NETWORK LISER

Discussion Paper Series

IZA DP No. 18938

September 2026

Technology and Retirement

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ISSN: 2365-9793

IZA DP No. 18938 September 2026

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Abstract

As populations age, longer working careers become more essential, and technological advancements may prolong or shorten career spans. We examine how exposure to industrial robots, information and communication technology (ICT), and artificial intelligence (AI) relate to retirement expectations among workers in 20 European countries. To this end, we link individual-level data from the European Working Conditions Survey (2005–2024) with lagged technology-exposure measures. Technology exposure shows little systematic association with preferred retirement timing. Nevertheless, robots and especially AI are linked to the perception of being able to work until age 60. These associations vary across workers and tasks, suggesting that job design and worker adaptation determine whether technology supports longer working lives.

JEL classification

I31, J26, O33

Keywords

retirement, expectations, technological change, robots, ICT, AI

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* *Acknowledgments*: This project has received funding from the 2025 Netspar International Comparative Research Grant. The authors thank Eduard Suari-Andreu, Lisa Brüggen, Marie Brière, Mathijs van Dijk, Ricky Kanabar, Benjamin Lerch, and participants at the 2026 International Pension Workshop for valuable feedback and suggestions. We also thank Tudor Albu and Nicholas Patreane for research assistance, and Marta Pallavicini for help with the literature review. We are also grateful to Sophia MacGoris of Eurofound for early access to the 2024 EWCS, Piotr Lewandowski for providing the AI exposure data, and Stefan Jestl for advice on the EU KLEMS data. All errors are our own.

Declaration of generative AI and AI-assisted technologies in the writing process: During the preparation of this work, the authors used Grammarly and ChatGPT [versions 5.2 and 5.6 Sol] and Codex [Version GPT-5.4] to edit parts of the paper and for data coding in Stata. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the final content.

1. Introduction

Although automation via robots, ICT, and AI has advanced for decades, aggregate employment in developed economies has not declined significantly (Autor, 2015; del Rio-Chanona et al., 2025; Hötte et al., 2023). Yet, this apparent stability masks substantial reallocation: technological change has sharply reduced employment in agriculture, routine-intensive occupations, and parts of manufacturing, while employment gains elsewhere, particularly in services, have generally prevented these losses from causing mass unemployment (Autor, 2015; Hötte et al., 2023; Jestl, 2024).

Workers may also adjust to technological change via labor-force entry and exit. Younger workers in Germany become less likely to enter occupations undergoing rapid robotization (Dauth et al., 2021), while older workers in the US leave the labor force through early retirement (Di Giacomo & Lerch, 2026). Emerging evidence on generative AI points to a different pattern: AI exposure increases older workers' employment exits, primarily through unemployment rather than retirement or labor-force withdrawal (Sanzenbacher, 2026).

Although several studies examine actual retirement and labor-force exit in response to technological change (e.g., Ahituv & Zeira, 2011; Casas & Román, 2023; Di Giacomo & Lerch, 2026; Yashiro et al., 2022), fewer studies directly examine retirement expectations (see Lee, 2024 and Messe et al., 2014 for exceptions). If technological change alters expectations about one's working life, changes in retirement plans may constitute an additional adjustment channel that precedes displacement or labor-force exit.

This raises a central question: does technological change accelerate or delay retirement intentions and expectations about people's working lives? The answer is theoretically ambiguous. On the one hand, technological change may encourage earlier retirement by making existing skills obsolete, increasing job insecurity, or reducing job quality. On the other hand, it may prolong working lives by improving productivity, reducing physical strain, and creating new tasks that complement workers' skills. Whether retirement acts as an adjustment margin, therefore, depends on which of these opposing channels dominates.

Robotization, ICT, and AI all operate at the task level rather than the occupation level, but they differ in the types of tasks they affect. Robotization primarily affects routine, physical, and manual tasks, while ICT has historically automated routine cognitive tasks (Webb, 2019). AI is a set of technologies that help machines interpret, act, and emulate human cognitive abilities (Cazzaniga et al., 2024). As such, AI overlaps with non-routine, cognitive, and language-intensive tasks, typically performed by high-skilled workers (Eloundou et al., 2024; Felten et al., 2021). Yet, all three types of technologies not only automate and displace tasks but also create new ones and complement existing ones (Acemoglu & Restrepo, 2019; Autor, 2015; Autor et al., 2024). Understanding which channel (i.e., displacement, augmentation, or task creation) dominates, and in which settings, matters for explaining people's retirement behavior in response to technological change.

For example, robotization can reduce injuries and physical strain (Gihleb et al., 2022; Gunadi & Ryu, 2021; Nikolova et al., 2025) and, as such, prolong workers' working lives. As a result of reduced physical burden, many occupations requiring physical fitness can become safer and less demanding, potentially allowing workers to shift to higher-value tasks or perform their tasks with less physical strain. At the same time, evidence suggests that robotization erodes mental health (Abeliansky et al., 2024), job satisfaction (Schwabe & Castellacci, 2020), autonomy and meaningfulness (Nikolova et al., 2024), and increases work intensity (Antón et al., 2023). These poor working conditions and job quality may, in turn, push workers to plan exits from the labor force earlier than the statutory retirement age. In fact, poor working conditions and low autonomy seem particularly detrimental for the mental health of older workers experiencing reform-induced later retirement (Lugova et al., 2026).

Furthermore, ICT can delay retirement when coupled with skill upgrading and training, but accelerates labor market exit when it induces skill obsolescence among older workers (Messe et al., 2014). ICT and robot adoption reduced the employment share of older women, although the authors suggest that age differences in skills and adaptability may partly explain this pattern (Albinowski & Lewandowski, 2024).

The effects of AI on retirement remain poorly understood. However, the one existing study finds that AI exposure is associated with a lower probability of early retirement mainly among tertiary-educated workers (Casas & Román, 2024). Some studies provide evidence that AI reduces the physical burden of tasks and yields small improvements in health satisfaction (Giuntella, Konig, et al., 2025), which may increase people’s actual and desired working lives.

This paper contributes to the literature by being, to the best of our knowledge, the first to jointly examine how robotization, ICT, and AI exposure shape different dimensions of retirement intentions and expected working life across 20 European countries. To do so, we use repeated cross-sectional surveys of workers linked to lagged industry- and occupation-level technology measures. Specifically, we analyze repeated cross-sections of workers aged 60 and younger from the European Working Conditions Survey (EWCS) for 2005, 2010, 2015, and 2024. Our dependent variables capture several aspects of retirement expectations, including preferred retirement age, preferred early retirement, uncertainty about desired retirement age, perceived ability to work until at least age 60, and unwillingness to continue working until 60. We link these outcomes to lagged measures of robotization and ICT intensity, both measured at the country-industry-year level (2-digit industry), and to AI exposure measured at the country-occupation-year level (2-digit occupation).

We find little evidence that exposure to robots, ICT, or AI systematically relates to preferred retirement age, early-retirement preferences, or retirement uncertainty on average. The only exception concerns workers’ perceived ability to continue working at older ages. In the 2015–2024 sample, a one-standard-deviation increase in robot and AI exposure corresponds to increases of approximately 0.4 and 4.4 percentage points, respectively, in perceived work ability (relative to the sample mean of 74.4%). These are relatively small effect sizes.

Instrumental-variable estimates based on leave-one-out peer exposure measures support the main conclusion but also reveal statistically significant associations with preferred retirement age. A one-standard-deviation increase in robot exposure corresponds to a reduction in preferred retirement age of about 0.9 months, whereas an equivalent increase in ICT exposure corresponds to an increase of about 2 months; both effects are small. The IV estimates also indicate that ICT exposure is associated with a lower probability of preferring early retirement, less retirement uncertainty, and a greater perceived ability to work until age 60. AI exposure remains positively associated with perceived work ability. Despite these additional relationships, most estimated magnitudes remain modest.

The associations vary across workers and employment contexts. ICT exposure relates more positively to preferred retirement age among older workers and women. AI exposure is associated with a later preferred retirement age among low- and medium-skilled workers, while the corresponding point estimate turns negative among high-skilled workers. Its positive association with perceived work ability also weakens among older workers, men, and workers in Southern and Central and Eastern Europe. We also find differences by education, task content, tenure, and training, although these patterns vary across technologies and retirement outcomes.

Taken together, the results support the theoretical ambiguity surrounding technological change and retirement. Technological change therefore does not uniformly encourage either earlier or later retirement. Its relationship with retirement expectations depends on the technology, the outcome, and workers' characteristics.

2. Determinants of retirement (intentions)

The literature on the determinants of retirement intentions is quite extensive. Early retirement depends on workers’ health, work ability, job quality, training opportunities, and expectations about life after leaving their main job. Poorer self-rated health, lower work ability, and greater effort-reward imbalance are associated with trajectories involving earlier preferred retirement ages (Sousa-Ribeiro et al., 2024). Against this backdrop, firms can delay retirement by sustaining employability: both firm-provided training and access to training opportunities improve later-life employment prospects and raise expected retirement age, including among older workers (de Grip et al., 2020; Picchio & van Ours, 2013). In general, good working conditions are associated with later retirement ages. For example, using the EWCS, the same dataset as this project, Nikolova and Cnossen (2020) show that across European countries, experiencing a ten-point increase in work meaningfulness (on a 0-100 scale) can delay the desired retirement age by 2.5 years, on average.

Finally, retirement is not always a one-way transition, since many workers expect to combine retirement with some continued work, and these pre-retirement expectations strongly predict subsequent unretirement or partial retirement, underscoring the importance of using forward-looking preferences rather than treating retirement as a purely final exit decision (Maestas, 2010).

3. Technological change and retirement

Technological change can affect both retirement intentions and actual retirement behavior, but the evidence points to mixed effects that are often heterogeneous across workers and contexts.

Early studies mainly focused on ICT and workplace computerization. Using data from the National Longitudinal Survey of Older Men linked to industry-level productivity growth and occupation-level training requirements, Bartel and Sicherman (1993) distinguish between persistent technological change and unexpected technological shocks. Workers in industries with persistently faster technological change retire later, consistent with the greater training requirements of technologically dynamic industries. By contrast, unexpected increases in technological change induce earlier retirement, particularly among older workers for whom retraining offers fewer returns. They also find that workers in occupations requiring more training tend to retire later. Their results therefore suggest that technological change can either extend or shorten working lives, depending on whether it generates sustained demand for training or unexpectedly depreciates workers' existing skills.

Furthermore, Ahituv and Zeira (2011) identify two opposing channels through which technological change can affect retirement. Aggregate technological progress raises productivity and wages, encouraging workers to remain employed, whereas sector-specific technological change erodes existing skills and encourages older workers to leave employment. Using Health and Retirement Study data for U.S. men aged over 50 linked to sector-level productivity growth, they find evidence for the skill-erosion channel. Older workers exposed to faster sector-specific technological change are more likely to leave the labor force, primarily through unemployment and disability. The direct association with reported retirement is weaker, which the authors attribute to retirement often following an intervening period of unemployment. Messe et al. (2014) combine retirement intentions among employed French men aged 50–55 with industry-occupation measures of technological change and skill-updating training constructed from workers aged 24–49. They find that technological change leads workers to prefer earlier retirement in jobs with low training rates. In jobs with a high probability of skill updating, however, technological change leads workers to prefer later retirement. More broadly, using longitudinal Dutch data from the European Community Household Panel, Picchio and van Ours (2013) find that employer-provided training improves subsequent employment prospects and reduces labor-market exit, including among workers aged 50–64.

More recent research on automation and AI also finds mixed effects on older workers' employment and retirement. Using longitudinal data from China, Giuntella et al. (2025) find that greater exposure to industrial robots reduces employment and labor-force participation and increases the likelihood of earlier retirement, with stronger labor-market effects among older and less-educated workers. Casas and Román (2023) similarly find that greater occupation-level automation risk increases the probability of early retirement in Europe, particularly among workers without higher education. Using US Health and Retirement Study data linked to O*NET, Lee (2024) shows that greater skill-specific automatability increases both actual retirement likelihood and expectations of retiring before age 65. Among workers with comparable levels of automatability, high-school graduates have a 6.3% higher retirement hazard than workers with graduate degrees. Van der Velde (2022) reports more institutionally contingent results: workers in routine-intensive occupations leave the labor market slightly earlier in Germany but not in Great Britain, while differences in working hours remain limited. Related evidence from Finland reinforces the importance of institutions. Yashiro et al. (2022) find that workers aged 50–64 with greater exposure to digital technologies face a higher risk of leaving employment, particularly when extended unemployment benefits provide an accessible exit pathway. Overall, these studies suggest that technological change can shorten or extend working lives depending on the technology, workers' skills and education, and the institutional pathways available for leaving employment.

However, not all studies conclude that technological change necessarily pushes workers into earlier retirement. Focusing specifically on AI, Casas and Román (2024) used SHARE data on older European workers and found that AI exposure was associated with a lower likelihood of early retirement, particularly among highly educated workers and in occupations characterized by both high current AI advances and strong expectations of future AI development. By contrast, the effects were considerably weaker for less-educated workers. The authors argue that AI may complement rather than substitute older workers' skills by improving productivity and reducing physically demanding tasks. Nguyen-Thi et al. (2024) find no overall relationship between digital skills and early retirement, although higher digital skills predict less early retirement among women and some older and highly educated groups. In a separate EU-SILC analysis, a larger share of workers in highly automated occupations is associated with a lower probability of early retirement (Nguyen-Thi et al., 2024).

Overall, the literature suggests that the effects of technological change on retirement behavior are not uniform, but depend strongly on the type of technology involved as well as workers' education, skills, and access to training opportunities. Technological change may push some workers into earlier retirement through displacement effects, while for others it may encourage longer working lives by complementing existing skills and improving working conditions.

This project advances existing studies in two main ways. First, existing studies focus on actual retirement transitions, and older workers may suffer from selection bias. This is because looking at older workers who survive automation may not yield representative results (Messe et al., 2014). By contrast, this project looks at all workers and their retirement intentions. We consider workers across all age groups (excluding those older than 60), capturing how individuals plan to adjust their working lives in response to technological change and pension incentives before they exit the labor market. This makes retirement expectations particularly valuable for policymakers seeking to anticipate future retirement patterns, especially given that such expectations strongly predict actual retirement timing (Haider & Stephens, 2007). Second, prior work typically isolates a single form of technology (e.g., robots or ICT) or uses aggregate measures of automation exposure that do not distinguish between particular technologies. This project instead simultaneously studies exposure to robots, ICT, and AI within a unified framework, leveraging harmonized variation across countries, industries, and occupations, and incorporating novel AI exposure measures at the 2-digit occupation level from Lewandowski et al. (2025).

4. Conceptual framework

Industrial robots automate routine manual tasks and can affect retirement through opposing channels. By performing physically demanding, repetitive, or dangerous tasks, robots can reduce injuries and physical strain (Gihleb et al., 2022), thereby improving workers' ability to remain employed at older ages. However, robots can also substitute for workers, depreciate their skills, and increase employment insecurity. Giuntella et al. (2025) find that robot exposure reduces employment and labor-force participation in China and increases early retirement, particularly among older workers. Di Giacomo and Lerch (2026) similarly find that robot adoption increases labor-force non-participation in the United States, with early retirement accounting for nearly 40% of the resulting increase. Robotization may harm workers' mental health (Abeliansky et al., 2024) and shift work toward more routine and less abstract or social tasks (Nikolova et al., 2025). In summary, robots may extend working lives if they reduce physical demands and complement workers, but encourage earlier retirement when displacement, skill obsolescence, or declining job quality dominates.

Second, ICT may affect retirement expectations by changing task content, skill requirements, and work organization. Computer use can reduce physical tasks, while information technologies can improve efficiency, flexibility, and worker autonomy (Martin & Hauret, 2022). These changes may make continued employment more attractive. However, communication technologies can increase monitoring and work intensity, extend work into leisure time, and blur the boundary between work and private life. They may therefore increase stress and work-life conflict and make earlier retirement more attractive. These effects depend on how employers implement the technology, whether workers receive adequate training, and workers' ability to adapt their skills (Martin & Hauret, 2022). The relationship between ICT exposure and retirement expectations is therefore theoretically ambiguous.

Third, like previous technologies, AI can perform routine tasks, mostly in the cognitive domain, such as coding. But AI differs from both robots and ICT because it overlaps with the capabilities of high-skilled workers and can perform certain non-routine tasks (Eloundou et al., 2024; Felten et al., 2021). As such, it complements certain occupations (e.g., judges, lawyers) that are too important for society to leave to technology (Cazzaniga et al., 2024). At the same time, AI may generate greater uncertainty about skill obsolescence and future employability, especially among high-skilled workers performing tasks vulnerable to AI substitution (e.g., clerical work) (Cazzaniga et al., 2024).

Evidence on AI's labor-market consequences remains limited. Evidence to date does not show economy-wide employment losses from AI, although effects differ across occupations and worker groups (Comunale & Manera, 2024; del Rio-Chanona et al., 2025; HAI, 2026). Nevertheless, Sanzenbacher (2026) finds that, following ChatGPT's launch, U.S. workers aged 55 and older in occupations with greater AI exposure became more likely to leave employment. These additional exits occurred primarily through unemployment rather than retirement or labor-force withdrawal. This result suggests that aggregate stability may conceal adjustment costs for older workers in highly exposed occupations. Likewise, evidence to date does not point to widespread negative job-quality implications of working with AI. For example, Giuntella, Konig, et al. (2025) show that AI is associated with declines in physical intensity, small improvements in health satisfaction, and no further changes in job quality. Likewise, Bryson et al. (2026) find no association between AI and job satisfaction, but they do find that personal AI use is associated with greater work engagement in Finland. Noy and Zhang (2023) even show that working with GenAI improves short-term job satisfaction in an experimental setting. Nevertheless, AI is also associated with mistrust and fear (Glikson & Woolley, 2020; Nikolova & Angrisani, 2025), which may influence people's decisions to retire after exposure to this technology.[1]

Overall, the literature reviewed in Sections 3 and 4 does not offer a clear prediction about the effects of technological change on retirement. In fact, different mechanisms may operate in opposite directions. For example, technological change may encourage longer working lives by reducing physical job demands and improving work ability, while simultaneously shortening expected working lives through lower job quality, increased job insecurity, skill obsolescence, or distrust of new technologies. The overall relationship between exposure to robots, ICT, and AI and retirement expectations therefore remains an empirical question.

The balance between these opposing channels is also likely to differ across groups of workers. First, age may moderate the relationship between technological exposure and retirement expectations. Older workers have shorter remaining career horizons and therefore weaker incentives to acquire technology-specific skills, potentially making technological change a push factor into earlier retirement (Ahituv & Zeira, 2011). Consistent with this mechanism, Albinowski and Lewandowski (2024) find particularly adverse employment effects of ICT exposure among older women in cognitive occupations with relatively weak ICT skills. At the same time, older workers may benefit disproportionately from technologies that reduce physical job demands, particularly industrial robots, thereby improving their ability to remain employed at older ages. Second, education and skill level may shape workers' responses to technological change because different technologies affect different tasks. AI, in particular, overlaps with many cognitive tasks performed by highly educated and high-skilled workers, potentially increasing concerns about skill obsolescence in some occupations while complementing workers in others (Cazzaniga et al., 2024). Conversely, lower-skilled workers may benefit relatively more from technologies that reduce physically demanding work. Third, technological change may affect men and women differently because they perform different tasks, even within the same occupations

[1] Recent experimental evidence identifies potential work well-being costs of AI, which, however, appear small in magnitude. Nikolova (2026) finds that respondents expect AI-only and hybrid AI-human workplace safety systems to produce lower job satisfaction, work meaningfulness, and social value than human supervision. Nikolova et al. (2026) further show that attributing identical creative work to AI rather than a human modestly reduces perceived task meaning and rather substantively reduces voluntary effort.

and industries, and because they differ in adopting new technologies and their associated labor market returns. Recent evidence also points to gender differences in the effects, adoption, and exposure to new technologies. ICT adoption reduced the employment share of older women, although it also reduced that of prime-aged men (Albinowski & Lewandowski, 2024). Men adopt and use generative AI more often than women, with substantial gaps in the United States (Angrisani et al., 2026) and across more than 100 countries (Cranney et al., 2026).[2] Robots also widen gender inequality but through a different channel. Using European data, Aksoy et al. (2021) find that robotization raises earnings for both men and women but increases the gender pay gap because men in medium- and high-skill occupations capture a disproportionate share of the productivity gains. Access to employer-provided training may play an important role by facilitating adaptation to new technologies and reducing skill obsolescence (Bartel & Sicherman, 1993; Messe et al., 2014). We therefore examine whether the relationship between technological exposure and retirement expectations varies by age, gender, education, and workplace characteristics.

5. Data and variables

5.1. EWCS

The European Working Conditions Survey (EWCS) is a repeated cross-sectional survey conducted by Eurofound that collects detailed information on workers' socio-demographic characteristics, employment conditions, and workplace environment across European countries. We use five retirement-related dependent variables from the 2005, 2010, 2015, and 2024 waves. The 2021 EWCS wave includes no retirement-related questions.

We construct a harmonized dataset for cross-wave analysis by combining several EWCS data files. First, we rely on the integrated 1991-2015 EWCS file (Eurofound, 2026b). We use the 2005-2015 data in the file because it includes the technology variables. The integrated file provides harmonized identifiers and classifications across waves, including consistent country codes and occupation and industry classifications (ISCO codes and NACE Rev. 2).[3] This cumulative file serves as the backbone of the analysis dataset we create in this paper. It ensures that key structural variables are comparable over time. However, the cumulative file does not contain all retirement-related variables for the earlier waves. Therefore, we supplement it with wave-specific individual-level datasets for 2005 (Eurofound, 2022a), 2010 (Eurofound, 2022b), and 2015 (Eurofound, 2024), from which we extract the retirement outcomes. We then merge these cleaned wave-specific files into the harmonized backbone to obtain a consistent dataset across waves. Finally, we add the most recent EWCS 2024 wave, which is available as a standalone

[2] At the same time, women tend to work in more AI-exposed occupations (Cazzaniga et al., 2025).

[3] The 2005 EWCS reports one- and two-digit occupational codes based on the ISCO-88 classification, whereas the 2010 and later waves use ISCO-08. Although the two classifications share the same categories for the one-digit occupations, we cannot guarantee that they are identical across the two years. This difference should not affect our analyses that combine the 2005 wave with later waves because all specifications include year fixed effects. Moreover, excluding the one-digit ISCO control variables does not alter our findings (results available upon request). For 2015 and 2024, we use two-digit ISCO-08 codes to merge the EWCS data with the measures from Lewandowski et al. (2025).

dataset with comparable coding of occupations (ISCO-08), industries (NACE Rev.2), and socio-demographic characteristics.

The resulting dataset is a pooled cross-section of individual workers observed in four survey years (2005, 2010, 2015, and 2024), with harmonized occupation, industry, and country identifiers that allow us to merge the EWCS data with external measures of technological exposure. We use a sample of 20 countries for which all required external data sources are available. The 2024 EWCS does not contain information for the United Kingdom.

Workers observed at older ages are a selected group who have remained in the labor force despite exposure to technological change (Messe et al., 2014). In our sample, approximately 10% of respondents are aged 60 or older. We therefore exclude these individuals and restrict the analysis to workers aged 60 and younger. This restriction allows us to focus on forward-looking retirement expectations among the broader working population, rather than on a selected group of older workers who have already remained employed.[4]

The first outcome, preferred retirement age (retireage), measures the age until which respondents would like to work (Table 1). In the 2015 wave, respondents were asked, "Thinking about retirement, until what age do you want to work?" and could report a numeric age, but the survey enumerators also recorded "Refused," "Don't know," or "As late as possible" answers. We treat "don't know" and refusal responses as missing for preferred retirement age; we also use "don't know" responses to construct the uncertainty indicator described below. Responses of "as late as possible" are assigned the country-, year-, and gender-specific statutory retirement age. In 2024, we assign the corresponding "as late as possible" response the statutory retirement age, while we assign "as early as possible" the country-, year-, and gender-specific early retirement age, using the statutory age when an early retirement age is unavailable. For the handful of respondents with missing gender, we use the average of the male and female statutory retirement ages. Because the 2024 question was administered only to respondents aged 45 or older, we impute preferred retirement age for younger respondents. For the 9,477 respondents aged 44 or younger, we impute each individual's preferred retirement age using a prediction model estimated on the 2015 data that includes age, gender, education, occupation, industry, and country indicators. We then shift the predicted values upward by 1.14 years to match the observed difference in average retirement intentions between the 2015 (preferred retirement age = 61.97, std. dev. = 4.06) and 2024 (preferred retirement age = 63.11, std. dev. = 3.63) samples among respondents aged between 45 and 60. Excluding observations with imputed values does not alter our main findings (See Tables A3 and A4).

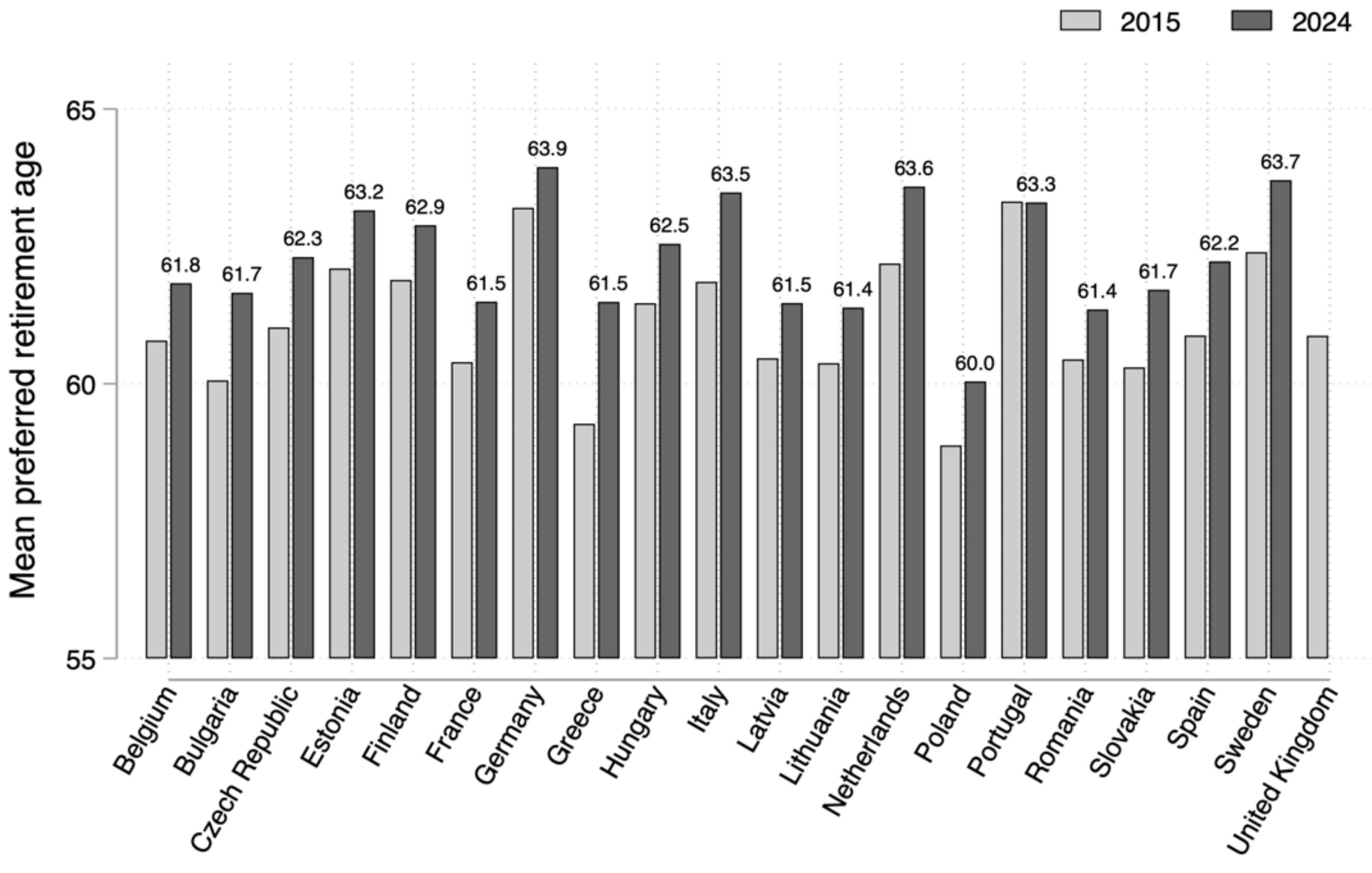
Although our measure captures stated retirement preferences rather than realized retirement behavior, this is not necessarily a limitation. Retirement decisions are inherently forward-looking and depend on workers' beliefs about their future employment prospects, health, and financial circumstances. If technological change affects these beliefs, studying retirement expectations is informative. Moreover, the distribution of reported preferred

[4] Including these older individuals does not change the main conclusions (see Tables A1 and A2).

retirement ages in our data is concentrated around plausible retirement ages, rather than around unconstrained ideal retirement ages, suggesting that respondents report realistic expectations rather than purely hypothetical preferences (Figure 1).

Figure 1 shows substantial cross-country variation in preferred retirement ages. Preferred retirement ages increased in nearly all countries between 2015 and 2024, with Portugal as the main exception, where the average remained unchanged at 63.3 years. In 2024, Germany, Sweden, the Netherlands, and Italy recorded some of the highest preferred retirement ages. As statutory retirement ages have increased across Europe, workers appear to have adjusted their retirement expectations accordingly. Across all countries, the average preferred retirement age rose from 61.1 years in 2015 to 62.5 years in 2024, an increase of 1.4 years, consistent with findings from other data sources (Hess, 2017; Hess et al., 2021).

Figure 1: Preferred retirement age

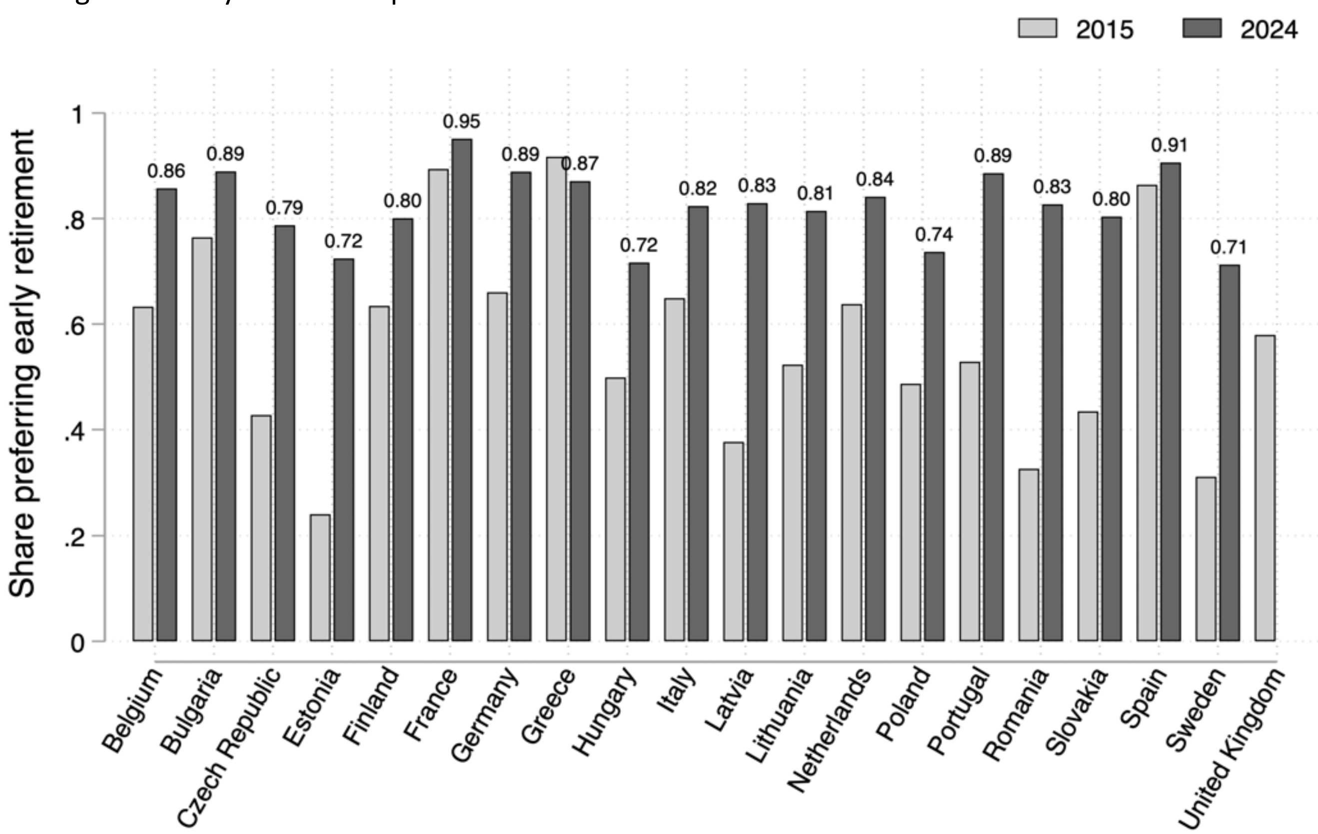


Note: Bars report weighted country-level means of the preferred retirement age based on the analysis sample in Table 4, Models (1) and (2).

Our second dependent variable, early retirement preference (retire_early), is a binary indicator of whether respondents want to retire before the statutory retirement age. We code this variable as one when the preferred retirement age falls below the statutory retirement age and zero otherwise. We obtain statutory retirement ages from the Mutual Information System on Social Protection (MISSOC). For the handful of cases where respondents do not report gender, we use the average of the male and female statutory retirement ages. The early retirement variable is only available in 2015 and 2024.

Figure 2 reports the share of respondents who would prefer early retirement. The prevalence of preferred early retirement remained high throughout the period and increased in most countries between 2015 and 2024. In 2015, the share ranged from around 24% in Estonia to more than 90% in Greece and nearly 90% in France. By 2024, the share had clearly risen across Europe, exceeding 80% in many countries and surpassing 90% in France and Spain. The largest increases occurred in Romania, Estonia, Latvia, Sweden, Slovakia, and the Czech Republic, while Greece was the only country to record a noticeable decline. Despite substantial cross-country variation, the results indicate that a large majority of workers in most European countries would still prefer to retire before reaching the statutory retirement age, even as preferred retirement ages have increased over time.

Figure 2: Early retirement preferences

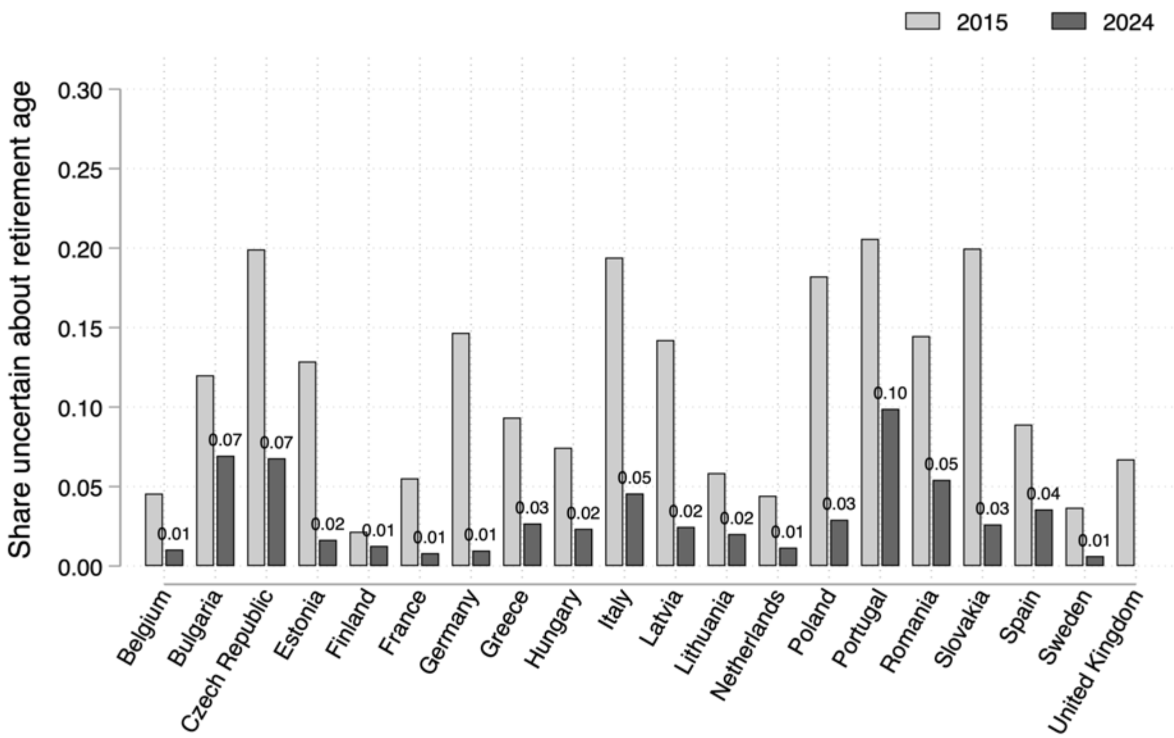


Note: Bars report weighted country-level means of the share of respondents wanting to retire earlier than the statutory retirement age based on the analysis sample in Table 4, Models (1) and (2).

Third, we also consider uncertainty about the desired retirement age (uncertain_retire). We code retirement uncertainty as 1 when respondents answer "don't know" to the preferred retirement-age question and 0 when they provide an interpretable answer. In 2024, respondents younger than 45 were not asked this question; when we impute their preferred retirement age, we assign the uncertainty indicator a value of zero by construction.

Figure 3 reports the share of respondents classified as uncertain about their preferred retirement age. Comparisons with 2024 require caution because respondents younger than 45 did not receive the retirement-age question in that wave and therefore could not report uncertainty. We code these respondents as not uncertain, which mechanically lowers the reported 2024 share. Consequently, the apparent decline in uncertainty may reflect the change in survey routing rather than a genuine increase in certainty about retirement timing.

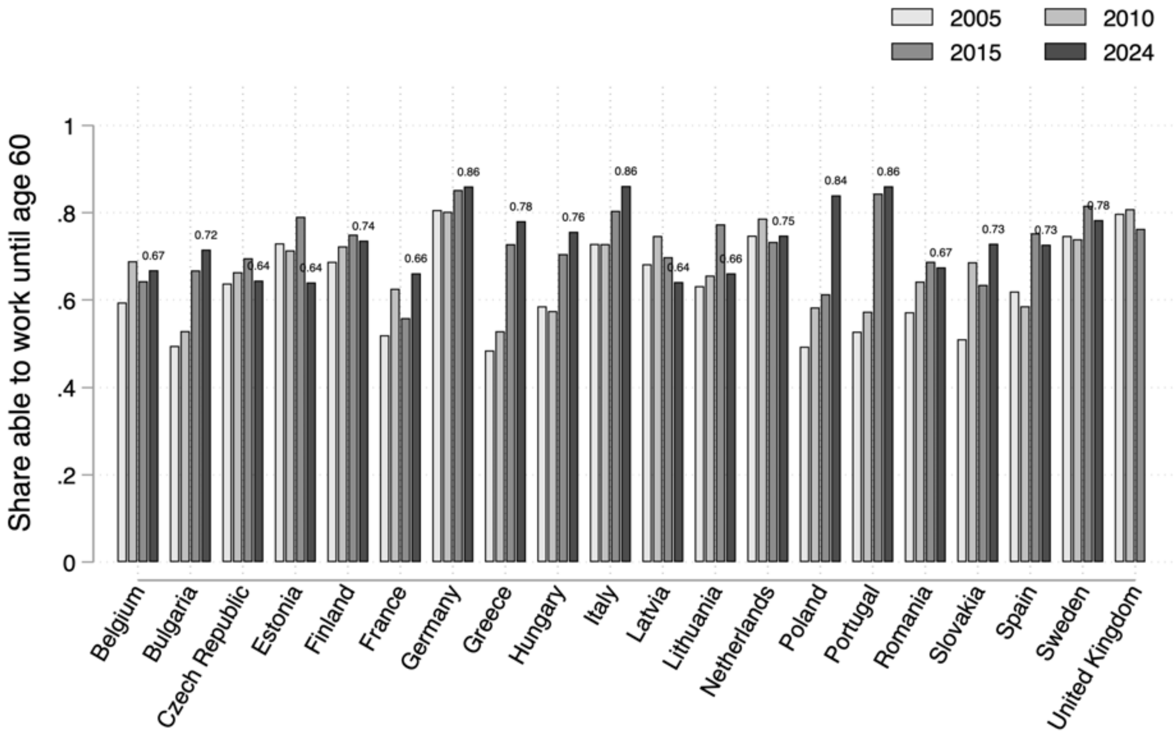
Figure 3: Uncertainty about retirement age



Notes: Bars report weighted country-level means of the share of respondents who are uncertain about when they will retire based on the analysis sample in Table 4, Model (3).

Fourth, across the survey waves, the variable perceived ability to continue working (able_work) captures whether respondents believe they can continue working later in life, but the exact survey question varies slightly across years. In the 2005 and 2010 waves, the survey asks respondents who are 60 and younger whether they think they will be able to do their current job or a similar one when they are 60 years old, with possible answers being "yes," "no," and "I would not want to."

Figure 4: Perceived ability to work until at least age 60



Notes: Bars report weighted country-level means of the share of respondents reporting they can work until at least age 60, based on the analysis sample in Table 4, Model (4).

In 2015, respondents aged 55 or younger were asked whether they thought they could perform their current or a similar job until age 60, whereas respondents aged 56 or older were asked whether they could perform such a job in five years. We code the variable as 1 for “yes” and 0 for “no,” and treat “don’t know” and refusal responses as missing. In 2024, respondents followed one of three age-specific routes. Respondents aged 45–54 answered a binary question about whether they would be able to perform their current or a similar job until age 60, and respondents aged 55 or older answered the corresponding question referring to five years. Respondents younger than 45 instead reported the age until which they thought they would be able to work in their current or a similar job. For these younger respondents, we code the indicator as one when the reported age is at least 60 and zero when a valid reported age is below 60; we treat “don’t know” and refusal responses as missing. Thus, able_work is a harmonized indicator of respondents’ perceived ability to continue working until age 60 or, for older respondents, for another five years. The regressions include year fixed effects and age controls, which account for average differences across survey waves and age groups. However, they cannot fully eliminate differences arising from the age-specific question wording.

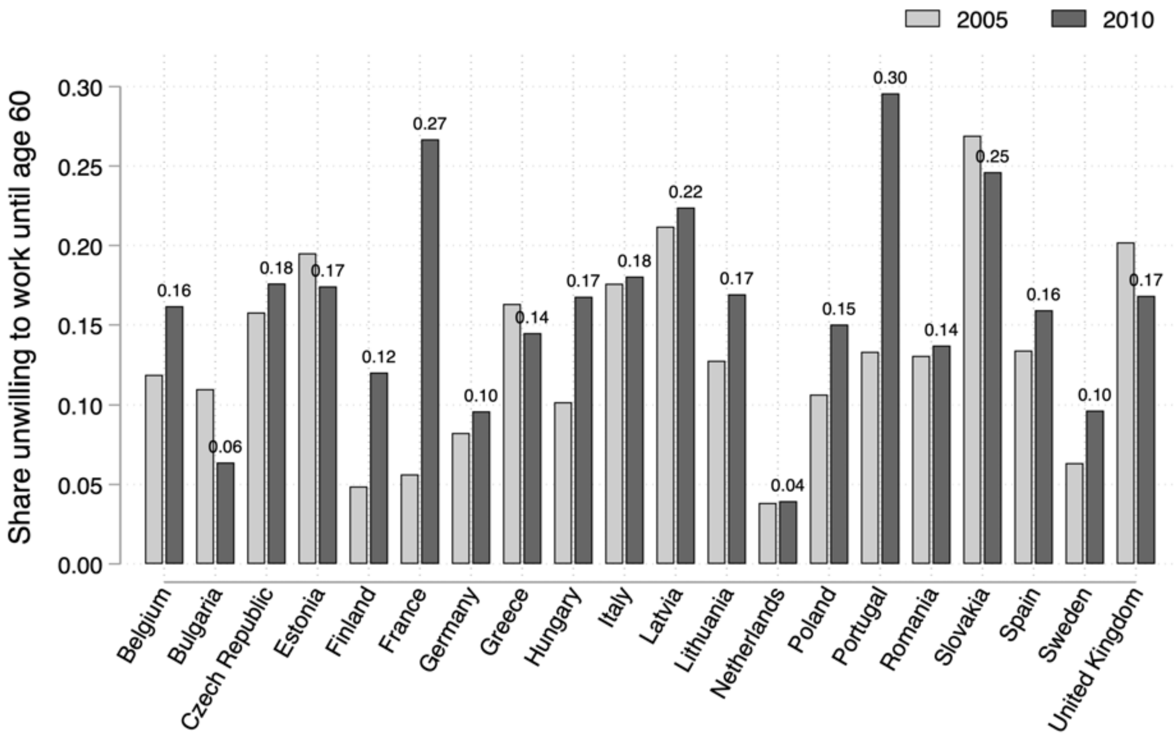
Figure 4 shows substantial cross-country variation and changes over time in respondents’ perceived ability to continue working. Between 2005 and 2015, the share increased particularly strongly in Portugal, Greece, Hungary, and Lithuania. However, comparisons across waves require caution because the question wording and age-specific routing differ. In particular, the measure refers to working until age 60 for younger respondents but to continuing for another five years for older respondents. Across 25 European OECD countries and the United States, 59% of adults remained continuously employed throughout their 50s; among this group, only 31% remained continuously employed throughout their 60s (OECD, 2025). Although these figures reflect realized employment rather than perceived work ability, they provide context for the challenges of extending working lives. In 2024, Germany, Italy, and Portugal had the highest shares (86% each), followed by Poland (84%), while the Czech Republic, Estonia, and Latvia had the lowest (64% each).

The fifth dependent variable, unwillingness to continue working until age 60, captures respondents' reluctance to remain in employment at older ages. We construct this binary indicator for the earlier waves (2005 and 2010) using the answer "I would not want to" to the question of whether respondents think they can continue working in the same job at age 60.

Figure 5 shows the share of respondents with a low willingness to work longer in the same job. This could reflect inability, unwillingness, or simply a desire for a career change. In 2005, the highest shares were observed in Slovakia (27%), Latvia (21%), the United Kingdom (20%), Estonia (20%), and Italy (18%), while the Netherlands (4%), Finland (5%), France (6%), and Sweden (6%) recorded the lowest levels. By 2010, low willingness to work longer had increased markedly in several countries, most notably in Portugal, where the share more than doubled from 13% to 30%, and in France, where it rose from 6% to 27%. In contrast, the Netherlands consistently showed the lowest reluctance to extend working life. Overall, the results point to considerable cross-country heterogeneity in attitudes toward longer working lives, with particularly strong resistance observed in parts of Southern and Eastern Europe by 2010.

Because the retirement outcomes come from different survey questions and waves, the regressions do not use a single common sample with the same number of observations across all dependent variables. Preferred retirement age and early retirement use the same analysis sample, while uncertainty, perceived ability to work until age 60, and unwillingness to continue working use the observations for which each outcome is observed. This avoids mechanically dropping valid respondents, especially because uncertainty about retirement age is defined from 'don't know' responses and is therefore structurally distinct from observed preferred retirement ages.

Figure 5: Unwillingness to continue working until age 60



Notes: Bars report weighted country-level means of the share of respondents reporting that they are unwilling to work until age 60 based on Table 4, Model (5).

Table 1: Dependent variables

Dependent variable	Wave(s)	Question number	Question wording (simplified)	Age-based survey routing	Coding in paper
Preferred retirement age (retireage)	2015	Q92	“Until what age do you want to work?”	Asked to all respondents	Continuous age. “As late as possible” assigned statutory retirement age; DK/refusal coded missing.
	2024	q103_1	“Thinking about retirement, until what age do you want to work?”	Asked only if age ≥45	Continuous age. “As late as possible” assigned statutory retirement age; “As early as possible” assigned early retirement age Respondents ≤44 imputed using prediction model

Dependent variable	Wave(s)	Question number	Question wording (simplified)	Age-based survey routing	Coding in paper
					estimated on 2015 data.
Early retire (retire_early)	2015, 2024	Derived from retireage	Preferred retirement age relative to statutory retirement age	Same as retireage	1 if preferred retirement age < statutory retirement age; 0 otherwise.
Uncertainty about retirement age (uncertain_retire)	2015, 2024	Q92 / q103_1	"Until what age do you want to work?"	Same as retireage	1 if respondent answers "don't know"; 0 otherwise.
Perceived ability to continue working (able_work)	2005	Q35	"Do you think you will be able to do the same job you are doing now when you are 60 years old?"	Asked only if respondent <60	1 = Yes; 0 = No; DK/refusal missing. "I wouldn't want to" used for the unwillingness variable.
	2010	Q75	"Do you think you will be able to do the same job you are doing now when you are 60 years old?"	Asked only if respondent <60	Same coding as 2005.
	2015	Q93	"Do you think you will be able to do your current job or a similar one until you are 60 years old?" (≤55) or "in five years' time?" (≥56)	Asked to all respondents	1 = Yes; 0 = No; DK/refusal missing.
	2024	q105 / q104_1	"Do you think you will be able to do your current job or a similar one until you are 60 years old?" (respondents aged 45-54), "Do you think you will be able to do your current job or a similar one in five years' time?" (respondents aged 55+), and reported numeric age until which the respondent expects to be able to work (respondents younger than 45).	Age-specific routing	Ages ≥45: Yes = 1, No = 0, DK/refusal missing. Ages <45: valid reported age ≥60 = 1; valid reported age below 60 = 0; DK/refusal missing.
Unwillingness to continue working (low_willing)	2005, 2010	Q35 / Q75	Same question as able_work	Asked only if respondent <60	1 if respondent answers "I wouldn't want to"; 0 otherwise.

Notes: The table demonstrates the coding and harmonization of the dependent variables across EWCS 2005, 2010, 2015, and 2024. Our regression analyses use outcome-specific samples because the dependent variables come from different survey questions and waves.

The EWCS also provides individual- and job-level control variables, including age group, gender, household composition, working hours, and education, as well as occupation (ISCO 1-digit), sector (manufacturing vs. non-manufacturing), firm size, self-employment status, and the presence of a secondary job. All specifications also include country and year fixed effects to capture unobserved heterogeneity across institutional contexts and over time.

5.2. Robot exposure

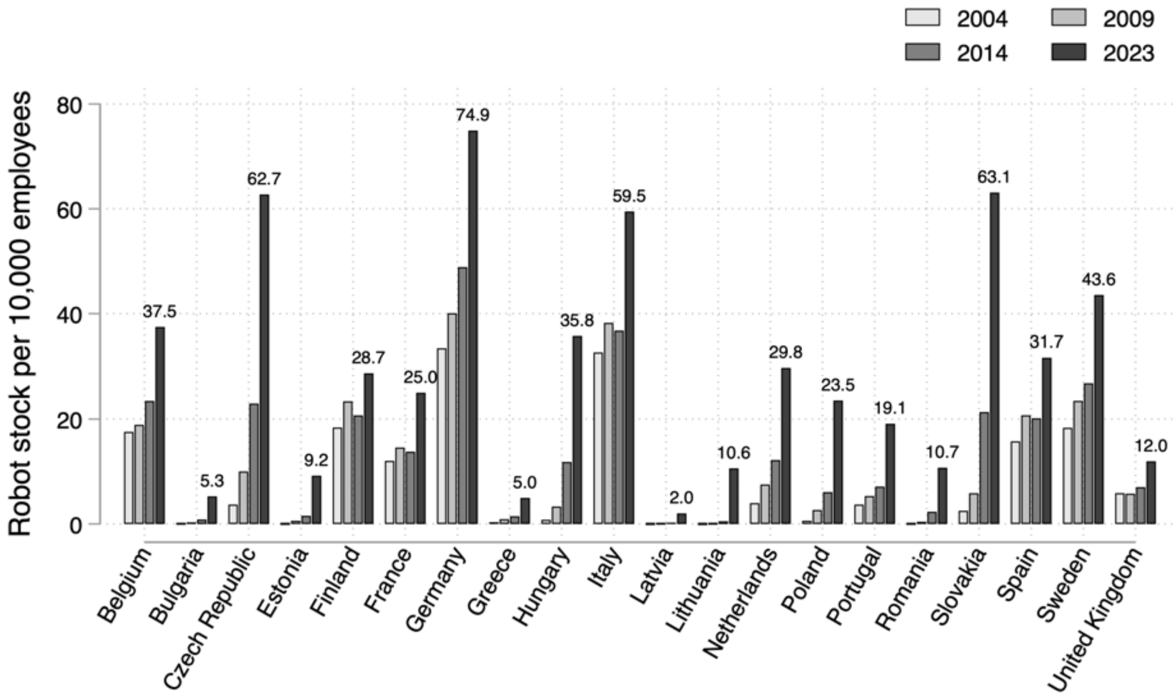
We construct our measure of robotization using industry-level data from the International Federation of Robotics (IFR), which provides annual information on the stock of installed industrial robots by country and industry (Müller, 2025). Robot exposure is the number of robots in t-1 per 10,000 workers in a country–industry cell. The numerator is the stock of operational robots reported by the IFR, adjusted to allocate robots classified as "unspecified industry" proportionally across industries based on their observed shares of robot use (Aksoy et al., 2021; Graetz & Michaels, 2018). Industry-level robot stocks are missing in the early years for Bulgaria, Greece, Lithuania, and Latvia. We therefore allocate each country's total robot stock across industries using the industry distribution observed in the first subsequent year with detailed industry data. In practice, we impute 2004 values using 2006 industry shares and apply these shares to distribute the country-level robot stock across industries (Aksoy et al., 2021; Graetz & Michaels, 2018).

To avoid endogeneity between robot adoption and current labor market outcomes, we fix the denominator (i.e., the number of workers in a particular country and industry) at its year-2000 level, which predates most of the large-scale diffusion of industrial robots. We used employment data from EU KLEMS national accounts to construct this denominator.

Because the IFR and EU KLEMS datasets use slightly different industry classifications, we harmonize them using correspondence tables from Nikolova et al. (2024) and Nikolova et al. (2025). This procedure produces a common set of 15 industries. The industries are: Food and beverages; Textiles; Wood and paper; Chemicals, plastics, and non-metallic minerals; Basic and fabricated metals; Electrical and electronic equipment; Industrial machinery; Automotive and other transport equipment; Other manufacturing industries; Agriculture, forestry and fishing; Mining and quarrying; Electricity, gas and water supply; Construction; Education and research; and Other non-manufacturing activities. We calculate robot density as robot stock per 10,000 country–industry employees, using employment in 2000 as the fixed denominator.

In the empirical analysis, we use robot density at levels, lagged by one period relative to the survey year (t–1), and standardize the measure to facilitate the interpretation of coefficients across specifications. Figure 6 shows substantial cross-country variation in robot adoption between 2004 and 2023. Germany exhibits the highest levels of robotization throughout the period, with robot density exceeding 70 robots per 10,000 employees by 2023. In contrast, countries such as Greece, Romania, Bulgaria, and the Baltic states remain at comparatively low levels of robotization over the entire period. Most countries display a marked increase in robot density after 2014.

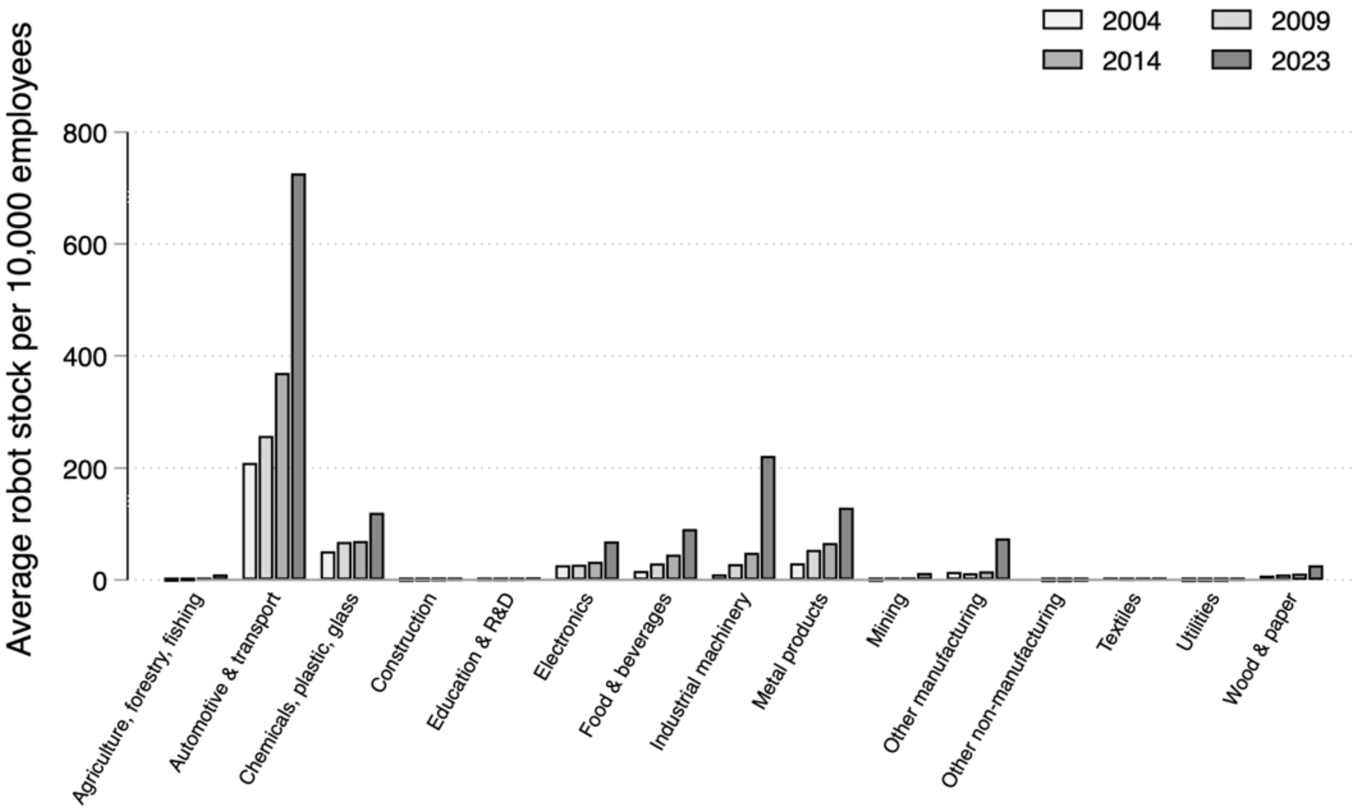
Figure 6: Robotization by country



Notes: The figure shows the average robot density (number of industrial robots per 10,000 employees) by country and year (2004, 2009, 2014, 2023). Robot density is computed using total robot stock (IFR) and employment in the year 2000 (EU KLEMS). Values are shown in levels. For Bulgaria, Greece, Lithuania, and Latvia, observations for 2004 are imputed using the first available year with data. The United Kingdom is included in this figure but is not part of the 2024 EWCS survey sample.

Figure 7 reveals substantial sectoral heterogeneity in robot adoption. The automotive manufacturing sector exhibits by far the highest robot density, increasing from roughly 200 robots per 10,000 employees in 2004 to more than 700 by 2023.

Figure 7: Robotization by industry



Notes: The figure shows the average robot density (number of industrial robots per 10,000 employees) by industry and year (2004, 2009, 2014, 2023). We construct robot density from International Federation of Robotics (IFR) data on the stock of operational robots, divided by employment in 2000 from EU KLEMS. Values are shown in levels. For Bulgaria, Greece, Lithuania, and Latvia, we impute 2004 observations using the first available year. We harmonize industries to 15 comparable sectors across datasets.

5.3. ICT exposure

We measure exposure to information and communication technologies (ICT) using industry-level capital stock data from the capital accounts files of the EUKLEMS–INTANProd productivity database (EUKLEMS & INTANProd, 2026).

The EUKLEMS capital accounts data distinguish three ICT asset categories: i) communications equipment, ii) information technology equipment, and iii) computer software and databases. We sum these three components (Kq_IT, Kq_CT, and Kq_Soft_DB) to obtain total ICT capital stock for each country–industry–year cell. These variables are reported as chain-linked volumes in constant 2015 prices. To ensure cross-country comparability, like Diessner et al.

(2025), we convert all local currency values into euros using Eurostat exchange rates for 2015 (European Commission, Eurostat, 2026).

As with the robot variable, the EUKLEMS industry classification does not perfectly match the industries used in the EWCS and IFR data. We harmonize industries using correspondence tables between NACE Rev.2 codes and the aggregated sectors used in the analysis, following the literature (e.g., Aksoy et al., 2021; Nikolova et al., 2024; Nikolova et al., 2025). This procedure yields a consistent set of 15 industries across the datasets.

We impute missing ICT capital values at the country-industry-year level, following Jestl (2024), using averages from structurally similar countries within the same industry and year. Specifically, we impute Bulgaria and Romania using Greece and Slovakia; Estonia using Finland and Latvia; Lithuania using Finland; Hungary using Austria and the Czech Republic; Poland using the Czech Republic and Slovakia; and Portugal using Spain and France. Italy has missing observations only in 2021 and for a subset of industries (manufacturing and industrial machinery). For these cases, we replace missing values with the corresponding 2020 values within the same country–industry cell.

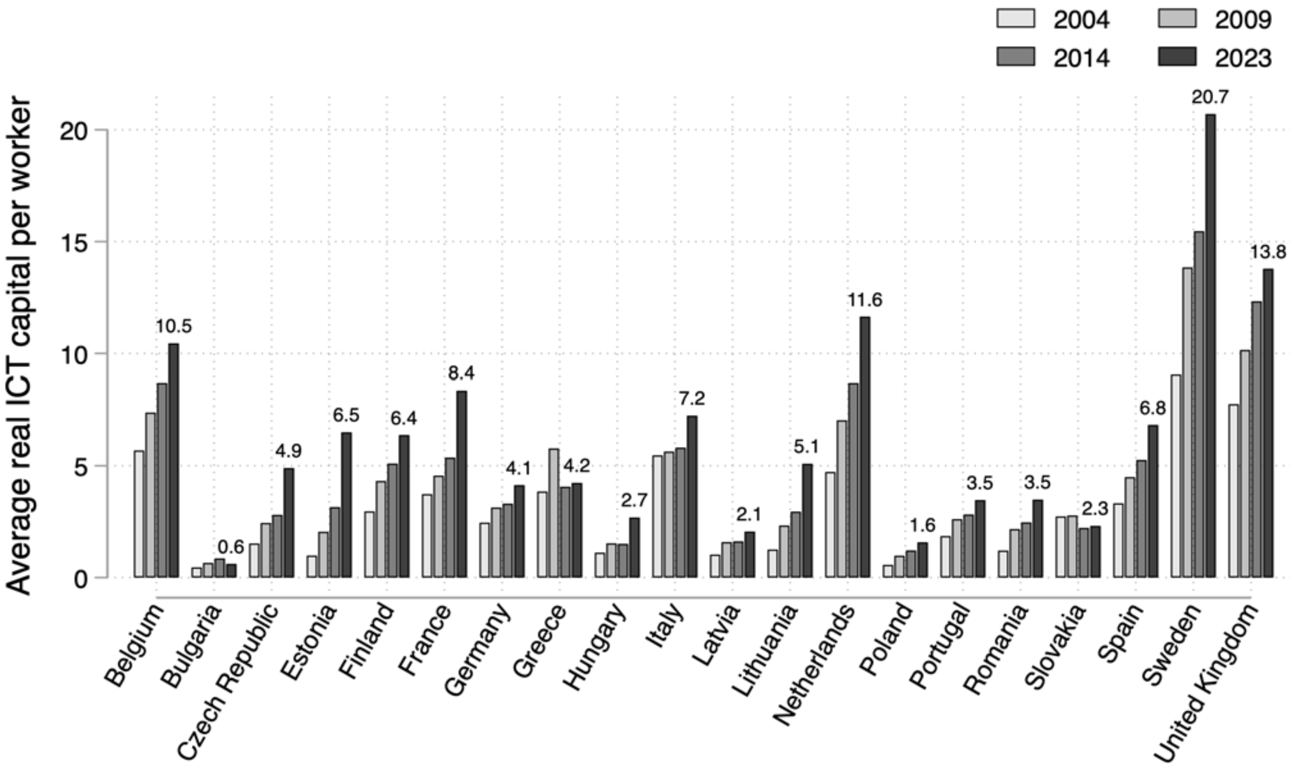
After imputation, we ensure consistency with national accounts aggregates. EUKLEMS provides total ICT capital at the country–year level, even for countries with missing industry-specific data. For country–years affected by imputation, we rescale industry-level values proportionally so that their sum matches the observed national total. This preserves the cross-industry distribution implied by the imputation while aligning with aggregate data.

The EUKLEMS capital accounts end in 2021, while our analysis includes the EWCS 2024 wave. We extend the series by carrying forward 2021 values to 2023 for each country–industry pair, assuming smooth short-run evolution of ICT capital.

We then merge the capital stock data with EUKLEMS employment data for 2000 for each industry and country and construct ICT intensity as ICT capital per worker, expressed in thousands of euros (2015 prices). We therefore calculate ICT intensity by dividing real ICT capital by country–industry employment in 2000. In the empirical analysis, we use ICT exposure in levels and lag it by one year (t–1) relative to the survey year. We standardize the variable to have a mean of zero and a variance of one to facilitate comparison across technology measures.

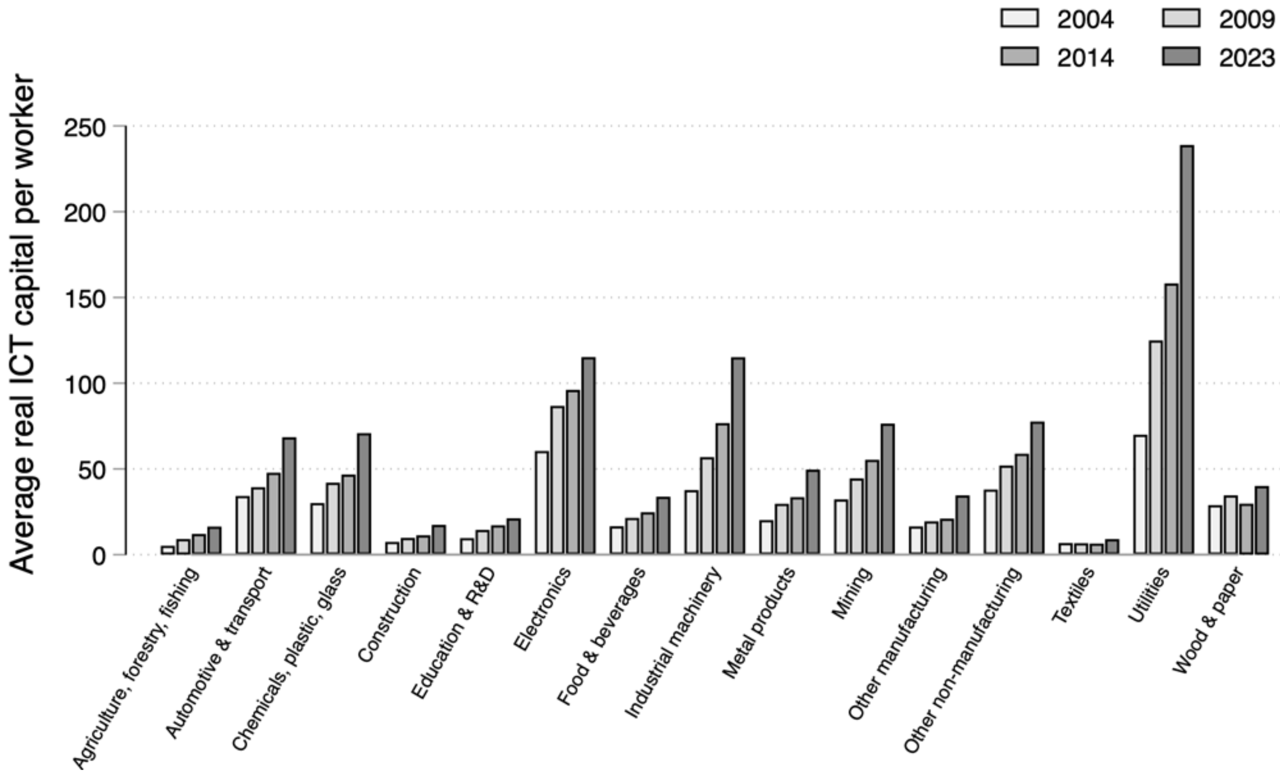
By 2023, Sweden and the United Kingdom have the highest levels of ICT capital per worker, followed by the Netherlands and Belgium (Figure 8). In contrast, Bulgaria remains at the lowest level throughout the period. Most countries display steady increases in ICT capital intensity between 2004 and 2023. Furthermore, Figure 9 shows that ICT capital intensity is concentrated in technologically advanced manufacturing sectors, with the highest levels in utilities, industrial machinery, and electronics, while textiles, agriculture, and construction show comparatively low ICT intensity throughout the period.

Figure 8: ICT capital by country



Notes: The figure shows average real ICT capital per worker (1,000 EUR, 2015 prices) by country and year (2004, 2009, 2014, 2023). ICT capital is constructed from EUKLEMS–INTANProd data as the sum of computing equipment, communications equipment, and software and databases (Kq_IT, Kq_CT, Kq_Soft_DB). The measure is converted to euros using 2015 exchange rates and divided by employment. We obtain country-level values by aggregating industry-level data. Values are shown in levels. We impute missing observations using information from structurally similar countries within the same industry and year, then rescaled imputed values to match observed national totals. Values for 2023 are extrapolated from 2021. Industries are harmonized to 15 sectors to ensure comparability across datasets.

Figure 9: ICT capital by industry



Notes: The figure shows average real ICT capital per worker (1,000 EUR, 2015 prices) by industry and year (2004, 2009, 2014, 2023). ICT capital is constructed from EUKLEMS–INTANProd data as the sum of computing equipment, communications equipment, and software and databases (Kq_IT, Kq_CT, Kq_Soft_DB). The measure is converted to euros using 2015 exchange rates and divided by employment. Values are in levels. Missing observations are imputed using information from structurally similar countries within the same industry and year, and imputed values are rescaled to match observed national totals. We extrapolate 2023 values from 2021. We harmonize industries to 15 sectors to ensure comparability across datasets.

5.4. AI exposure

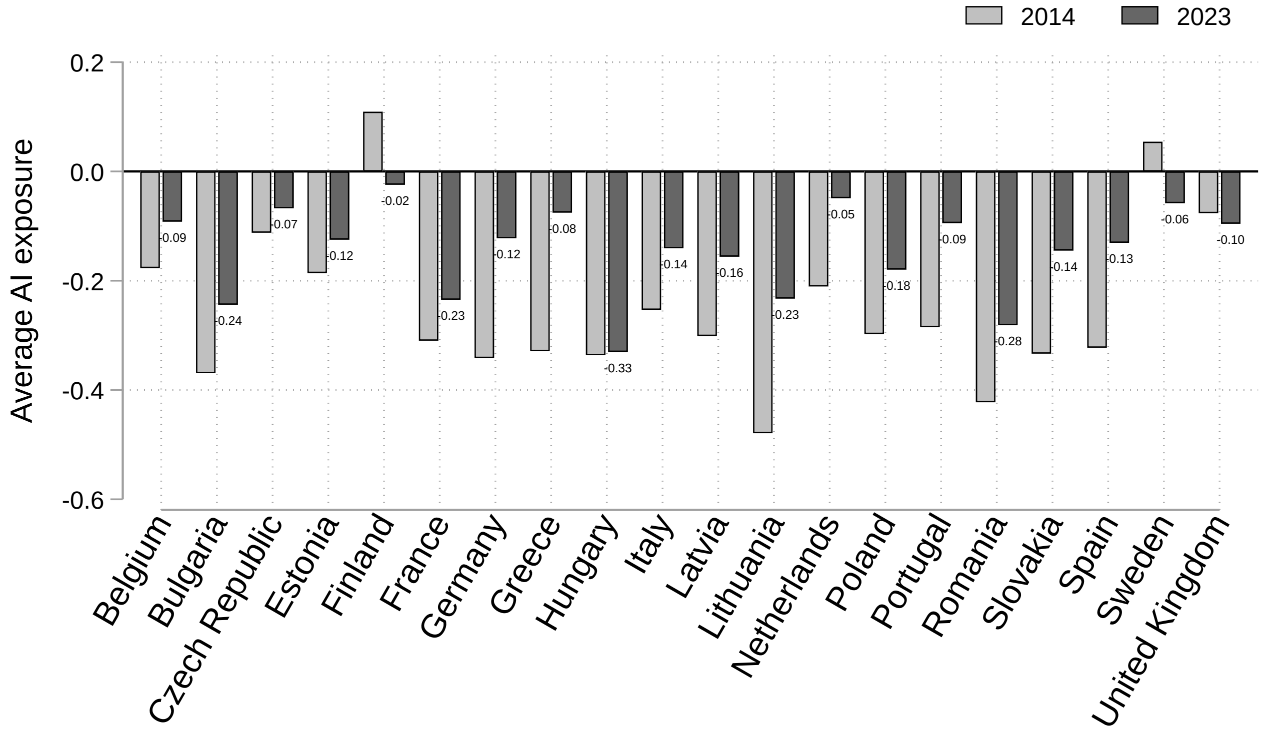
We measure workers' exposure to AI using the novel, task-adjusted, country- and occupation-level AI exposure index developed by Lewandowski et al. (2025). Their measure extends the Artificial Intelligence Occupational Exposure (AIOE) index of Felten et al. (2021), which links AI capabilities to occupational abilities in the U.S. O*NET database. To achieve an internationally comparable measure, Lewandowski et al. (2025) translate these ability-based exposures into task-based measures using worker-level information from international surveys (primarily PIAAC, complemented by STEP and the China Urban Labor Survey). Lewandowski et al. (2025) first map abilities to PIAAC survey questions using US data, regressing the O*NET importance and prevalence of abilities in each 2-digit ISCO occupation on 18 PIAAC questions related to routine and non-routine content, as well as ICT use and time management. Abilities are narrowed to those with the highest exposure and most reliable fit to PIAAC data. The estimated coefficients then serve as weights to convert each worker's survey responses into O*NET ability scores, to which the AI exposure scores of Felten et al. (2021) are applied and averaged across abilities and within each worker, yielding a worker-level exposure score. These scores can in turn be aggregated to the occupation and country levels, reflecting the extent to which workers perform tasks that AI can potentially automate or complement. The data cover two periods: 2011-2018 and 2022-2023 and exclude agricultural occupations.

For countries without task survey data, Lewandowski et al. (2025) estimate AI exposure via separate occupation-level regressions per 1-digit ISCO group, using a stepwise-selected set of covariates for each, augmented with 2-digit occupation fixed effects. The covariates capture economic development, technology adoption, human capital, globalization, and infrastructure. The resulting models use country-specific data to predict AI exposure. In our sample, Belgium, the Czech Republic, Spain, France, Hungary, Italy, Poland, and Slovakia are estimated exclusively from survey data, while the rest use predicted values for at least one time period or ISCO aggregation level.[5]

We match the 2011-2018 AI exposure data to the 2015 EWCS and the 2022-2023 AI exposure data to the 2024 EWCS using the 2-digit ISCO 08 codes provided in the Lewandowski dataset. We standardized the AI exposure scores to ensure comparability with the other technology variables. Figure 10 shows substantial cross-country variation, with higher exposure in countries such as the Netherlands, Sweden, and Greece and lower exposure in several Central and Eastern European countries. Figure 11 illustrates the distribution of AI exposure across occupations in our sample, showing that exposure is highest among clerical, professional, and managerial occupations and lowest among manual and elementary occupations.

[5] Lewandowski et al. (2025) report AI exposure on a scale standardized relative to the U.S. mean and standard deviation, so that values capture distance from the U.S. benchmark. In our regressions, we further standardize this variable within the estimation sample to mean zero and standard deviation one, purely to make coefficient magnitudes comparable to those of the other technology measures. This re-scaling does not affect the ranking of countries or occupations, but coefficients should be interpreted as the effect of a one-standard-deviation increase in AI exposure within our sample rather than relative to the original U.S. scale.

Figure 10: AI exposure by country



Notes: The figure shows country averages of the AI exposure index from Lewandowski et al. (2025) for 2011-2018, which we consider the reference period 2014, and 2022-2023, which we consider the reference period 2023. The values are standardized to have a mean of 0 and a standard deviation of 1.

Figure 11: AI exposure by occupation

Notes: The figure shows occupational averages of the AI exposure index from Lewandowski et al. (2025) for 2011-2018, which we consider the reference period 2014, and 2022-2023, which we consider the reference period 2023.

6. Methods

We estimate the relationship between technological exposure and retirement expectations using pooled cross-sections of workers from the EWCS for the years 2005, 2010, 2015, and 2024. Some analyses cover only 2015-2024, and some cover only 2005-2010, based on variable availability. The analysis sample includes individuals aged 60 or younger, and we exclude observations with missing information on the outcome variables.

Our baseline empirical specification is:

$$Y_{icjt} = \beta_1 \text{Robot}_{cjt-1} + \beta_2 \text{ICT}_{cjt-1} + \mathbf{X}'_{icjt}\gamma + \delta_c + \delta_j + \delta_t + \varepsilon_{icjt}, \tag{1}$$

where Y_{icjt} denotes retirement-related outcomes for individual i in country c, technology-specific exposure cell j (2-digit industry for robots and ICT or 2-digit occupation for AI), and year t. The main explanatory variables capture exposure to robotization and ICT, measured at the country–industry-year level and lagged by one period to mitigate simultaneity concerns. We standardize all technology variables to have a mean of zero and a standard deviation of one to compare the magnitude of increases in different technologies for retirement outcomes.

In specifications that include AI, we extend the model to:

$$Y_{icjt} = \beta_1 \text{Robot}_{cjt-1} + \beta_2 \text{ICT}_{cjt-1} + \beta_3 \text{AI}_{ct-1} + \mathbf{X}'_{icjt}\gamma + \delta_c + \delta_j + \delta_t + \varepsilon_{icjt}, \tag{2}$$

where AI exposure is measured at the country–occupation-year level and is available for 2015 and 2024 only, and excludes the agricultural sector.

The vector $\mathbf{X}_{icjt}$ includes individual and job characteristics: age group, gender, household composition, working hours, education, sector (manufacturing vs. non-manufacturing), firm size, self-employment status, and secondary job status. All specifications include country and year fixed effects, as well as occupation fixed effects (ISCO 1-digit), to account for time-invariant differences across countries, occupations, and survey waves. All control variables include a "missing information" indicator with no interpretation, which preserves the number of observations and avoids bias from dropping missing observations.

We estimate all models using weighted least squares, applying EWCS sampling weights and standard errors clustered at the country–industry level. When the dependent variables are binary, we estimate weighted OLS linear probability models.

To examine heterogeneity, we augment the baseline model with interaction terms between each measure of technology exposure and indicators for age groups, gender, sector (manufacturing vs. non-manufacturing), worker skill level (based on the 1-digit ISCO codes), education level (tertiary vs. non-tertiary), tenure at the firm, and training. We also explore whether results depend on the types of tasks that workers do, i.e., routine, physical, social, and cognitive, based on the classification of Nikolova et al. (2025). Finally, we report how the results depend on the country context. We report p-values for tests of whether interaction effects differ significantly from zero.

7. Summary statistics

Tables 2 and 3 present weighted summary statistics for the outcome-specific analysis samples. Table 2 includes all available survey waves, although wave coverage differs across outcomes. Preferred retirement age, early retirement preferences, and retirement uncertainty use data from 2015 and 2024; perceived ability to continue working uses data from 2005, 2010, 2015, and 2024; and unwillingness to continue working uses data from 2005 and 2010. Table 3 covers 2015 and 2024 because the AI exposure measure is available only for these waves.

Overall, the average preferred retirement age is about 61.8 years, and about 73% of respondents prefer to retire before the statutory retirement age. Approximately 7% are uncertain about when they want to retire. About 70% of respondents in Table 2 and 75% in Table 3 expect to be able to continue working until at least age 60. In the pooled 2005–2010 sample, approximately 15% report that they would not want to continue working until age 60. The samples contain relatively similar proportions of men and women, consist predominantly of workers outside manufacturing, and include a larger share of workers with medium education than with either low or high education.

Table 2: Selected summary statistics for Table 4 analysis samples

	Retirement age/Early retirement		Uncertain		Able to work		Unwilling	
	mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.
Preferred retirement age	61.749	(4.461)						
Early retire	0.726	(0.446)						
Uncertain			0.072	(0.258)				
Able to work					0.702	(0.457)		
Unwilling							0.151	(0.358)
Age 15–35	0.322	(0.467)	0.325	(0.468)	0.333	(0.471)	0.376	(0.484)
Age 36–45	0.283	(0.451)	0.281	(0.450)	0.286	(0.452)	0.293	(0.455)
Age 46–60	0.395	(0.489)	0.394	(0.489)	0.381	(0.486)	0.331	(0.471)
Female	0.475	(0.499)	0.477	(0.499)	0.467	(0.499)	0.460	(0.498)
Male	0.524	(0.499)	0.523	(0.499)	0.533	(0.499)	0.540	(0.498)
Gender missing	0.000	(0.015)	0.000	(0.015)	0.000	(0.014)		
Manufacturing	0.156	(0.363)	0.156	(0.363)	0.164	(0.370)	0.175	(0.380)
Non-manufacturing	0.844	(0.363)	0.844	(0.363)	0.836	(0.370)	0.825	(0.380)
Firm size: <250	0.602	(0.490)	0.591	(0.492)	0.706	(0.456)	0.844	(0.363)
Firm size: 250+	0.116	(0.321)	0.112	(0.315)	0.120	(0.325)	0.121	(0.326)
Firm size: missing	0.282	(0.450)	0.297	(0.457)	0.174	(0.379)	0.036	(0.185)
Low education	0.155	(0.362)	0.158	(0.365)	0.168	(0.374)	0.186	(0.389)
Medium education	0.469	(0.499)	0.474	(0.499)	0.466	(0.499)	0.478	(0.500)
High education	0.374	(0.484)	0.365	(0.482)	0.341	(0.474)	0.288	(0.453)
Education missing	0.002	(0.050)	0.003	(0.052)	0.025	(0.157)	0.048	(0.213)
Not self-employed	0.861	(0.346)	0.859	(0.348)	0.854	(0.353)	0.853	(0.354)
Self-employed	0.139	(0.346)	0.141	(0.348)	0.146	(0.353)	0.147	(0.354)
Observations	38,842		41,903		70,148		40,104	

Note: All statistics use sampling weights.

Table 3: Selected summary statistics for Table 5 analysis samples

	Retirement age/Early retirement		Uncertain		Able to work	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
Preferred retirement age	61.752	(4.460)				
Early retire	0.728	(0.445)				
Uncertain			0.072	(0.258)		
Able to work					0.744	(0.436)
Age 15–35	0.324	(0.468)	0.328	(0.469)	0.311	(0.463)
Age 36–45	0.282	(0.450)	0.280	(0.449)	0.275	(0.447)
Age 46–60	0.393	(0.489)	0.392	(0.488)	0.413	(0.492)
Female	0.482	(0.500)	0.483	(0.500)	0.482	(0.500)
Male	0.518	(0.500)	0.516	(0.500)	0.517	(0.500)
Gender missing	0.000	(0.015)	0.000	(0.016)	0.000	(0.020)
Manufacturing	0.160	(0.367)	0.160	(0.367)	0.159	(0.366)
Non-manufacturing	0.840	(0.367)	0.840	(0.367)	0.841	(0.366)
Firm size: <250	0.598	(0.490)	0.587	(0.492)	0.574	(0.494)
Firm size: 250+	0.118	(0.323)	0.114	(0.317)	0.121	(0.326)
Firm size: missing	0.284	(0.451)	0.300	(0.458)	0.305	(0.460)
Low education	0.150	(0.357)	0.153	(0.360)	0.151	(0.358)
Medium education	0.468	(0.499)	0.473	(0.499)	0.461	(0.498)
High education	0.379	(0.485)	0.371	(0.483)	0.387	(0.487)
Education missing	0.002	(0.049)	0.003	(0.051)	0.002	(0.046)
Not self-employed	0.873	(0.333)	0.871	(0.335)	0.874	(0.332)
Self-employed	0.127	(0.333)	0.129	(0.335)	0.126	(0.332)
Observations	37,778		40,740		35,217	

Note: All statistics use sampling weights.

8. Main results

Tables 4 and 5 provide little evidence that technology exposure relates systematically to retirement timing. Table 4 uses all available survey waves for each outcome and excludes AI exposure. Neither robot nor ICT exposure is significantly associated with preferred retirement age, early-retirement preferences, uncertainty about retirement timing, or unwillingness to continue working. The only statistically significant estimate is the positive association between robot exposure and perceived ability to work until at least age 60 based on Model (4). A one-standard-deviation increase in robot exposure is associated with a 0.5 percentage-point increase in this outcome, a small effect size given the sample mean of 70.2%.

Table 5 includes AI exposure and restricts the analysis to the 2015–2024 sample. Robot and AI exposure are both positively associated with perceived ability to work until at least age 60. A one-standard-deviation increase in exposure is associated with a 0.4-percentage-point increase for robots and 4.4 percentage points for AI. None of the three exposure measures is significantly associated with preferred retirement age, early-retirement preferences, or uncertainty about retirement timing. Differences between Tables 4 and 5 may reflect both the different sample composition and the inclusion of AI exposure.

Overall, technology exposure shows little systematic association with preferred retirement timing. The clearest result concerns perceived ability to continue working, particularly its association with AI exposure in the common 2015–2024 sample. We next assess the robustness of these results before examining heterogeneity across workers.

Table 4: Technology exposure and retirement outcomes, all available years, excluding AI

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work	(5) Unwillingness
Robots	-0.022	0.001	0.001	0.005**	0.006
	(0.022)	(0.002)	(0.001)	(0.002)	(0.005)
ICT	0.056	-0.002	-0.000	-0.002	0.003
	(0.037)	(0.004)	(0.001)	(0.004)	(0.005)
Mean DV	61.749	0.726	0.072	0.702	0.151
R^2	0.135	0.202	0.057	0.102	0.043
Observations	38,842	38,842	41,903	70,148	40,104

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2005, 2010, 2015, 2024); Unwilling = indicator equal to one if the respondent reports that they would not want to continue working until age 60 (2005, 2010). Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Technology exposure and retirement outcomes: AI sample

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.022	0.001	0.001	0.004**
	(0.022)	(0.003)	(0.001)	(0.002)
ICT	0.050	-0.001	0.000	0.004
	(0.038)	(0.004)	(0.001)	(0.003)
AI	0.054	-0.004	0.004	0.044***
	(0.054)	(0.006)	(0.004)	(0.007)
Mean DV	61.752	0.728	0.072	0.744
R^2	0.133	0.199	0.057	0.110
Observations	37,778	37,778	40,740	35,217

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

9. Robustness checks

Including workers older than 60. The main analysis excludes workers older than 60 because those who remain employed at older ages despite technological change constitute a selected group. Tables A1 and A2 replicate Tables 4 and 5 after including these workers. The estimates closely resemble the baseline results. In Table A1, robot exposure remains positively associated with perceived ability to continue working until at least age 60, while ICT exposure remains statistically insignificant across all outcomes. In the AI sample reported in Table A2, robot and AI exposure remain positively and significantly associated with perceived ability to continue working, while the ICT coefficient is positive but statistically insignificant. None of the technologies significantly predict preferred retirement age, early-retirement preferences, or uncertainty about retirement timing.

Excluding observations with imputed preferred retirement age. Similarly, excluding the imputed retirement-age observations from the 2024 survey does not alter the substantive conclusions (Tables A3 and A4).

Controlling for health and OSH. Table A5 examines whether the main estimates remain robust to health- and workplace-related controls in the 2015–2024 sample used in Table 5. The specifications sequentially add self-reported health satisfaction, perceived health risks at work, and occupational safety and health (OSH) representation.[6] These measures likely correlate with retirement preferences and expectations, and technological exposure may itself affect them. They may therefore constitute "bad controls," and these analyses are only exploratory.

Table A5 shows that workers reporting high health satisfaction prefer later retirement, have a lower probability of preferring early retirement, and are substantially more likely to expect they can continue working until at least age 60. Perceived health risks at work show the opposite pattern. The patterns related to having an OSH delegate are not clear-cut.

Adding these controls leaves the main conclusions broadly unchanged. Robot and ICT exposure remain unrelated to preferred retirement age, early-retirement preferences, and uncertainty about retirement timing. Robot exposure remains positively associated with perceived ability to work until at least age 60. The corresponding ICT coefficient remains smaller and statistically insignificant throughout. The positive association between AI exposure and perceived work ability remains statistically significant but declines in magnitude. Overall, observed health and workplace conditions partially attenuate the AI coefficient but do not eliminate the main association.

Instrumental variables techniques. In our main specifications, we lag the robotization, ICT, and AI measures to mitigate reverse causality issues. But several endogeneity concerns remain. First, technology adoption may respond to unobserved industry characteristics, such as changes in labor demand, working conditions, or workforce composition, that also affect retirement expectations. Second, workers may sort into industries and occupations with different levels of technological exposure based on unobserved characteristics related to retirement preferences. For example, workers with higher levels of openness may be more likely to sort into industries with higher levels of technological adoption and may be more likely to delay retirement.[7]

To assess the robustness of our findings to endogeneity concerns, we instrument each technology measure with a leave-one-out peer-exposure measure. For robots and ICT, we calculate the mean exposure in the same industry and year across all other sample countries. For

[6] We classify respondents reporting good or very good health as having relatively good health, while grouping fair, bad, and very bad health in the reference category and retaining missing responses as a separate category. Perceived health risks at work indicate whether respondents believe that their work endangers their health. OSH representation indicates whether an occupational safety and health representative operates at the respondent's workplace. We also retain missing responses to these variables as separate categories to preserve the sample size, but we attach no substantive interpretation to their coefficients.

[7] A related concern is that industry-level measures of technology exposure may contain measurement error, which can attenuate estimated coefficients.

AI, we calculate the corresponding mean for the same two-digit occupation and period across all other countries.

The instrument exploits the cross-country diffusion of technologies within comparable industries (and occupations, respectively, in the case of AI). Technological advances “at the technological frontier” that make robots more productive in automobile manufacturing, for example, should encourage adoption in that industry in other countries. Similarly, reductions in ICT costs or advances in AI capabilities should affect the same industries or occupations internationally. Peer exposure therefore captures shifts in the industry- or occupation-specific technological frontier that predict exposure in the respondent’s country. The leave-one-out construction removes the direct contribution of domestic adoption, limiting the influence of country-specific labor-market conditions and retirement preferences on the instrument.

Instrument validity also requires satisfying the exclusion restriction. Conditional on the included controls and fixed effects, peer technology adoption in the same industry or occupation abroad must affect a worker’s retirement expectations only through domestic technology exposure. This condition would fail if common international shocks influenced both foreign technology exposure and domestic retirement expectations through other channels. Potential threats include shifts in international demand, import competition, offshoring, regulatory changes, and the simultaneous diffusion of related technologies. Common occupation-specific changes in job content or labor demand also raise concerns for the AI instrument. Country and year fixed effects absorb economy-wide national shocks and common aggregate time shocks, but they do not fully absorb international industry-year or occupation-year shocks. We therefore present the IV estimates as robustness checks rather than definitive causal estimates.

Appendix Table A6 reproduces Table 4 using a 2SLS estimator. Appendix Tables A7 and A8 report the corresponding first-stage regressions for robot and ICT exposure. Appendix Table A9 reproduces the specifications in Table 5 using IV, while Appendix Tables A10–A12 denote the associated first-stage regressions for robot, ICT, and AI exposure. We standardize the domestic technology measures and their corresponding leave-one-out instruments to have a mean of zero and a standard deviation of one.

The first-stage estimates show that the peer measures strongly predict the corresponding domestic technology measures. A one-standard-deviation increase in peer robot exposure predicts a 0.725–0.758-standard-deviation increase in domestic robot exposure (Tables A7 and A10). A one-standard-deviation increase in peer ICT exposure predicts a 0.444–0.486-standard-deviation increase in domestic ICT exposure (Tables A8 and A11). For AI exposure, the corresponding coefficient ranges from 0.950 to 0.956 (Table A12). The Kleibergen–Paap *F*-statistics range from 23.11 to 49.10 when we instrument robot and ICT exposure jointly (Table A6) and from 15.26 to 15.60 when we instrument all three technologies jointly (Table A9).

The IV estimates in Table A6 differ from the baseline estimates. A one-standard-deviation increase in robot exposure is associated with a 0.077-year reduction in preferred retirement age, compared with an insignificant estimate of −0.022 in Table 4. ICT exposure is associated with a

0.166-year increase in preferred retirement age, compared with an insignificant baseline estimate of 0.056. These IV estimates correspond to approximately 0.9 fewer months of preferred working life for robot exposure and 2 months for ICT exposure. ICT exposure is also associated with a 1.5-percentage-point reduction in the probability of preferring early retirement, a 0.6-percentage-point reduction in uncertainty, and a 1.6-percentage-point increase in perceived ability to continue working. Robot exposure has a smaller positive association of 0.4 percentage points with perceived work ability. Neither technology is significantly associated with unwillingness to continue working.

Table A9 reports the IV estimates for the AI sample. Robot exposure is negatively associated with preferred retirement age, while ICT exposure is positively associated with preferred retirement age and negatively associated with early-retirement preferences. ICT exposure also has a small, marginally significant negative association with uncertainty about retirement timing. AI exposure is not statistically associated with preferred retirement age, early-retirement preferences, or uncertainty. However, a one-standard-deviation increase in AI exposure is associated with a 5.1-percentage-point increase in the probability of reporting an ability to continue working until at least age 60. This estimate slightly exceeds the corresponding baseline association of 4.4 percentage points in Table 5. For perceived work ability, the robot estimate is insignificant, while the ICT estimate is positive and marginally significant.

10. Heterogeneity analysis

10.1. By age

Retirement intentions and expectations about working life in old age may be more relevant for older than younger workers. Older workers could be particularly vulnerable to automation because of a lack of digital skills (Cazzaniga et al., 2024) and may, as a result, plan an earlier exit from the labor force. In general, technological change accelerates skill obsolescence among older workers, who may find it too late in their careers to adjust quickly to new technologies (Ahituv & Zeira, 2011; Albinowski & Lewandowski, 2024).

Potentially, technologies such as robots could alleviate the physical burden of work and prolong working lives. Consistent with this view, older workers appear less likely than younger workers to perceive automation as a direct threat to their careers. They may instead associate technological progress with broader improvements in work and society in Norway (Schwabe, 2019). Moreover, theoretical work suggests that smart machines may substitute for younger, less-skilled workers while complementing older, more-skilled workers, potentially increasing older employees' productivity and job quality (Sachs & Kotlikoff, 2012). Empirical evidence on robot adoption also points to greater complementarity between robots and older workers and greater substitutability between robots and younger workers (Battisti & Gravina, 2021). Finally, technological progress also raises average wages, which may incentivize older workers to remain longer in the workforce (Ahituv & Zeira, 2011).

To examine whether the associations between technological exposure and retirement expectations vary by age, we interact each technology measure with indicators for workers aged 35–49 and 50–60, using workers aged 15–34 as the reference group. Table 6 reveals several age differences. Most notably, the association between ICT exposure and preferred retirement age becomes more positive with age. Relative to workers aged 15–34, the estimated association is 0.221 years more positive among workers aged 35–49 and 0.298 years more positive among workers aged 50–60. The joint test rejects equality of the ICT associations across age groups (p=0.003).

Age differences also emerge in uncertainty about preferred retirement age. Relative to workers aged 15–34, the associations of ICT and AI exposure with uncertainty are more positive in both older age groups. The association with robots is also more positive among workers aged 35–49. The joint tests reject equality across age groups for robots, ICT, and AI.

For early-retirement preferences, the association with AI exposure is more negative among workers aged 50–60 than among workers aged 15–34. For perceived work ability, the association with robot exposure is more negative among workers aged 50–60. The association with ICT exposure is more positive in both older age groups, while the association with AI exposure is more negative among workers aged 50–60. These interactions are statistically significant, and the joint tests reject equality across age groups for robots, ICT, and AI.

Overall, Table 6 suggests that technological exposure does not relate uniformly more or less favorably to retirement expectations among older workers. The direction and magnitude of the age differences depend on both the technology and the outcome.

Table 6: Technology exposure and retirement outcomes, heterogeneity by age

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.044	0.003	-0.002	0.010*
	(0.033)	(0.004)	(0.002)	(0.005)
ICT	-0.128**	0.008	-0.005**	-0.012*
	(0.063)	(0.010)	(0.003)	(0.007)
AI	0.103*	0.003	-0.004	0.062***
	(0.058)	(0.008)	(0.005)	(0.010)
Age 35-49	0.034	0.017	-0.015*	0.068***
	(0.143)	(0.016)	(0.008)	(0.020)
Age 50-60	0.885***	0.009	-0.030**	0.102***
	(0.166)	(0.018)	(0.012)	(0.023)
Age 35-49 x Robots	0.037	-0.004	0.003***	-0.002
	(0.032)	(0.004)	(0.001)	(0.007)
Age 50-60 x Robots	0.015	-0.001	0.004	-0.017***
	(0.054)	(0.006)	(0.003)	(0.006)
Age 35-49 x ICT	0.221***	-0.010	0.006**	0.021***
	(0.077)	(0.009)	(0.003)	(0.008)
Age 50-60 x ICT	0.298***	-0.020	0.012***	0.025***
	(0.087)	(0.017)	(0.004)	(0.009)
Age 35-49 x AI	-0.075	-0.003	0.010**	-0.017*
	(0.073)	(0.007)	(0.004)	(0.009)
Age 50-60 x AI	-0.099	-0.022**	0.012***	-0.036***
	(0.075)	(0.009)	(0.004)	(0.013)
Mean DV	61.752	0.728	0.072	0.744
P: Robots x Age groups	0.433	0.616	0.015	0.000
P: ICT x Age groups	0.003	0.518	0.011	0.017
P: AI x Age groups	0.412	0.012	0.016	0.013
R-squared	0.137	0.200	0.059	0.113
Observations	37,778	37,778	40,740	35,217

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work =

indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. 'P:' reports the *p*-value from a joint test that both age-group interaction coefficients equal zero. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

10.2. By gender

Table 7 shows no evidence that the associations between robot exposure and retirement outcomes differ by gender. None of the interaction terms between robot exposure and the male indicator are statistically significant.

For ICT exposure, the only statistically significant gender difference concerns preferred retirement age. ICT exposure is positively associated with preferred retirement age among women, whereas the corresponding association among men is close to zero and slightly negative. The interactions for early-retirement preferences, uncertainty, and perceived work ability are not statistically significant.

For AI exposure, the only significant gender difference concerns perceived ability to continue working until at least age 60. The association is 1.6 percentage points less positive among men than among women. The table provides no evidence of gender differences for the other retirement outcomes.

Table 7: Technology exposure and retirement outcomes, heterogeneity by gender

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.005	0.004	0.003	0.002
	(0.046)	(0.003)	(0.004)	(0.004)
ICT	0.207***	0.001	-0.001	0.007
	(0.059)	(0.005)	(0.002)	(0.004)
AI	0.057	0.000	0.006	0.051***
	(0.055)	(0.007)	(0.004)	(0.008)
Male	0.919***	-0.016	-0.004	0.046***
	(0.083)	(0.010)	(0.004)	(0.007)
Male × Robots	-0.022	-0.004	-0.003	0.002
	(0.039)	(0.003)	(0.004)	(0.004)
Male × ICT	-0.233***	-0.002	0.002	-0.003
	(0.069)	(0.006)	(0.002)	(0.005)
Male × AI	0.009	-0.010	-0.005	-0.016**
	(0.064)	(0.007)	(0.003)	(0.007)
Mean DV	61.752	0.728	0.072	0.744
P: Robots × Male	0.570	0.141	0.491	0.520
P: ICT × Male	0.001	0.717	0.443	0.520
P: AI × Male	0.887	0.153	0.133	0.018
R^2	0.134	0.199	0.058	0.110
Observations	37,767	37,767	40,728	35,199

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one-standard-deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. 'P:' reports *p*-values for tests of the null hypothesis that each interaction coefficient equals zero. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

10.3. By sector

Table 8 provides limited evidence of sectoral heterogeneity. Relative to non-manufacturing, the association between robot exposure and preferred retirement age is more positive for respondents working in the manufacturing sector, although the difference is only marginally significant. The association between robot exposure and retirement uncertainty is more negative for respondents in manufacturing. The association between ICT exposure and perceived ability to continue working until at least age 60 is also more negative in manufacturing, although this difference is only marginally significant. The association between robot exposure and perceived work ability is also more positive in manufacturing than in non-manufacturing. The remaining interaction estimates do not differ significantly by sector. Because robot exposure is concentrated in manufacturing, the robot estimates for non-manufacturing workers require particular caution.

Table 8: Technology exposure and retirement outcomes, heterogeneity by sector

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-3.217*	0.135	0.151***	-0.233**
	(1.771)	(0.142)	(0.057)	(0.103)
ICT	0.044	-0.001	0.001	0.005
	(0.039)	(0.004)	(0.001)	(0.003)
AI	0.072	-0.005	0.002	0.044***
	(0.055)	(0.006)	(0.004)	(0.007)
Manufacturing	0.222	0.007	-0.019**	0.034*
	(0.254)	(0.020)	(0.008)	(0.018)
Manufacturing × Robots	3.198*	-0.134	-0.151***	0.238**
	(1.770)	(0.142)	(0.057)	(0.103)
Manufacturing × ICT	-0.043	0.002	0.003	-0.011*
	(0.073)	(0.008)	(0.004)	(0.006)
Manufacturing × AI	-0.079	0.004	0.007	0.007
	(0.073)	(0.008)	(0.005)	(0.008)
Mean DV	61.752	0.728	0.072	0.744
P: Robots × Sector	0.072	0.345	0.009	0.021
P: ICT × Sector	0.552	0.817	0.418	0.081
P: AI × Sector	0.283	0.638	0.133	0.364
R^2	0.133	0.199	0.058	0.110
Observations	37,778	37,778	40,740	35,217

Notes: All regressions include ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. 'P:' reports p-values for tests of the null hypothesis that each interaction coefficient equals zero. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

10.4. By education and skill level

Table 9 shows that the associations between technology exposure and several retirement outcomes differ by occupational skill level. The association between AI exposure and preferred retirement age is 0.356 years more negative among high-skilled workers than among lower-skilled workers. Among high-skilled workers, ICT exposure has more positive associations with preferred retirement age and perceived ability to work until at least age 60. Robot exposure is more negatively associated with preferred retirement age and more positively associated with early-retirement preferences among high-skilled workers, although the former difference is only marginally significant. The robot association with retirement uncertainty is also more positive among high-skilled workers, again with only marginal significance.

Table 10 also reveals differences by educational attainment. At average levels of technology exposure, tertiary-educated workers report higher preferred retirement ages and greater perceived ability to work until at least age 60. Relative to workers without tertiary education, the association between robot exposure and preferred retirement age is more negative among tertiary-educated workers, while its associations with early-retirement preferences and retirement uncertainty are more positive. The association between ICT exposure and preferred retirement age is more positive among tertiary-educated workers, whereas its association with early-retirement preferences is more negative. The association between AI exposure and early-retirement preferences is more positive among this group.

Table 9: Technology exposure and retirement outcomes, heterogeneity by worker skill level

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	0.001	-0.002	-0.000	0.005*
	(0.026)	(0.003)	(0.001)	(0.002)
ICT	-0.053	0.004	-0.001	-0.010**
	(0.051)	(0.005)	(0.002)	(0.005)
AI	0.256***	-0.016	-0.001	0.060***
	(0.076)	(0.013)	(0.006)	(0.009)
High-skilled	-0.087	0.006	-0.028**	0.060***
	(0.263)	(0.028)	(0.013)	(0.020)
High-skilled × Robots	-0.056*	0.007**	0.002*	0.001
	(0.031)	(0.003)	(0.001)	(0.003)
High-skilled × ICT	0.164**	-0.008*	0.003	0.022***
	(0.067)	(0.004)	(0.003)	(0.006)
High-skilled × AI	-0.356***	0.021	0.009	-0.026*
	(0.096)	(0.017)	(0.007)	(0.015)
Mean DV	61.752	0.728	0.072	0.744
P: Robots × Skill	0.071	0.041	0.083	0.821
P: ICT × Skill	0.015	0.067	0.369	0.000
P: AI × Skill	0.000	0.221	0.221	0.079
R^2	0.134	0.200	0.058	0.111
Observations	37,778	37,778	40,740	35,217

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. 'P:' reports *p*-values for tests of the null hypothesis that each interaction coefficient equals zero. High-skilled is defined as managers, professionals, technicians, and associate professionals (ISCO-08 codes 1-3), and 0 otherwise. All regressions use survey weights.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Technology exposure and retirement outcomes, heterogeneity by worker education level

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.000	-0.002	-0.000	0.003
	(0.024)	(0.003)	(0.001)	(0.003)
ICT	-0.013	0.004	-0.001	0.001
	(0.046)	(0.004)	(0.002)	(0.004)
AI	0.089	-0.013	0.001	0.042***
	(0.069)	(0.008)	(0.005)	(0.008)
Tertiary education	0.467***	-0.004	-0.021**	0.028**
	(0.119)	(0.018)	(0.008)	(0.013)
Tertiary education × Robots	-0.058**	0.008***	0.003***	0.006
	(0.023)	(0.003)	(0.001)	(0.004)
Tertiary education × ICT	0.129**	-0.010**	0.003	0.006
	(0.053)	(0.004)	(0.002)	(0.005)
Tertiary × AI	-0.053	0.016**	0.006	0.005
	(0.089)	(0.008)	(0.004)	(0.011)
Mean DV	61.752	0.728	0.072	0.744
P: Robots × Education	0.013	0.004	0.009	0.190
P: ICT × Education	0.017	0.032	0.167	0.236
P: AI × Education	0.549	0.033	0.191	0.638
R^2	0.134	0.200	0.057	0.110
Observations	37,702	37,702	40,647	35,155

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. 'P:' reports *p*-values for tests of the null hypothesis that each interaction coefficient equals zero. Tertiary education is defined as having a tertiary education degree and as 0 for having an elementary or high-school education. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

10.5. By worker firm tenure and training

Table 11 provides limited evidence that the associations between technology exposure and retirement expectations differ by tenure. Relative to workers with less than two years at their current employer, the association between ICT exposure and preferred retirement age is 0.209 years more positive among workers with longer tenure.

Tenure differences also emerge for retirement uncertainty. The associations of ICT and AI exposure with uncertainty are more positive among workers with at least two years at their current employer. The difference for ICT is marginally significant, whereas the difference for AI is statistically significant. The robot interactions and all remaining interactions are statistically insignificant. Given the likely endogeneity of tenure, these differences require cautious interpretation. Overall, firm tenure plays a limited role, although it moderates the association between ICT exposure and preferred retirement age and the associations of ICT and AI exposure with retirement uncertainty.

Table 11: Technology exposure and retirement outcomes, heterogeneity by tenure

	(1)	(2)	(3)	(4)
	Retirement age	Early retirement	Uncertain	Able to work
Robots	-0.026	0.002	-0.001	0.009
	(0.044)	(0.005)	(0.002)	(0.006)
ICT	-0.118**	0.008	-0.004	0.000
	(0.055)	(0.008)	(0.002)	(0.008)
AI	0.108	0.000	-0.006	0.050***
	(0.080)	(0.010)	(0.005)	(0.009)
Tenure ≥ 2 years	-0.277***	0.034***	-0.016***	0.021*
	(0.091)	(0.010)	(0.005)	(0.011)
Tenure × Robots	0.006	-0.001	0.002	-0.006
	(0.036)	(0.005)	(0.002)	(0.007)
Tenure × ICT	0.209***	-0.011	0.005*	0.005
	(0.062)	(0.007)	(0.003)	(0.010)
Tenure × AI	-0.064	-0.006	0.012***	-0.008
	(0.084)	(0.009)	(0.004)	(0.009)
Mean DV	61.752	0.728	0.072	0.744
P: Robots × Tenure	0.876	0.807	0.324	0.394
P: ICT × Tenure	0.001	0.134	0.082	0.577
P: AI × Tenure	0.443	0.544	0.008	0.407
R^2	0.134	0.200	0.058	0.110
Observations	37,778	37,778	40,740	35,217

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. 'P:' reports *p*-values for tests of the null hypothesis that each interaction coefficient equals zero. Tenure refers to the number of years at the same firm. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Receiving training may increase retirement age (Bartel & Sicherman, 1993; Messe et al., 2014). We therefore examine whether the relationship between technology exposure and retirement expectations differs between workers who received employer-provided training and those who did not.

Table 12 shows no evidence that training moderates the associations between robot exposure and retirement expectations. By contrast, the associations involving ICT exposure differ consistently by training participation. Among workers who have undergone training, ICT exposure is more strongly positively associated with preferred retirement age, retirement uncertainty, and perceived ability to work until age 60. It also has a more negative association with early-retirement preferences, although this difference is only marginally statistically significant. The results for preferred retirement age and perceived work ability broadly align with Messe et al. (2014).

Most AI interactions are not statistically significant. Overall, the estimates show several differences by training participation for ICT exposure, one difference for AI exposure, and no statistically significant differences for robot exposure.

Table 12: Technology exposure and retirement outcomes, heterogeneity by training

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.012	-0.002	-0.001	0.006*
	(0.038)	(0.004)	(0.001)	(0.003)
ICT	-0.079	0.005	-0.005**	-0.011*
	(0.054)	(0.005)	(0.002)	(0.006)
AI	0.077	-0.012*	0.005	0.048***
	(0.063)	(0.007)	(0.005)	(0.008)
Training	-0.248***	0.030***	-0.017***	-0.003
	(0.071)	(0.007)	(0.004)	(0.007)
Training × Robots	-0.011	0.003	0.002	-0.003
	(0.036)	(0.004)	(0.002)	(0.004)
Training × ICT	0.176***	-0.009*	0.008***	0.020***
	(0.048)	(0.005)	(0.003)	(0.007)
Training × AI	-0.032	0.012**	-0.002	-0.005
	(0.051)	(0.005)	(0.004)	(0.007)
Mean DV	61.750	0.728	0.072	0.744
P: Robots × Training	0.769	0.450	0.300	0.461
P: ICT × Training	0.000	0.059	0.003	0.008
P: AI × Training	0.529	0.023	0.636	0.479
R^2	0.134	0.200	0.058	0.110
Observations	37,701	37,701	40,649	35,151

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. 'P:' reports p-values for tests of the null hypothesis that each interaction coefficient equals zero. Training refers to on-the-job training or other employer-provided training. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

11. Technology, tasks, and retirement

While robots, ICT, and AI can all automate routine tasks, they differ in the nature of the activities they affect. Robots are primarily associated with automating routine manual tasks, ICT with automating routine cognitive tasks, and AI with automating routine cognitive tasks as well as an increasing range of non-routine cognitive activities. We explored how the tasks that individual workers perform influence the relationship between technologies and retirement outcomes. To this end, we construct four task indices following Nikolova et al. (2025), which adapts the task framework of Acemoglu and Autor (2011) to harmonized worker-level data from the European Working Conditions Survey (EWCS). We recode the survey items so higher values consistently represent greater task intensity and standardize them across the pooled survey waves. Because most items use ordinal response scales, we estimate a polychoric correlation matrix for each domain and apply principal component analysis separately to each matrix. We retain the first principal component and standardize each resulting index to a mean of zero and a standard deviation of one.[8] The task indices are moderately correlated and therefore capture distinct dimensions of work activities: the strongest correlation occurs between physical and routine tasks (0.37), with comparatively weak correlations across the remaining task domains. [9]

Table 13 reports regressions that interact each technology measure with all four standardized task indices simultaneously. Because the task indices are standardized, each main technology coefficient represents its estimated association when all four task indices are at their mean values. A significant interaction indicates that the association changes with task intensity, but does not necessarily mean that the conditional association at either task level is itself statistically significant. The joint tests show that the robot interactions are collectively significant for all four outcomes. The ICT interactions are jointly significant for perceived work ability and marginally significant for preferred retirement age, while the AI interactions are jointly significant only for perceived work ability.

Several individual differences involve routine-task intensity. As routine intensity increases, the ICT association with preferred retirement age becomes more negative, while the robot association becomes more positive. In both cases, the point estimate changes direction, although the baseline coefficients are not statistically significant and the ICT interaction is only marginally significant. Greater routine intensity also makes the robot association with retirement uncertainty

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[8] The physical task index includes (i) working in tiring or painful positions and (ii) carrying or moving heavy loads. The routine task index includes (i) repetitive hand or arm movements, (ii) monotonous tasks, (iii) work pace determined by automatic machine speed or product movement, (iv) short repetitive tasks of less than one minute, (v) short repetitive tasks of less than ten minutes, (vi) inability to choose or change the order of tasks, and (vii) inability to choose or change the speed or rate of work. The abstract task index includes (i) solving unforeseen problems, (ii) performing complex tasks, (iii) learning new things, and (iv) applying one's own ideas at work. The social task index includes (i) dealing directly with customers, pupils, patients, or other non-employees, (ii) work pace determined by customer or client demands, and (iii) supervising other employees. Nikolova et al. (2025) include handling angry clients or customers" in their index but we exclude it here because it is not available in 2005. Robot exposure shows no statistically significant association with any task index, but the patterns are in line with Nikolova et al. (2025). ICT exposure is associated with lower perceived physical, abstract, and social tasks and more perceived routine tasks. AI exposure is linked with lower physical and routine-task intensity, while its associations with abstract and social tasks are statistically insignificant. Because these regressions remain descriptive and task content may respond endogenously to technology exposure, we interpret them cautiously.

[9] The first principal component explains 76.5% of the variation in physical tasks, 38.6% in routine tasks, 57.9% in abstract tasks, and 53.4% in social tasks. KMO statistics indicate acceptable, although not strong, factorability for the routine and abstract indices (0.654 and 0.676) and only marginal factorability for the social index (0.503). The physical index has a KMO of 0.500, but this statistic provides little diagnostic information for a two-item index. Cronbach's alphas indicate moderate internal consistency for the physical, routine, and abstract indices (0.625, 0.599, and 0.615) and weaker consistency for the social index (0.458).

and the ICT association with perceived work ability more negative. The AI association with perceived work ability becomes more positive, although this interaction is only marginally significant.

Other task domains reveal additional differences. Greater social-task intensity makes the robot association with perceived work ability more positive and its association with retirement uncertainty more negative. Greater abstract-task intensity makes the robot association with perceived work ability more negative and its association with early-retirement preferences marginally more positive. For ICT, greater social-task intensity makes the association with retirement uncertainty more negative, while greater abstract-task intensity makes the association with preferred retirement age marginally more positive. None of the interactions with physical-task intensity is statistically significant. Overall, task-related heterogeneity is most consistent for robot exposure, whereas the differences involving ICT and AI are concentrated in particular outcomes.

Table 13: Technology exposure and retirement outcomes: task heterogeneity

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.015	0.001	-0.001	0.012***
	(0.020)	(0.003)	(0.001)	(0.002)
ICT	0.025	0.001	-0.002	0.001
	(0.038)	(0.004)	(0.002)	(0.004)
AI	0.032	-0.005	0.003	0.034***
	(0.051)	(0.006)	(0.004)	(0.007)
Physical tasks	-0.252***	0.010**	-0.003	-0.081***
	(0.043)	(0.004)	(0.002)	(0.007)
Routine tasks	-0.052	0.008**	-0.001	-0.016***
	(0.033)	(0.003)	(0.002)	(0.003)
Abstract tasks	-0.089***	0.012***	-0.009***	0.015***
	(0.033)	(0.004)	(0.003)	(0.004)
Social tasks	0.016	-0.008*	0.000	-0.013**
	(0.047)	(0.005)	(0.002)	(0.005)
Robots × Physical	0.021	-0.003	0.001	0.002
	(0.014)	(0.002)	(0.001)	(0.002)
Robots × Routine	0.021**	-0.001	-0.004***	-0.001
	(0.009)	(0.001)	(0.001)	(0.002)
Robots × Abstract	-0.003	0.002*	-0.000	-0.006***
	(0.015)	(0.001)	(0.001)	(0.002)
Robots × Social	0.016	0.000	-0.004***	0.007***
	(0.016)	(0.002)	(0.001)	(0.002)
ICT × Physical	0.026	0.001	0.001	0.000
	(0.028)	(0.002)	(0.001)	(0.004)
ICT × Routine	-0.057*	-0.001	-0.000	-0.008**
	(0.032)	(0.003)	(0.002)	(0.004)
ICT × Abstract	0.069*	-0.004	0.003	0.002
	(0.038)	(0.003)	(0.002)	(0.004)
ICT × Social	0.034	0.001	-0.003**	-0.001
	(0.026)	(0.003)	(0.001)	(0.003)
AI × Physical	0.019	-0.001	-0.002	0.003
	(0.042)	(0.004)	(0.002)	(0.006)
AI × Routine	0.035	0.001	0.002	0.008*
	(0.027)	(0.003)	(0.002)	(0.005)
AI × Abstract	0.008	-0.000	0.002	-0.006
	(0.029)	(0.002)	(0.002)	(0.004)
AI × Social	-0.034	0.003	-0.001	-0.006
	(0.035)	(0.003)	(0.002)	(0.004)
Mean DV	61.759	0.731	0.066	0.746
P: Robots × all	0.009	0.020	0.000	0.000

tasks				
P: ICT × all tasks	0.059	0.573	0.109	0.017
P: AI × all tasks	0.573	0.819	0.648	0.003
R^2	0.137	0.198	0.055	0.142
Observations	35,094	35,094	37,589	32846

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country-industry level; AI = occupation-level AI exposure index. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Task indices follow Nikolova et al. (2025) and are constructed using polychoric principal component analysis (PCA) of EWCS task items. Physical tasks include tiring positions and heavy loads; routine tasks capture repetitive and machine-paced work; abstract tasks capture problem-solving and learning activities; social tasks capture interpersonal interactions and supervisory responsibilities. All task indices are standardized to mean zero and standard deviation one. Interaction coefficients indicate whether the relationship between technology exposure and retirement outcomes varies by task intensity. *p*-values reported in the table correspond to joint tests of the significance of all task interactions for each technology measure. Standard errors clustered at the country-industry level are reported in parentheses. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

12. The role of the institutional context

The institutional context may influence how workers respond to technological change because retirement incentives, pension generosity, labor market flexibility, and opportunities for later-life employment differ across welfare state regimes. Northern and Continental European countries generally have stronger social protection systems (Ferrera, 1996; Kammer et al., 2012) and higher labor market participation at older ages (EC, 2024). Meanwhile, Southern European countries tend to rely more heavily on early retirement pathways (Börsch-Supan et al., 2009) and family-based support (Bambra & Eikemo, 2009; Ferrera, 1996). Central and Eastern European countries, in turn, often exhibit less generous pension systems and more unstable labor market trajectories, which may affect how workers adjust to technological change and retirement decisions.

Table 14 shows some evidence that the associations between technology exposure and retirement outcomes differ across institutional contexts. For robot exposure, regional differences emerge for preferred retirement age and early-retirement preferences. Relative to Northern and Continental Europe, the negative point estimate for preferred retirement age is offset in Central and Eastern Europe, while the positive point estimate for early-retirement preferences reverses. The positive association between robot exposure and retirement uncertainty is also offset in Central and Eastern Europe, although the joint evidence of regional heterogeneity for this outcome is only marginally significant. In Southern Europe, the robot association with preferred retirement age is more positive, although this difference is also only marginally significant.

Regional differences are particularly evident for AI exposure. Its positive association with preferred retirement age in Northern and Continental Europe reverses in Central and Eastern Europe. Its positive association with perceived ability to continue working is weaker in both Southern Europe and Central and Eastern Europe. Regional differences in the AI association with retirement uncertainty also emerge, driven mainly by Central and Eastern Europe.

The results provide little evidence of regional heterogeneity in the associations involving ICT exposure. However, the ICT association with retirement uncertainty is more negative in Southern Europe, although the corresponding joint test across regions is not statistically significant. Overall, institutional context is associated with several differences involving robot and AI exposure, while the associations involving ICT exposure remain broadly similar across regions.

Table 14: Technology exposure and retirement outcomes: institutional context

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.047***	0.004**	0.002**	0.005***
	(0.015)	(0.002)	(0.001)	(0.002)
ICT	0.020	-0.001	0.002	0.003
	(0.047)	(0.005)	(0.002)	(0.003)
AI	0.125**	-0.004	0.004	0.054***
	(0.061)	(0.006)	(0.004)	(0.007)
Southern	2.024***	-0.017	0.139***	0.219***
	(0.243)	(0.026)	(0.011)	(0.031)
CEE	-0.366	-0.143***	0.123***	0.043*
	(0.223)	(0.028)	(0.011)	(0.022)
Southern × Robots	0.128*	-0.015	-0.004	0.005
	(0.073)	(0.009)	(0.004)	(0.009)
CEE × Robots	0.048**	-0.007**	-0.003**	-0.002
	(0.022)	(0.003)	(0.001)	(0.003)
Southern × ICT	0.090	-0.003	-0.008**	0.010
	(0.096)	(0.013)	(0.004)	(0.007)
CEE × ICT	0.094	0.010	-0.003	-0.011
	(0.077)	(0.017)	(0.006)	(0.009)
Southern × AI	-0.058	-0.008	0.005	-0.030***
	(0.078)	(0.008)	(0.005)	(0.007)
CEE × AI	-0.284***	0.008	-0.006**	-0.018**
	(0.074)	(0.008)	(0.003)	(0.007)
Mean DV	61.752	0.728	0.072	0.744
P: Robots × Region	0.030	0.034	0.052	0.652
P: ICT × Region	0.394	0.807	0.134	0.132
P: AI × Region	0.000	0.186	0.047	0.000
R^2	0.134	0.200	0.058	0.111
Observations	37,778	37,778	40,740	35,217

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country-industry level; AI = occupation-level AI exposure index. Countries are grouped into three regions: Northern/Continental Europe (Belgium, Germany, Finland, France, Netherlands, Sweden, United Kingdom), Southern Europe (Spain, Greece, Italy, Portugal), and Central and Eastern Europe (Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Romania, Slovakia). Northern/Continental Europe serves as the reference category. Interaction coefficients indicate whether the relationship between technology exposure and retirement outcomes differs across institutional contexts. P-values reported in the table correspond to joint tests of the significance of all regional interaction terms for each technology measure. Standard errors clustered at the country-industry level are reported in parentheses. All regressions include sampling weights * p < 0.1, ** p < 0.05, *** p < 0.01.

13. Discussion and conclusion

This paper examines how exposure to industrial robots, ICT, and AI relates to retirement expectations among workers aged 60 and younger across 20 European economies. We find little systematic associations between technology exposure and preferred retirement age, early-retirement preferences, or uncertainty about retirement timing. The clearest average result concerns perceived ability to continue working until at least age 60, which is positively associated with robot and AI exposure in the 2015–2024 sample. We document some heterogeneity in the associations across age, gender, education, skill level, task composition, and region, but the patterns are not systematic.

Our study has several limitations. First, the repeated cross-sectional design cannot follow the same workers as technology exposure changes, and the industry- and occupation-level measures may not capture workers' actual technology use. Second, worker sorting and unobserved country-industry or country-occupation shocks may also confound the estimates. Third, the heterogeneity analysis tests many interactions, so individual subgroup estimates require cautious interpretation. Finally, the leave-one-out instruments strongly predict domestic exposure, but their exclusion restriction may be violated if common international industry and occupation shocks are present.

Taken at face value, our findings indicate that technological exposure has not led to large average differences in retirement expectations across the 20 economies we study. One possible explanation for the insignificant estimates is that the three technologies we consider have reached different stages of diffusion. ICT and industrial robots have reshaped workplaces for several decades. By the period covered in our study, workers, firms, and institutions may already have adjusted to them. AI, by contrast, remains at an earlier stage of adoption. Although AI could transform a broad range of cognitive tasks, the evidence to date indicates relatively limited effects on employment and wages (Comunale & Manera, 2024; del Rio-Chanona et al., 2025). Moreover, retirement expectations may reflect beliefs about how AI will affect future work rather than workers' recent exposure. As firms adopt AI more widely, these expectations may increasingly shape retirement decisions.

Recent reports from Eurofound (Eiffe et al., 2025) and the OECD (2025) show that extending working lives requires more than retirement-age reforms. It also entails sustainable, age-friendly jobs that support health, autonomy, skill development, and continued employability. Technology may support longer working lives when it reduces physical demands, accommodates age-related limitations, and complements workers' skills. Policies can facilitate this process through lifelong learning, employer-provided training, and job redesign that improves working conditions, particularly for workers whose skills or tasks face substantial technological exposure.

At the same time, policymakers should not view longer working lives solely as a fiscal necessity or pursue them through top-down measures. Previous evidence associates continued employment under voluntary and flexible arrangements with greater well-being than retirement (Nikolova & Graham, 2014), suggesting that work can remain a source of purpose, social engagement, and life satisfaction at older ages. Forced delays to retirement through pension reforms, however, can harm mental health, particularly among workers in low-quality jobs (Lugova et al., 2026) or occupations at high risk of automation (Bertoni et al., 2023). Policymakers and employers must therefore do more than extend working lives. They must ensure that technological change supports job quality and sustainable employment throughout the life course.

Finally, our study offers several possible avenues for future research. We provide a broad comparative analysis of robotization, ICT, and AI across 20 European countries, but this breadth limits our ability to examine adjustment processes in detail. Future studies could use longitudinal data from individual countries to follow workers before and after the diffusion of AI and other technologies. Such research could establish whether changes in technological exposure precede changes in retirement expectations and, ultimately, realized retirement behavior, providing stronger evidence about causality.

Data sources and replication files

Replication files are available here: https://zenodo.org/records/22706637

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APPENDIX

Table A1: Technology exposure and retirement outcomes, all available years, including workers older than 60, excluding AI

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work	(5) Unwilling
Robots	-0.016	0.000	0.001	0.005**	0.006
	(0.021)	(0.002)	(0.001)	(0.002)	(0.005)
ICT	0.055	-0.001	0.000	-0.003	0.004
	(0.037)	(0.004)	(0.001)	(0.004)	(0.005)
Mean DV	62.063	0.697	0.074	0.698	0.151
R^2	0.183	0.242	0.058	0.101	0.043
Observations	43,594	43,594	47,171	74,556	40,134

Notes: This replicates Table 4 but includes workers older than 60. All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2005, 2010, 2015, 2024); Unwilling = indicator equal to one if the respondent reports that they would not want to continue working until age 60 (2005, 2010). Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Technology exposure and retirement outcomes, including workers older than 60, 2015–2024 sample, including AI exposure

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.016	0.001	0.001	0.004**
	(0.021)	(0.002)	(0.001)	(0.002)
ICT	0.046	0.000	0.001	0.004
	(0.037)	(0.004)	(0.001)	(0.003)
AI	0.044	-0.004	0.004	0.043***
	(0.053)	(0.005)	(0.004)	(0.006)
Mean DV	62.039	0.701	0.073	0.734
R^2	0.177	0.235	0.058	0.110
Observations	42,138	42,138	45,539	39,247

Notes: This replicates Table 5 but includes workers older than 60. All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024). Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Technology exposure and retirement outcomes, all available years, without imputations, excluding AI

	(1) Retirement age	(2) Early retirement
Robots	-0.004	0.002
	(0.041)	(0.005)
ICT	0.074	-0.005
	(0.052)	(0.004)
Mean DV	61.680	0.628
R^2	0.112	0.157
Observations	29,365	29,365

Notes: This is a replication of columns (1) and (2) of Table 4, but excluding the imputations for the preferred retirement age for those 44 and younger in the 2024 survey. All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one time period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024). Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Technology exposure and retirement outcomes, without imputations, 2015–2024 sample, including AI exposure

	(1) Retirement age	(2) Early retirement
Robots	-0.005	0.003
	(0.041)	(0.005)
ICT	0.065	-0.004
	(0.053)	(0.004)
AI	0.066	0.003
	(0.077)	(0.008)
Mean DV	61.679	0.630
R^2	0.111	0.155
Observations	28,493	28,493

Notes: This is a replication of columns (1) and (2) of Table 5, but excluding the imputations for the preferred retirement age for those 44 and younger in the 2024 survey. All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024). Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Technology exposure and retirement outcomes: health and workplace controls

	Retirement age			Early retirement			Uncertain			Able to work		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Robots	-0.022	-0.025	-0.025	0.001	0.001	0.001	0.001	0.001	0.001	0.004**	0.004**	0.003*
	(0.023)	(0.023)	(0.023)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
ICT	0.049	0.044	0.045	-0.001	-0.000	-0.001	0.000	0.000	0.001	0.004	0.003	0.003
	(0.038)	(0.040)	(0.039)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
AI	0.042	-0.048	-0.053	-0.003	0.004	0.005	0.004	0.002	0.001	0.040***	0.023***	0.024***
	(0.054)	(0.055)	(0.054)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
Health sat.	0.493***	0.331***	0.335***	-0.041***	-0.028***	-0.029***	0.002	0.000	0.001	0.141***	0.110***	0.109***
	(0.081)	(0.076)	(0.076)	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)	(0.012)	(0.010)	(0.010)
Health sat. missing	-0.222	-0.197	-0.178	0.026	0.023	0.017	0.092	0.071	0.071	-0.043	-0.050	-0.054
	(1.145)	(1.137)	(1.134)	(0.099)	(0.099)	(0.099)	(0.075)	(0.071)	(0.070)	(0.112)	(0.110)	(0.110)
Health risk		-0.877***	-0.870***		0.069***	0.067***		-0.013***	-0.012***		-0.165***	-0.167***
		(0.082)	(0.082)		(0.007)	(0.008)		(0.004)	(0.004)		(0.015)	(0.015)
Health risk missing		-0.169	-0.172		0.020	0.020		0.100***	0.099***		-0.046*	-0.045*
		(0.189)	(0.187)		(0.027)	(0.026)		(0.017)	(0.016)		(0.026)	(0.026)
OSH delegate			-0.127			0.035***			-0.019***			0.032***
			(0.084)			(0.007)			(0.005)			(0.007)
OSH delegate missing			0.051			-0.002			0.021**			-0.006
			(0.102)			(0.011)			(0.010)			(0.017)
Mean DV	61.752	61.752	61.752	0.728	0.728	0.728	0.072	0.072	0.072	0.744	0.744	0.744
R^2	0.135	0.141	0.142	0.200	0.204	0.206	0.057	0.061	0.063	0.125	0.149	0.151
Observations	37,778	37,778	37,778	37,778	37,778	37,778	40,740	40,740	40,740	35,217	35217	35,217

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean = 0, std. dev.= 1): Robots = robot density (robots per 10,000 workers); ICT = real ICT capital per worker at the country-industry level; AI = occupation-level AI exposure index. Models sequentially add controls for self-assessed health, work-related health risks, and occupational safety and health (OSH) representation. Self-assessed health is recoded into three categories: good/very good health, very bad/bad/fair health, and missing. Health risks at work and OSH representation are coded to retain missing values as separate categories. Dependent variables: Retirement age = preferred retirement age; Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age; Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age; Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60. Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Technology exposure and retirement outcomes: IV

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work	(5) Unwilling
Robots	-0.077***	0.005	0.001	0.004*	0.006
	(0.024)	(0.003)	(0.001)	(0.002)	(0.007)
ICT	0.166**	-0.015**	-0.006**	0.016**	-0.005
	(0.079)	(0.007)	(0.003)	(0.007)	(0.007)
Mean DV	61.749	0.726	0.072	0.702	0.151
F-stat	23.11	23.11	23.62	29.60	49.10
Observations	38,842	38,842	41,903	70,148	40,104

Notes: This replicates Table 4 using a 2SLS estimator. All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots and ICT are treated as endogenous and instrumented using leave-one-out peer exposure measures defined at the industry-year level. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2005, 2010, 2015, 2024); Unwilling = indicator equal to one if the respondent reports that they would not want to continue working until age 60 (2005, 2010). Standard errors are clustered at the country-industry level. All regressions use survey weights. We report the Kleibergen-Paap *F*-statistics. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: First-stage regressions for robotization: Table A6 IV

	(1) Retirement age and early retirement sample	(2) Uncertain sample	(3) Able to work sample	(4) Unwilling sample
Peer robots	0.729***	0.737***	0.753***	0.725***
	(0.163)	(0.164)	(0.154)	(0.194)
Peer ICT	-0.017	-0.018	-0.016	-0.010
	(0.018)	(0.018)	(0.015)	(0.013)
R^2	0.665	0.661	0.660	0.516
Observations	38,842	41,903	70,148	40,104

Notes: The table reports the first-stage regression results related to Table A6, and the dependent variable in all columns is robotization. See the notes to Table A6 for further details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: First-stage regressions for ICT: Table A6 IV

	(1) Retirement age and early retirement sample	(2) Uncertain sample	(3) Able to work sample	(4) Unwilling sample
Peer robots	0.005	0.004	-0.002	0.047
	(0.025)	(0.024)	(0.026)	(0.057)
Peer ICT	0.468***	0.463***	0.470***	0.444***
	(0.069)	(0.067)	(0.061)	(0.045)
R^2	0.623	0.626	0.626	0.704
Observations	38,842	41,903	70,148	40,104

Notes: The table reports the first-stage regression results related to Table A6, and the dependent variable in all columns is ICT. See the notes to Table A6 for further details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Technology exposure and retirement outcomes: IV AI Sample

	(1) Retirement age	(2) Early retirement	(3) Uncertain	(4) Able to work
Robots	-0.077***	0.005	0.001	0.003
	(0.024)	(0.003)	(0.001)	(0.002)
ICT	0.162**	-0.014**	-0.005*	0.014*
	(0.081)	(0.007)	(0.003)	(0.007)
AI	0.036	-0.008	0.004	0.051***
	(0.056)	(0.007)	(0.004)	(0.008)
Mean DV	61.752	0.728	0.072	0.744
F-stat	15.26	15.26	15.60	15.33
Observations	37,778	37,778	40,740	35,217

Notes: This replicates Table 5 using a 2SLS estimator. All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. We lag and standardize the technology variables (mean 0, std. dev. 1); we treat robots, ICT, and AI as endogenous and instrument them with leave-one-out peer exposure measures. We define peer robot and peer ICT instruments at the industry-year level, while the peer AI instrument is defined at the occupation-year level. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables: Retirement age = preferred retirement age (years; 2015, 2024); Early retirement = indicator equal to one if the preferred retirement age is below the statutory retirement age (2015, 2024); Uncertain = indicator equal to one if the respondent reports not knowing their preferred retirement age (2015, 2024); Able to work = indicator equal to one if the respondent expects to be able to work until at least age 60 (2015, 2024); Standard errors are clustered at the country-industry level. All regressions use survey weights. We report the Kleibergen-Paap rk Wald *F*-statistics. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: First-stage regressions for robotization: Table A9 IV

	(1) Retirement age and early retirement sample	(2) Uncertain sample	(3) Able to work sample
Peer robots	0.729***	0.737***	0.758***
	(0.163)	(0.164)	(0.165)
Peer ICT	-0.017	-0.017	-0.020
	(0.018)	(0.018)	(0.019)
Peer AI	0.023	0.025	0.023
	(0.021)	(0.021)	(0.021)
R^2	0.665	0.661	0.685
Observations	37,778	40,740	35,217

Notes: The table reports the first-stage regression results related to Table A9, and the dependent variable in all columns is robotization. See the notes to Table A9 for further details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11: First-stage regressions for ICT: Table A9 IV

	(1) Retirement age and early retirement sample	(2) Uncertain sample	(3) Able to work sample
Peer robots	0.005	0.004	0.002
	(0.024)	(0.024)	(0.025)
Peer ICT	0.467***	0.461***	0.486***
	(0.069)	(0.068)	(0.072)
Peer AI	-0.044**	-0.043**	-0.044**
	(0.020)	(0.020)	(0.022)
R^2	0.622	0.625	0.620
Observations	37,778	40,740	35,217

Notes: The table reports the first-stage regression results related to Table A9, and the dependent variable in all columns is ICT. See the notes to Table A9 for further details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12: First-stage regressions for AI: Table A9 IV

	(1) Retirement age and early retirement sample	(2) Uncertain sample	(3) Able to work sample
Peer robots	-0.003	-0.003	-0.004
	(0.002)	(0.002)	(0.002)
Peer ICT	-0.008*	-0.007	-0.006
	(0.004)	(0.004)	(0.004)
Peer AI	0.956***	0.955***	0.950***
	(0.021)	(0.020)	(0.019)
R^2	0.940	0.940	0.941
Observations	37,778	40,740	35,217

Notes: The table reports the first-stage regression results related to Table A9, and the dependent variable in all columns is AI exposure. See the notes to Table A9 for further details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Technology exposure and task content

	(1) Physical	(2) Routine	(3) Abstract	(4) Social
Robots	-0.008	-0.001	-0.002	-0.003
	(0.005)	(0.008)	(0.005)	(0.006)
ICT	-0.035***	0.024**	-0.021**	-0.029**
	(0.010)	(0.011)	(0.010)	(0.012)
AI	-0.200***	-0.091***	0.022	0.009
	(0.015)	(0.023)	(0.016)	(0.048)
Mean DV	-0.073	-0.013	0.070	0.015
R^2	0.221	0.197	0.259	0.244
Observations	37,675	37,675	37,675	37,675

Notes: All regressions include a sector indicator (manufacturing vs. non-manufacturing), ISCO 1-digit occupation, country, and year fixed effects, and controls for age group, gender, household size, hours worked, education, firm size, self-employment status, and secondary job status. Technology variables are lagged one period and standardized (mean 0, std. dev. 1): Robots = robot density (robots per 10,000 workers); ICT measures real ICT capital per worker at the country–industry level (in constant 2015 euros), constructed as the sum of IT equipment, communications equipment, and software and database capital; AI = occupation-level AI exposure index. Coefficients represent the effect of a one standard deviation increase in exposure. Dependent variables are standardized task indices constructed using polychoric principal component analysis: physical, routine, abstract, and social tasks. Standard errors are clustered at the country-industry level. All regressions use survey weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$