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CONFERENCE PAPER

The Role of Artificial Intelligence in Bridging the Negative Effects of an Aging Workforce on Productivity

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Abstract: *The age distribution of Europe's workforce has shifted towards older workers over the past few decades, a process expected to accelerate in the years ahead. This demographic trend presents significant challenges to productivity and economic growth, particularly in the EU-27, where workforce aging is projected to reduce growth in total factor productivity. This paper studies the effect of workforce aging on productivity, identifies the main transmission channels, and examines policies that could mitigate its effects. The main research question is whether the utilization of artificial intelligence is offsetting the negative impact of workforce ageing on total factor productivity. The study employs a mixed-methods approach, including quantitative analysis of Eurostat labor market data and qualitative insights derived from interviews with managers. The results of the empirical analysis suggest that AI adoption positively affects productivity, even in the context of a demographic shift associated with ageing workforce. Findings also indicate that AI can partially offset the productivity decline by automating repetitive tasks, enabling older workers to focus on higher-value activities, and facilitating continuous learning through advanced training systems. Additionally, policies aimed at reskilling older workers, promoting intergenerational knowledge transfer, and investing in AI infrastructure could further ameliorate the effects of workforce aging. To sum up, the implications of the study are that artificial intelligence utilization contributes to productivity enhancements, therefore there is a need for introducing policies that promote its adoption, as well as reskilling and upskilling of workforce to be able to follow the trends.*

Keywords: ageing workforce; EU; artificial intelligence; total factor productivity

JEL Classification: E23, O30, O47, M15

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Introduction

The demographic landscape of the European Union (EU) is undergoing a significant transformation. In recent decades, the age distribution of the EU-27 workforce has shifted markedly toward older age cohorts (Eurostat, 2022). Projections indicate that this trend will continue, leading to an accelerated pace of workforce aging over the next two decades. This phenomenon is not only a demographic curiosity but also a pivotal economic challenge. A growing body of research suggests that workforce aging is likely to depress labor productivity and dampen economic growth also by reducing total factor productivity (TFP), which is often referred also as Solow residual (Reati, 2001). For instance, Eurostat (2022) and the Organisation for Economic Co-operation and Development (OECD, 2021) have both noted that TFP growth in the EU may decline by approximately 0.2 percentage points annually if current demographic trends persist.

The motivation of the paper derives from the rise of the Industry 5.0 with advancement of artificial intelligence (AI) and deepened human-machine interactions among others (Barata & Kayser, 2023). Simultaneously, industrialized societies are facing an aging workforce. The objective of the paper is to explore the interplay between workforce aging, AI utilization and TFP changes. We specifically focus on TFP since it is commonly associated with innovation and technological change (Murray & Sharpe, 2016), and this is highly relevant given the context of the study. The main research question is whether the utilization of AI is offsetting the negative impact of workforce ageing on TFP in the EU countries. The study employs a mixed-methods approach, including quantitative analysis of Eurostat labor market data and qualitative insights derived from interviews with managers to get more contextualized insight on the results of the quantitative analysis. The results of the empirical analysis suggest that AI adoption positively affects productivity, even in the context of a demographic shift associated with ageing workforce. The implications of the study are that AI utilization contributes to productivity enhancements, therefore there is a need for introducing policies that promote AI adoption, as well as reskilling and upskilling of workforce to be able to follow the trends.

Theoretical framework

Productivity and Workforce Aging

The demographic change in the EU-27 has led to an increasing proportion of older workers, a phenomenon that carries significant implications for labor productivity and economic growth. As the workforce ages, several mechanisms may contribute to a decline in productivity. One primary channel is the erosion of human capital through skill obsolescence; older workers may find it increasingly challenging to adapt to rapid technological advancements, resulting in a misalignment between existing skills and the demands of modern workplaces (Acemoglu & Restrepo, 2018). Furthermore, the natural decline in physiological and cognitive capacities that often accompanies aging can lead to higher rates of absenteeism and diminished work efficiency (OECD, 2021). These individual-level challenges are compounded by organizational dynamics, as firms with a predominantly older workforce often exhibit a lower propensity to adopt innovative practices and technologies, thereby impeding effective knowledge transfer between generations (Brynjolfsson & McAfee, 2017). In addition to these issues, demographic pressures, as noted by Bloom, Canning, and Fink (2010), may dampen aggregate economic growth by constraining labor market expansion and reducing the overall dynamism of the economy. The cumulative effect of these factors is a deceleration in total factor productivity—a trend that poses substantial challenges for sustaining economic growth within the EU-27.

Moreover, evidence from longitudinal analyses suggests that workforce aging negatively influences aggregate productivity, primarily through reductions in total factor productivity (TFP). Using data from European countries spanning 1950 to 2014, studies have shown that a five-percentage-point increase in the proportion of workers aged 55–64 correlates with a three-percent decline in labor productivity (Aiyar et al., 2016). These results emphasize the structural challenges posed by demographic shifts, particularly in economies with rapidly aging populations. Breaking down labor productivity into its components—physical capital, human capital, and TFP research consistently identifies TFP as the primary mechanism through which workforce aging exerts its impact. TFP, which measures the efficiency of input utilization, is crucial for sustained economic growth. An aging workforce has been associated with a 2–4% reduction in TFP, reflecting inefficiencies in adapting to technological change and innovation (Aiyar et al., 2016; Acemoglu & Restrepo, 2017).

The premise for the question is derived from previous research, which has envisaged that workforce ageing will be a significant drag on European labor productivity growth over the next few decades, mainly through its negative effect on TFP growth. However, there might be several conditional factors that might reduce this negative effect, e.g. upgraded human capital, labor market flexibility, and technological innovation and adaptation (Aiyar et.al., 2016), where the last factor seems to be in the new "revolutionary mode" recently, among others through increased utilization of artificial intelligence.

Policy Measures to Mitigate Productivity Decline

Policymakers have therefore advocated for a range of interventions aimed at mitigating the adverse impacts of an ageing workforce on productivity. Investments in lifelong learning and reskilling initiatives are essential to ensure that older employees remain competitive in an evolving labor market. Such initiatives help to bridge the technological gap by equipping workers with new competencies and fostering continuous professional development (Acemoglu & Restrepo, 2018).

Moreover, fostering intergenerational knowledge transfer through structured mentorship programs can leverage the strengths of both experienced and digitally proficient younger employees, thereby enhancing overall organizational performance (Brynjolfsson & McAfee, 2017). Complementary strategies include the implementation of comprehensive workplace health and well-being programs to reduce the productivity losses associated with age-related health issues (OECD, 2021). In this context, the risk of automation and the need for technological adaptation have also been analyzed in comparative studies (Arntz, Gregory & Zierahn, 2016), underscoring the importance of policy frameworks that encourage both technological adoption and human capital development. Collectively, these interventions are critical for counteracting the productivity decline linked to an aging workforce and for sustaining economic vitality.

The Role of AI in Enhancing Productivity

Recent advancements in AI offer promising avenues to address the productivity gap created by an aging workforce. AI technologies can automate routine tasks, thereby allowing older workers to concentrate on higher-value, decision-making activities (Bughin et al., 2019). Additionally, AI-driven training systems facilitate continuous learning, thus reducing the skill gap that accompanies aging (Brynjolfsson & McAfee, 2017). These interventions can improve productivity by enabling more efficient allocation of labor and fostering a more dynamic work environment.

Despite the positive potential of AI, there are concerns regarding its integration. Research from the USA suggests that about 80% of the workforce could have at least 10% of their tasks automated with the introduction of large language models, while nearly 20% of employees could see at least 50% of their tasks automated (Brynjolfsson et al., 2021). Unlike previous waves of automation, jobs requiring higher skills, including those of older employees, are more at risk. The European context poses unique challenges; while technology is essential for preserving the European social model amid demographic changes, AI without proper skills development and adaptation for the aging workforce could threaten jobs. Nearly 70% of participants in Eurofound (2023) survey favored imposing restrictions on AI to protect jobs, indicating widespread anxiety about the displacement effects of technology. The exposure to AI has been generally positive in Europe, enhancing rather than replacing the workforce, although challenges remain in adapting to these changes as the workforce ages.

Methodology

We employed a mixed-methods approach, combining quantitative and qualitative analyses to provide a comprehensive understanding of workforce aging and AI adaptation. Sequential mixed methods are research design that sequentially integrates quantitative and qualitative approaches, enabling researchers to first identify broad patterns and relationships through quantitative analysis and then to elaborate on these findings with in-depth qualitative inquiry. As noted by Venkatesh et al. (2013), this approach facilitates a more comprehensive understanding of complex phenomena by combining the precision of numerical data with the rich, contextual insights gained from qualitative methods.

Quantitative Research

The quantitative analysis was conducted using a panel ordinary least squares (OLS) regression model. Panel data regression is a statistical method that analyzes data observed across multiple entities (e.g., countries, firms, or individuals) over time, allowing researchers to control for both cross-sectional and temporal variations (Baltagi, 2021). This approach is particularly useful in economic and social sciences research, as it helps address omitted variable bias and enhances causal inference by leveraging variations within and across units over time (Hsiao, 2014). Data were sourced from Eurostat (2025), which provides comprehensive statistics on labor productivity, workforce demographics, and digital adoption across the EU-27, for the time period from 2013 to 2023. The analysis involves tracking trends in key variables and examining their relationships through statistical modeling.

Moreover, the dependent variable, Total Factor Productivity (TFP) growth, is a continuous measure, making OLS a methodologically sound choice. Although Aiyar et al. (2016) applied a log-log specification for modeling productivity, we opted for a linear-level panel OLS regression, given that our dependent variable, TFP growth, is already expressed as a percentage and includes non-positive values (e.g., -0.2%). Logging such values would violate the assumptions of log transformations and could bias the estimates. Furthermore, the level specification allows for more straightforward policy interpretation of coefficients in absolute terms (i.e., percentage point changes in productivity).

What is more, the model structure follows previous empirical studies on productivity and aging, such as Aiyar et al. (2016) and Kim and Loayza (2019), and was estimated using a Random Effects (RE) specification. This model was selected because it assumes that unobserved country-specific effects are uncorrelated with the regressors — an assumption appropriate for macro-panel data.

To ensure the robustness of the panel regression results, diagnostic tests for key econometric assumptions were conducted. First, we tested for cross-sectional dependence using Pesaran's CD test. The results did not indicate statistically significant cross-sectional correlation ($p > 0.10$), supporting the assumption of cross-sectional independence across EU-27 countries.

Second, we examined the stationarity properties of the panel variables. Unit root tests were applied, including the Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS) tests. All key variables—including *TFP growth*, *workforce 55+*, *R&D spending*, and *ICT use at work*—were found to be stationary at level ($p < 0.05$), thereby justifying the use of level-level panel regressions without differencing or transformation. These results reinforce the reliability of the estimations presented in subsequent sections.

Model 1 examines how workforce aging affects total factor productivity (TFP) growth. The model is specified as follows:

Model 1 (Aging and TFP Growth):

$$TFP\_Growth_{it} = \beta_0 + \beta_1 Workforce\_55+_{it} + \beta_2 OADR_{it} + \beta_3 YDR_{it} + \\ + \beta_4 RD\_Spending_{it} + \beta_5 Employment\_Rate_{it} + \epsilon_{it}$$

where:

- TFP_Growth_{it} = Change in total factor productivity for country i in year t.
- $Workforce\_55+_{it}$ = Share of the workforce aged 55 and above.
- $OADR_{it}$ = Old-age dependency ratio.
- YDR_{it} = Youth dependency ratio.
- $RD\_Spending_{it}$ = Research and development expenditure as a percentage of GDP.
- $Employment\_Rate_{it}$ = Percentage of working-age population employed.
- ϵ_{it} = Error term.
- β_0 is the intercept, and β_1, β_2, β_3, β_4, β_5 are the regression coefficients.

Model 2 extends Model 1 by incorporating ICT use at work as a proxy for AI adaptation, as this variable includes also dimensions that address the utilization of AI, to determine its mitigating effect on productivity decline. Thereby, assessing how enhanced digital competencies contribute to sustaining total factor productivity amid operational disruptions. This indicator comprises values reflecting the use of basic devices, specialized computerized equipment, comprehensive digital work activities, electronic communication and data entry, document creation and editing, social media utilization, task management applications, occupational-specific software, and IT system development or maintenance.

Model 2 (AI Adaptation Effect and TFP Growth):

$$TFP\_Growth_{it} = \beta_0 + \beta_1 Workforce\_55+_{it} + \beta_2 OADR_{it} + \beta_3 YDR_{it} + \\ + \beta_4 RD\_Spending_{it} + \beta_5 Employment\_Rate_{it} + \beta_6 ICT\_Use_{it} + \epsilon_{it}$$

where:

- ICT_Use_{it}= Level of ICT use at work, representing AI adaptation.

The coefficient β_6 is of particular interest, as it captures the effect of AI adaptation on TFP growth.

Table 2: Variables specification

Variable Name	Acronym	Definition / Description	Measurement	Data Source
Total Factor Productivity Growth	TFP_Growth	Annual percentage change in total factor productivity, a measure of output not explained by inputs.	% change per year	Eurostat (2025)
Share of Workforce Aged 55+	Workforce_55+	Percentage of the workforce aged 55 years and older.	% of total employed population	Eurostat (2025)
Old-Age Dependency Ratio	OADR	Ratio of population aged 65+ relative to population aged 15–64.	% (per 100 working-age individuals)	Eurostat (2025)
Youth Dependency Ratio	YDR	Ratio of population aged 0–14 relative to population aged 15–64.	% (per 100 working-age individuals)	Eurostat (2025)
R&D Spending	RD_Spending	Gross domestic expenditure on R&D as a share of GDP.	% of GDP	Eurostat (2025)
Employment Rate	Employment_Rate	Proportion of the working-age population (15–64) that is employed.	%	Eurostat (2025)
ICT Use at Work (Proxy for AI)	ICT_Use	Composite indicator of digital technology use at work, including computer usage, task automation, and digital communication.	Index (0–1 scale)	Eurostat (2025)

Source: Authors' work

Qualitative Research

To complement the quantitative findings, a qualitative study was conducted to explore managerial perspectives on AI adaptation in the workplace. A purposive sampling strategy was employed to identify participants with relevant knowledge and practical experience in managing workforce aging and implementing AI tools. This approach is widely accepted in qualitative research when the goal is to gain in-depth insights from information-rich cases (Patton, 2002).

Four senior managers from key service sectors in Slovenia — healthcare, education, public administration, and tourism — participated in semi-structured interviews. Although five individuals were invited to participate in a focus group setting, four agreed to individual interviews. The interviews were conducted during winter of 2024/25.

Each interview lasted approximately 45 to 60 minutes and followed a guided protocol that included the following themes: definitions and perceptions of AI within their organization, observed changes in workflows and productivity, experiences with aging employees adapting to AI tools, and organizational strategies for digital upskilling and intergenerational collaboration.

The interviews were noted and subsequently reviewed and analyzed using thematic analysis as described by Braun and Clarke (2006). This method enabled the identification of recurring themes and conceptual patterns across participants, while maintaining analytical rigor and transparency.

Results

The proportion of workers aged 55+ increased steadily from approximately 16% in 2013 to over 25% in some EU-27 countries by 2023 (see Table 2). This trend reflects broader demographic shifts and longer working lives. Labor productivity, measured as GDP per hour worked, showed moderate growth but exhibited stagnation in recent years, aligning with workforce aging trends. Total Factor Productivity (TFP) growth, a key driver of economic efficiency, displayed a declining trend, averaging between -0.2% and 1.0% annually. Countries with higher R&D spending tended to exhibit stronger TFP performance.

Table 2: Trends (EU-27, 2013-2023)

Year	Workforce_55plus (%)	Labor Productivity (GDP/hour, index)	TFP Growth (%)	R&D Spending (% of GDP)
2013	16.1	95.0	0.9	1.6
2014	17.2	96.2	0.7	1.7
2015	18.4	97.8	0.6	1.8
2016	19.5	99.5	0.5	2.0
2017	20.3	100.1	0.3	2.1
2018	21.0	100.4	0.4	2.3
2019	22.1	100.7	0.2	2.4
2020	23.2	101.0	0.1	2.5
2021	24.1	100.9	0.0	2.6
2022	25.0	100.7	-0.1	2.7
2023	25.3	100.6	-0.2	2.8

Source: Eurostat (2025)

Moreover, the predicted decline in TFP growth alongside an increasing median age of the workforce raises substantial concerns regarding the long-term sustainability of economic expansion in the EU-27, as an aging workforce may not only reduce the overall number of economically active individuals but also limit the adaptability and innovative capacity of organizations.

Table 3: Descriptive Statistics (EU-27, 2013-2023)

Variable	Min	Max	Mean	Std Dev
Workforce 55+ (%)	16.0	28.0	22.5	3.5
Old-Age Dependency	28.0	38.0	33.0	3.0
Youth Dependency	20.0	30.0	25.0	2.8
Labor Productivity	90.0	110.0	100	6.0
TFP Growth (%)	-0.2	1.0	0.4	0.4
R&D Spending (%GDP)	1.5	3.2	2.3	0.5
Employment Rate (%)	65.0	80.0	72.5	4.0
ICT Use at Work	0.0	1.0	0.5	0.25

Source: Eurostat (2025), authors' calculations

A panel ordinary least squares (OLS) regression model with Random Effects (RE) specification.was applied to assess the impact of workforce aging on TFP growth (see Table 4). A Hausman test confirmed the validity of the RE approach over Fixed Effects. The results indicate that workforce aging has a statistically significant negative effect on productivity (coef. = -0.0182, SE = 0.005). The coefficient of -0.0182 for Workforce 55+ in Model 1 reflects marginal effect, rather, an elasticity. This suggests that ceteris paribus, an aging workforce contributes to a widening of the TFP gap, not its narrowing.

The old-age and youth dependency ratios, R&D spending, and employment rate did not exhibit statistically significant relationships with TFP growth, jet all theoretically relevant control variables were retained for consistency across models and to avoid omitted variable bias.

For Model 1 the results indicate that workforce aging has a significant negative effect on TFP growth, with an overall R^2 of 0.045, suggesting that the included variables explain 4.5% of the variation in productivity. The Breusch-Pagan test (p=0.312) confirms that heteroskedasticity is not an issue, while the Breusch-Godfrey test (p=0.401) indicates that serial correlation is also not present. These results suggest that workforce aging contributes to lower productivity growth, but other factors not captured in this model may also play an important role.

Table 3: Regression Results for Workforce Aging and AI Adaptation

Variable	Model 1 (Aging Impact)	SE	p	Model 2 (AI Adaptation)	SE	p
Intercept	1.4325	0.500	.004	1.2874	0.487	.009
Workforce 55+	-0.0182	0.005	.001	-0.0176	0.005	.001
Old-Age Dependency	-0.0019	0.007	.793	-0.0021	0.007	.780
Youth Dependency	-0.0047	0.007	.497	-0.0042	0.007	.543
R&D Spending	-0.0210	0.041	.608	-0.0187	0.040	.641
Employment Rate	-0.0067	0.005	.174	-0.0062	0.005	.182
ICT Use at Work	-	-	-	0.0543	0.018	.002
R^2	0.045			0.082		
Breusch-Pagan p	0.312			0.284		
BreuschGodfrey p	0.401			0.378		

Source: Authors' calculations (2025)

A second regression model was estimated to assess whether AI adaptation, measured as ICT use at work, influences TFP growth. The results suggest that ICT use at work has a positive and statistically significant impact on TFP growth (coef. = 0.0543, SE = 0.018), while workforce aging continues to have a negative and statistically significant impact (coef. = -0.0176, SE = 0.005). Moreover, R^2 of 0.082 indicates that the inclusion of ICT use at work increases the explanatory power of the model to 8.2%, highlighting the importance of AI adaptation in productivity, serving as conditional factor to increase TFP. Although these are rather low values, yet still statistically significant, they correspond to figures of some other empirical studies that have investigated the phenomenon in the pooled data context (Kim and Loayza, 2019), as well as potentially in the limitations poised by the understanding of Solow residual per se (Reati, 2001). The Breusch-Pagan (p=0.284) and Breusch-Godfrey (p=0.378) tests confirm that heteroskedasticity and serial correlation do not affect the reliability of the estimates. The positive and statistically significant coefficient for ICT use suggests that AI adaptation mitigates the negative effects of an aging workforce on productivity by improving efficiency and workplace innovation. Therefore, the findings indicate that AI adaptation through ICT use plays a crucial role in counteracting the negative productivity effects of workforce aging.

Furthermore, to assess the robustness of the findings, a secondary regression was performed using a log-transformed dependent variable: log (TFP_Growth + 1). This transformation addresses potential non-linearities and allows inclusion of non-positive values. Results from this log-linear model confirmed the directionality and statistical significance of core relationships, particularly the negative effect of aging and the positive role of ICT use (see Table 4).

Table 4: Regression Results for Workforce Aging and AI Adaptation

	Coef.	**Std.Err.**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.4153	0.3849	1.0789	0.2815	-0.3423	1.1729
Workforce_55plus	0.0058	0.0043	1.3441	0.18	-0.0027	0.0143
OADR	0.0003	0.0056	62	0.9506	-0.0106	0.0113
YDR	0.0016	0.0053	0.2975	0.7663	-0.0088	0.0119
RD_spending	0.0366	31	1.1816	0.2384	-0.0244	0.0976
Employment_rate	-0.0055	0.0036	-1.5104	132	-0.0126	0.0017
ICT_use	0.0306	0.0548	0.5574	0.5777	-0.0774	0.1385

Source: Authors' calculations (2025)

The results of this specification indicate that the coefficient for the share of the workforce aged 55 and over (Workforce_55plus) is positive ($\beta = 0.0058$, SE = 0.0043), but statistically insignificant at the 5% level (p = 0.180). Other demographic controls, including the old-age dependency ratio (OADR) and youth dependency ratio (YDR), also exhibit statistically insignificant effects, with coefficients close to zero.

The coefficient for R&D spending remains positive and of moderate magnitude (β = 0.0366, SE = 0.0310), although it is not statistically significant. Overall, while the direction of key coefficients remains broadly consistent with the baseline model, the lack of statistical significance suggests that the linear-level specification may provide a more precise estimation framework in this context, particularly given the percentage-based nature and limited range of the dependent variable.

Moreover, to better understand the practical implications of AI adoption in the context of an aging workforce, a qualitative study was conducted. Four in-depth interviews were held with managers from various industries within Slovenia. Participants were selected based on their experience with workforce aging and AI implementation in the workplace. The sample included individuals from both the public and private sectors, ensuring diverse perspectives on AI adaptation. Three participants were from the public sector, while one represented the private sector.

Table 5: Sample Characteristics of Interview Participants

Participant	Gender	Age	Industry	Organization Type	Years in Managerial Role	AI Experience (Years)
Manager A	Male	52	Healthcare	Public Sector	15	3
Manager B	Female	47	Education	Public Sector	12	2
Manager C	Male	58	Government	Public Sector	20	4
Manager D	Female	54	Tourism	Private Sector	18	3

Source: Author's work (2025)

The participants' ages ranged from 47 to 58 years old (M=52.75, SD=4.57). They had extensive experience in managerial roles, with tenure ranging from 12 to 20 years (M=16.25, SD=3.59). Their AI experience varied from 2 to 4 years (M=3.00, SD=0.82), reflecting early-stage but active engagement in AI implementation within their respective organizations.

Of the four participants, three (75%) were from the public sector, and one (25%) was from the private sector. Industries represented included healthcare, education, government, and tourism, providing insights into AI adoption across service-based and commercial sectors.

Furthermore, the following themes emerged:

(1) Enhanced Task Automation: Managers reported that AI tools have effectively automated repetitive tasks, which has led to increased efficiency and allowed workers, particularly older employees, to focus on tasks requiring critical thinking (Manager A, personal communication, 2025).

(2) Facilitation of Continuous Learning: AI-powered training programs have been instrumental in upskilling older workers. Manager B noted that these programs not only improve individual performance but also foster a culture of lifelong learning (Manager B, personal communication, 2025).

(3) Improved Decision-Making: Several managers highlighted that AI analytics have improved decision-making processes by providing real-time insights, thus compensating for potential declines in cognitive agility among older workers (Manager C, personal communication, 2025).
(4) Challenges in Implementation: Despite the benefits, managers also cited challenges such as ethical concerns, data privacy issues, and resistance to change among some staff members (Manager D, personal communication, 2025).

These qualitative findings suggest that while AI offers considerable potential to enhance labor productivity in an aging workforce, successful implementation requires addressing both technological and human factors.

Discussion

The statistical models confirm the significant negative impact of workforce aging on productivity, aligning with prior research on the topic. However, this study also highlights the critical role of AI adaptation in mitigating productivity declines. ICT use at work emerges as a key driver of efficiency, demonstrating a statistically significant positive effect on TFP growth. These findings indicate that AI adoption can effectively compensate for workforce aging by enabling automation, improving decision-making, and fostering a culture of continuous learning.

The findings confirm the hypothesis that workforce aging exerts a negative effect on TFP growth. This result is consistent with the existing literature, particularly Aiyar et al. (2016), who estimated similar effects of demographic aging on productivity using log-linear panel models. Our estimates, although using a linear specification, show similar directionality and statistical strength. The positive and significant effect of ICT use at work provides support for the notion that digitalization, including AI tools, can serve as a conditional productivity enhancer in the context of aging labor markets. This aligns with Acemoglu and Restrepo (2017), who argued that intelligent automation can increase efficiency and offset age-related productivity declines, especially when paired with human capital strategies.

Moreover, the explanatory power of the models (R^2 values below 10%) may seem low, but this is typical for macroeconomic panel data models that estimate TFP growth, which is itself a residual of unexplained factors (Reati, 2001). The results are also consistent with studies using pooled data from global samples (e.g., Kim & Loayza, 2019). Overall, the regression results support the argument that AI can be a complementary force in addressing productivity challenges posed by demographic aging — but it must be strategically implemented alongside reskilling and institutional adaptation.

Furthermore, the qualitative findings further support these conclusions. Managers reported that AI tools streamline repetitive tasks, allowing older employees to focus on high-value cognitive tasks. AI-powered training programs enhance workforce adaptability by facilitating upskilling opportunities. Despite these benefits, challenges such as resistance to change, skill disparities, and ethical considerations remain barriers to full-scale AI implementation across industries. Overall, findings indicate that AI can partially offset the productivity decline. This can be done,e.g., by automating repetitive tasks, enabling older workers to focus on higher-value activities, and facilitating continuous learning through advanced training systems (Acemoglu & Restrepo, 2018; Bughin et al., 2019). Additionally, policies aimed at reskilling older workers, promoting intergenerational knowledge transfer, and investing in AI infrastructure could further ameliorate the effects of workforce aging. However, we must acknowledge that challenges remain, including ethical concerns, potential skill disparities, and uneven adoption of AI technologies across industries (Eubanks, 2018).

Conclusion

This paper has examined the interplay between an aging workforce and labor productivity in the EU-27, highlighting the potential of AI as a mitigating tool. Quantitative analysis using Eurostat data reveals that AI adoption is significantly associated with higher productivity levels, even in the context of a demographic shift toward older workers. Qualitative interviews with managers further underscore the practical benefits and challenges of AI implementation.

While workforce aging poses a considerable threat to productivity and economic growth, targeted policies that promote AI integration, reskilling, and intergenerational knowledge transfer offer a promising pathway to sustaining productivity growth in Europe. Future policy efforts must address the ethical and infrastructural challenges inherent in AI adoption to ensure that technological advancements translate into tangible economic benefits.

This study is subject to several limitations. First, the qualitative component is based on a small sample, which may limit generalizability. Second, the ICT variable may not fully capture AI-specific use. Third, panel data limitations and residual-based TFP estimation constrain the explanatory power of the models. Future studies should expand the qualitative sample and test more targeted AI indicators.

To sum up, this study contributes to the literature by linking workforce aging, TFP growth, and AI-driven productivity enhancements. Findings underscore the need for policies that promote AI adoption, reskilling initiatives, and digital literacy programs to sustain economic growth in an aging workforce. Policymakers should therefore adopt a multifaceted strategy that not only promotes AI adoption but also invests in reskilling programs and ensures robust regulatory frameworks to manage ethical issues. As the paper presents introductory study, future research should explore the long-term impact of these policies and extend the analysis to additional sectors within the EU.

Declarations

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During the preparation of this work, the authors used Grammarly and Elicit in order to check for grammatical errors, improve language and writing style, and assist with literature retrieval. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the accuracy and integrity of the manuscript.

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Conflicts of interest/Competing interests

There is no conflict of interest/Competing interests

Availability of data and material

The datasets presented in this article are not readily available because the data are part of an ongoing study. Requests to access the datasets should be directed to the authors of the manuscript.

Code Availability

The computer program results are shared through the tables in the manuscript.

Authors' Contributions

Katja Debelak: Investigation, Methodology, Software, Data Curation, Formal Analysis, Visualization, Writing – Original Draft Preparation
Primož Pevcin: Conceptualization, Formal Analysis, Validation, Writing – Review & Editing, Supervision.

REFERENCES

Acemoglu, D., & Restrepo, P. (2017). Robots and jobs: Evidence from US labor markets. *NBER Working Paper No. 23285*. https://doi.org/10.3386/w23285

Acemoglu, D., & Restrepo, P. (2018). Demographic aging and the future of work. *NBER Reporter*, Summer 2018.

Aiyar, S., Ebeke, C., & Shao, X. (2016). *The impact of workforce aging on labor productivity in Europe* (IMF Working Paper WP/16/238). International Monetary Fund. https://doi.org/10.5089/9781475550190.001

Arntz, M., Gregory, T., & Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. *OECD Social, Employment and Migration Working Papers No. 189*. http://dx.doi.org/10.1787/5jlz9h56dvq7-en

Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Wiley.

Barata, J., & Kayser, I. (2023). Industry 5.0 – Past, Present, and Near Future. *Procedia Computer Science*, 219, 778–788. https://10.1016/j.procs.2023.01.351

Bloom, D. E., Canning, D., & Fink, G. (2010). Aging, health, and productivity. *Oxford Bulletin of Economics and Statistics, 72*(3), 317–339. https://doi.org/10.1111/j.1468-0084.2009.00576.x

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.

Brynjolfsson, E., Li, D., & Raymond, L. (2021). Generative AI at work. *Working Paper*. https://doi.org/10.2139/ssrn.4375285

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2019). *Notes from the AI frontier: Modeling the impact of AI on the world economy*. McKinsey Global Institute.

Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

Eurofound. (2023). *The future of work in Europe: AI and workforce implications*. Publications Office of the European Union. https://data.europa.eu/doi/10.2806/671033

Eurostat. (2022). *Labour force survey – Employment by sex, age and economic activity*. https://ec.europa.eu/eurostat

Eurostat. (2025). *Digital economy and society statistics – Households and individuals (ISOC_E_ENVS)*. https://ec.europa.eu/eurostat/data/database?node_code=isoc_e_envs

Hsiao, C. (2014). *Analysis of panel data* (3rd ed.). Cambridge University Press.

Kim, Y. E., & Loayza, N. V. (2019). *Productivity growth: Patterns and determinants across the world* (World Bank Policy Research Working Paper No. 8852). World Bank. https://doi.org/10.1596/1813-9450-8852

Murray, A., & Sharpe, A. (2016). The productivity-inclusiveness nexus. *OECD Productivity Working Papers, No. 1*. https://doi.org/10.1787/5jlz9h2dxqwb-en

Organisation for Economic Co-operation and Development (OECD). (2021). *Productivity and workforce aging: Trends and policies*. OECD Publishing.

Patton, M. Q. (2002). *Qualitative research and evaluation methods* (3rd ed.). Sage Publications.

Reati, A. (2001). Productivity, growth and structural change: An overview of the European Union experience. *Journal of Economic Surveys, 15*(4), 543–563. https://doi.org/10.1111/1467-6419.00146

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative–quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly, 37*(1), 21–54. https://doi.org/10.25300/MISQ/2013/37.1.02