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Artificial intelligence: Redefining the retirement pattern

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ABSTRACT

An endogenous economic growth model is developed, where the decisions to use artificial intelligences (AIs) in the workplace and to extend working life are endogenous and interdependent. There are four sources of heterogeneity among workers: differences in initial productivity, variations in the aging process, restricted access to jobs with AI investment, and uneven impact of AIs among those who have access. It is shown that those who do not use AIs in their jobs maintain a traditional pattern of retirement, with the most educated and/or healthy among them extending their working lives. In contrast, the retirement pattern for AI-using workers changes, and it is the users who derive the most benefit from AIs who will extend their working lives. This is because AIs compensate for the skills that tend to deteriorate with age, thus allowing for greater permanence in the labour market.

1. Introduction

In recent years, the number of research papers on the economic impact of new technologies linked to artificial intelligence (AIs) has grown exponentially (Qin et al., 2024). One of the most discussed aspects is their impact on employment and wages. As is usual, there are conflicting opinions, and the debate remains open. The lack of consensus is due to both the high degree of uncertainty about the evolution of this technology and its applications, as well as what the forthcoming training and employment policies will be (Aghion et al., 2019; Agrawal et al., 2019). Another issue is the lack of sufficiently high-quality data, which constitutes a barrier to accurately measuring the impact of AIs on the labour market (Frank et al., 2019). Well-written literature reviews include Lu and Zou (2021) and Abrardi et al. (2022).

On the one hand, the economic literature establishes that AIs have engendered what is called intelligent automation, which reduces the costs of implementation and maintenance compared to traditional automation (von Garrel and Jahn, 2023). In addition to cost reduction, the emergence of machines equipped with AIs is providing greater flexibility and adaptability. Acemoglu and Johnson (2023) add that companies and their managers are more inclined to use intelligent machines in order to avoid possible claims for wage improvements and better working conditions. Consequently, intelligent automation is fueling workers' fears of being displaced to lower-paying jobs, or even being pushed out of the labour market.

On the other hand, previous technological changes have also led to similar fears about high unemployment rates and low wages, fears that have not materialized. The reason is that while jobs are made redundant, others emerge linked to new products and services. The question is, if this time too, the destroyed positions are being reinstated and at what pace. The evidence is not conclusive, although it could be that the rate of new job creation does not compensate for the intensification in automation (Autor et al., 2022). In this perspective, Acemoglu et al. (2023) advise that a more economically desirable path would be to promote AIs complementary to work,

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identifying the fields of education and health, along with vocational professions such as construction trades and general maintenance, as suitable candidates.

Indeed, the complementarity between AIs and humans in business is gaining significant importance (Raisch and Krakowski, 2021). This complementarity is fueled by the fact that AIs provide large volumes of useful information very quickly, which substantially improves human decision-making (Agrawal et al., 2019; Acemoglu, 2024). Additionally, tasks automated by AIs are freeing up time for other tasks that require human intervention, such as process control or closer communication with customers. By allowing for improved productivity, Ernst et al. (2018) note that AIs improve the wages of those who use them.

The literature also lacks consensus on which type of workers are most affected, positively or negatively, by AIs. Lu and Zhou (2021) and Autor (2024) argue that the ability of AIs to endow machines with "intelligence" allows them to replace skilled workers, although empirical evidence does not detect that the employment of this type of workers has fallen (Lane, 2024). One reason is that the most qualified are precisely those who have access to AI-related jobs and hence, improvements in their productivity through AIs (Grant and Üngör, 2024). Another factor to consider is age. Using the European survey on health, aging, and retirement (SHARE), between the period 2004–2016, Casas and Román (2024) find that those skilled workers most exposed to AIs both now and in the future are the most likely to extend their working lives. This work advances in this line, analyzing how the collaboration between AIs and workers influences the retirement decision. An endogenous economic growth model is constructed in which the decisions to use or not use AIs in the workplace and to extend or not extend working life are endogenous and interrelate among themselves.

In this framework, workers are not homogenous, being four sources of heterogeneity. Firstly, workers are endowed with different initial productivity levels, reflecting that not everyone starts with the same educational level. Second, those initially endowed with lower productivity do not have access to jobs in which companies invest in AIs. Those with a higher initial productivity level do have access, but they must make an additional learning effort to adapt to the specific AIs in which the company invests. In return, the use of these AIs increases their productivity, although not everyone benefits equally from their use, which constitutes the third source of heterogeneity. We assume that those with an "intermediate" initial productivity level are the ones who benefit the most from using AIs in their work. Lastly, the deterioration in productivity due to aging differs among workers.

The model shows a gap between workers whose initial training allows them to opt for jobs in which companies invest in AIs and those who do not. Workers with a lower initial productivity level do not use the AIs because the companies do not make them available to them. As a result, the decision to extend their working life follows the patterns prior to the appearance of AIs. Those more educated and healthier are the ones who extend their working lives, as they suffer less deterioration associated with age and, therefore, a smaller decline in productivity linked to age. Workers with higher initial productivity levels do use AIs, first because they can, since the companies they work for undertake the necessary investments, and second because they want to, since the salary increase from using specific AIs in their job compensates for the learning effort. Artificial intelligence is reshaping workforce dynamics by supporting skills that typically decline with age (Cai and Stoyanov, 2016). This technological assistance enables workers to maintain their productivity more effectively, potentially allowing them to extend their professional careers beyond traditional expectations.

The structure of the article is as follows. Section 2 presents the framework. Section 3 identifies which measures can make AI users and non-users extend their working lives, and the last section closes with the conclusions obtained.

2. Framework

2.1. Production

There is a single productive sector that employs three types of production factors: capital exclusively formed by AIs, AI-using workers, and non-AI-using workers. The capital in the form of AIs is denoted as K and captures the investments in AIs made by the company. For instance, the investment in developing an algorithm to analyse databases on the behaviour of current and potential customers, generating strategic information for the company constitutes a type of capital (Corrado et al., 2021). The other two production factors are linked to labour input, distinguishing two categories of workers: those who use AIs in executing their tasks, U, and those who do not, N. We consider that AIs can increase labour productivity by taking on repetitive tasks, allowing workers who use them to focus on higher value-added activities, and by generating valuable strategic information for decision-making. However, investment in AIs in a company does not guarantee that all workers in that company will adopt and use them. Following the previous example, although the company invests in an algorithm to analyse databases, this AI-formed capital will be used by some workers and not by others, depending on the tasks assigned to each employee and/or their training. Therefore, the production function of the economy in period t, Y_t, is given by:

$$Y_t = K_t^{\alpha}(A_t U_t)^{1-\alpha} + BN_t^{1-\alpha}, \tag{1}$$

where A_t (B) is the productivity index of workers who use (do not use) AIs in their work tasks. It is considered that the productivity of workers who do not use AIs is constant, while the level of productivity of workers who use AIs depends on the productivity generated by the total of these workers, $\overline{U}$, in such a way that:

$$A_t = f(\overline{U}_{t-1})A_{t-1}, \tag{2}$$

with $f' > 0$, $f'' < 0$, $\lim_{\overline{U}\to\infty} f' = 0$ and $f(0) > 1$, in order to guarantee that $A_t \geq A_{t-1} \geq A, \forall t$ (Hashimoto and Tabata, 2010). We denote $A_0 = A$ as the level of productivity in the initial period that is considered as given. This specification presents two characteristics. Firstly, it is quasi-labour augmenting (Prettner and Strulik, 2020), in such a way that investments in AIs complement exclusively the workers who use them, but not the workers who do not use them. Secondly, the existence of positive externalities associated with the number of AI-using workers is assumed, such that the networks formed by AI users add an extra positive effect (Anthony et al., 2023). Consequently, this positive externality is the engine of growth in this model.

It is considered that the economy is relatively small and open, so that capital moves freely and the interest rate r is determined by the international market. Under perfect competition, the optimal value of the production factors is given by:

$$\frac{\partial Y_t}{\partial K_t} = \alpha \widehat{k}_t^{\alpha-1} = r, \tag{3}$$

$$\frac{\partial Y_t}{\partial U_t} = (1-\alpha)\widehat{k}_t^{\alpha} A_t = w_{u,t}, \tag{4}$$

$$\frac{\partial Y_t}{\partial N_t} = (1-\alpha)N_t^{-\alpha} = w_{n,t}, \tag{5}$$

where $w_{u,t}$ is the wage rate of the workers who employ (do not employ) AIs and $\widehat{k}_t = \frac{K_t}{A_t U_t}$. The free mobility of capital implies that the capital-to-total productivity ratio of AI-using workers is constant, $\widehat{k}_t = \widehat{k}$

2.2. Households

The economy adopts an overlapping generations model so that in each period t a new generation is born, normalized to size 1. Each individual's life consists of two stages or periods[1]: the stage as a young adult or first period, during which the individual always works, and the stage as an older adult or second period, during which the individual may choose to continue working or retire. At the beginning of the first period, individuals are not homogenous and each one is endowed with an initial individual productivity level, θ_i. It is assumed that this initial productivity level follows a continuous uniform distribution over the interval $(0,1)$. There is a correlation between the initial productivity level and the performance of tasks that can be assisted by AI. Specifically, those individuals with an initial productivity level lower than $\underline{\theta}$ perform tasks in which AIs cannot assist them, while those with an initial productivity level above $\underline{\theta}$ can be assisted by AIs, with $\underline{\theta}$ being a given parameter. There are two explanations for why AIs are not effective and/or efficient for certain workers. The first explanation relates to the characteristics of the tasks linked to the job. The second reason is that initial training may constitute a barrier to the use of AIs. For example, consider an unskilled worker in the caregiving sector. Many of the tasks inherent to their job, such as feeding and cleaning dependent people, are unlikely to be performed by AIs[2]. At the same time, this worker may have an initial training barrier to using AIs in their daily activities if they are not familiar with using computers. By contrast, in the same caregiving sector, a skilled worker does not have this initial training barrier to using AIs, and several of their tasks, such as recording all interventions and medications received by the dependent, can be performed by AIs, drastically reducing the possibility of human errors.

It should be noted that these workers with higher initial training, who can potentially benefit from AIs in their workplace, need specific additional training. It is assumed that this learning takes place during work time, so it does not have an opportunity cost in terms of time, but it does entail a loss of utility due to the extra effort required for this worker to learn to use specific AIs while continuing with their job tasks. In other words, the availability of AIs that assist the worker in their duties does not mean that this worker will automatically use them. Consequently, in the first period, workers decide whether to adopt the use of AIs in their work tasks or not. Additionally, and to keep the model as stylized as possible, it is considered that the price for AI investments incorporates the price for the training offered to workers. That is, r includes the cost of investing in AIs plus the cost of training provided to potential workers who can use them.

In the second period, workers decide whether to retire or continue working. It is assumed that there is a probability of being alive during the second period, $1-p$. Continuing to work in this second period provides additional income but also implies an opportunity cost by giving up the leisure associated with retirement.

The utility function of a representative individual from generation t is given by[3]:

$$EU\left(c_{i,t}^{y}, c_{i,t+1}^{o}, u_{i,t}, e_{i,t+1}\right) = c_{i,t}^{y}(1-\lambda)^{u_{i,t}} {c_{i,t+1}^{o}}^{\beta(1-p)} (1-\xi)^{e_{i,t+1}\beta(1-p)}, \tag{6}$$

where $c_{i,t}^{y}$ and $c_{i,t+1}^{o}$ are the consumption levels of the individual in the first (young adult) and second (older adult) period, $u_{i,t}$ takes the

[1] A third stage might be introduced in which everybody is retired. This does not change the outcomes but it adds more complexity to the framework.

[2] Robotarm My Spoon is an example of robot which can assist dependent people. However, its price and its limited functions makes it no suitable to be adopted massively by care service sector.

[3] This utiliy function is a monotonous increasing transformation of $\ln\left(c_{i,t}^{y}\right) + u_{i,t}\ln(1-\lambda) + \beta(1-p)\left[\ln\left(c_{i,t+1}^{o}\right) + e_{i,t+1}\ln(1-\xi)\right]$.

value 1 if she opts to use AIs and 0 if not, and $e_{i,t+1}$ takes the value 1 if she opts to extend her working life and 0 if she decides to retire. The parameters λ and ξ reflect the loss of utility due to the effort to learn to use AI technologies[4] in the first period and by forgoing the pleasures of increased leisure time in the second period, respectively. The parameter β is the consumption discount rate. As usual, it is assumed that the effective consumption discount rate is less than 1, $\beta(1-p) < 1$.

The constraints faced by an individual from generation t are given by:

$$c^y_{i,t} + s_{i,t} = w_{i,t}\theta^y_{i,t}, \tag{7}$$

$$c^o_{i,t+1} = Rs_{i,t} + w_{i,t+1}\theta^o_i e_{i,t+1}. \tag{8}$$

$s_{i,t}$ denotes saving, $w_{i,t}$ is the wage rate that can take two values w_u or w_n, depending on whether the worker uses AIs in their workplace or not, and R is the effective return on their savings. For simplicity, there are no bequests, but there is a perfect insurance market so that $R = \frac{1+r}{1-p}$ (Blanchard, 1985). Finally, $\theta^y_{i,t}$ and θ^o_i represent the individual productivity levels as a young adult and as an older adult, respectively, which adopt the following functional forms:

$$\theta^y_i = \theta_i + \eta(1-\theta_i)\left(\theta_i - \underline{\theta}\right)u_{i,t}, \tag{9}$$

$$\theta^o_i = \delta_h\theta_i + \eta(1-\theta_i)\left(\theta_i - \underline{\theta}\right)u_{i,t}. \tag{10}$$

Eqs. (9) and (10) reflect that the productivity level of each individual has two components: human and artificial. The intrinsically human component corresponds to the traditional concept of human capital (education and health). During the first period, it takes the value of the initial productivity θ_i, and during the second period, it takes the value $\delta_h\theta_i$, with $0 < \delta_h < 1$, which captures the drop in initial productivity as a result of biological deterioration linked to age.

The artificial component is provided by the use of AIs, increasing the productivity of the workers. This model assumes that AIs increase labour productivity, according to several empirical papers. For instance, Damioli et al. (2021), find that the use of AIs significantly increases labour productivity from a global sample of 5257 companies for 2000–2016 period. Czarnitzki et al. (2023) extend this analysis by incorporating several types of AIs and differentiating between companies that develop their AIs and companies that acquire AIs developed by other companies, reaching the same positive conclusion in terms of productivity. However, they use panel data from a single country and a short period of time. Genz et al. (2021) provide further evidence that new technologies, including AIs, increase productivity and, therefore, are associated with wage growth, predominantly benefiting workers in technological fields and vocational professions. Focusing on specific occupations, Peng et al. (2023) demonstrate that GitHub Copilot can significantly increase the productivity of programmers. It must be noted that productivity gains from the use of AIs are not homogenous for all workers, and it appears that the most favoured are not the most productive (Noy and Zhang, 2023; Brynjolfsson et al., 2023). Specifically, Eqs. (9) and (10) reflect that the productivity increase from the use of AIs takes the form of an inverted U for those with an initial productivity level between $[\underline{\theta}, 1]$, with η being a scale parameter.

Another source of heterogeneity in workers is that biological deterioration does not have a uniform character. It is considered that the human component of productivity that the individual retains during the second period, once the biological deterioration is accounted for, adopts the following functional form:

$$\begin{aligned} &\delta_h = \sigma(1-p) + (1-\sigma)\theta_i^{\psi}, \quad &\theta_i \le \underline{\theta}, \\ &\delta_h = (1-p), &\theta_i > \underline{\theta}, \end{aligned} \tag{11}$$

with $0 < \sigma < 1$ and $0 < \psi < 1$. It is assumed that the probability of being alive in the second period $1-p$ is also an indicator of individual health. Logically, if a higher probability of living in the second period means that the individual reaches this period with better health, it is reasonable to think that the level of productivity upon reaching this second period will be higher. On the other hand, it is undeniable that the characteristics of the job impact the degree of biological deterioration. Especially hard jobs involve a greater accumulation of health deficits and decrease productivity at work as the worker ages (Majchrowska and Broniatowska, 2019; Strulik, 2022). These health deficits linked to job are not present among those whose use AIs. For example, collaborative robots, or co-robots, which combine robotics and AIs, can perform these tasks, increasing the productivity of the workers who employ them (Ranasinghe et al., 2025). It is considered that individuals with an initial productivity level less than or equal to $\underline{\theta}$ perform “health-deterioration” tasks, while individuals with an initial productivity level greater than $\underline{\theta}$ perform "health-neutrally" tasks. This specification reflects a certain parallelism with the health differential between white-collar and blue-collar workers (Case and Deaton, 2005). The parameter ψ reflects that the worsening in health intrinsically linked to the tasks performed at work is assumed to be less for those who have a relatively higher initial productivity level. The parameter σ assesses the weights that health related to the individual and health linked to the occupation performed have in the level of productivity that the individual maintains in the second period.

Appendix 1 presents the solution of the individual problem. The optimal levels of individual consumption and savings are, respectively:

[4] An additional loss of utility could have been introduced, associated with a potential need for an update in the use of AI in the second period, due to more technological advancements. Qualitatively, the results remain unchanged.

$$c^y_{i,t} = \frac{1}{1+\beta(1-p)}\left(w_{i,t}\theta^y_i + w_{i,t+1}\theta^o_i e_{i,t+1}\right), \tag{12}$$

$$c^o_{i,t+1} = \frac{R\beta(1-p)}{1+\beta(1-p)}\left(w_{i,t}\theta^y_i + w_{i,t+1}\theta^o_i e_{i,t+1}\right), \tag{13}$$

$$s_{i,t} = \frac{\beta(1-p)}{1+\beta(1-p)}w_{i,t}\theta^y_i - \frac{1}{1+\beta(1-p)}w_{i,t+1}\theta^o_i e_{i,t+1}. \tag{14}$$

These optimal values are conditioned on the dichotomous decisions to adopt AIs in work tasks and extend working life. Table 1 captures the expected utilities for each option, with $\Gamma = R^{\beta(1-p)}\beta^{\beta(1-p)}(1-p)^{\beta(1-p)}$. Note that those who use AIs in their work tasks in the first period and extend their working life will continue to use them in the second period without any added loss of utility in this second period. Appendix 2 lists the parameters and variables of the framework.

3. Results

The equilibrium in the goods and labor markets is presented in the following propositions.

Proposition 3.1

The number of non-AI-using workers in each period is constant and equal to $N = \underline{\theta} + (1-p)(\underline{\theta} - \widetilde{\theta})$, where $\widetilde{\theta} = \frac{1}{(1-\sigma)}[(1-\Xi)-\sigma(1-p)]^{\frac{1}{\psi}}$, $\Xi = (1-\xi)^{\frac{\beta(1-p)}{1+\beta(1-p)}}$, if the following conditions are fulfilled:

(i) The initial investment in AIs is sufficiently high such that $K_0 > \frac{1-N_0}{N_0}\left(\frac{1}{\Lambda A}\right)^{\frac{1}{\alpha}}$, with $N_0 > 0$ and $\Lambda = (1-\lambda)^{\frac{\beta(1-p)}{1+\beta(1-p)}}$.

(ii) The parameter ξ, which reflects the loss of utility due to not enjoying leisure associated with retirement, is bounded such that $[1-\sigma(1-p)] > \Xi > [1-(1-\sigma)^{\psi}\underline{\theta}^{\psi} - \sigma(1-p)]$.

The proof of Proposition 3.1 is included in Appendix 3.

Proposition 3.2.

The number of AI-using workers in each period is constant and equal to $U = (1-\underline{\theta}) + (1-p)(\overline{\theta} - \widetilde{\theta})$, where $\widetilde{\theta}$ and $\overline{\theta}$are endogenous productivity levels solutions to the second-degree equation:

$$\frac{(1-\theta_i)\left(\theta_i - \underline{\theta}\right)}{\theta_i} = \frac{1}{\eta}\frac{(\Xi^{-1}-1) - f(\overline{U})(1-p)}{f(\overline{U}) - (\Xi^{-1}-1)},$$

where $\overline{U}$ is the productivity level of this group of workers, given by:$\overline{U} = \int_{\underline{\theta}}^{1}[\theta_i + \eta(1-\theta_i)(\theta_i - \underline{\theta})]di + (1-p)\int_{\widetilde{\theta}}^{\overline{\theta}}[(1-p)\theta_i + \eta(1-\theta_i)(\theta_i - \underline{\theta})]di$,and only if conditions (i) and (ii) outlined in Proposition 3.1 are met and the parameter η is sufficiently large such that $1 + \underline{\theta} - \frac{(\Xi^{-1}-1) - f(\overline{U})(1-p)}{\eta[f(\overline{U}) - (\Xi^{-1}-1)]} > 0$.

The proof of Proposition 3.2 is included in Appendix 4.

Proposition 3.3.

In equilibrium, the economy and the wage rate for AI-using workers grow at a positive and constant rate $f(\overline{U})$, while the wage rate for non-AI-using workers remains constant, provided that conditions (i) and (ii) outlined in Proposition 3.1 are met.

The proof of Proposition 3.3 is included in Appendix 5.

Fig. 1 illustrates the group of workers who adopt or do not adopt AIs, and among them, who choose to extend or not extend their working lives.

The economic explanation for each of these results is outlined below. Firstly, this framework reveals that all workers who can potentially benefit from AIs, either due to their initial training or the characteristics of their job, will use them. The rationale is based on condition (i). This condition stipulates that the initial capital in the form of AI investments must be sufficiently high, such that the wage

Table 1
Expected utilities based on individual decision to adopt AI and extend working life or retire.

	Extend Working Life l	Retire
No AI Adoption	$EU\left(c^y_{i,t}, c^o_{i,t+1}, 0, 1\right) = \Gamma(1-\xi)^{\beta(1-p)}$ $\{w_{n,t}\theta_i + w_{n,t+1}[\sigma(1-p) + (1-\sigma)\theta^{\psi}_i]\theta_i\}^{1+\beta(1-p)}$.(15)	$EU\left(c^y_{i,t}, c^o_{i,t+1}, 0, 0\right) = \Gamma\left(w_{n,t}\theta_i\right)^{1+\beta(1-p)}$.(16)
AI Adoption	$EU\left(c^y_{i,t}, c^o_{i,t+1}, 1, 1\right) = \Gamma(1-\lambda)(1-\xi)^{\beta(1-p)}$ $\{w_{u,t}[\theta_i + \eta(1-\theta_i)(\theta_i - \underline{\theta})] + w_{u,t+1}[(1-p)\theta_i + \eta(1-\theta_i)(\theta_i - \underline{\theta})]\}^{1+\beta(1-p)}$.(17)	$EU\left(c^y_{i,t}, c^o_{i,t+1}, 1, 0\right) =$ $= \Gamma(1-\lambda)\left(w_{u,t}[\theta_i + \eta(1-\theta_i)(\theta_i - \underline{\theta})]\right)^{1+\beta(1-p)}$.(18)

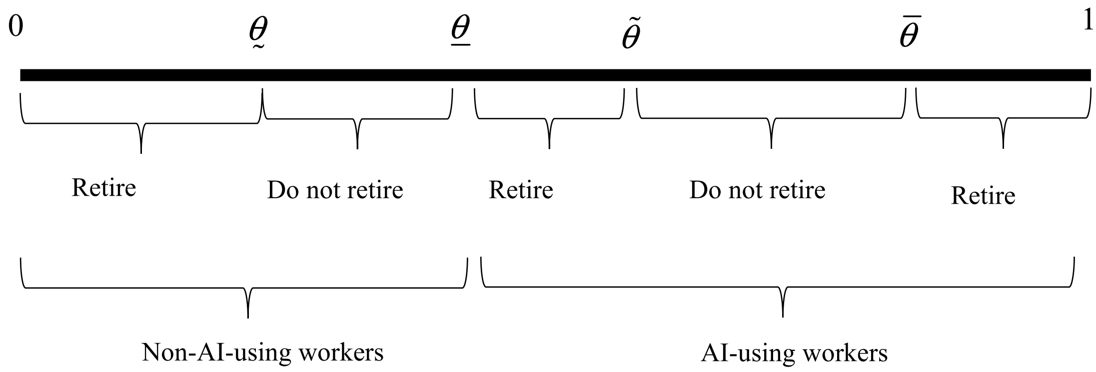

Fig. 1. Endogenous retirement and work continuation decisions among AI users and non-users.

gap between those who use and those who do not use AIs is large enough to compensate the former for their learning effort. The wage rate of AI users positively depends on the capital invested in AIs, while the wage rate of non-users is independent of it. The higher the level of AI investment in the company, the greater the gap between the wage rates of AI users and non-users. With a sufficiently large initial aggregate AI capital, the initial wage gap offsets the loss of utility due to the effort of learning. Since $A_t \geq A_{t-1} \geq A, \forall t$, this initial labour gap can be constant or increase but never decrease.

Secondly, an initial productivity level below $\underline{\theta}$ constitutes an overwhelming barrier for workers, excluding them from using AIs, either due to their initial training or because they access job positions not equipped with AIs. Condition (ii) ensures that a proportion of these workers will opt to extend their working lives. Specifically, it is the workers in this group with higher initial productivity who will prolong their working lives, because they occupy less health-damaging job positions, thus the productivity they maintain in the second period is relatively greater. This result aligns with previous literature which indicates that the more educated and healthier individuals are those who prolong their working lives (Nagarajan and Sixsmith, 2023).

Thirdly, AIs induce a change among their users in terms of who prolongs their working lives. Through productivity linked to the exclusively human component, the initial level of productivity that AI users maintain in the second period is the same for all, as it has been assumed that individual health $1 - p$ is the same for all workers and the occupations performed by AI-using workers are health-neutrally. Through productivity provided by AIs, this contribution is not identical for all AI users, but is greater for those in the middle part of the initial productivity distribution, i.e., around $\frac{\theta+1}{2}$. These workers, while not initially the most productive, are those who will prolong their working lives, because AIs provide them with greater productivity throughout their working lives, and therefore, the wage income from continuing to work will more significantly offset the loss of utility due to the leisure they forego.

Finally, since the growth engine depends on the size of the AI users' network, economies whose productive and/or educational structures are such that $\underline{\theta}$ is low, will grow faster than economies with productive and/or educational structures where most of their workers cannot benefit from AIs, either because they occupy job positions in which AIs are not sufficiently productive for companies to invest in them or because their initial level of training is such that they lack sufficient digital competencies.

This work is close to Ahituv and Zeira (2011), who identify the wage effect as the push effect that the increase in wages, due to new technologies, has on workers to continue working, and the erosion effect as the brake effect due to the effort of adjusting to these new technologies. These authors note that the workers most affected by technological change and who are older are the ones who retire earlier, because their working lives are short and they no longer have time to adjust to the new technologies. Like these authors, this model captures both the wage incentive and the adjusting effort disincentive. Unlike them, we identify a shift in the retirement pattern between AI users and non-users. Another near work is Casas and Román (2024), who distinguish between the current impact of AIs and expectations about their future impact. They observe that skilled workers and those in jobs exposed to AIs, who expect the future impact of AIs to be high, significantly reduce their chances of retiring at earlier ages. Workers prolong their working lives if AIs benefit them now and in the future. Our work completes the argument: workers whose jobs or initial training prevent them from benefiting from AIs in the present will not be able to offset the loss of productivity associated with age in the future with the extra "artificial" productivity provided by AIs. Workers who can benefit from AIs in the present will also be able to offset the loss of productivity in the future with the extra "artificial" productivity provided by AIs. Skills such as reasoning, spatial visualization, memory, and processing speed decrease with age (Salthouse, 2010), but AIs precisely provide these skills. Consequently, it can be inferred that the retirement pattern will change for AI users and those who benefit the most from them will have greater incentives to prolong their working lives. It is reasonable to think that workers in technological, educational, and healthcare sectors, and interestingly, those with vocational training, who currently benefit the most from AIs (Genz et al., 2021; Acemoglu et al., 2023) will have longer working lives in the future.

Shifting the focus to policy considerations, AIs seem to permeate everything in developed countries, but this is not the case for all workers. The importance of training in AIs is reiterated, both in initial education and in lifelong learning, to ensure that new technologies extend their presence. While the more workers use AIs, the greater the boost these will provide to the growth of economies, there will always be another group of workers covering jobs in which investments in AIs will not be undertaken simply because they are not profitable for the company. Occupations characterized by extensive human interaction—encompassing care work (including household management, childcare, elder support, and dependent assistance), hospitality services (spanning hotels, restaurants, bars, and cafés), and agricultural roles with limited technological automation—will continue to rely heavily on human workers. These workers will be outside the AI training circuit and what matters to various administrations and governments is to ensure their health at work, in order to prolong their working lives and reduce pension expenditure as these workers age. Facilitating good health in the workplace is crucial for this group of workers.

In occupations in which AIs are useful from a technological point of view, it is not enough that companies invest in them and offer training to workers on their time. The wages of potential AI-using workers must improve enough to compensate them for the effort of learning their use. When administrations encourage technological training throughout the working life, they must ensure that the increases in income derived from producing more and/or better are sufficient to compensate the companies for the costs of investing in such technology, training workers, and providing additional remuneration to them. If not, companies will not invest in AIs in spite of their technical feasibility. If these costs do not fall, companies will not invest in AIs and the threshold $\underline{\theta}$ will not lessen. The economy will grow at a faster rate only in those countries that introduce effective measures to lower the costs associated with investing in AIs, training in AIs, and remunerating AI users. Some of the costs may be temporary, such as those for training, but the investment costs in AIs (companies often pay a subscription fee to developers for the maintenance of and updates to AIs) and the additional remuneration to AI-using workers will be prolonged over time. Nevertheless, as the technology continues to advance, the greater the productivity provided by these AIs to workers of younger and older ages (higher η), the greater the number of AI users among those who could use them, and the greater the economic growth.

The model has several limitations. It is assumed that among those who perform tasks that can be assisted by AIs, the most favoured are those who are at an intermediate level of productivity, and not the most productive. Although there is some research pointing in this direction, the current evidence is not conclusive. As research specifies the typology of workers whose productivity increases most through the use of AIs, alternative specifications can be included. Another limitation is that it is assumed that AIs complement the labour factor and do not replace it. The incorporation of AIs that replace workers, no matter if highly qualified or not, will act to push these workers to shorten their working lives (Włoch et al., 2025). It is also not taken into account that companies are not homogenous. Large (and technological) companies have access to a greater amount of data from their clients than small companies, so that this data, conveniently transformed into useful information by AIs, gives them a comparative advantage over small companies and therefore, greater market power (Mihet and Philippon, 2019). Finally, it is assumed that the productivity provided by AIs is the same in the first and second periods, but this is not the case. Ranasinghe et al. (2025) analyse the collaboration between autonomous robots and workers of different ages, finding that although the speed of task execution increases in both groups, it is higher among the younger ones. Incorporating this bias does not change the qualitative results of the model. However, administrations concerned about the increase in the pension bill should take note of this bias and promote the development of AIs that improve the productivity of older workers (Bogataj et al., 2019).

4. Conclusions

The theoretical framework analysed establishes that all workers who can benefit from the use of AIs will adopt them if the increase in their wage compensation outweighs the effort of learning. This occurs when the investment in AIs and the salaries of those who use AIs are positively related. However, those with low initial productivity face a barrier that prevents them from accessing jobs that incorporate AIs, either due to their lack of initial training or because their positions do not justify the corporate investment in this technology. In this context, these workers will maintain the traditional retirement pattern, with the most educated and healthy among them extending their working lives. Conversely, the decision to prolong working life does not follow these patterns among AI-using workers. Those who increase their productivity the most through the use of AIs are the ones who will decide to extend their working lives. This points to workers in the education, health, and technology sectors, as well as workers with vocational training, as those more predisposed to longer working lives in the AI era.

Administrations must design policies that take into account this heterogeneity. Firstly, while initial and ongoing training programs in AIs are essential to expand their use, the effectiveness of these programs might be scarce in certain sectors (for example, care and hospitality) where investments by companies in AIs are not profitable. In these cases, it is a priority to enhance health programs at work to prolong the working lives of these workers and reduce pension expenditure. Secondly, the profitability of investing in AIs by companies depends on their ability to offset the costs of implementation, training, and wage improvement for the workers who adopt them. The productivity generated by AIs must be sufficient to justify these investments. Administrations should support companies by subsidizing these costs, and in return, companies should adequately remunerate AI-using workers if they want them to train and extend their working lives. Thirdly, although administrations should promote the development of AIs that complement workers of any age, they should particularly encourage those that complement older workers in the ever-increasing growth of today's aging population.

CRediT authorship contribution statement

Rosa Aísa: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Josefina Cabeza:** Formal analysis, Software, Validation.

Declaration of competing 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.

Appendix 1. Solution to the optimization problem of a representative individual from generation t

The Lagrangian for the optimization problem can be expressed as:

$$\text{Lagrangian} = \ln\left(c^{y}_{i,t}\right) + u_{i,t}\ln(1-\lambda) +$$
$$\beta(1-p)\left[\ln\left(c^{o}_{i,t+1}\right) + e_{i,t+1}\ln(1-\xi)\right] + \nu\left(w_{i,t}\theta^{y}_{i} + w_{i,t+1}\theta^{o}_{i}e_{i,t+1} - c^{y}_{i,t} - \frac{c^{o}_{i,t+1}}{R}\right).$$

The first-order conditions are given by:

$$\frac{\partial \text{Lagrangian}}{\partial c^{y}_{i,t}} = \frac{1}{c^{y}_{i,t}} - \nu = 0,$$

$$\frac{\partial \text{ Lagrangian}}{\partial c^{o}_{i,t+1}} = \frac{\beta(1-p)}{c^{o}_{i,t+1}} - \frac{\nu}{R} = 0,$$

$$\frac{\partial \text{Lagrangian}}{\partial \nu} = w_{i,t}\theta^{y}_{i} + w_{i,t+1}\theta^{o}_{i}e_{i,t+1} - c^{y}_{i,t} - \frac{c^{o}_{i,t+1}}{R} = 0.$$

From the first two conditions, it is derived that the optimal consumption levels are such that:

$$c^{o}_{i,t+1} = R\beta(1-p)c^{y}_{i,t},$$

Substituting this equation into the individual's budget constraint yields that the optimal level of consumption for a representative individual of generation t in the first period is:

$$c^{y}_{i,t} = \frac{1}{1+\beta(1-p)}\left(w_{i,t}\theta^{y}_{i} + w_{i,t+1}\theta^{o}_{i}e_{i,t+1}\right),$$

and thus, their optimal level of consumption in the second period is:

$$c^{o}_{i,t+1} = \frac{R\beta(1-p)}{1+\beta(1-p)}\left(w_{i,t}\theta^{y}_{i} + w_{i,t+1}\theta^{o}_{i}e_{i,t+1}\right).$$

Replacing the optimal consumption level in the first period into Eqn. (7) yields the optimal level of individual savings:

$$s_{i,t} = \frac{\beta(1-p)}{1+\beta(1-p)}w_{i,t}\theta^{y}_{i} - \frac{1}{1+\beta(1-p)}w_{i,t+1}\theta^{o}_{i}e_{i,t+1}.$$

Appendix 2. List of variables and parameters.

Y_t	Production in period t.	Endogenous variable
K_t	Investment in AIs in period t.	Exogenous variable
A_t	Productivity index of AI-using workers in period t.	Endogenous variable
U_t	Number of workers using AIs in period t.	Endogenous variable
N_t	Number of workers not using AIs in period t.	Endogenous variable
B	Productivity index of non-AI-using workers.	Exogenous parameter
α	Marginal productivity of investments in AIs.	Exogenous parameter
$\overline{U}_t$	Total productivity of the group of AI-using workers in period t.	Endogenous variable
r	Interest rate.	Exogenous variable
$w_{u,t}$	Wage rate of AI-using workers in period t.	Endogenous variable
$w_{n,t}$	Wage rate of workers not using AIs in period t.	Endogenous variable
$c^{y}_{i,t}$	Consumption level of an individual in period t of generation t (young adult).	Endogenous variable
$c^{o}_{i,t+1}$	Consumption level in period $t+1$ of an individual from generation t (older adult).	Endogenous variable
$u_{i,t}$	Decision to use or not use AIs by an individual from generation t.	Dichotomous endogenous variable
$e_{i,t+1}$	Decision to extend or not the working life by an individual from generation t.	Dichotomous endogenous variable
λ	Loss of utility due to the effort to learn specific AIs for the job.	Exogenous parameter
ξ	Loss of utility for giving up leisure linked to retirement.	Exogenous parameter

(*continued on next page*)

(continued)

β	Inter-temporal discount rate of consumption.	Exogenous parameter
$(1-p)$	Probability of being alive during the second period.	Exogenous parameter
R	Effective interest rate.	Exogenous variable
$s_{i,t}$	Saving level of an individual from generation t.	Endogenous variable
η	Scale parameter for productivity increase through the use of AIs.	Exogenous parameter
δ_h	Fraction of initial productivity once aging is discounted.	Exogenous variable
σ	Weight of individual health in δ_h (for the less productive).	Exogenous parameter
$(1-\sigma)$	Weight of health associated with the job in δ_h (for the less productive).	Exogenous parameter
ψ	Elasticity of δ_h with respect to the initial productivity level (for less productive).	Exogenous parameter
θ_i	Initial productivity level of a worker.	Exogenous variable
θ_i^y	Productivity level of a worker in the first period (young adult).	Endogenous variable
θ_i^o	Productivity level of a worker in the second period (older adult).	Endogenous variable
$\underline{\theta}$	Threshold of initial productivity below which it is not possible to access jobs with AI investments.	Exogenous variable
$\underset{\sim}{\theta}$	Threshold of initial productivity below which non-AI-using workers do not extend their working life.	Endogenous variable
$\widetilde{\theta}$	Threshold of initial productivity below which AI-using workers do not extend their working life.	Endogenous variable
$\overline{\theta}$	Threshold of initial productivity above which AI-using workers do not extend their working life.	Endogenous variable

Appendix 3. Demonstration of proposition 3.1

On the one hand, workers with an initial productivity level above $\underline{\theta}$ might decide not to use AIs in their work if the productivity increase provided by AIs does not compensate for the loss of utility due to the learning effort. Analytically, this occurs if $EU\left(c_{i,t}^y, c_{i,t+1}^o, 0, 0\right) > EU\left(c_{i,t}^y, c_{i,t+1}^o, 1, 0\right)$, considering those who do not prolong their working life. From Eqs. (4), (5), (16), and (18), it is derived that this inequality holds for those workers with a level of productivity such that:

$$\frac{(1-\theta_i)\left(\theta_i - \underline{\theta}\right)}{\theta_i} < \frac{1}{\eta}\left[\left(\frac{1}{N_t\widehat{k}}\right)^{\alpha}\frac{1}{\Lambda A_t} - 1\right],$$

with $\Lambda = (1-\lambda)^{\frac{\beta(1-p)}{1+\beta(1-p)}}$. This inequality requires that $\left(\frac{1}{N_t\widehat{k}}\right)^{\alpha}\frac{1}{\Lambda A_t} > 1$. Evaluating the same at period 0 and substituting in this expression $\widehat{k} = \frac{K_0}{AU_0}$, $U_0 = 1 - N_0$, and rearranging terms, it is verified that the level of aggregated capital is bounded to fulfill the inequality:

$$K_0 < \frac{1-N_0}{N_0}\left(\frac{1}{\Lambda A}\right)^{\frac{1}{\alpha}}.$$

Hence, as long as the initial capital is sufficiently high, $K_0 > \frac{1-N_0}{N_0}\left(\frac{1}{\Lambda A}\right)^{\frac{1}{\alpha}}$, with $N_0 > 0$, all workers with an initial productivity level above $\underline{\theta}$ will decide to use AIs in their work. The explanation is that the aggregated capital is positively associated with the wage rate of the workers who use AIs, but not with the wage rate of those who do not use them. A higher level of aggregated capital, a greater gap between the wage rates of those who use AIs and those who do not. With a sufficiently large initial level of aggregated capital, the initial wage gap compensates for the loss of utility due to the learning effort. Since $A_t \geq A_{t-1} \geq A, \forall t$, this initial wage gap in labour terms does not decrease and, therefore, it holds that $EU\left(c_{i,t}^y, c_{i,t+1}^o, 0, 0\right) < EU\left(c_{i,t}^y, c_{i,t+1}^o, 1, 0\right), \forall t$. This wage gap also compensates for the loss of utility due to the learning effort for longer working lives, so that $EU\left(c_{i,t}^y, c_{i,t+1}^o, 0, 1\right) < EU\left(c_{i,t}^y, c_{i,t+1}^o, 1, 1\right)$. In short, all workers with an initial productivity level above $\underline{\theta}$, whether they retire or not in the second period, will use AIs in their work.

On the other hand, the architecture of the model itself establishes that individuals with a productivity level below $\underline{\theta}$ cannot use AIs, either because their initial training is a barrier or due to the characteristics of their job. They can decide whether to extend their working life or not. From Eqs. (3), (14), and (15), it is obtained that those who opt to extend their working life have an initial productivity level such that:

$$\theta_i > \theta\text{-}t = \frac{1}{(1-\sigma)}\left[(1-\Xi)\left(\frac{N_{t+1}}{N_t}\right)^{\alpha} - \sigma(1-p)\right]^{\frac{1}{\psi}}$$

Consequently, the number of workers from generation t who will not use AIs in their job and extend their working life is $\underline{\theta} - \theta\text{-}t$. This group will increase in size the more the wage rate in the second period increases relative to the first period, as more workers will offset via wages the loss of utility by not enjoying leisure linked to retirement. However, the wage rate of this group of workers is negatively related to its size, and if this size grows, it means a lower salary. Therefore, $N_t = N_{t+1}, \ \forall t$, and, in equilibrium, this group of workers has a constant size, $\underline{\theta} - \underset{\sim}{\theta}$, with $\underset{\sim}{\theta} = \frac{1}{(1-\sigma)}[(1-\Xi) - \sigma(1-p)]^{\frac{1}{\psi}}$. The existence of an interior solution implies that $0 < \underset{\sim}{\theta} < \underline{\theta}$, that is, the parameter ξ must meet that $1-\sigma(1-p) > \Xi > 1-(1-\sigma)^{\psi}\underline{\theta}^{\psi} - \sigma(1-p)$.

In summary, only workers with a productivity level below $\underline{\theta}$ will not adopt AIs in their work tasks. This group comprises for each t the workers born in t and those born in t-1 who extend their working life, $N = \underline{\theta} + (1-p)(\underline{\theta} - \underset{\sim}{\theta})$

Appendix 4. Demonstration of Proposition 3.2

Proposition 3.1 implies that the number of workers using AI in each time period is constant, $U_t = U$. It remains to determine which of these do not retire. From Eqs. (5), (17), and (18), it is found that these workers opt to extend their working life if the initial level of productivity is such that:

$$\left[f(\overline{U}) - \left(\Xi^{-1}-1\right)\right]\eta \frac{(1-\theta_i)\left(\theta_i - \underline{\theta}\right)}{\theta_i} > \left(\Xi^{-1}-1\right) - f(\overline{U})(1-p)$$

Three possibilities emerge. If $(\Xi^{-1}-1) < f(\overline{U})(1-p)$, this inequality holds for any initial productivity level between $\underline{\theta}$ and 1. All decide to extend their working life because the wage yield, once biological deterioration is discounted, compensates for the loss of utility from forgoing the leisure of retirement. If $(\Xi^{-1}-1) > f(\overline{U})$, the opposite occurs and this entire group of workers decides to retire. The third and last possibility is that $f(\overline{U})(1-p) < (\Xi^{-1}-1) < f(\overline{U})$, a condition that leads to a solution where some workers choose to retire and others to continue working. Solving the quadratic equation:

$$\left[f(\overline{U}) - \left(\Xi^{-1}-1\right)\right]\eta \frac{(1-\theta_i)\left(\theta_i - \underline{\theta}\right)}{\theta_i} = \left(\Xi^{-1}-1\right) - f(\overline{U})(1-p),$$

it is verified that there are two solutions:

$$\theta_i = \frac{1+\underline{\theta} - \frac{\left(\Xi^{-1}-1\right) - f(\overline{U})(1-p)}{\eta\left[f(\overline{U}) - \left(\Xi^{-1}-1\right)\right]} \pm \left(\left\{1+\underline{\theta} - \frac{\left(\Xi^{-1}-1\right) - f(\overline{U})(1-p)}{\eta\left[f(\overline{U}) - \left(\Xi^{-1}-1\right)\right]}\right\}^2 + 4\underline{\theta}\right)^{\frac{1}{2}}}{2}$$

Assuming a value η sufficiently large to ensure that:

$$1+\underline{\theta} - \frac{(\Xi^{-1}-1) - f(\overline{U})(1-p)}{\eta\left[f(\overline{U}) - (\Xi^{-1}-1)\right]} > 0,$$

there are two unique solutions denoted as $\widetilde{\theta}$ and $\overline{\theta}$ with $\underline{\theta} < \widetilde{\theta} < \overline{\theta} < 1$. Therefore, U comprises all those born in any given time period t with an initial productivity level between $\underline{\theta}$ and 1 and those born in $t-1$ with an initial productivity level between $\widetilde{\theta}$ and $\overline{\theta}$, $U = (1-\underline{\theta}) + (1-p)(\overline{\theta} - \widetilde{\theta})$, with $\overline{U}$ being the productivity level of this group of workers:

$$\overline{U} = \int_{\underline{\theta}}^{1}\left[\theta_i + \eta(1-\theta_i)\left(\theta_i - \underline{\theta}\right)\right]di + (1-p)\int_{\widetilde{\theta}}^{\overline{\theta}}\left[(1-p)\theta_i + \eta(1-\theta_i)\left(\theta_i - \underline{\theta}\right)\right]di,.$$

Appendix 5. Demonstration of proposition 3.3

From expression (2), it is obtained that the growth rate of the economy is constant and equal to $\frac{A_t}{A_{t-1}} = f(\overline{U})$.

Moreover, expressions (3),(4), (5) evaluated at equilibrium, lead to:

$$\widehat{w}_u = (1-\alpha)\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}},$$

$$w_n = (1-\alpha)\left[\underline{\theta} + (1-p)\left(\underline{\theta} - \underset{\sim}{\theta}\right)\right]^{-\alpha}$$

where $\widehat{w}_u = \frac{w_{u,t}}{A_t}$.

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