



The impact of artificial intelligence in the early retirement decision

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Abstract

This paper examines the impact of Artificial Intelligence (AI) on early retirement (ER) decisions in Europe. For the analysis, we utilize microdata from the Survey of Health, Ageing and Retirement in Europe, along with occupation-level data on AI advances and AI exposure. Initially, we investigate the influence of AI advances and AI exposure separately, finding in both instances a significant reduction in ER likelihood, though this only applies to workers with higher education. Subsequently, we explore the interaction between AI advances and AI exposure concerning ER probability. This interaction proves critical in determining AI's impact on ER transitions. Specifically, we observe a significant reduction in ER probabilities for workers whose occupations exhibit high levels of AI advances and high expectations for further implementation of this technology in the future. Finally, we jointly analyse the interaction between AI advances, AI exposure, and education level. This analysis highlights that workers' ER probabilities may either increase or decrease in response to the AI revolution, depending on their education level and the characteristics of their occupations in terms of AI advances and AI exposure.

Keywords Older workers · Ageing · Digitalization · Technological change

JEL classification H55 · J24 · J26 · M51 · O33

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1 Introduction

The potential effect on the employment of the technologies that make up the so-called Fourth Industrial Revolution is one of the main topics in current economic research.¹ In general, the destructive and displacing effect of these technologies has been the most covered and widespread in the literature (Autor 2015; Frey and Osborne 2017; Acemoglu and Restrepo 2020a). Nevertheless, other authors have highlighted the potential of the current technological change for increasing productivity (Graetz and Michaels 2018) and create employment (Damioli et al. 2023). In addition, other authors have denied the alarmist Luddite vision of massive job destruction due to automation (Arntz et al. 2016, 2017; Dauth et al. 2017; Lorenz et al. 2023).

The current and potential impact of AI on the labour markets constitutes one of the main aspects of this industrial revolution, since experts estimate that there is a 50% chance of AI outperforming human in all tasks in 120 years (Grace et al. 2018). These estimates raise a debate about whether human work will be replaced by this new technology or, on the contrary, will be complemented by it, raising its productivity in an extraordinary way. In this respect, some authors have already classified the AI as a *transformative technology* rather than a destructive one due to its complementarity degree with human labour (Fossen and Sorgner 2019, 2021). Therefore, we would talk about AI complementing *Human Intelligence* (HI)² in a way that human labour productivity can take advantage of both. This fact creates itself a paradigm for human capital, which can now be enhanced by a kind of *artificial capital*.

Additionally, the ageing of the population is another of the main economic concerns in industrialized countries. In fact, governments not only take measures to mitigate ER but also to delay the statutory retirement ages (European Commission 2021). The paradigm of an ageing population accompanied by a reduction in the working-age population, presents an important demographic change with numerous consequences in various social, political and economic fields. For instance, the specific political behaviour of the elderly in an ageing population may imply a reduction in education spending and an increase in healthcare spending (Vlandas et al. 2021).

Given these very concrete technological and demographic circumstances in advanced economies, we are in a unique moment in economic history where multiple crucial processes collapse. This encounter of demographic and technological change with the ageing of the population and the rising of new disruptive technologies is originating several economic and political debates. Regarding the economic debate on technological change, Jimeno (2019) remarks that there is uncertainty about the degree to which new machines and human labour will be complements or substitutes in the production of existing tasks embedded in the production of goods and services. On the other hand, Acemoglu and Restrepo (2017) highlight how the current technological change could be burying the negative economic effects of the

¹ See Raj and Seamans (2019) for a literature review.

² See Stadlmann and Zehetner (2021) for an example of comparison between *HI* and *AI* competences.

ageing of the population assumed by economic literature³, since the countries undergoing more rapid demographic change are more likely to adopt robots (Acemoglu and Restrepo 2022).

This article provides new insights to this collision of technological and demographic change by analysing the effect of AI on the ER decisions in Europe. Although ER decisions have been widely studied, and the analysis of the AI characteristics is one of the main topics in recent literature, the nexus between these two concepts stills unexplored. In order to develop our analysis, we use microdata from the Survey of Health, Ageing and Retirement in Europe (SHARE), a measure of *AI advances* (Felten et al. 2018) and a measure of *AI exposure* (Felten et al. 2021). In addition, considering both *AI advances* and *AI exposure* we proportionate a new technological classification of occupations in 4 *Intelligence terrains (I-terrains)*. For those occupations with a low level of advancement in this matter, we speak of occupations of the *HI terrain*. For occupations with a high level of current *AI advances* but low expectations of future development, we speak of the *narrow AI terrain*. For those occupations with low current advances of AI but great development potential in the future, we speak of the *future AI terrain*. Finally, for those occupations with a high level of advances and a high expectation of development in the future, we are talking about the *AI terrain*.

We find that workers more affected by the AI revolution are less likely to transition to ER when the impact of this new technology implies current advances and expectations of future developments. When considering separately *AI advances* and *AI exposure*, we observe that AI-impact reducing the ER probability either via current advances or future expectations requires tertiary education to be significant. Indeed, we find a mediating effect of education between AI and ER. These results qualify the conclusions on the influence of the Fourth Industrial Revolution on transitions to ER, pointing out that this technological revolution is made up of a conglomerate of technologies with specific characteristics that can affect various aspects of the labour market in different ways. In this sense, although it has been documented that the automation process pushes old workers to ER (Yashiro et al. 2021; Casas and Román 2023), the AI revolution affects the ER decision in the opposite direction. To reach a conclusion about the global effect that AI and the automation process can have on ER would require a broader analysis.

Our results align with recent evidence that robots demonstrate higher complementarity with older workers (Battisti and Gravina 2021). Drawing a connection with the theory of Ahituv and Zeira (2011), we posit that, in the face of AI-driven technical change, the wage effect – the rise in aggregate wages – surpasses the erosion effect. This suggests that the learning efforts dedicated to new technologies yield fewer gains for older workers, as they have shorter career horizons. Indeed, wage increases resulting from AI-induced productivity enhancements modify the price of leisure, potentially influencing retirement decisions in a manner similar to financial retire-

³ The ageing population have been assumed by some economists to have negative effects on economic growth, either because of the lower labour force participation and productivity of older workers (Gordon 2016) or because ageing creates an excess of savings over desired investment, leading to secular stagnation (Hansen 1938).

ment incentives (Kerkhofs et al. 1999; Hofer and Koman 2006; Raab 2011; Hanel and Riphahn 2012). Furthermore, our findings fit into the concept of “right” AI as proposed by Acemoglu and Restrepo (2020b), indicating a positive economic impact from AI implementation for both older workers specifically and society generally.

In addition, our analysis resonates with literature that explores the links between ER and occupational characteristics, with our unique contribution being the focus on the technological aspects of occupations. Thus, this paper is in line with work like Hayward (1986), which assesses the impact of occupational characteristics on the ER of men, and Schreurs et al. (2011), which examines ER intentions among blue- and white-collar workers. Lastly, in sync with Agarwal and Gort (2002), we observe that AI’s role in reducing ER probabilities for workers who are more significantly affected by this transformative technology may be tied to the expansion phase of these tech-intensive industries. However, this beneficial effect of AI in mitigating ER transitions may not be long-lasting. Alternatively, this positive effect might stem from the labour-friendly characteristics of this disruptive technology.

The rest of the paper is structured as follows: Section 2 presents the literature review and the main hypotheses, Section 3 presents the data used, as well as the methodology, the sample and the variables. Section 4 presents the main results and Section 5 summarizes the conclusions.

2 Background and hypotheses

Since this technological change encompasses a conglomerate of diverse technologies and processes, we define a conceptual framework to delimitate the technological target of analysis of this study. Taking as a baseline the simplified vision of the technological change provided by Fossen and Sorgner (2019), we can label the technological change as *digitalization* and identify both digitalization sides: a destructive side and a transformative side. The *destructive digitalization* is equated by these authors as *computerization*, a process that can be defined as computer-based automation and mainly involves *robotization*, which is labelled as robot-based automation, and Machine Learning. The International Federation of Robots (IFR) defines an industrial robot as an “automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications”, while Brynjolfsson and Mitchell (2017) define Machine Learning as a subfield of AI that studies the question “How can we build computer programs that automatically improve their performance at some task through experience?”⁴

⁴ The categorization of Machine Learning as a “destructive” technology and AI as a “transformative” technology is a simplification, and the reality is far more nuanced. Both Machine Learning and AI have the potential to both destroy and create jobs, depending on how they are implemented and the specific circumstances. They are tools, and their impact is largely dependent on how they’re used. Machine Learning is often associated with job displacement because many of its applications involve automating tasks that were previously performed by humans, while AI is a broader term that encompasses not just Machine Learning but also other technologies that are designed to mimic human intelligence and behaviour.

The concept of *destructive digitalization* emerges as the natural progression of task automation, a process initiated with the introduction of the first machines (Hitomi 1994). Its impact on ER has been examined in Casas and Román (2023). Consistent with this understanding of the effect of *destructive digitalization* on ER decisions, Hudomiet and Willis (2022) highlight that many older workers in the US retired earlier than “normal” when automation first infiltrated their occupations. Therefore, this paper focuses on studying the implications of *transformative digitalization* for the ER decision, a topic that, to the best of our knowledge, has yet to be explored in the literature. According to Broussard (2018), there are definitions for both “narrow AI” and “general AI”. Concretely, the ‘narrow’ definition of AI refers to computer software that involves highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future, while the ‘general’ definition of AI refers to computer software that can think and act on its own, which does not yet exist. This paper addresses the impact of both AI definitions by considering current advances and future expectations regarding this technology.

This so-called *transformative digitalization* is going to impact occupations that were previously considered safe in past technological revolutions. In fact, it will affect all occupations to a greater or lesser extent (Acemoglu and Restrepo 2018; Grace et al. 2018) in a way that some jobs that were not known to be affected by previous waves of automation may now be subject to higher AI exposure (Tolan et al. 2021). Indeed, high-skill occupations are most exposed to AI and this fact of AI-exposed jobs being predominantly those involving high levels of education and accumulated experience, yields that older workers who are most exposed to AI (Webb 2020).

The AI revolution promises to bring multi-level changes to the economy. For instance, Adner et al. (2019) foresee qualitative -and not only quantitative- changes due to three fundamental processes underlying the digital transformation—representation, connectivity, and aggregation—, indicating that these processes will continue to push firms in all industries to create and capture value differently, develop new business models, manage new forms of intellectual property, grow scale and scope differently, and create new opportunities and challenges for organization design and management practices. Moreover, the accelerated spread of this technology has been documented from different perspectives. For instance, Acemoglu et al. (2022) document rapid growth in AI related vacancies over 2010–2018, finding that AI-exposed establishments are reducing hiring in non-AI positions even as they expand AI hiring, without finding discernible impact of AI exposure on employment or wages at the occupation or industry level. Related to this rapid spread of AI technologies, Martínez-Plumed et al. (2020) remark the importance to consider the notion of technology “hyper adoption” when analysing the process of AI progress, since this theory states that people adapt to and adopt new technologies much faster than they used to do in the past.

The examination of the impact of AI on ER schemes is particularly noteworthy when we consider the literature underlines that new technologies interface differently with workers based on age. Given the technologies of the fourth industrial revolution, although the interaction of AI with various worker cohorts depending on age has not been scrutinised, it has been found that robots exhibit different substitutability-complementarity relations with workers contingent upon their ages (Battisti and Gravina,

2021). Thus, it seems reasonable to anticipate that AI would likewise exhibit this distinct substitutability-complementarity relation with workers contingent upon their ages. Certainly, literature has stressed out the fact that older workers tend to have more work experience and are therefore, at a similar education level, more qualified, so the tasks performed by older workers might be more complex than those of younger workers (Bordot 2022).

In this line, research has demonstrated that older workers exhibit flexibility, trainability, and cost-effectiveness on par with their younger colleagues (McNaught and Barth 1992; Sterns and Miklos 1995). These studies further suggest that in practical scenarios, older workers do not significantly lag behind their younger counterparts when it comes to making mistakes in computer-based work (Birdi et al. 1997). Additionally, older workers have been found to perform equally well as younger employees across a variety of remote work tasks (Sharit et al. 2004). However, the relationship between an increased proportion of elderly workers and labour productivity is more nuanced than previously understood. While Hernæs et al. (2023) indicate a small positive effect on labour productivity with a higher share of older workers, they also note a significant reduction in the hiring of younger workers. This complex interaction underscores the need for a more differentiated examination of the ageing workforce's impact on productivity. Allen (2023) further elaborates on this complexity, indicating that despite the rising employment rates for workers over 55, the direct correlation between age, productivity, and labour costs does not present a clear-cut narrative. The increase in labour costs associated with older workers does not unequivocally translate to increased productivity, offering a perspective that challenges the simplistic association between older workers' share in firms and productivity enhancement.

As an example of a specific AI application, we can consider the AI language modelling and its significant impacts on various occupations and industries. Felten et al. (2023) have shown how occupations like telemarketers and post-secondary teachers are particularly susceptible, with sectors like legal services, securities, and commodities bearing significant exposure. This draws attention to the economic impacts and necessitates contemplation from policymakers and stakeholders. Building on this, Floridi and Chiriatti (2020) posit that the distinction between human and artificial sources of texts will blur. Complementing these studies, Eloundou et al. (2023) find that the introduction of Generative Pre-trained Transformer (GPT) models could affect nearly 80% of the U.S. workforce, with around 19% of workers experiencing substantial impacts on their tasks. These potential implications of AI language modelling underscore the far-reaching economic, social, and policy repercussions, thereby warranting careful consideration.

Pettersen (2019) highlights the extensive promotion of AI as a tool to improve organizational performance and productivity since the 1960s. Today, AI is once again the centre of attention due to its potential role in big business, akin to the rise of big data in the 1990s. However, the author argues that discussions around the potential threat of AI to jobs often overlooks the complex nature of knowledge work, which involves highly complex problem-solving that requires contextual, social, and relational understanding. These elements have no universal rules or solutions, making it challenging to program them into computer systems or replace them with AI. The

article draws upon philosopher Herbert Dreyfus' thesis on AI to emphasize the limitations of current AI systems in fully replacing human knowledge work.

Literature has raised a debate about whether AI complements or replaces labour (Tschang and Almirall 2021). Many studies indicate multiple instances of high complementarity between human labour and AI. Regarding productivity, Yang (2022) estimates the impact of AI technology on the productivity and employee profiles of firms in Taiwan's electronics industry from 2002 to 2018, using a keyword-matching method to parse the text of Taiwan patent grants. The study finds that AI technology is positively associated with productivity and employment, and that it crucially alters firms' workforce compositions. Regarding employment, Damioli et al. (2023) investigate the job-creation impact of AI technologies on the supply side, where AI development is viewed as product innovations in upstream sectors. The study analyses a longitudinal sample of over 3,500 frontrunner companies that patented AI-related inventions worldwide between 2000 and 2016, using system GMM estimates of dynamic panel models. The results indicate a positive and significant impact of AI patent families on employment, suggesting that AI product innovation has a labour-friendly nature.

Also studying the implications of AI for employment, Alekseeva et al. (2021) estimate the demand for AI specialists across occupations, sectors, and firms using data on skill requirements in online job postings. They find a significant increase in demand for AI skills across most industries and occupations in the U.S. economy between 2010 and 2019, with the highest demand in information technology (IT) occupations, followed by architecture and engineering, scientific, and management occupations. The study also shows that firms with larger market capitalization, higher cash holdings, and higher investments in R&D have a higher demand for AI skills, and that job postings requiring AI skills within the same firm or job title have a wage premium of 11% and 5%, respectively. Managerial occupations have the highest wage premium for AI skills, and firms that demand AI skills more intensively also offer higher salaries in non-AI jobs.

The studies discussed previously, which underscore the labour-friendly traits of AI, provide the foundational basis for the formulation of the first hypothesis of this study. This hypothesis posits that AI could potentially lessen the likelihood of ER. There are several factors that contribute to this assumption, which need to be explored in detail. Firstly, the advent of AI has brought forth an array of applications that can simplify complex tasks across myriad occupations. This could lead to a significant reduction in workplace stress and fatigue, which are known factors contributing to ER decisions. Thus, the reduced workload, facilitated by AI, could encourage older employees to continue working longer than they might have otherwise. Secondly, AI can play an instrumental role in replacing physically demanding tasks, particularly pertinent for older workers who might struggle with the rigours of manual labour. AI-driven robots and machines can undertake these strenuous tasks, thus reducing the physical demands placed on older employees, which in turn could lower the incidences of work-related injuries and health problems, often cited as reasons for ER. Finally, the adoption of AI intersects significantly with the usage of home-based IT technologies. AI's facilitation of remote work - whether through sophisticated communication tools, project management applications, or cloud-based collaborative

platforms - can create a more accessible work environment for older workers. This flexibility is especially beneficial for those with mobility issues or those who prefer a work-life balance that conventional office environments might not offer (Dropkin et al. 2016). Consequently, these opportunities for continued employment could persuade older workers to delay their retirement.

Therefore, the first hypothesis of this study, rooted in the labour-friendly characteristics of AI, postulates that AI's potential to decrease workload, replace physically demanding tasks, and facilitate home-based IT work environments may reduce the likelihood of ER amongst older workers.

H1. *Workers facing a higher impact of AI in their current occupation are less likely to retire early.*

Capital-skill complementarity theory argues that unskilled workers are displaced by the combination formed by equipment capital and skilled workers (Griliches 1969; Krusell et al., 2000). This theory remains applicable in the context of the digital transformation with projected increases in employment in higher-skilled occupations in the face of technological advancements (Eder et al. 2022). Taking into account the consideration of ageing in the framework of the capital-skill complementarity assumption, Sachs and Kotlikoff (2012) present a simple framework in which smart machines substitute directly for young unskilled labour, whereas they are complementary to older skilled workers. This phenomenon of older, skilled workers complementing new capital devices has also been studied at the microeconomic level. Findings indicate that older employees who use a PC at work have a higher probability of remaining employed in the future (Biagi et al. 2013). Thus, computer users tend to retire later than non-users (Friedberg 2003). Additionally, there is a positive correlation between educational level and computer use (Schleife 2006).

In reinforcing this narrative, Aisa et al. (2023) provide a crucial examination of how automation and ageing intersect to affect older workers' participation in the workforce. They identify a significant skill mismatch arising from rapid advancements in automation, disproportionately impacting low-skilled older workers by accelerating their transition into retirement. Conversely, they underscore the unique position of highly skilled older workers, who not only are more likely to remain employed but also contribute valuably to further automation advancements.

In this line, Venti and Wise (2015) highlight the importance of education in shaping economic outcomes and the need to consider multiple pathways through which education influences retirement decisions by examining the relationship between education and ER using Social Security Disability Insurance (DI) and early claiming of Social Security retirement benefits data. They find that individuals with less than a high school degree are more likely to participate in DI and claim Social Security benefits early than those with a college degree or more.

Related to this fact, we can consider that workers with higher education are usually the workers performing the high paying jobs so we could also observe this phenomenon by targeting the financial situation instead of the education level. Radl (2012) explores ageism in the workplace, a form of discrimination against older employees that can hinder the extension of their professional careers, emphasizing the influence of social class on retirement age norms and observing that those from higher social classes often retire later due to factors such as improved work conditions, advanced

educational qualifications, and stronger financial security, which collectively enable them to prolong their working lives. Then, this fact of workers in higher social classes (generally, educated workers) having later retirement age norms goes hand-by-hand with the fact of technological progress raising the demand for educated workers (Autor et al. 1998).

The aforementioned literature relating education, skills and technological progress lead us to the proposition of the second hypothesis of this study stating that education plays a relevant role mediating in the relationship between AI and the ER probability. This hypothesis is consistent with the skill-biased technical change theory: unskilled workers are negatively impacted by technological progress while skilled workers benefit from it.

H2. *Education plays a mediating role in the relationship between AI and the likelihood of ER.*

3 Data

We construct our dataset upon three data levels. First, we use microdata as a baseline. Second, we merge occupation-level data collecting *AI advances* and *AI exposure* (Felten et al. 2018, 2021). Finally, we merge country-level data about GDP growth (World Bank), harmonized unemployment rate (Eurostat) and old-aged pensions in PPS per inhabitant (Eurostat).

Regarding the microeconomic baseline data, we use the SHARE⁵, a research infrastructure developed from 2004 until nowadays. This database, the largest pan-European social science panel study providing internationally comparable longitudinal micro data which allow insights in the fields of public health and socio-economic living conditions of European individuals, accounts for 480,000 in-depth interviews with 140,000 people aged 50 or older from 28 European countries and Israel. From its beginnings, SHARE has released 8 waves. This survey constitutes a baseline database to study retirement (and particularly ER) from economical and sociological aspects among others.

Our sample covers 118,979 observations (from 17,573 individuals) from 50 to 66 years in the period 2004–2016. The geographical coverage is formed by 24 European countries: Austria, Germany, Sweden, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Czech Republic, Poland, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Romania and Slovakia.

This sample is constructed taking as a baseline the Job Episodes Panel.⁶ Then, we merge extra variables from waves 1, 2, 4, 5, 6 and 7. These added variables include

⁵ The SHARE has become a standard database to analyse concrete aspect of retirement in recent years. Concretely, as a few examples of the use of this database to study ER we can mention Siegrist et al. (2007), who study the link between psychosocial quality and ER; Hochman and Lewin-Epstein (2013), who analyse the role of grandparenthood in the ER decision; Eder (2016), who study the impact of inheritances on the retirement behaviour; or Markova and Tosheva (2020), who focus on the exploration of determinants for the phenomenon in Bulgaria.

⁶ DOI: <https://doi.org/10.6103/SHARE.jep.710>. See Brugiavini et al. (2019) and Antonova et al. (2014) for methodological details.

information on physical health, financial status, and education. Finally, we add external information sources: the main explanatory variables at occupation level containing *AI advances* and *AI exposure* and macroeconomic controls at country level (GDP, unemployment rate and old-aged pensions in PPS per inhabitant).

3.1 Modelling approach

Our dependent variable (early retirement) takes value 1 when a worker decides to retire before his statutory retirement age and 0 when the individual remains working. Thus, given the binary nature of our dependent variable, we estimate the probability of ER using logit models and report average marginal effects.⁷

As main explanatory variables we consider two occupation-level variables measuring current advances and future expectations of AI impacts (*AI advances* and *AI exposure*) and a variable collecting 4 technological terrains regarding the AI current advances and future expected impacts at occupation level. Both main explanatory variables rely on the occupation-level measures provided by Felten et al. (2018, 2021)⁸ that are explained below as well as the process of construction of the *I-terrains* variable.

3.2 AI advances (Felten et al. 2018)

This variable collects the *AI advances* from 2010 to 2015 so it provides a measure for current degree of development of AI for each occupation. This measure fits with the ‘narrow’ definition of AI, in which AI refers to computer software that involves highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future (Broussard 2018). This ‘narrow’ definition of AI could be equated to some extent with Machine Learning.⁹

3.3 AI exposure (Felten et al. 2021)

For the development of this measure, the authors go in the opposite direction to that followed in the elaboration of the previous measure, by applying in this occasion a forward-looking approach. Concretely, they base this measure on the meaningful scientific progress in AI applications, covering the fundamental applications in which,

⁷ Our findings remain robust across various specifications of the variance-covariance matrix for the estimated parameters. Additionally, we assess the significance of the panel-level variance component through likelihood-ratio tests, which consistently indicate the suitability of employing the pooled estimator. To account for potential clustering effects, we calculate standard errors clustered at the individual level.

⁸ The AI variables have been obtained through a crosswalk between the Standard Occupational Classification (SOC-2010) and the International Standard Classification of Occupations (ISCO-2008) of the variables provided by Felten et al. (2018, 2021). Our research is not without limitations. One important limitation relies upon the assumption that the crosswalk between SOC-10 and ISCO-08 is perfect and the job content of an occupation in the US is the same as that of an occupation in any of the countries of our sample. This assumption has been made previously to adapt similar technological measures with the same source (see, for instance, Casas and Román 2023; Crowley et al. 2021; Haiss et al. 2021; Gardberg et al. 2020).

⁹ See Brynjolfsson and Mitchell (2017) and Brynjolfsson et al. (2018) for a discussion.

Table 1 Description of the AI variables

| Variable | Description |
|--|--|
| <i>AI advances</i> [Felten et al. 2018] | AI progress in the occupation from 2010 to 2015. Backward-looking vision of AI. |
| <i>AI exposure</i> [Felten et al. 2021] | Experts' estimation of AI potential in the forthcoming years. Forward-looking vision of AI. |

Table 2 Descriptive statistics of the AI variables

| | AI advances [Felten et al. 2018] | AI exposure [Felten et al. 2021] |
|------------------------|-------------------------------------|-------------------------------------|
| Mean | 3.437 | -0.005 |
| Median | 3.473 | -0.019 |
| Standard deviation | 0.648 | 0.945 |
| Minimum | 1.417 | -2.123 |
| Maximum | 5.294 | 1.446 |
| Number of observations | 424 | 424 |

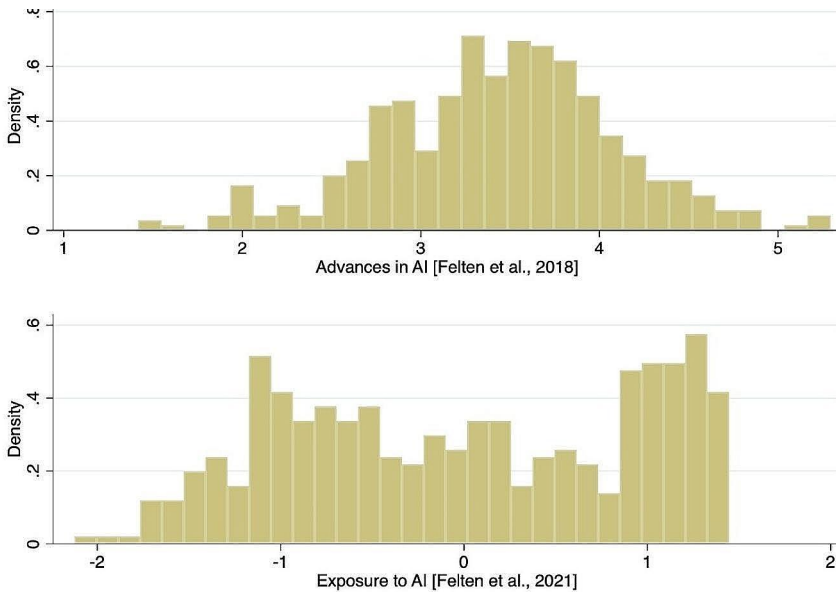


Fig. 1 Histograms of the AI variables

according to experts in the field, AI is likely to have implications for the workforce. Then, this measure fits the ‘general’ definition of AI, referring to computer software that can think and act on its own, which does not yet exist.

Table 1 collects a brief description of the AI variables, while Table 2 collects the descriptive statistics of these AI variables. As we can observe in Fig. 1, the variable

collecting AI advances presents a bell shape while the variable collecting AI exposure present a flat shape slightly close to a U-shape.

3.4 I-terrains

A possibility to collect together both current advances and future developments in AI in one variable is to perform a technological classification of occupations in *Intelligence terrains* that considers the *human-artificial intelligence* dichotomy depending on the degree of *AI advances* in the occupation and its exposure to future AI applications. From now on, we refer to this classification as the *I-terrains*, collected in Table 3. As we can see, this classification comprises 4 clearly differentiated occupational terrains, so we consider a variable that takes values from 1 to 4:

- 1. *HI terrain*: occupations with low effect of AI in current advances and exposure to future developments.
- 2. *Narrow AI definition*: occupations with high *AI advances* but low exposure to future developments.
- 3. *Future AI applications*: occupations with low current *AI advances* but high expectation of future developments.
- 4. *AI terrain*: occupations with both high advances of AI and exposure to new functionalities.

Our technological classification is inspired by the classification presented by Fossen and Sorgner (2019), which maps occupations considering the transformative and destructive sides of digitalization, equating transformative digitalization to AI and destructive digitalization to computerization. Our classification focuses on the analysis of transformative digitalization from a temporal perspective, considering both the current level of *AI advances* and the expectation of future developments.

We consider as control variables the main explicative variables covered by the ER literature. Starting from *age*, we also consider *gender*, *cohabiting situation*, *health status*, *financial situation*, *tertiary education*, *job status*, *contract type*, *sector*, *GDP growth*, *harmonised unemployment rate*, *the generosity of the social security system*. Below, we provide information about the characteristics of each control variable, as well as some references to previous studies in the literature where they have been considered for the analysis of ERs:

- *Gender* (see, for instance, Dahl et al. 2003): This is a binary variable taking value of 0 if the individual is male, 1 for females.
- *With partner* (see, for instance, Kubicek et al. 2010): Another binary variable tak-

Table 3 The technological classification of *I-terrains*

| | | AI advances [Felten et al. 2018] | |
|---|------|----------------------------------|---------------------------|
| | | Low | High |
| <i>AI exposure</i> [Felten et al. 2021] | High | Future AI applications (FA) | AI terrain (AIT) |
| | Low | HI terrain (HIT) | Narrow AI definition (ND) |

ing value of 1 if the individual is cohabiting, 0 otherwise.

- *Health* (see, for instance, Holtzman et al. 1980; Bazzoli 1985; Jones et al. 2010): Health status is measured in a range from 1 to 5: 1 poor, 2 fair, 3 good, 4 very good and 5 excellent.
- *Financial situation* (see, for instance, De Wind et al. 2014): The financial situation is collected as the ability to make ends meet in a 1 to 4 scale: 1 with great difficulty, 2 with some difficulty, 3 fairly easily and 4 easily.
- *Tertiary education* (see, for instance, Allel et al. 2021): Binary variable taking value of 1 if the individual accounts for higher education, 0 otherwise.
- *Job status* (see, for instance, Quinn 1977): The variable collecting the job status takes value of 1 for employees, 2 for civil servants and 3 for self-employees.
- *Contract type* (see, for instance, Livanos and Nunez 2017): This variable takes value 1 if the job was always full time, 0 otherwise.
- *Sector* (see, for instance, Kieran 2001): We use the basic classification in three separated industries: 1 Primary, 2 Manufacturing and Construction and 3 Services.
- *GDP growth* (see, for instance, Kim 2009): real GDP growth rate from the World Bank.
- *Harmonised unemployment rate* (see, for instance, Bould 1980; Laczko et al. 1988): in PPS per inhabitant from Eurostat.
- *The generosity of the social security system* (see, for instance, Blöndal and Scarpetta 1997; Blundell et al. 2002): in PPS per inhabitant from Eurostat.

4 Results

This section presents the main results obtained in this study. The results are presented in a three-part structure. In the first place, descriptive statistics are introduced along with a mapping of ER transitions considering the I-terrains. Second, the impacts of *AI advances* and *AI exposure* in the ER probability are analysed providing a special focus to education under the consideration of a mediating role. Finally, the *AI advances-exposure* interaction is explored considering the I-terrains and providing again insights regarding education.

4.1 Descriptive statistics and the mapping of ER transitions in I-terrains

The descriptive statistics are presented in Table A1 in the appendix, showing the differences between the total sample, the observations that concern the transitions to ER and the observations in which the transition does not occur. As we can observe, the mean of the AI exposure variable for the total sample is 0.04, while the mean of this variable is -0.03 for observations collecting a switch to ER and 0.04 for the rest of observations. Regarding the AI advances variable, the mean for the total sample is 3.32, while the mean of this variable is 3.31 for observations collecting a switch to ER and 3.33 for the rest of observations. Thus, first descriptive evidence clearly indicates that the AI advances and exposure on the occupations of early retirees are

less prominent than these effects on the occupations of individuals who do not end their working life early. This same effect can be observed for the variable collecting the I-terrains. The mean of this variable is 2.71 for observations that do not transition to ER, while it is 2.6 for observations that transition to ER. We can observe that the share of observations in the AI terrain switching to ER is lower compared with the share of observations in the AI terrain in the total sample and non-switching to ER. Complementary to this fact, the share of observations switching to ER in the HI terrain and the Narrow AI definition are higher.

In the statistics of the rest of the variables, we can observe the effects widely collected by the ER literature. For instance, in the observations regarding the transition to ER, we observe a higher proportion of individuals with simply fair or poor health, a higher proportion of civil servants, a lower proportion of self-employed workers, a higher percentage of individuals from the primary and secondary sectors, and lower GDP growth.

Figure 2 shows 6,358 transitions to ER from 393 different occupations. Each bubble represents an occupation, with its size indicating the number of ERs from that occupation, and its centre located at the point on the map determined by the occupation's degree of *AI advances* and its score for *AI exposure*. As we can observe, there are a large number of occupations both in the narrow AI terrain and in the AI terrain more broadly. Specifically, of the 393 occupations with transitions to ER, we find 137 in the narrow AI terrain and 159 in the AI terrain, indicating that 296 of the 393 occupations with transitions to ER present a high degree of progress in AI, while the remaining 97 present a low degree of progress in AI, with 60 of them belonging to the HI terrain. As expected, the terrain with the fewest number of occupations is that of future AI applications, which includes those occupations that currently have a low degree of progress in AI but have a high expectation of future AI development.

Table 4 complements the mapping of transitions to ER offered in Fig. 2, by listing the 30 occupations with the highest number of transitions to ER, ordered from highest to lowest according to the ratio of ERs to total number of workers. As we can see in Table 4, among these 30 occupations with the highest number of transitions to ER, we find 6 occupations in the HI terrain, 10 occupations in the narrow AI terrain, 5 in the terrain of future AI applications, and 9 in the AI terrain.

4.2 ER, AI advances, AI exposure and education

Table 5 shows the results of 5 logistic regression models with AI advances as the main regressor. Each model progressively adds more control variables, with the first estimation being the most parsimonious, considering only gender, age, cohabitation status, and country and year dummies. The second model adds health and financial situation controls. The third model adds education, while the fourth model adds labour variables (job status, type of contract, and industry), and the fifth model adds country-specific macroeconomic controls (GDP growth rate, unemployment rate, old-aged pensions in PPS per inhabitant). As we can see, the significance of progress in AI fades when we include the education control in the estimations from model 3 onwards. This indicates the possible mediating effect of education on the relationship between the probability of ER and the degree of progress in AI.

Similarly to Tables 5 and 6 presents the results of another 5 logistic regression models with an increasing number of controls, this time with AI exposure as the main explanatory variable. Although the effect of AI exposure on the probability of ER is significantly negative in all estimations, we observe a decrease in its significance once we introduce the education variable. Again, this suggests a possible mediating effect of education on the relationship between the probability of ER and *AI exposure*. Consequently, the mediating effect of education on the relationship between AI and the probability of ER would occur both when considering current progress in AI and future development expectations.

In order to further explore the mediating effect of education on the relationship between AI and the probability of ER, Fig. 3; Table 7 examine the interaction between education and AI variables. By including the interaction between *AI advances* and education in Model V, and between *AI exposure* and education in Model X, we observe that the negative effect of AI on the probability of ER is only significant for individuals with higher education. In both cases, the effect is not significant for individuals without higher education. This non-significant positive effect of the degree of *AI advances* for individuals without higher education negates the negative significance of ER probability in Model III.

4.3 ER and the AI advances-exposure interaction

Once we have concluded that the effect of AI on the probability of ER is significantly negative for individuals with higher education from both a retrospective view of current advances and a prospective view of potential impact, we move on to study the complete map by analysing the interaction between the degree of *AI advances* and expectations of future development. In order to do this, we use the technological classification in *I-terrains*. Given the relevant role that education has been shown to play, we also independently analyse how the degree of *AI advances* and *AI exposure* interact for individuals with and without higher education.

Table 8 presents five models with increasing order of control variables, analogously to Tables 5 and 6, with the difference that this time the *I-terrains* are presented as the main explanatory variable. We observe that, taking the *HI terrain* as a reference, only workers in the *AI terrain* have significantly lower probabilities of ER once we control for demographic characteristics, health and financial status. This indicates that both a high degree of *AI advances* and high *AI exposure* are needed for an occupation to experience a decrease in the probability of ER of its workers. In fact, the degree of *AI advances* affects the probability of ER of each occupation differently depending on the degree of *AI exposure* of that occupation. Similarly, the degree of *AI exposure* affects the probability of ER differently depending on the degree of *AI advances* that each occupation has experienced.

This interaction between the degree of *AI advances* and *AI exposure* can be seen in Fig. 4. The upper graph of Fig. 4 considers the effect of *AI exposure* on the probability of ER depending on the degree of *AI advances*, while the lower graph shows the effect of the degree of *AI advances* on the probability of ER depending on *AI exposure*. These graphs have been obtained from an estimation with all control variables considering the interaction between both variables.

Table 4 ER transitions and occupation titles

| ISCO-08 Title | ISCO-08 | #ER transitions | Total workers | Ratio:#ER/total workers | AI exposure | AI advances | I-terrains |
|---|---------|-----------------|---------------|-------------------------|-------------|-------------|------------|
| 1 Toolmakers and related workers | 7222 | 61 | 125 | 0.488 | -0.583 | 3.525 | ND |
| 2 Bricklayers and related workers | 7112 | 100 | 211 | 0.474 | -1.495 | 3.24 | ND |
| 3 Mail carriers and sorting clerks | 4412 | 57 | 128 | 0.445 | -0.909 | 2.736 | HIT |
| 4 Manufacturing labourers not elsewhere classified | 9329 | 62 | 143 | 0.434 | -1.362 | 2.888 | HIT |
| 5 Agricultural and industrial machinery mechanics and repairers | 7233 | 77 | 181 | 0.425 | -1.047 | 4.026 | ND |
| 6 Motor vehicle mechanics and repairers | 7231 | 67 | 162 | 0.414 | -0.939 | 3.614 | ND |
| 7 Electrical mechanics and fitters | 7412 | 54 | 137 | 0.394 | -0.761 | 3.833 | ND |
| 8 Secondary education teachers | 2330 | 115 | 297 | 0.387 | 1.191 | 3.601 | AIT |
| 9 Heavy truck and lorry drivers | 8332 | 94 | 252 | 0.373 | -0.501 | 3.791 | ND |
| 10 Secretaries (general) | 4120 | 99 | 267 | 0.371 | 1.099 | 2.58 | FA |
| 11 Vocational education teachers | 2320 | 56 | 151 | 0.371 | 0.352 | 3.528 | AIT |
| 12 Accounting and bookkeeping clerks | 4311 | 61 | 168 | 0.363 | 1.186 | 2.588 | FA |
| 13 General office clerks | 4110 | 236 | 659 | 0.358 | 1.238 | 2.58 | FA |
| 14 Shopkeepers | 5221 | 92 | 260 | 0.354 | 0.575 | 3.352 | AIT |
| 15 Freight handlers | 9333 | 68 | 193 | 0.352 | -0.923 | 3.518 | ND |
| 16 Primary school teachers | 2341 | 109 | 324 | 0.336 | 1.087 | 3.6 | AIT |
| 17 Accounting associate professionals | 3313 | 104 | 310 | 0.335 | 1.04 | 2.848 | FA |
| 18 Cleaners and helpers in offices, hotels and other establishments | 9112 | 123 | 380 | 0.324 | -1.516 | 1.915 | HIT |
| 19 Car, taxi and van drivers | 8322 | 66 | 209 | 0.316 | -0.633 | 3.461 | ND |

Table 4 (continued)

| ISCO-08 Title | ISCO-08 | #ER transitions | Total workers | Ratio:#ER/total workers | AI exposure | AI advances | I-terrains |
|---|---------|-----------------|---------------|-------------------------|-------------|-------------|------------|
| 20 Managing directors and chief executives | 1120 | 67 | 220 | 0.305 | 0.954 | 3.797 | AIT |
| 21 Accountants | 2411 | 58 | 192 | 0.302 | 1.426 | 3.295 | AIT |
| 22 Administrative and executive secretaries | 3343 | 55 | 184 | 0.299 | 0.957 | 2.843 | FA |
| 23 Shop sales assistants | 5223 | 159 | 547 | 0.291 | -0.016 | 3.071 | ND |
| 24 University and higher education teachers | 2310 | 63 | 218 | 0.289 | 1.24 | 3.401 | AIT |
| 25 Cooks | 5120 | 78 | 274 | 0.285 | -0.603 | 2.965 | HIT |
| 26 Subsistence crop farmers | 6310 | 61 | 214 | 0.285 | -1.601 | 2.747 | HIT |
| 27 Nursing professionals | 2221 | 108 | 391 | 0.276 | 0.22 | 4.484 | AIT |
| 28 Domestic cleaners and helpers | 9111 | 54 | 199 | 0.271 | -1.481 | 1.849 | HIT |
| 29 Health care assistants | 5321 | 74 | 286 | 0.259 | -0.701 | 3.045 | ND |
| 30 Child care workers | 5311 | 67 | 278 | 0.241 | 0.024 | 3.355 | AIT |

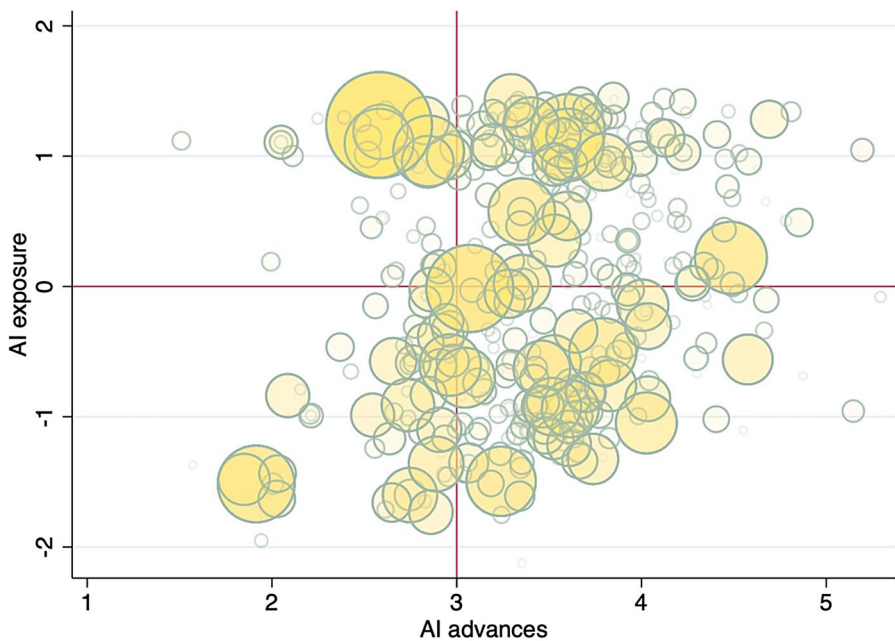


Fig. 2 ER transitions and *I*-terrains. *Note:* Compiled by the authors from the SHARE data, this figure visualizes each occupation as a bubble, where the bubble's size indicates the number of early retirements from that occupation

As we can observe, *AI exposure* significantly increases the probability of ER when the degree of *AI advances* is less than 2.4, while it significantly decreases the probability of ER when the degree of advances is greater than 3.1. On the other hand, we observe that the degree of *AI advances* significantly increases the probability of ER when the *AI exposure* variable takes a value less than -0.4 , while it significantly decreases the probability of ER when the *AI exposure* variable takes values above 0.5. Therefore, the effect of AI on ER depends on the degree of advances and exposure, requiring a high impact of both variables for a significant decrease to occur. Additionally, when one variable takes a value below a certain threshold, the other variable has a significant positive effect on the probability of ER.

Figure 5 shows the effect that the interaction between the degree of advances and the degree of *AI exposure* has on the probability of ER. As we can see in the figure, each point in the interaction between the degree of advances and the degree of *AI exposure* results in a specific probability of ER, thus creating a graph in the form of contour lines in which the probability of ER varies depending on the area observed. As we can see in the graph labels, this interaction between the degree of *AI advances* and *exposure* to the interstitial interest is nothing more than our proposal of *I*-terrains. Therefore, we divide the graph into four sections determined by the threshold values of both variables and name each region according to the corresponding *I*-terrain.

As we deduced in Fig. 4, the probability of ER is affected by the interaction between both AI variables at the extremes of the graph presented in Fig. 5. Specifically, in the lower-left corner and the upper-right corner, we observe lower prob-

Table 5 Determinants of the ER transitions with special focus on *AI advances* – Logit estimations

| Model | I | II | III | IV | V |
|--|-------------------|-------------------|-------------------|-------------------|-------------------|
| Predicted probability (y) | 0.0534 | 0.0534 | 0.0534 | 0.0534 | 0.0534 |
| Independent variables (x) | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ |
| <i>Main regressors</i> | | | | | |
| AI advances | -5.61 | -2.92*** | 2.36 | -0.06 | -0.05 |
| <i>Controls</i> | | | | | |
| Female ^a | 35.99 | 14.16*** | 39.18 | 15.25*** | 45.80 |
| Age | 34.87 | 72.95*** | 34.90 | 72.98*** | 35.25 |
| With partner ^a | 9.37 | 3.44*** | 9.14 | 3.36*** | 10.10 |
| Health (ref. Excellent) | | | | | |
| Very good | | 7.53 | 7.53 | 7.99 | 8.04 |
| Good | | 21.29 | 19.18 | 5.09*** | 19.34 |
| Fair | | 37.20 | 33.63 | 7.65*** | 33.41 |
| Poor | | 65.67 | 60.38 | 8.11*** | 61.73 |
| Ability to make ends meet (ref. With great difficulty) | | | | | |
| With some difficulty | | 8.48 | 8.99 | 1.97** | 7.88 |
| Fairly easy | | 0.18 | 2.96 | 0.65 | 2.55 |
| Easily | | -0.69 | 5.34 | 1.11 | 4.24 |
| <i>Education</i> | | | | | |
| Tertiary educationa | | | -30.62 | -11.83*** | -31.02 |
| <i>Job characteristics</i> | | | | | |
| Job status (ref. Employee) | | | | | |
| Civil servant | | | | 17.43 | 17.08 |
| Self-employed | | | | -32.50 | -32.52 |
| Full time ^a | | | | 27.16 | 27.14 |
| Sector (ref. Primary) | | | | | |
| Manufacturing and Construction | | | | 3.32 | 3.15 |
| Services | | | | -15.96 | -16.34 |
| | | | | | 0.65 |
| | | | | | -3.56*** |
| | | | | | -11.89*** |
| | | | | | 5.90*** |
| | | | | | -10.03*** |
| | | | | | 8.49*** |

Table 5 (continued)

| Model | I | II | III | IV | V |
|---------------------------------|-----------|-----------|-----------|---------|--------------|
| <i>Macroeconomic variables</i> | | | | | |
| GDP growth | | | | | -0.60 -1.06 |
| Harmonised unemployment rate | | | | | 2.50 5.38*** |
| Old age pensions pps per capita | | | | | 0.02 1.58 |
| Country dummies (ref. Spain) | Yes | Yes | Yes | Yes | Yes |
| Wave dummies (ref. 2004) | Yes | Yes | Yes | Yes | Yes |
| Log likelihood | -19,026.1 | -18,938.9 | -18,873.3 | -18,740 | -18,721.3 |
| #obs | 118,979 | 118,979 | 118,979 | 118,979 | 118,979 |

Note * $0.1 > p \geq 0.05$; ** $0.05 > p \geq 0.01$; *** $p < 0.01$. a Dummy variable.

Table 6 Determinants of the ER transitions with special focus on *AI exposure* – Logit estimations

| Model | VI | VII | VIII | IX | X |
|---|-------------------|-------------------|-------------------|-------------------|-------------------|
| Predicted probability (y) | 0.0534 | 0.0534 | 0.0534 | 0.0534 | 0.0534 |
| Independent variables (x) | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ | $\frac{dy}{dx}\%$ |
| <i>Main regressors</i> | | | | | |
| AI exposure | -9.89 | -8.06*** | -2.69 | -2.02** | -1.84* |
| <i>Controls</i> | | | | | |
| Female ^a | 41.05 | 16.31*** | 39.13 | 15.57*** | 46.46 |
| Age | 34.96 | 73.17*** | 34.91 | 72.97*** | 35.26 |
| With partner ^a | 9.66 | 3.55*** | 9.24 | 3.39*** | 10.20 |
| <i>Health (ref. Excellent)</i> | | | | | |
| Very good | | 7.55 | 1.95* | 1.92* | 2.04** |
| Good | | 20.17 | 5.37*** | 4.99*** | 18.95 |
| Fair | | 35.25 | 8.03*** | 7.49*** | 32.94 |
| Poor | | 63.48 | 8.46*** | 8.04*** | 60.84 |
| <i>Ability to make ends meet (ref. With great difficulty)</i> | | | | | |
| With some difficulty | | 9.58 | 2.08** | 2.11** | 7.61 |
| Fairly easy | | 2.59 | 0.56 | 0.88 | 2.58 |
| Easily | | 2.94 | 0.61 | 1.43 | 4.80 |
| <i>Education</i> | | | | | |
| Tertiary educationa | | | -27.96 | -10.35*** | -29.26 |
| <i>Job characteristics</i> | | | | | |
| Job status (ref. Employee) | | | | | |
| Civil servant | | | | 17.57 | 6.11*** |
| Self-employed | | | | -32.53 | -10.10*** |
| Full time ^a | | | | 27.53 | 8.64*** |
| <i>Sector (ref. Primary)</i> | | | | | |
| Manufacturing and Construction | | | | 3.84 | 0.80 |
| Services | | | | -14.50 | -3.21*** |
| | | | | | 3.71 |
| | | | | | -14.80 |
| | | | | | -3.26*** |
| | | | | | -10.87*** |
| | | | | | 17.23 |
| | | | | | 5.99*** |
| | | | | | -32.55 |
| | | | | | -10.09*** |
| | | | | | 27.53 |
| | | | | | 8.62*** |
| | | | | | 0.77 |

Table 6 (continued)

| Model | VI | VII | VIII | IX | X |
|---------------------------------|-----------|-----------|-----------|-----------|-----------|
| <i>Macroeconomic variables</i> | | | | | |
| GDP growth | | | | | -0.60 |
| Harmonised unemployment rate | | | | | -1.05 |
| Old age pensions pps per capita | | | | | 2.52 |
| Country dummies (ref. Spain) | Yes | Yes | Yes | Yes | 5.41*** |
| Wave dummies (ref. 2004) | Yes | Yes | Yes | Yes | 1.58 |
| Log likelihood | -18,996,9 | -18,921.7 | -18,871.9 | -18,738.3 | -18,719.5 |
| #obs | 118,979 | 118,979 | 118,979 | 118,979 | 118,979 |

Note * $0.1 > p \geq 0.05$; ** $0.05 > p \geq 0.01$; *** $p < 0.01$. a Dummy variable.

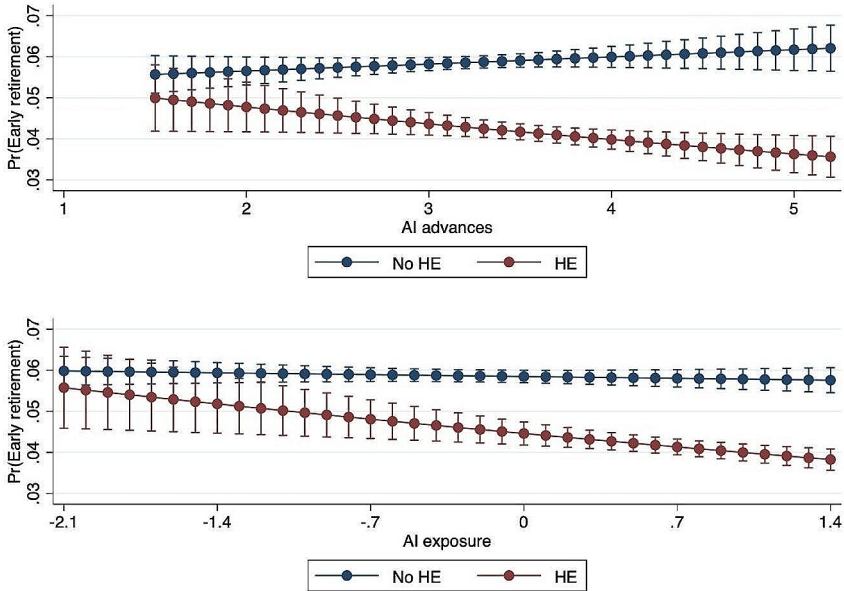


Fig. 3 ER probability, AI and education. Note: HE refers to Higher Education

Table 7 Predicted ER probability, AI and education

| Education | Marginal effect of AI | | | |
|--------------------------|-----------------------|--------|--------|----------|
| | No HE | | HE | |
| | dy/dx | z-stat | dy/dx | z-stat |
| AI advances ^a | 0.0017 | 1.29 | -0.004 | -2.25** |
| AI exposure ^b | -0.0006 | -0.76 | -0.005 | -3.10*** |

Note ^a Predicted probabilities and marginal effects are from a model similar to model V in Table 6 but including interaction term between AI advances and higher education dummy

^b Predicted probabilities and marginal effects are from a model similar to model X in Table 7 but including interaction term between high AI exposure and higher education dummy

HE refers to Higher Education

abilities of ER. That is, the lowest probabilities of ER occur when both variables coincide at their extremes, that is, either the degree of AI advances and the position are low, or both variables take high values. This decrease in the probability of ER is significantly greater when both variables take values above determined thresholds, as corroborated by Table 8, where we observe that the probability of ER in the AI terrain is significantly lower than the probability of ER in the HI terrain once we control for demographic characteristics, health and financial status.

Conversely, we observe the highest probabilities of ER in the upper-left and lower-right corners of the graph, where high values of one variable interact with low values of the other. More specifically, the highest probabilities of ER are found in the lower-right corner. This suggests that these higher probabilities of ER occur in situations

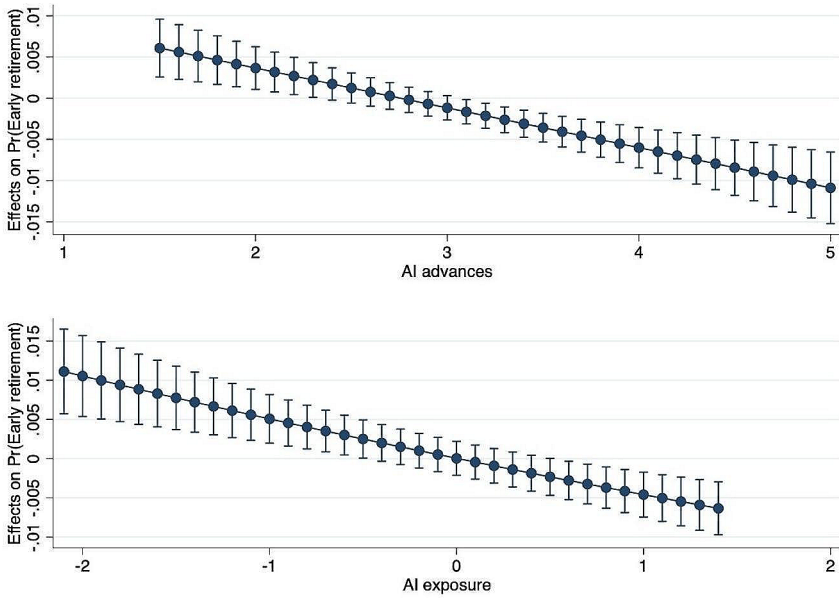


Fig. 4 Interaction between *AI advances* and *AI exposure*

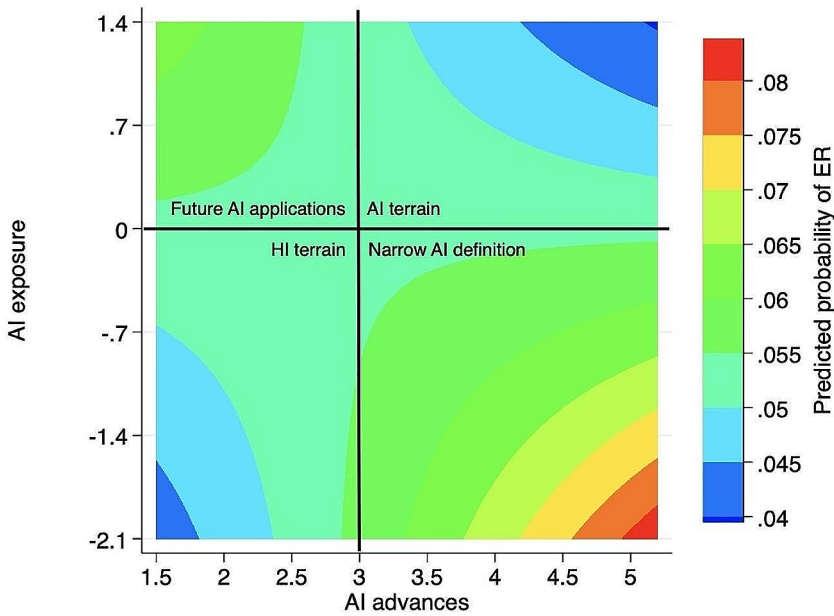


Fig. 5 ER probability and AI advances-exposure interaction

Table 8 Determinants of the ER transitions with special focus on the *I-terrains* – Logit estimations

| Model | XI | XII | XIII | XIV | XV |
|--|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Predicted probability (y) | 0.0534 | 0.0534 | 0.0534 | 0.0534 | 0.0534 |
| Independent variables (x) | $\frac{dy}{dx} \cdot \%$ | $\frac{dy}{dx} \cdot \%$ | $\frac{dy}{dx} \cdot \%$ | $\frac{dy}{dx} \cdot \%$ | $\frac{dy}{dx} \cdot \%$ |
| <i>Main regressors</i> | | | | | |
| I-terrains (ref. HI terrain) | | | | | |
| Narrow AI definition | 0.14 | 0.96 | 1.37 | 0.39 | -1.01 |
| Future AI applications | -9.81 | -2.28** | -2.06 | -0.49 | -5.50 |
| AI terrain | -25.18 | -7.25*** | -10.03 | -2.77*** | -12.45 |
| <i>Controls</i> | | | | | |
| Female ^a | 39.96 | 15.36*** | 39.16 | 15.06*** | 46.34 |
| Age | 34.98 | 73.15*** | 34.92 | 73.01*** | 35.28 |
| With partner ^a | 9.36 | 3.44*** | 9.09 | 3.34*** | 10.11 |
| Health (ref. Excellent) | | | | | |
| Very good | | 7.84 | 2.02** | 1.95* | 8.06 |
| Good | | 20.27 | 5.38*** | 4.98*** | 18.87 |
| Fair | | 35.12 | 7.99*** | 7.47*** | 32.68 |
| Poor | | 62.91 | 8.39*** | 8.01*** | 60.44 |
| Ability to make ends meet (ref. With great difficulty) | | | | | |
| With some difficulty | | 9.43 | 2.05** | 2.12** | 8.30 |
| Fairly easily | | 2.79 | 0.61 | 0.92 | 3.59 |
| Easily | | 4.00 | 0.83 | 1.55 | 5.97 |
| <i>Education</i> | | | | | |
| Tertiary educationa | | | -25.63 | -9.25*** | -26.79 |
| <i>Job characteristics</i> | | | | | |
| Job status (ref. Employee) | | | | | |
| Civil servant | | | | 18.33 | 6.21*** |
| Self-employed | | | | -32.24 | -9.97*** |
| Full time ^a | | | | 27.72 | 8.72*** |
| | | | | | 27.71 |
| | | | | | 8.69*** |
| | | | | | -9.63*** |
| | | | | | 1.24 |
| | | | | | 0.79 |
| | | | | | 1.83* |
| | | | | | 5.03*** |
| | | | | | 7.46*** |
| | | | | | 8.14*** |
| | | | | | 3.74*** |
| | | | | | 2.06** |
| | | | | | 2.05** |
| | | | | | 5*** |
| | | | | | 7.45*** |
| | | | | | 8.09*** |
| | | | | | 16.38*** |
| | | | | | 73.67*** |
| | | | | | 3.84*** |
| | | | | | 3.74*** |
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Table 8 (continued)

| Model | XI | XII | XIII | XIV | XV |
|---------------------------------|-----------|-----------|-----------|-----------|-----------|
| Sector (ref. Primary) | | | | 4.54 | 0.95 |
| Manufacturing and Construction | | | | -13.57 | -3.02*** |
| Services | | | | | -13.90 |
| <i>Macroeconomic variables</i> | | | | | -3.08*** |
| GDP growth | | | | | -0.59 |
| Harmonised unemployment rate | | | | | 2.51 |
| | | | | | *** |
| Old age pensions pps per capita | | | | | 0.02 |
| Country dummies (ref. Spain) | Yes | Yes | Yes | Yes | Yes |
| Wave dummies (ref. 2004) | Yes | Yes | Yes | Yes | Yes |
| Log likelihood | -18,978.8 | -18,906.1 | -18,866.2 | -18,731.5 | -18,712.8 |
| #obs | 118,979 | 118,979 | 118,979 | 118,979 | 118,979 |

Note * 0.1 > p ≥ 0.05; ** 0.05 > p ≥ 0.01; *** p < 0.01. ^a Dummy variable

where an occupation is highly impacted by AI advances but associated with low AI exposure. This observation underscores the significance of future AI development expectations when analysing the impact of the current degree of AI advances on a given occupation, particularly given AI's status as an emerging technology.

4.4 ER, the AI advances-exposure interaction and education

The interaction between the degree of *AI advances* and *AI exposure* varies depending on education, as shown in Fig. 6. For workers with higher education, the degree of *AI advances* has a significant negative effect on the probability of ER for *AI exposure* values greater than 0.5 (bottom-right graph), while *AI exposure* has a significant negative effect when the degree of *AI advances* is higher than 3 (up-right graph). For workers without higher education, the degree of *AI advances* has a significant positive effect on the probability of ER for *AI exposure* values less than -0.4 and a significant negative effect for *AI exposure* values greater than 1.1 (bottom-left graph). On the other hand, *AI exposure* has a significant positive effect when the degree of *AI advances* takes values less than 2.3, while having a significant negative effect when the degree of *AI advances* takes values greater than 3.2 (up-left graph).

Continuing with the findings presented in Fig. 6, we can see that the interaction between advancements and *AI exposure* has different effects on the likelihood of ER depending on whether individuals have a higher education degree or not. Figure 7 reproduces the graph presented in Fig. 5, disaggregating individuals with and without higher education degrees. As we can observe, the top graph shows how the interaction between the degree of advancement and *AI exposure* affects the likelihood of ER for individuals with a higher education degree, while the bottom graph shows the effect of the same interaction on the likelihood of ER for individuals without a higher education degree.

In both graphs in Fig. 7, we can see the same effects discussed in Fig. 5. That is, the lower likelihoods of ER are found in the corners where low values of both variables or high values of both variables, while the highest values in the likelihood of ER occur in the corners where we find high values of a variable and low values of the other variable. Although this pattern is observed in both graphs, we can clearly see that it has a different impact depending on whether individuals have a higher education degree or not.

Specifically, the likelihood of ER is lower for individuals with a higher education degree when low or high values coincide for both the degree of advancement and exposure to AI. On the other hand, the likelihood of ER is higher for individuals without a higher education degree when we find low values of *AI advances* and high values of *AI exposure* or viceversa. That is, for individuals with a higher education degree, the likelihood of ER is lower in the bottom-left and top-right corners of the graph, while for individuals without a higher education degree, the likelihoods of ER are higher in the top-left and bottom-right corners of the graph if we consider a reference value for the ER probability around 0.05.

Before we move onto the conclusions of this study, it is critical that we assess the validity of our initial hypotheses in light of the results presented. The first hypothesis, denoted as H1, postulates that workers facing significant AI impacts in their current

occupations are less likely to opt for ER. From our analysis, we observe this hypothesis holds true under specific conditions - particularly, when the worker's occupation experiences both a high degree of AI advances and high AI exposure. This suggests that AI's potential to augment jobs and enhance productivity can indeed influence retirement decisions. However, if the extent of AI advances or AI exposure is insufficient, H1 may not remain valid. In such scenarios, the likelihood of ER may rise, influenced by the intricate interplay of AI advances, AI exposure, and unique worker characteristics.

The second hypothesis, H2, indicates that education plays a pivotal role in mediating the relationship between AI and the likelihood of ER. According to H2, the educational level of workers can equip them with necessary skills to adapt to AI-driven changes in the workplace, which may influence their retirement decisions. The data presented in Fig. 3 and 6, and 7, as well as Table 7, substantiate the validity of H2. These findings imply that well-educated workers are better positioned to navigate AI-induced changes, thereby reducing their inclination towards ER. This validation highlights the significance of continuous learning and skills development in the era of AI. We will delve deeper into these findings and their implications in the concluding section of this study.

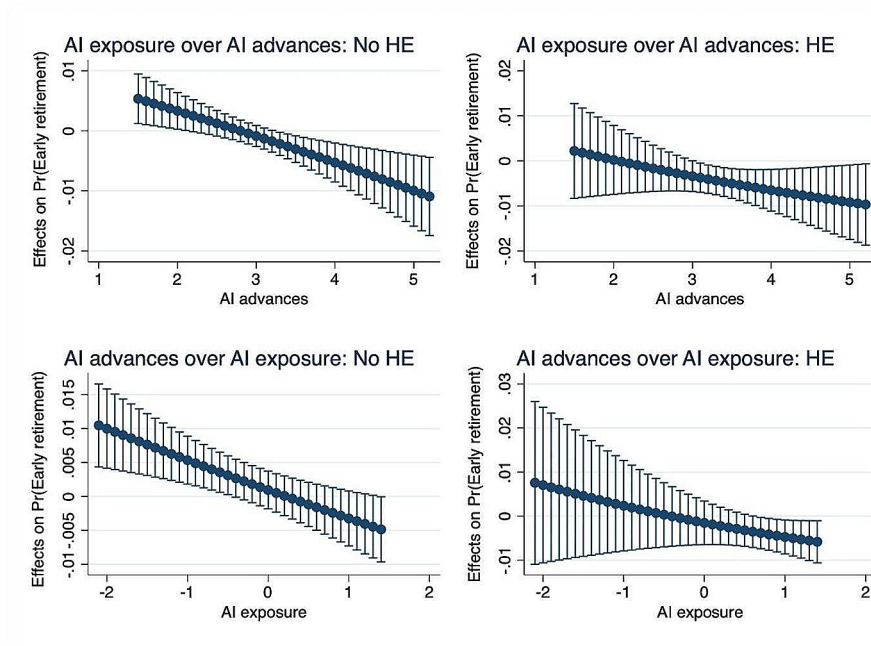


Fig. 6 Interaction between *AI advances* and *AI exposure* at different education levels. *Note:* HE refers to Higher Education

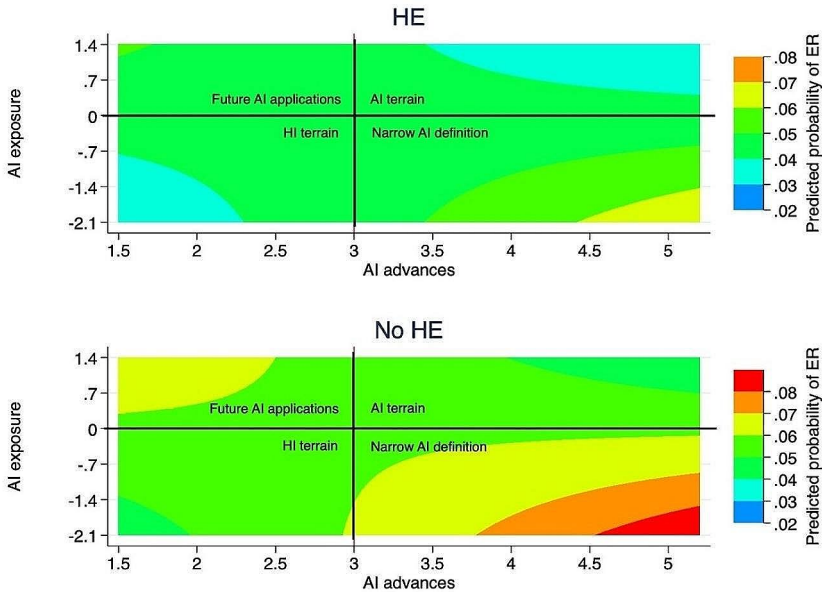


Fig. 7 ER probability, *AI advances-exposure interaction* and education. Note: HE refers to Higher Education

5 Conclusions

This paper examines the implications of Artificial Intelligence (AI) on early retirement (ER) decisions in Europe. To carry out this analysis, we base our research on the Survey of Health, Ageing and Retirement in Europe (SHARE). We incorporate a variable that represents current *AI advances* (Felten et al. 2018) as a retrospective view of AI, and another variable that represents *AI exposure* (Felten et al. 2021) as a prospective view of AI. We then scrutinise the interaction between *AI advances* and *AI exposure* in relation to the probability of ER, paying special attention to the mediating effect of education. To enhance the comprehensibility of our findings regarding the interaction between *AI advances* and *exposure*, we propose a classification of occupations into four intelligence domains. These domains reflect the suitability of occupations for either human or artificial intelligence, integrating both the retrospective and prospective views of AI through the variables of AI advances and AI exposure respectively.

We find that occupations characterized by high levels of *AI advances* and high levels of *AI exposure* are associated with a significant reduction in the probability of remaining in the workforce, both for individuals with higher education and those without. However, when these conditions are not present, the impact of AI on the probability of ER depends on whether or not the individual has a higher education degree.

Specifically, when we examine the impact of AI on retirement probabilities taking into account a continuous variable that measures the level of *AI advances* in each occupation, we observe that the current level of *AI advances* has a significant impact in reducing the probability of ER only for individuals with higher education degrees. In fact, for individuals without a higher education degree, the level of *AI advances* leads to a non-significant increase in the probability of ER, which causes this variable to have no significant effect when considering the entire sample. Similarly, when we examine the impact of AI on retirement probabilities taking into account a continuous variable that measures *AI exposure*, we observe that such *AI exposure* has a significant impact in reducing the probability of ER only for individuals with higher education degrees. In the case of individuals without a higher education degree, the impact is in the same direction, reducing the probability of ER, but is not significant.

Moreover, the interaction between the level of *AI advances* and *AI exposure* is particularly relevant since the impact of AI on the ER probability depends on both the current degree of advances and the expectations of future development. An augmentation in the level of *AI advances* may increase or decrease the probability of ER, depending on the degree of *AI exposure* in the occupation. The same effect is observed in the opposite direction, indicating that an increase in *AI exposure* may increase or decrease the probability of ER, depending on the current level of *AI advances*.

The analysis of the AI advances-exposure interaction reveals that, in order to find a significant ER probability reduction from *AI advances*, a high *AI exposure* is needed. For a scenario in which there are high *AI advances* in an occupation but low expectancy of further development, there are not sufficient incentives to maintain a worker away from ER and the “wage effect” of the technological change (Ahituv and Zeira 2011) would not be enough to prevent the worker from taking the ER decision. On the other hand, if we consider an occupation with low *AI advances* but high expectations of future developments, these incentives to keep the worker facing the development of this new technology are reduced since this worker does not have experience in this regard and it would be more efficient for this performance to be carried out by younger workers with a broader work horizon. Therefore, the incentives for workers to keep working longer in order to take advantage of the transformative side of the technological change are only significant in the scenario in which this worker is already experienced with AI (the occupation considered has experienced high *AI advances*) and there is high expectation of further AI implementations.

As AI continues to transform industries and workplaces, older workers may face unique challenges and opportunities. On the one hand, older workers may have more difficulty adapting to new technologies and may be at risk of being left behind as the job market evolves. On the other hand, older workers may have valuable skills and experience that can be leveraged in new ways with the help of AI. For instance, AI can assist older workers with tasks that may be physically demanding or require a high degree of precision. Additionally, older workers may have a wealth of institutional knowledge and problem-solving skills that can be combined with AI to drive innovation and improve business outcomes. However, it will be important for organizations to provide training and support for older workers to ensure they are equipped with the skills needed to work effectively with AI.

Tertiary education can play a critical role in helping older workers acquire the knowledge and skills they need to work effectively with AI and finding ways to add value in areas where AI cannot yet replace human judgment and creativity. This may involve retraining programs, continuing education courses, or even pursuing entirely new degree programs that are more relevant to the changing job market. At the same time, there is a need for educational institutions to adapt their curricula and teaching methods to better prepare students for the AI-driven future of work. This may involve incorporating AI-related topics into existing courses or even developing entirely new courses that focus specifically on AI and its applications in different industries.

While the effect of destructive digitalization on ER decisions has been addressed in the literature (Casas and Román 2023) and this paper focuses on studying the implications of transformative digitalization for the ER decision, future research is required to analyse the net impact of digitalization as a whole. This encompasses both its destructive and transformative elements in the spirit of Fossen and Sorgner (2019), aiming to provide a clear and complete picture of the full effects of digitalization on ER depending on the characteristics of older workers. Such comprehensive analysis is pivotal for understanding the aggregate impact of technological advancements on the workforce, enabling policymakers, educators, and industry leaders to craft strategies that maximize the benefits of digitalization while mitigating its potential drawbacks. Exploring these dynamics further will not only extend the discourse initiated by our current study but will also contribute valuable insights to the evolving field of AI, work, and retirement.

6 Appendix

Table A1 Descriptive statistics

| | Total sample | Switching to ER (S) | Non switching to ER (NS) | | | |
|------------------------|------------------------|------------------------|--------------------------|--------|-------|--|
| #obs. (#ind.) | 118,979 (17,573) | 6,358 (6,357) | 112,621 (17,002) | | | |
| Variable | Mean (S.D. overall) | Mean (S.D. overall) | Mean (S.D. overall) | Min | Max | Difference of means NS-S ^a |
| <i>AI exposure</i> | 0.04 (0.96) | -0.03 (0.97) | 0.04 (0.96) | -2.123 | 1.446 | 0.08*** |
| <i>AI advances</i> | 3.32 (0.63) | 3.31 (0.62) | 3.33 (0.63) | 1.509 | 5.294 | 0.02** |
| <i>I-terrains</i> | 2.7 (1.15) | 2.6 (1.13) | 2.71 (1.15) | 1 | 4 | 0.11*** |
| HI terrain | 17.76 | 19.03 | 17.68 | 0 | 1 | -1.34*** |
| Narrow AI definition | 31.46 | 34.74 | 31.27 | 0 | 1 | -3.5*** |
| Future AI applications | 13.24 | 13.38 | 13.23 | 0 | 1 | -0.15 |

Table A1 Descriptive statistics

| | Total sample | Switching to ER (S) | Non switching to ER (NS) | | | |
|---------------------------------|-------------------|---------------------|--------------------------|-------|---------|----------|
| AI terrain | 37.54 | 32.84 | 37.81 | 0 | 1 | 4.97*** |
| Female | 0.514 | 0.483 | 0.516 | 0 | 1 | 0.03*** |
| Age | 55.4 (3.58) | 59.2 (3.29) | 55.2 (3.47) | 50 | 66 | -4.05*** |
| With partner | 0.799 | 0.807 | 0.799 | 0 | 1 | -0.01 |
| Health | 2.8 (1.01) | 3.0 (1.02) | 2.8 (1.01) | 1 | 5 | -0.21*** |
| Excellent | 10.88 | 8.04 | 11.04 | 0 | 1 | 3*** |
| Very good | 23.78 | 19.28 | 24.04 | 0 | 1 | 4.75*** |
| Good | 40.39 | 40.83 | 40.36 | 0 | 1 | -0.47 |
| Fair | 20.60 | 25.01 | 20.35 | 0 | 1 | -4.66*** |
| Poor | 4.35 | 6.84 | 4.21 | 0 | 1 | -2.63*** |
| Ability to make ends meet | 2.9 (0.97) | 2.9 (0.97) | 2.9 (0.97) | 1 | 4 | 0.03*** |
| With great difficulty | 8.91 | 8.89 | 8.91 | 0 | 1 | 0.03 |
| With some difficulty | 26.89 | 28.61 | 26.79 | 0 | 1 | -1.82*** |
| Fairly easily | 31.08 | 30.94 | 31.09 | 0 | 1 | 0.15 |
| Easily | 33.12 | 31.57 | 33.21 | 0 | 1 | 1.64*** |
| Tertiary education | 0.301 | 0.233 | 0.305 | 0 | 1 | 0.07*** |
| Job status | | | | | | |
| Employee | 52.51 | 50.39 | 52.63 | 0 | 1 | 2.23*** |
| Civil servant | 36.77 | 40.59 | 36.55 | 0 | 1 | -4.04*** |
| Self-employed worker | 10.73 | 9.01 | 10.82 | 0 | 1 | 1.81*** |
| Full time | 0.87 | 0.90 | 0.87 | 0 | 1 | -0.03*** |
| Sector | | | | | | |
| Primary | 8.12 | 9.30 | 8.05 | 0 | 1 | 1.24*** |
| Manufacturing and Construction | 24.17 | 28.48 | 23.92 | 0 | 1 | -4.56*** |
| Services | 67.71 | 62.22 | 68.02 | 0 | 1 | 5.80*** |
| GDP growth | 1.96 (3.42) | 1.70 (3.57) | 1.97 (3.41) | -14.8 | 11.9 | 0.27*** |
| Harmonised unemployment rate | 8.82 (4.38) | 8.81 (4.63) | 8.82 (4.36) | 2.9 | 27.5 | 0.01 |
| Old age pensions pps per capita | 2041.4 (889.4) | 2001.6 (851.1) | 2043.7 (891.5) | 504.7 | 3,929.8 | 42.11*** |

Note ^a Tests of equality of means between observations not switching to early retirement (NS) and observations switching to early retirement (S); Ho: Mean (NS) – Mean (S)=0; * 0.1 > p ≥ 0.05; ** 0.05 > p ≥ 0.01; *** p < 0.01

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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