ time\ t_{\ ISCO,c}}{Number\ of\ workers\ aged\ 55{-}59\ at\ time\ t{-}5_{\ ISCO,c}},$$

where t equals 2021 or 2016. Similarly, for the retention rate of 50–54-year-olds. Following this equation, for each occupation, we have two observations: the retention rate from 2011-2016 and from 2016-2021. This allows us to form a panel (two observations) in country by ISCO observations.

We then regress the occupation-level retention rates on ICT capital per employee in 2011 (2016) and overall occupational level employment growth. The equation (Eq. 4.2) takes the following form:

[4] The total ICT capital is determined exclusively when all three indicators are available within the year-country cluster. Notably, Bulgaria (BG), Croatia (HR), Ireland (IE), Poland (PL), and Portugal (PT) lack information on all three indicators. Cyprus (CY), Hungary (HU) and Romania (RO) lack information on two out of three indicators. Last, Malta (MT) has no data on Computer software and databases.

$$\textbf{Eq. 4.2}: Retention\ of\ older\ workers_{ISCO,c} = \alpha + \beta_1 \times ICT\ capital\ per\ worker_{ISCO,c} + \beta_2 \times employment\ growth_{ISCO,c,y} + \beta_3\ i.ISCO\ x\ i.country\ +\ \beta_4\ i.year\ \times i.country\ \ + \epsilon$$

where the calculation of the $employment\ growth$ involved determining the difference between the number of individuals employed in the age group 15-64 at time t and $t-5$ and then dividing this difference by the number of individuals employed at time $t-5$ by ISCO, country and year.

To filter out trends unrelated to the development in ICT capital per worker, we control for ISCO by country fixed effects to account for the initial country-by-ISCO-specific differences in retention rates. We add control for year-by-country fixed effects to take into account country-specific changes in the retention rate of older workers, which may be correlated with ICT capital investment (e.g. changes to pension legislation). Additionally, we conduct analyses at both the ISCO 2-digit and more granular ISCO 3-digit levels.

Table 1 presents descriptive statistics on the retention rate and the ICT capital stock. The mean retention rate equals 67% at the ISCO 2-digit level and 69.9% at the ISCO 3-digit level, indicating that approximately two-thirds of workers aged 55-59 are still working 5 years later. Furthermore, for all occupations at ISCO 2-digit level, we observe a mean growth of more than 4.8% in 5 years (absolute growth). At the ISCO 3-digit level, the growth is slightly higher, with a mean value of 5.5%.

Table 1. Descriptive statistics, sample of older workers (55-59 year olds) and ICT capital (EU-27)

Variable	Mean (std.dev.)	Min.	Max.
ISCO 2-digit level (N=1,319)			
Retention of older workers	.671 (.230)	.210	1.529
Percentage change in employment	.048 (.206)	-.567	1.190
Average ICT capital per older worker (ages 55-59)			
Total ('000 Euro per worker)	14,996 (32,862)	0	210,472
ISCO 3-digit level (N=3,377)			
Retention of older workers	.699 (.276)	.197	1.797
Percentage change in employment	.061 (.264)	-.65	1.709
Average ICT capital per older worker (ages 55-59)			
Total	16,392 (34.992)	.082	225,543

Note: LFS 2011-2020 for individuals residing the EU-27. The calculation of the retention rate takes into account the weighting variable provided within LFS. Average ICT capital expressed in chained linked volumes (2015) in thousands of national currencies per older worker (ages 55-59) within each country, year and ISCO code group.

Endogeneity

To give the parameters in specification 4.2 a causal interpretation it may be necessary to instrument our key explanatory variable, ICT capital per worker, due to potential correlation with the error term. This would happen if e.g., companies are facing labour shortages in some occupations and react by both investing in ICT capital and incentivise workers to stay in the occupation.

To address endogeneity concerns we employ IV regressions constructing a country by ISCO by year instrument based on ISCO by year specific average ICT capital per worker in all other countries (than the country of observation). A similar instrument has previously been used by Albinowski and Lewandowski (2022); however, in our sample, this instrument turns out to be weak in many instances.

Results

Table 2 shows results from estimating equation 4.2 on the full sample and separately on a sample for men and women, respectively, for the 55-59-year-olds. We also perform the estimations at samples consisting of occupations at the 2-digit level and occupations at the 3-digit level. For the sample at ISCO 2 and ISCO 3-digit levels, the OLS estimates are all insignificant. In four regressions the coefficients are very small (total sample and for the subsamples of women at both ISCO 2 and ISCO 3 level). For men, the coefficients are larger, implying at the ISCO 2 level that an increase in ICT capital of 1,000 euros results in a decrease in retention rate of 0,58 percentage points. In the ISCO 3 sample, the coefficient implies a decline of almost one percentage point.

Turning to the IV estimates, we first note that the instrument only has strong predictive power in the subsample of women, both at ISCO 2 and 3-digits. In these two regressions, coefficient estimates are economically significant - close to half a percentage point lower retention rate per 1,000 euro ICT capital per worker - but statistically insignificant. In the sample of ISCO 3-digit occupations for men and in the total sample, we find large statistically significant negative effects of ICT capital on retention rates. However, because the instrument is weak, confidence intervals around the point estimates are likely to narrow.

Table 3 shows the results for the regressions related to the occupation-specific retention rate of 50-54 year-olds. Note sample sizes are slightly larger than for the 2-digit ISCO case due to fewer cells having too few observations. The same is the case for the ISCO 3-digit samples.

At the ISCO 2-digit occupational level, the OLS estimates are positive, and for the sample of women, it is significant at the 10% significance level. In the IV regressions coefficients turn negative. The IV specifications show good instruments for the total and the sample of women. In the full sample, the coefficient is significant at the 10% significance level and economically very large. This would indicate that the 50-54-year-olds are more affected by increasing ICT capital usage than the older age group.

At the ISCO 3-digit occupational level none of the estimates are significant. The instruments are weaker than in the 2-digit case.

Table 2. Regression results for the retention rate of older workers (55-59-year-olds, ISCO 2-digit, EU)

	OLS – EU Total	OLS – EU Men	OLS – EU Women	IV – EU Total	IV – EU Men	IV – EU Women
ISCO 2-digit level						
ICT capital stock per worker ('000 euro)	.0001 (.0023)	-.0058 (.0039)	.0001 (.0036)	-.0070 (.0141)	-.0382 (.0241)	-.0042 (.0147)
Pct. change in total employment	.446*** (.039)	.437*** (.0650)	.477*** (.059)	.451*** (.040)	.443*** (.068)	.478*** (.058)
Number of observations	1,120	774	558	1,120	774	558
R2	.79	.75	.79			
Kleibergen-Paap rk Wald F statistic				12.31	6.87	21.8
ISCO 3-digit level						
ICT capital stock per worker ('000 euro)	-.0027 (.0045)	-.0094 (.0058)	.0001 (.0046)	-.0308*** (.0116)	-.0539** (.0220)	-.0045 (.0122)
Pct. change in total employment	.515*** (.034)	.534*** (.049)	.403*** (.069)	.521*** (.037)	.539*** (.052)	.403*** (.060)
Number of observations	1,460	830	592	1,460	830	592
R2	.78	.74	.77			
Kleibergen-Paap rk Wald F statistic				4.86	3.76	21.42

Data: LFS 2011-2020 for individuals residing the EU-27. Dependent variable: share of older workers in employment in ISCO 2- and 3-digit. All regressions include ISCO by country and country-by-year fixed effects. Average ICT capital expressed in chained linked volumes (2015) in thousands of euros per worker within each country, year and ISCO code group. Regressions only include those ISCO code cells where we have at least 20 or more observations for older workers (ages 55-59 and 60-64) within a country, year, ISCO group. The number of (older) workers is calculated taking into account the weighting variable provided within LFS.
*** (**) ((*)) indicates significance at the 1% (5%) ((10%)) significance level.

Table 3. Regression results for the retention rate of older workers (50–54-year-olds, ISCO 2-digit, EU)

	OLS – EU Total	OLS – EU Men	OLS – EU Women	IV – EU Total	IV – EU Men	IV – EU Women
ISCO 2-digit level						
ICT capital stock per worker ('000 euro)	.0033 (.0028)	.0004 (.0050)	.0080* (.0041)	-.0542* (.0304)	-.0189 (.0330)	-.0079 (.0185)
Pct. change in total employment	.678*** (.047)	.751*** (.077)	.721*** (.059)	.703*** (.050)	.754*** (.077)	.728*** (.059)
Number of observations	1,370	958	822	1,370	958	822
R2	.70	.65	.68			
Kleibergen-Paap rk Wald F statistic				21.77	12.34	23.92
ISCO 3-digit level						
ICT capital stock per worker ('000 euro)	.0008 (.0025)	-.0042 (.0058)	-.0029 (.0050)	-.0128 (.0148)	-.0250 (.0216)	.0080 (.0172)
Pct. change in total employment	.771*** (.034)	.825*** (.049)	.780*** (.053)	.774*** (.035)	.828*** (.021)	.778*** (.053)
Number of observations	2,152	1,222	1,000	2,152	1,222	1,000
R2	.72	.69	.68			
Kleibergen-Paap rk Wald F statistic	.			8.59	4.29	15.92

Data: LFS 2011-2020 for individuals residing the EU-27. Dependent variable: share of older workers in employment in ISCO 2- and 3-digit. All regressions include ISCO by country and country-by-year fixed effects. Average ICT capital expressed in chained linked volumes (2015) in thousands of euros per worker within each country, year and ISCO code group. Regressions only include those ISCO code cells where we have at least 20 or more observations for older workers (ages 50-54 & 55-59) within a country, year, ISCO group. The number of (older) workers is calculated taking into account the weighting variable provided within LFS.
*** (**) ((*)) indicates significance at the 1% (5%) ((10%)) significance level.

Concluding remarks based on EU-LFS

Drawing on the EU-LFS 2011-2021 dataset, we find weak evidence supporting the notion that technological change (digitalisation) has diminished the employment prospects of older workers. Most majority of the estimated coefficients, representing the effect of ICT capital on the occupation-specific retention rate of older workers, are negative. However, few are significant, and instruments are often weak. Given the imprecision of the estimates obtained in most specifications, we exercise caution in drawing conclusions about the causal relationship between digitalisation and the employment of older workers based on the EU-LFS sample. The insignificance of most of the results also prevent us for making any statements about the difference in impact between men and women.

4.2. Analysis based on SHARE

An important issue associated with digitalisation at the workplace relates to the fact that, in order to perform their work, workers have to acquire digital skills, but a high level of technological chance can also create the incentives for older workers to retire earlier. This may represent a paradox in the link between digitalisation and early retirement. The impact of technical changes can be dual-edged. While technological change can diminish personal competencies if individuals do not pursue continuous learning (Hudomiet & Willis, 2021), it can also boost individual productivity, which may in turn lead to increased wages (Ahituv & Zeira, 2011). Such outcomes hold particular significance for older individuals due to wage variations across their career span and potential age-related biases in technological advancements. Given that organisational and technological changes may affect older workers' job opportunities, our research focuses on the link between early retirement and technological advancements.

While several studies focus on the influence of automation at the occupational level or at the sector-level on early retirement, very few use individual digital skills. Some consider digital skills at the individual level, however they primarily focus only on the intention to retire early (Lakomy, 2023), not an in-depth examination of the impact of digital skills on the effective transition from employment to early retirement. In addition, few studies take into account the heterogeneity of the effects of digital skills in terms of worker demographics such as age, gender, educational background, and occupational tasks. Finally, identifying the impact of digital skills on early retirement is challenging due to its endogenous nature. Factors influencing older individuals' digital skills are likely also linked to early retirement. Without addressing this endogeneity, interpreting statistical associations as causal is not relevant. In this analysis, we seek to fil these gaps by handling the reverse causality potential and presenting nuanced evidence of the multifaceted impacts of digital skills on both intended and effective early retirement.

Methodology

As our dependent variables, intended early retirement and effective early retirement, are binary, taking value 1 when a worker decides to retire before country-specific official retirement age[5] and 0 when the individual remains working. Given this binary nature, we may estimate the probability of early retirement using logit models. However, a concern with logit models is that non-random variation in digital skills may not be readily interpreted as a causal effect. Unobservable factors that affect digital skills are likely to also affect the choice to retire early in those occupations or sectors. To address this issue, we will adopt an instrumental variable (IV) strategy. As a source of variation, we use the EU KLEMS estimates for digital capital at the industry level (NACE 2-digit) in each country.

5 The calculation of early retirement for both genders takes into account the different retirement ages.

Digital capital consists of the three categories of computer equipment, communications equipment, and computer software and databases. We rely on the methodology introduced by Acemoglu and Restrepo (2020) to build instruments as the average digitalisation's exposure rates in sectors among countries not considered in our study, namely Bulgaria, Cyprus, Finland, Ireland, Netherlands, Poland, Portugal, Romania, Slovakia and the United Kingdom.

Below we present the main results organised in three parts. The first presents some descriptive statistics, in particular the distribution of the probability of early retirement and digital skills by gender, occupations and countries. The second presents the mains determinants of early retirement with a focus on the causal effects of self-perceived digital skills. The third focuses on the differentiated causal effects of digital skills by gender, age, education, job status and nature of occupations.

Descriptive statistics

Table 4 presents some descriptive statistics of our final sample. The first column covers all observa-tions. The second and third columns REPORT statistics for the subsamples of those not taking early retirement (EER=0) and those taking early retirement (EER=1). The final column presents the test for the difference of means. On average, 46% of workers aged 50+ surveyed would like to retire as early as they can from their current job. Only 5% actually retire before the official retirement age.

Table 4. Descriptive statistics of the sample

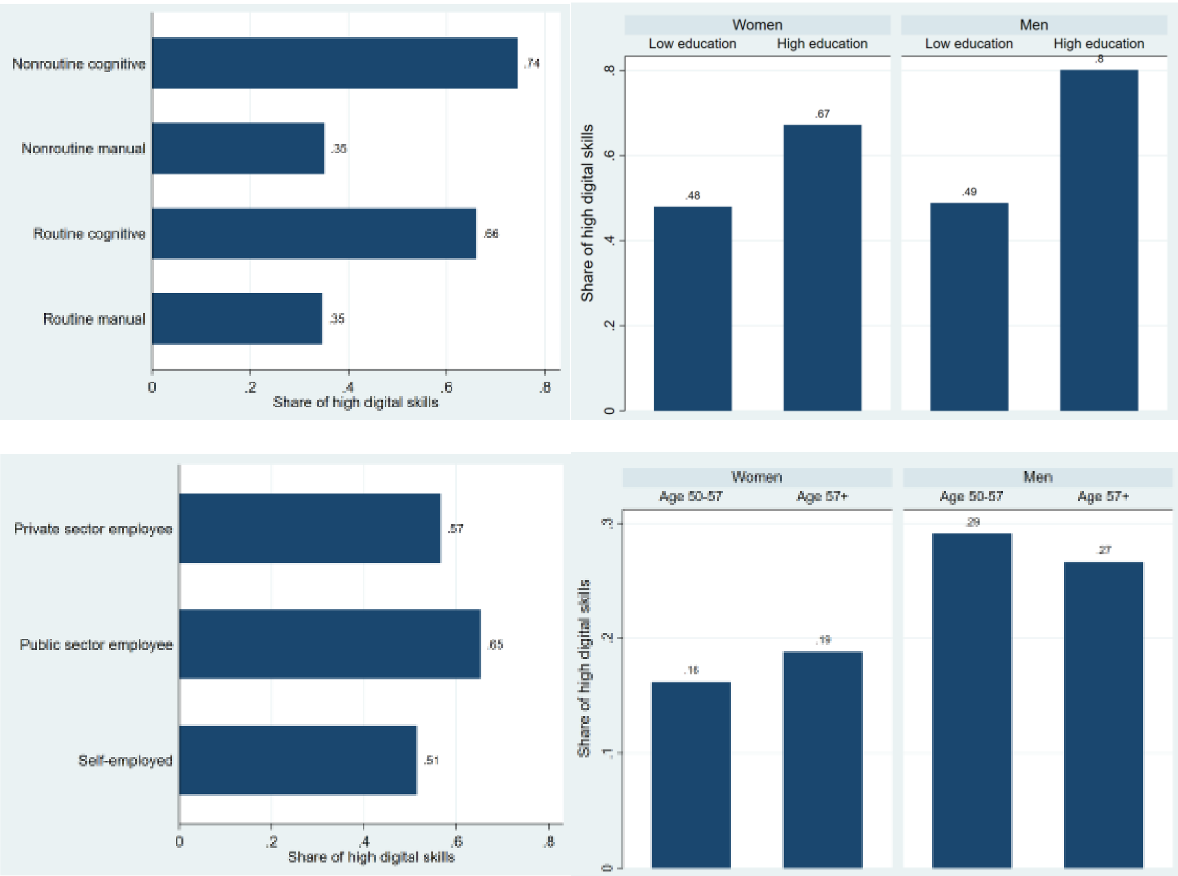
	Total Mean (Std. dev.) #obs.=6135	EER=0 Mean (Std. dev.) #obs.=5818	EER=1 Mean (Std. dev.) #obs.=316	Min	Max	Difference of means
Effective early retirement	0.05 (0.22)			0	1	
Intended early retirement	0.46 (0.49)			0	1	
Self-perceived computer skills	2.67 (1.24)	2.68 (1.23)	2.41 (1.36)	0	5	-0.27***
Women	0.47 (0.50)	0.47 (0.50)	0.41 (0.49)	0	1	-0.06***
Age 50-54	0.31 (0.46)	0.32 (0.47)	0.01 (0.08)	0	1	-0.31***
Age 55-59	0.49 (0.50)	0.50 (0.50)	0.28 (0.45)	0	1	-0.22***
Age 60+	0.20 (0.40)	0.17 (0.38)	0.71 (0.45)	0	1	-0.54***
Living with partner	0.73 (0.44)	0.73 (0.44)	0.73 (0.45)	0	1	0.00
Education: Secondary	0.60 (0.49)	0.59 (0.49)	0.72 (0.45)	0	1	-0.13***
Education: Post-secondary non tertiary	0.06 (0.24)	0.06 (0.24)	0.02 (0.14)	0	1	-0.04***
Education: Tertiary	0.34 (0.47)	0.34 (0.48)	0.26 (0.44)	0	1	-0.08***
Worked hours	38.18 (11.32)	38.20 (11.33)	37.82 (11.07)	5	168	-0.38***
Working conditions	2.39 (0.65)	2.39 (0.65)	2.36 (0.65)	1	4.67	-0.03***
High income	0.62 (0.49)	0.62 (0.49)	0.67 (0.47)	0	1	0.05***
Status: Private employees	0.57 (0.49)	0.58 (0.49)	0.46 (0.50)	0	1	-0.12***
Status: Civil servants	0.31 (0.46)	0.30 (0.46)	0.43 (0.50)	0	1	-0.13***
Status: Self-employed	0.12 (0.33)	0.12 (0.33)	0.11 (0.32)	0	1	-0.01
Sector: Manufacturing	0.14 (0.34)	0.14 (0.34)	0.13 (0.33)	0	1	-0.01
Sector: Services	0.75 (0.43)	0.75 (0.43)	0.75 (0.43)	0	1	0.00
Sector: Others	0.11 (0.32)	0.11 (0.31)	0.12 (0.33)	0	1	-0.01
Health: Poor	0.02 (0.14)	0.02 (0.13)	0.06 (0.24)	0	1	0.04***
Health: Fair	0.17 (0.38)	0.17 (0.38)	0.22 (0.41)	0	1	0.05***
Health: Good	0.42 (0.49)	0.42 (0.49)	0.38 (0.49)	0	1	-0.04***
Health: Very good	0.26 (0.44)	0.27 (0.44)	0.21 (0.41)	0	1	-0.06***
Health: Excellent	0.13 (0.33)	0.13 (0.33)	0.13 (0.34)	0	1	0.00

Note: Calibrated individual weights of SHARE waves 5 and 6 are used.

We observe that the levels of self-perceived digital skills and computer use are higher for those who remain employed. The average degree of occupation level automation is higher for those who retire early. Among age groups, we observe that the percentage of EER is higher in the 60+ group, with 71% retiring. Among education groups, workers with post-secondary non-tertiary education have the lowest percentage of early retirement. Among early retirees, the percentage of self-employed workers is the lowest.

Figure 1 illustrates the variation in average digital skills in the respondent's last job according to occupation, gender, and education. Individuals in occupations intensive in non-routine cognitive and routine cognitive tasks exhibit significantly higher levels of digital skills, with percentages of 74% and 66%, respectively, compared to those in non-routine manual or routine manual tasks, where the percentage is 35% for both categories. Gender differences are also observed in relation to education and digital skills. While the share of high digital skills within the low education category does not vary significantly between women and men-standing at 48% for women and 49% for men-men with high education levels demonstrate markedly higher digital skills at 80%, compared to women in the same category who exhibit a percentage of 67%.

Figure 1. Share of high digital skills by gender, age, education, status and occupations



Estimation results

Table 5 reports IV estimates of determinants the transition to early retirement. We first run Models 1 and 2 for the sample covering all observations. As many countries diversify retirement age by gender, we also run gender-specific regressions. The Models 3 and 4 are for the sample of women. The Models 5 and 6 are for the sample of men. For each sample, the first model integrates only the main regressor, digital skills, gender and age while the second is augmented by a number of job characteristics such as education, worked hours, working conditions, income, job status, sector, self-perceived health, nature of occupation, eligibility to public pension and an additional set of macro-economic variables such as country and waves dummies, country-specific harmonised unemployment rate, country-specific GDP growth and old age pension expenditures.

The pooled estimates (Models 1 and 2) in Table 5 indicate, independently of other controls and explanatory variables, that the effect of digital skills is insignificant. These results do not allow us to validate the hypothesis that having digital skills makes an individual more competitive and more confident in their ability to contribute, reducing their inclination to retire early (Autor, 2015).

Table 5. Determinants of early retirement – IV estimations

	Model 1 All	Model 2 Men	Model 3 Women	Model 4 Women	Model 5 Men	Model 6 Men
Digital skills	-0.268	-0.380	-0.703***	-0.963***	-0.034	0.140
	(0.203)	(0.474)	(0.159)	(0.080)	(0.243)	(0.502)
Age	1.038***	1.067***	0.790***	0.377	1.004***	1.117***
	(0.140)	(0.269)	(0.307)	(0.365)	(0.178)	(0.202)
Gender	0.157**	0.189				
	(0.083)	(0.161)				
Living with partner		0.039		0.120		-0.134
		(0.122)		(0.098)		(0.164)
High education		-0.262		0.090		-0.464**
		(0.280)		(0.136)		(0.258)
Worked hours		-0.002		0.005*		-0.008
		(0.005)		(0.003)		(0.006)
Working conditions		-0.289**		-0.379***		-0.288
		(0.166)		(0.121)		(0.215)
Income		0.331***		0.247**		0.260
		(0.097)		(0.100)		(0.199)
Cognitive abilities		-0.008		-0.061**		-0.056
		(0.044)		(0.022)		(0.043)
Health (ref. *Poor*)						
Fair		-0.415		-0.044		-0.551*
		(0.273)		(0.352)		(0.323)
Good		-0.541**		-0.042		-0.780***
		(0.315)		(0.356)		(0.319)
Very good		-0.460**		-0.002		-0.641**
		(0.401)		(0.394)		(0.350)
Excellent		-0.322**		-0.170		-0.684**
		(0.414)		(0.355)		(0.393)

	Model 1 All	Model 2 Men	Model 3 Women	Model 4 Women	Model 5 Men	Model 6 Men
Job status (ref. *Priv. employees*)						
Civil servants		0.278		0.016		0.583***
		(0.182)		(0.080)		(0.152)
Self-employed		-0.068		-0.261**		0.097
		(0.217)		(0.145)		(0.220)
Non-routine manual		-0.047		-0.293*		0.490
		(0.344)		(0.183)		(0.397)
Routine cognitive		-0.016		0.012		0.182
		(0.177)		(0.113)		(0.163)
Routine manual		-0.060		-0.038		0.593
		(0.390)		(0.252)		(0.398)
Sector (ref. Manufacturing)						
Services		-0.019		-0.008		-0.113
		(0.130)		(0.165)		(0.156)
Others		-0.062		0.038		-0.163
		(0.251)		(0.355)		(0.263)
Log of old age pension expenditures		0.040		-0.102**		0.114
		(0.084)		(0.044)		(0.070)
GDP growth		0.006		-0.066		0.048
		(0.072)		(0.057)		(0.185)
Harmonised unemployment rate		0.002		-0.016		0.185
		(0.140)		(0.110)		(0.143)
Wave dummy (ref. 2013)		Yes		Yes		Yes
Countries dummy (ref. Austria)		Yes		Yes		Yes
Kleibergen-Paap rk Wald F statistic	23.45	6.40	13.86	5.17	15.47	5.81
Observations	6,135	6,134	3,241	3,240	2,894	2,894

Note: SHARE waves 5, 6, 7. Robust standard errors in parentheses. The standard errors are clustered at sectors 2 digits to account for the construction of the instrumental variables, the digitalisation´s exposure at the occupational level.
**** p<0.01, ** p<0.05, * p<0.1*

Results in Table 5 also show that there is gender difference. Women with higher digital skills are less likely to retire early, as the estimates are negative and strongly significant (Models 3 and 4); whereas the estimates for men are not statistically significant (Models 5 and 6). However, it is important to note that the instrument is too weak in the specification with full controls (Model 4), based on the Kleibergen-Paap statistics, which is below 7. We cannot consider this as a significant and conclusive outcome.

We find differentiated effects for age, gender, education, job status, and health. Age is positive and strongly significant. We also observe a negative relationship between education and early retirement, but only for men (Model 6). This indicates that men with higher educational attainment are less likely to opt for early retirement. A plausible explanation for this could be that men with higher education often have careers that provide both intellectual satisfaction and better financial compensation, which might motivate them to extend their working years. There is also a gender difference by job status.

The estimate for self-employed women is negative and significant, while the estimate for civil servants in men is significant.

Self-perceived health emerges as a strong determinant of early retirement, but only for men (Model 6). This result highlights the gender difference in the relationship between health and early retirement and contributes to the literature on the topic which remains inconclusive (Wilson *et al.*, 2020, de Wind *et al.*, 2017, Sousa-Ribeiro *et al.*, 2021). Looking at the occupation the estimated effect of digital skills is negative and significant only for women in non-routine manual. As expected, the estimate of working conditions is negative and significant in the pooled sample and for women, in line with Moreira *et al.* (2018) and Sundstrup *et al.* (2021).

Table 6 reports the differentiated effect of digital skills by age groups and education. For each ages group and education groups, we report the IV estimates of the digital skills on the transition to early retirement for the pooled sample, women and men.

The results in Table 6 show an age difference in the effects of digital skills. Hence, there is a significant and negative estimate of digital skills for women in the age range of 50-57, while there is no statistically significant relationship for men. This suggests that women in this age category with stronger digital skills appear to be more inclined to continue working rather than retiring early. In contrast, for individuals aged 57 and over, the effect of digital skills on early retirement is both highly significant and negative for the entire pooled sample, encompassing both men and women. This finding suggests that, regardless of whether they fall within the younger or older cohorts, women benefit significantly from possessing advanced digital skills, indicating that digital skills consistently plays a role avoiding early retirement decisions among female individuals. These results are consistent with those of Jerbashian (2019), highlighting that women may benefit more from ICT adoption than men, as routine-replacing technologies increase returns to social skills, which tend to be higher among women than men (Deming, 2017).

Table 6. IV estimates of the effects of self-perceived digital skills on early retirement, by gender, age and education

		All	Women	Men
Age: 50-57	Digital skills	0.411	-1.068***	0.662
		(0.883)	(0.080)	(0.641)
	Kleibergen-Paap rk Wald F statistic	7.41	7.87	11.07
	N	2,658	1,197	1,120
Age: +57	Digital skills	-0.921***	-0.834**	-0.950***
		(0.074)	(0.369)	(0.026)
	Kleibergen-Paap rk Wald F statistic	7.12	7.15	11.65
	N	3,477	1,703	1,774
Low education	Digital skills	0.293	0.318	0.441
		(0.499)	(7.838)	(0.317)
	Kleibergen-Paap rk Wald F statistic	8.89	6.78	7.82
	N	3,483	1,769	1,714
High education	Digital skills	-0.768	-1.112***	-0.380
		(0.853)	(0.090)	(1.134)
	Kleibergen-Paap rk Wald F statistic	7.43	6.52	7.54
	N	2,652	1,472	1,180

Note: SHARE waves 5, 6, 7. Robust standard errors clustered at occupations in parentheses. The standard errors are clustered at sectors 2 digits to account for the construction of the instrumental variables, that is the digitalisation´s exposure at the occupational level.
*** p<0.01, ** p<0.05, * p<0.1. Regressions include controls for age, living with partner, education, income, cognitive abilities, health, worked hours, working conditions, macroeconomic variables.

Conversely, among men, for those aged more than 57, having strong digital skills is associated with a reduced likelihood of opting for early retirement. Table 4.5 indicates that older workers, particularly older men, tend to have lower digital skills. However, our findings suggest that older workers can benefit more from digital skills than younger ones, as these skills can help them remain in the labour market for longer periods.

Looking at education, results in Table 6 reveal that the estimate of digital skills is not statistically significant for individuals of the low education group. However, when focusing on women with high education levels, the estimate of digital skills for this specific demographic is negative and strongly significant on early retirement. This suggests that among highly educated women, possessing advanced digital skills is associated with a significant reduction in the probability of early retirement.

Table 7 reports the IV estimates of the effects of digital skills on early retirement by gender, job status and occupations. We observe that the estimate of digital skills is not statistically significant among individuals in the private sector. However, for civil servants, a gender-specific difference emerges, indicating that men with high digital skills are more likely to opt for early retirement, as the estimate is positive and significant. Interestingly, no such evidence is observed for women in the civil service.

In contrast, among women in self-employment, possessing high digital skills appears to be a moderating factor against early retirement when compared to those not having good digital skills. This distinctive gender-based variation in the impact of digital skills on retirement decisions emphasises the importance of considering both occupation and gender when assessing the relationship between technological proficiency and early retirement tendencies.

Results by occupations in Table 7 show that the estimates of digital skills on early retirement is strongly significant and negative in the pooled sample, as well as for both men and women within non-routine cognitive occupations. This finding suggests that individuals in roles characterised by non-routine cognitive tasks, regardless of gender, are more likely to delay early retirement when possessing advanced digital skills. The negative sign indicates a potential protective effect of digital skills in these occupations, emphasising their importance in influencing the retirement decisions of individuals engaged in non-routine cognitive tasks.

Table 7 reveals several differences between occupations. First, we can observe the absence of a causal effect of digital skills on early retirement in occupations intensive in non-routine manual tasks. This finding may be explained by the nature of non-routine manual occupations that are not dependent on advanced digital skills, as we can observe in the Figure 4.5. Jobs characterised by non-routine manual tasks often involve hands-on, physical activities that may not require extensive technological proficiency. Then, results also reveal that individuals working in occupations intensive in routine cognitive tasks, digital skills significantly reduce the likelihood of early retirement for both women and men.

Table 7. IV estimates of the effects of self-perceived digital skills, by gender, job status and occupations

		All	Women	Men
Private employees				
	Digital skills	0.339	-0.748	-0.055
		(0.644)	(1.567)	(0.582)
	Kleibergen-Paap rk Wald F statistic	8.56	6.15	11.15
	N	3,325	1,614	1,711
Civil servants				
	Digital skills	-0.898	-1.069	0.445*
		(0.199)	(0.045)	(1.585)
	Kleibergen-Paap rk Wald F statistic	7.57	7.15	8.33
	N	2,060	1,369	691
Self-employed				
	Digital skills	-0.548**	-0.951***	0.442
		(0.223)	(0.160)	(0.347)
	Kleibergen-Paap rk Wald F statistic	7.61	7.31	8.38
	N	750	254	492
Non-routine cognitive				
	Digital skills	-0.802***	-0.963***	-0.781***
		(0.163)	(0.266)	(0.229)
	Kleibergen-Paap rk Wald F statistic	6.78	7.52	7.45
	N	1,786	915	871
Non-routine manual				
	Digital skills	-0.450	-0.809	0.099
		(0.444)	(0.336)	(0.507)
	Kleibergen-Paap rk Wald F statistic	7.41	6.21	7.11
	N	1,355	278	805
Routine cognitive				
	Digital skills	-0.936***	-1.020***	-0.754*
		(0.145)	(0.032)	(0.446)
	Kleibergen-Paap rk Wald F statistic	7.32	7.12	10.45
	N	2,549	1,653	896
Routine manual				
	Digital skills	0.541	a	0.705**
		(0.425)	-	(0.345)
	Kleibergen-Paap rk Wald F statistic	7.44	-	6.21
	N	445	-	322

Notes: SHARE waves 5, 6, 7. Robust standard errors clustered at occupations in parentheses. The standard errors are clustered at sectors 2 digits to account for the construction of the instrumental variables, the digitalisation´s exposure at the occupational level.
*** p<0.01, ** p<0.05,* p<0.1. Regressions include controls for age, living with partner, education, income, cognitive abilities, health, worked hours, working conditions, macroeconomic variables. a insufficient observations (52 obs.).

These results are consistent with those of Lissitsa *et al.* (2017) supporting the fact that digital skills in the latter career may signal competence to employer, thus enhance job performance, job security, or greater opportunities for career advancement in these occupations, making employees more valuable to their employers. This may act as an incentive for individuals to continue working, reducing the likelihood of early retirement. Surprisingly, the results in Table 4 reveal that digital skills have a significantly positive effect on the probability of early retirement for men working in routine manual tasks, whereas no such evidence is found for women.

4.3. Analysis based on EU-SILC

The first step in the analysis of the relationship between digitalisation and the choice to retire early involves a descriptive analysis. This analysis examines changes in the inclination towards early retirement based on education, gender, age, and health status. The study utilises longitudinal EU-SILC data for the years 2016 to 2019. For the identification of early retirees, the analysis focuses on individuals who were working in any one of the years 2016 to 2018 and subsequently retired in the following years. This ensures that the analysis captures those who made the choice to retire early during the study period. The years prior to 2019 are used for this purpose. Following the descriptive analysis, logistic regression models are employed, with the share of workers with high exposure to automation as the primary regressor. The binary dependent variable indicates the choice to retire early, and the models are specified to account for variations in this choice based on education, gender, age, and health status.

Table 4.8 presents a summary of descriptive statistics for the final sample used in our analysis. This data is based on information from the EU-SILC dataset and additional sources related to the risk of exposure to automation. The first column provides statistics for all observations, while the second and third columns present statistics for two specific subgroups: individuals who retired early (ER=1) and those who did not retire early (ER=0). The following two columns represent minimal and maximal values, while the last one shows the difference in means and the statistical significance of this difference according to the t-test.

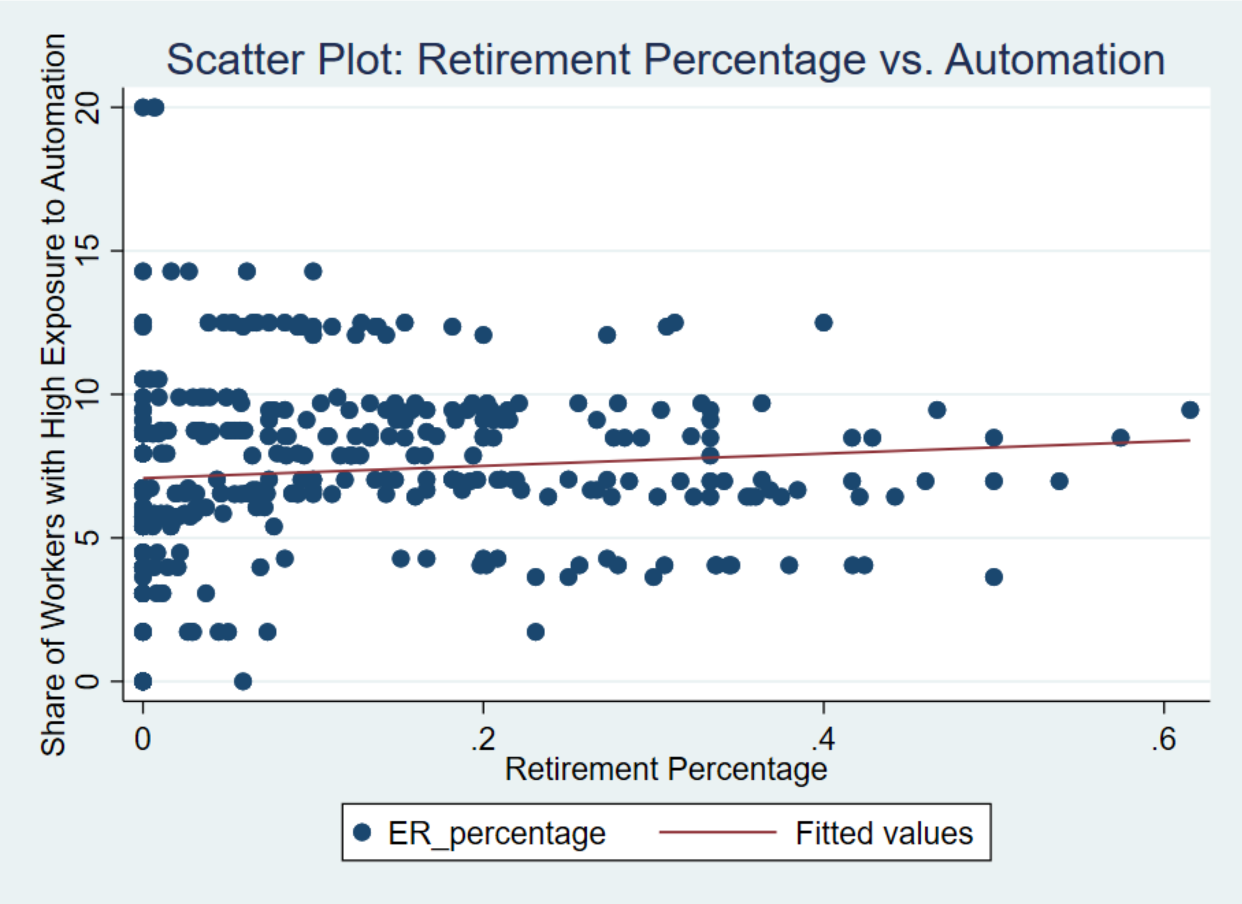
Table 8. Descriptive statistics of the sample based on the EU-SILC data

	Total Mean	ER=1 Mean	ER=0 Mean	Min	Max	Difference in means
Number of observations	15,353	1,117	14,236			
Early retirement	0.073 (0.26)			0	1	
Share of workers with high exposure to automation	0.12 (0.13)	0.11 (0.12)	0.12 (0.13)	0.00	0.61	-0.01**
Sex	1.51 (0.50)	1.47 (0.50)	1.52 (0.50)	1	2	-0.05***
Age	56.64 (4.34)	62.55 (2.58)	56.17 (4.10)	50	67	6.38***
Official retirement age	64.96 (1.73)	65.26 (1.82)	64.93 (1.73)	62	67	0.33***
Educational attainment	1.67 (0.93)	1.53 (0.88)	1.68 (0.94)	1	3	-0.15***
Marital status	2.30 (1.16)	2.27 (1.04)	2.30 (1.17)	1	5	-0,03*
Self-perceived general health	2.15 (0.72)	2.29 (0.76)	2.14 (0.71)	1	5	0.15***
Limitation in activities because of health problems	2.79 (0.47)	2.73 (0.52)	2.80 (0.46)	1	3	-0.07***
Number of years spent in paid work	32.19 (8.49)	38.87 (6.97)	31.65 (8.37)	1	55	7.22***

Notes: Analysis conducted on EU-SILC data spanning 2016-2019 encompasses individuals residing in the EU-11 countries, specifically Austria (AT), Belgium (BE), Czech Republic (CZ), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Italy (IT), Sweden (SE), and Slovakia (SK).
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Out of the 15,353 observations, 1,117 individuals opted for early retirement (ER=1), constituting approximately 7.3% of the total sample. The share of workers with high exposure to automation, a prime regressor in our subsequent logistic regression models, stands at 12%. Notably, early retirees (ER=1) have a slightly lower mean share of workers with high exposure to automation compared to those who did not retire early (ER=0). Analysing demographic factors, we observe that early retirees are, on average, older (62.55 years) than those who did not retire early (56.17 years). Educational attainment, as measured on a scale from 1 to 3, is slightly lower for early retirees (1.53) compared to non-early retirees (1.68). Marital status, self-perceived general health, limitation in activities due to health problems, and the number of years spent in paid work exhibit discernible differences between the two groups. All differences in means between individuals who retired early and those who did not are statistically significant at the 99% confidence level. The exception is observed in the variable related to the share of workers with high exposure to automation, where the difference is statistically significant at the 95% confidence level. Additionally, for the variable related to marital status, the observed difference is statistically significant at the 90% confidence level.

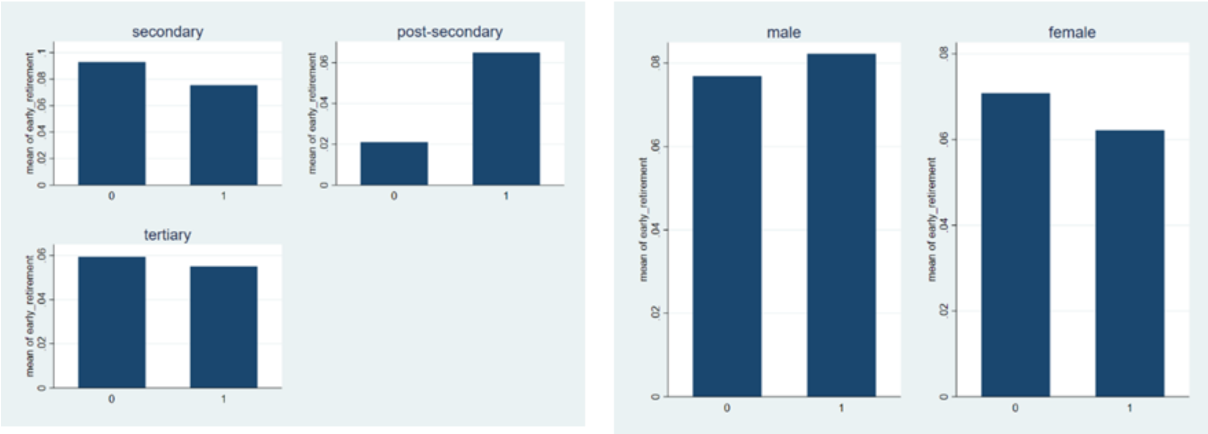
Figure 2. Early retirement and share of workers with high exposure to automation



Notes: Analysis conducted on EU-SILC data spanning 2016-2019 encompasses individuals residing in the EU-11 countries, specifically Austria (AT), Belgium (BE), Czech Republic (CZ), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Italy (IT), Sweden (SE), and Slovakia (SK).

Our initial data analysis indicates a noteworthy pattern: as the share of workers with high exposure to automation increases, retirement rates tend to increase. To elaborate, individuals employed in occupations with a high likelihood of automation are more inclined to choose early retirement. This positive association between early retirement and automation risk could be attributed to two key factors. One is the challenge of acquiring new skills in highly automated occupations. In such occupations, the required technological expertise may be higher than in occupations with a low level of automation. A high level of the required technological expertise may increase the cost of acquiring new skills in monetary and non-monetary terms. Additionally, the costs of acquiring new skills may increase due to the higher probability of technological change acceleration in occupations with a high level of automation. The other factor is the heightened risk of job loss due to automation, leading individuals to view early retirement as a more secure and stable option in uncertain times.

Figure 3. Early retirement prevalence in different education and gender groups and low (0) versus high (1) share of workers with high potential for automation



Notes: Analysis conducted on EU-SILC data spanning 2016-2019 encompasses individuals residing in the EU-11 countries, specifically Austria (AT), Belgium (BE), Czech Republic (CZ), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Italy (IT), Sweden (SE), and Slovakia (SK).

When scrutinising the interplay between early retirement, education levels, and the share of workers with high exposure to automation, a distinctive pattern emerges. Among individuals with secondary education, the propensity for early retirement is higher for those employed in occupations characterised by a lower share of workers with high exposure to automation. This finding suggests that, within this educational cohort, factors other than automation may significantly influence the decision to retire early. It's plausible that individuals with secondary education place a higher value on job satisfaction and financial stability, leading them to opt for early retirement in occupations perceived as more stable. Additionally, working in occupations with a lower level of automation, where those with secondary education are often employed, may have a negative impact on health. This potential health concern could be an important contributing factor influencing the decision to opt for early retirement. A parallel trend is observed among individuals with tertiary education. For those with tertiary education, it may be easier to adapt to automation, and that change could make their work easier, decreasing the probability of opting for an early retirement. However, a contrasting phenomenon is discerned for individuals with post-secondary education, as the pattern reverses. For this group, early retirement rates are higher among those working in occupations with an above-average share of workers with high exposure to automation. The observed higher likelihood of early retirement in occupations with a higher share of jobs at risk of automation for this group could be influenced by a strategic response to the rapidly evolving job market. They may be more attuned to the changing landscape of work and proactively choose early retirement in anticipation of potential challenges in adapting their skills to emerging job requirements.

Additionally, it appears that the impact of automation is hitting men differently than women. Namely, while early retirement rates for men are higher for those who work in occupations with a higher share of workers with high exposure to automation, early retirement rates are higher for women who work in occupations with a lower-than-average share of workers with high exposure to automation.

We employ a logistic regression model to estimate the relationship between the binary dependent variable, early retirement, and various independent variables. The dependent variable takes the value 0 if a person did not retire between 2016 and 2019, and 1 otherwise. The primary independent variable of interest is the country and occupation-specific share of workers with high exposure to automation. Additionally, control variables such as gender, educational attainment, age, health, region, and years worked are incorporated into the analysis. The sample comprises 15,359 observations from 11 EU countries, specifically Austria, Belgium, Czech Republic, Denmark, Estonia, Spain, Finland, France, Italy, Sweden, and Slovakia. The logistic model is employed to estimate the probability of early retirement, given the binary nature of the dependent variable.

A one-unit increase in the share of workers with high exposure to automation is associated with a decrease in the probability of early retirement. Specifically, a higher share of workers with high exposure to automation in the workplace is linked to a 0.54 percentage point decrease in the likelihood of early retirement. The coefficient is statistically significant at the 5% level, indicating a relatively robust relationship between the share of workers with high exposure to automation and the probability of early retirement. The negative coefficient for the share of workers with high exposure to automation suggests that, all else being equal, individuals in occupations with a higher share of workers with high exposure to automation are less likely to retire early. This aligns with the broader narrative of individuals in more technologically advanced occupations potentially experiencing prolonged careers.

When it comes to control variables, they show relatively diverse effects that are statistically significant in most cases. The coefficient for the gender dummy variable (female) is very small (0.001), indicating a minimal effect on the probability of early retirement. The impact of gender on the decision to retire early appears to be statistically insignificant. A decrease in educational attainment is associated with a decrease in the probability of early retirement. Specifically, a one-unit decrease in educational attainment leads to a 0.012 percentage point decrease in the likelihood of early retirement. The coefficient is statistically significant at the 1% level, indicating a robust relationship between educational attainment and the probability of early retirement. An increase in self-perceived general health is associated with a small increase in the probability of early retirement. Specifically, a one-unit increase in self-perceived general health leads to a 0.012 percentage point increase in the likelihood of early retirement. Once again, the coefficient is significant at the 1% level. Age is also positively impacting the decision to early retire and this impact is significant at the 1% level. The impact of hours worked is also significant and positive, but very low, since the marginal effect is only 0.003.

Table 9. Marginal effects of the main regressor – share of workers with high exposure to automation and other – control variables (logit model)

Share of workers with high exposure to automation	-0.541**
	(0.016)
Gender dummy (female)	0.002
	(0.004)
Educational attainment	-0.012***
	(0.002)
Self-perceived general health	0.012***
	(0.003)
Age	0.025***
	(0.001)
Number of years worked	0.003***
	(0.000)

Notes: Analysis conducted on EU-SILC data spanning 2016-2019 encompasses individuals residing in the EU-11 countries, specifically Austria (AT), Belgium (BE), Czech Republic (CZ), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Italy (IT), Sweden (SE), and Slovakia (SK). The dataset accounts for personal weights. This exploration aims to understand the factors influencing early retirement decisions in the context of a diverse European population during the specified timeframe.
*** p<0.01, ** p<0.05, * p<0.1.

The negative coefficient for educational attainment indicates that lower educational attainment is associated with a decreased likelihood of early retirement. This may be attributed to individuals with lower education levels having fewer alternative career options or financial resources, potentially leading them to continue working until traditional retirement ages. The positive coefficient for self-perceived general health suggests that individuals with better health are slightly more likely to retire early. This could be explained by healthier individuals feeling more confident in their ability to enjoy their retirement and having the financial means to do so. The positive coefficients for age and the number of years worked are consistent with existing literature, reflecting the common understanding that older individuals and those with longer work histories are more likely to retire early.

Individuals in occupations with high exposure to automation often experience a unique set of dynamics that influence their decisions regarding early retirement. Job security plays a pivotal role, as these occupations typically demand skill sets that remain in high demand amidst technological advancements, fostering a sense of stability and confidence in one's professional standing. Moreover, the financial considerations in such roles are noteworthy, as individuals may enjoy higher earning potential due to their specialised skills, prompting a preference for delaying retirement in order to accumulate greater financial resources for the post-work years. The nature of occupations with high exposure to automation also requires adaptability and a commitment to continuous learning to stay abreast of technological advancements. This inclination towards lifelong learning contributes to a mindset favouring prolonged engagement in the workforce. Career fulfilment emerges as a key motivator, especially for those involved in cutting-edge technologies. The satisfaction derived from contributing to innovative projects and staying at the forefront of their field becomes a compelling reason to extend one's career. Social and professional networks cultivated over years of employment further contribute to the decision to remain in the workforce, fostering a sense of community and belonging. Individuals perceive the work environment as less physically demanding, allowing them to maintain good health and well-being, and thereby supporting an extended working life. In essence, the decision to defer retirement in occupations with high exposure to automation is a multifaceted interplay of job security, financial considerations, adaptability, career fulfilment, social networks, and a unique perspective on health and well-being.

5. Summary and concluding remarks

We present one of the initial studies examining the impact of digitalisation and automation on employment of older workers and retirement decisions of senior workers across 27 European countries in a comprehensive EU-wide context. Our focus extends to understanding how these effects vary based on demographic factors such as gender and age. The assessments draw upon data from various European databases.

The first analysis uses data from the EU-LFS 2011-2021 dataset for the EU12 countries. We assess the impact of digitalisation through two sets of analyses. The first looks at occupational-level changes in the employment share of older workers as a function of the digital capital stock per worker within the occupation, as well as its relation to indicators of occupation risk of automation, AI exposure. The second set of analysis looks at 5-year occupational retention rates of 55-59 year olds and relate changes in these rates to exposure to ICT capital (at age 55-59). Our results show that there is very limited evidence suggesting an association between technological advancements and early retirement. However, we also emphasise that in most specifications our estimates are not estimated with sufficient precision to say anything definitive about the relationship between technological advancement and employment of older workers. As such, we are not able to move the weight of the evidence in relation to earlier literature suggesting the introduction of new technology may make it more difficult to keep older workers employed (Albinowski & Lewandowski, 2022; Hudomiet & Willis, 2022; Martin, 2018), additional research is considered essential to enhance our comprehension of the relation between technological advancements and early retirement.

While aggregated indicators at the occupation-level can offer a broad perspective on trends in early retirement, they may not capture the complexity and individual factors of the decision-making process such as working conditions, health status, financial considerations, job status, worked hours, etc. Therefore, we complement aggregated analyses based on EU-LFS with more granular, individual-level data to enhance the robustness and applicability of their results. Two datasets are used: SHARE data and EU-SILC data.

The analysis based on SHARE wave 5, 6, 7 covers 14 European countries and examines how digital skills impact early retirement for workers aged 50 and above. We conducted an instrumental variable analysis to explore the causal effects of subjective digital skills on the effective early retirement of individuals aged over 50. Our analysis included separate models for the overall sample, as well as gender-specific models for women and men. We integrated various job characteristics, such as education, worked hours, working conditions, income, job status, sector, subjective health, cognitive abilities, nature of occupation, eligibility for public pension, and macroeconomic variables. Several key results emerged.

First, contrary to the hypothesis that possessing digital skills enhances an individual's competitiveness and confidence, thereby reducing the incentive to retire early, our findings suggest that digital skills do not significantly impact effective early retirement. However, a notable gender difference was observed. Digital skills impact women's early retirement, as women with higher digital skills were less likely to retire early, while no significant evidence was found for men. Second, there is an age-differentiated effect of digital skills on early retirement. For employees aged 57 and over, both women and men with high digital skills were less likely to retire early compared to those in the same age group without digital skills. In contrast, for the younger age group (under 57), we only observed a negative effect on women. This indicates that the relationship between digital skills and early retirement varies across age groups and genders. Third, the effects of digital skills vary according to the educational background, with highly educated women benefiting significantly from advanced digital skills by maintaining them longer at work. The literature highlights that women tend to engage in a higher proportion of routine tasks compared to men across all sectors and occupations, and these tasks are particularly susceptible to being automated or digitised (Brussevich *et al.*, 2019). Nevertheless, our results suggest that highly educated older women may be in well-paying roles, providing an economic incentive to delay early retirement. The self-perceived digital skills may reflect their adaptability and commitment to continuous learning, influencing a propensity to prolong their careers, as indicated by Arntz *et al.* (2019). All together, these findings highlight the importance of educational background and gender as moderators of the relationship between digital skills and the decision to retire early. Fourth, job status played a crucial role in the relationship between digital skills and early retirement. We find that among civil servants, a gender-specific pattern emerges – men with high digital skills are more likely to retire early, while no such evidence is observed for women. Conversely, among self-employed women, high digital skills moderate early retirement tendencies as women in self-employment with high digital skills are less likely to retire early. Finally, individuals working in occupations intensive in non-routine cognitive tended to postpone early retirement when equipped with high digital skills. On the contrary, among those involved in routine manual tasks, men with high digital skills exhibited a notably positive impact on the likelihood of early retirement, with no corresponding evidence found for women in similar roles.

Using data from the European Union Statistics on Income and Living Conditions (EU-SILC) for the years 2016-2019, we explore the impact of the proportion of workers with high automation potential in specific occupations on the assessment of early retirement decisions. Early retirement is defined as individuals transitioning from the workforce to retirement during this period. Our analysis reveals a significant negative correlation between the share of workers in highly automated occupations and the likelihood of early retirement. This underscores that those in roles with increased automation potential are less inclined to opt for early retirement, highlighting the discernible influence of technological dynamics on retirement choices. Factors such as educational attainment, self-perceived general health, age, and years worked also positively contribute to shaping retirement trajectories in this changing occupational landscape.

This report highlights the importance of adopting a life course perspective when examining retirement decisions. To reduce early exits from the labour market, it is crucial to focus on the effects of lifelong digital training, as well as other factors such as health, working conditions, and pension systems.

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Appendices

Appendix 1: Classification of occupations into task groups in the ISCO-08 classification

Taskgroup	ISCO-08 code	Occupations
Non-routine cognitive		
	11	Chief Executives, Senior Officials, and Legislators
	12	Administrative and Commercial Managers
	13	Production and Specialised Services Managers
	14	Hospitality, Retail and Other Services Managers
	21	Science and Engineering Professionals
	22	Health Professionals
	23	Teaching Professionals
	24	Business and Administration Professionals
	25	Information and Communications Technology Professionals
	26	Legal, Social, and Cultural Professionals
	31	Science and Engineering Associate Professionals
	32	Health Associate Professionals
	35	Information and Communications Technicians
Routine cognitive		
	33	Business and Administration Associate Professionals
	34	Legal, Social, Cultural, and Related Associate Professionals
	41	General and Keyboard Clerks
	42	Customer Services Clerks
	43	Numerical and Material Recording Clerks
	44	Other Clerical Support Workers
	52	Sales Workers
Routine manual		
	72	Metal, Machinery, and Related Trades Workers
	73	Handicraft and Printing Workers
	75	Food Processing, Woodworking, Garment, and Other Craft and Related Trades Workers
	81	Stationary Plant and Machine Operators
	82	Assemblers
	94	Food Preparation Assistants
Non-routine manual		
	51	Personal Services Workers
	53	Personal Care Workers
	54	Protective Services Workers
	61	Market-oriented Skilled Agricultural Workers
	62	Market-oriented Skilled Forestry, Fishery, and Hunting Workers
	63	Subsistence Farmers, Fishers, Hunters, and Gatherers
	71	Building and Related Trades Workers (excluding Electricians)
	74	Electrical and Electronic Trades Workers
	83	Drivers and Mobile Plant Operators
	91	Cleaners and Helpers
	92	Agricultural, Forestry, and Fishery Labourers
	93	Labourers in Mining, Construction, Manufacturing, and Transport
	95	Street and Related Sales and Services Workers
	96	Refuse Workers and Other Elementary Workers

Source: Maciej and Lewandowski (2022)

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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