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AI and employment in Europe

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ABSTRACT

This paper contributes to the growing research on AI's labour market impact by presenting novel evidence on the heterogeneous employment effects of AI across EU countries from 2012 to 2022. While concerns persist about AI's disruptive potential, our findings show that occupations more exposed to AI technologies experience stronger employment growth, all else being equal. However, these effects are not uniform across the EU. Positive employment outcomes are concentrated in Innovation Leaders (Belgium, Denmark, Finland, the Netherlands and Sweden) and Strong Innovators (Austria, Cyprus, France, Germany, Ireland and Luxembourg), emphasising the context-dependent nature of AI's impact. These findings reflect the uneven distribution of innovation capabilities, with a country's innovation system and 'absorptive capacity' playing a crucial role in fully harnessing AI's potential for employment (and economic) growth. Ultimately, this research challenges the notion of AI as universally beneficial or harmful, highlighting its asymmetric effects across countries and occupations.

1. Introduction

The diffusion of artificial intelligence (AI) has revived concerns about technological unemployment, particularly among high-skill occupations traditionally shielded from automation risks (Webb et al., 2020). As a result, empirical efforts to test how well-grounded these fears are and to identify occupations, sectors, countries most at risk are flourishing (see Table 1).

While many studies report neutral or positive effects of AI on employment, others highlight its disruptive potential, particularly for tasks such as writing and content creation (Bonfiglioli et al., 2023; Hui et al., 2023). However, much of this evidence focuses on the US, leaving significant gaps in understanding AI's employment implications in Europe.

To address this gap, we examine the employment impact of AI at the country-occupation level in the EU from 2012 to 2022. Our contribution extends the literature in several ways. First, we explore the mediating role of task routinisation. Second, we investigate cross-country heterogeneity in the labour-AI nexus, examining how structural factors—such as R&D intensity, human capital, and absorptive capacity—shape a country's ability to leverage new technologies. Unlike Albanesi et al. (2023), our approach is grounded in the national systems of innovation framework, highlighting systemic differences across country clusters. Third, we focus on a more recent period.

Although positive employment effects prevail, they are asymmetrically distributed, concentrated in countries with stronger innovation systems. This research provides a novel perspective on the employment impact of AI, challenging the notion of AI as universally beneficial or harmful.

2. Data and descriptive evidence

Our key variable is occupational *AI exposure*[1,2] (Felten et al., 2021), measuring the degree of 'overlap' (A) between major AI applications and 52 workplace abilities (j), weighted by their prevalence (L_{jk}) and importance (I_{jk}) within each occupation (k), as follows:

$$AI_k = \frac{\sum_{=1}^{52} A_j * L_{jk} * I_{jk}}{\sum_{j=1}^{52} L_{jk} * I_{jk}} \tag{1}$$

As the AI indicator is agnostic regarding whether AI complements or substitutes labour, we examine if the impact of AI is 'mediated' or not by task routineness, in line with the routine-biased technological change

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[1] The AI indicator by Felten et al. (2021) is widely adopted and strongly correlated with actual AI adoption patterns, making it a reliable proxy. See Guarascio et al. (2023) for a detailed discussion of its validity relative to other measures.

[2] Under the assumption that AI-related workplace abilities in the US are similar to those in the EU, we reclassify 774 six-digit SOC to 427 four-digit ISCO-08 occupations, ultimately aggregating at 126 three-digit level.

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Table 1
Overview of selected studies on the employment impact of AI.

Study	Indicator	Coverage	Results
Acemoglu et al. (2022)	AI exposure, vacancy data	US, 2010–2018	No effects
Albanesi et al. (2023)	AI exposure	EU, 2011–2019	Positive
Bonfiglioli et al. (2023)	AI exposure	US, 2000–2020	Negative, especially low-skilled
Brey and van der Marel (2024)	AI adoption	EU, 2021	No effect
Damioli et al. (2024)	AI patents	Global, 2000–2016	Positive
Engberg et al. (2024)	AI exposure	Denmark, Portugal, Sweden, 2010–2023	Upskilling
Felten et al. (2021)	AI exposure	US, 2010–2016	High-skilled more exposed
Guarascio et al. (2023)	AI exposure	EU, 2011–2019	Positive
Hui et al. (2023)	Gen-AI	Global digital platform for freelancers 'Upwork', 2022–2023	Negative
Webb (2020)	O*NET/AI patents	US, 2000–2018	High-skilled more exposed
Yang (2022)	AI patents	Taiwan, 2002–2018	Positive

Notes: Studies were selected to provide a balanced overview of diverse approaches to measuring AI and estimating its employment effects. Source: Own elaborations.

literature (Acemoglu and Autor, 2011).[3] This allows testing whether AI-exposed occupations with more routine tasks face higher substitution risks, as during previous digitalisation waves, or if, instead, non-routine occupations are more at risk due to the peculiar characteristics of AI technologies.

North-Western Member States, including Benelux and Scandinavia, show high AI exposure, while South-Eastern Europe, including Italy, Spain, Bulgaria and Romania, shows the lowest (Fig. 1). This pattern aligns well with other key dimensions, including skill levels, sectoral specialisation and technological capabilities across countries (Reljic et al., 2023).

Fig. 2 shows employment dynamics in the EU27 by quartile of AI exposure. Occupations highly exposed to AI technologies (e.g., finance and legal professionals, numerical clerks) experienced uninterrupted employment growth and demonstrated resilience, even during the Covid-19 pandemic, which significantly disrupted labour markets. The pandemic-driven shift towards remote work, along with accelerated AI adoption, not only preserved existing jobs but seemingly facilitated the creation of new ones in tech-complementary roles. Conversely, occupations with low AI exposure (e.g., mining and construction laborers, painters, cleaning workers) had more modest growth of 5 %, with a stagnation phase between 2017 and 2019. Medium-high and medium-low AI exposure occupations followed a similar trajectory, diverging only with the onset of the pandemic.

Fig. 3 shows the positive correlation between AI exposure and annual employment growth over the last decade, displaying relevant heterogeneities by prevailing task type. Namely, the positive correlation appears to be primarily driven by the non-routine cognitive analytical occupations, which display a steeper slope. This may suggest that AI is more likely to complement rather than substitute humans in these roles, at least for now. In contrast, manual occupations exhibit a relatively flat slope, indicating negligible relationship with AI exposure, suggesting that manual tasks, routine or not, are less susceptible to AI.

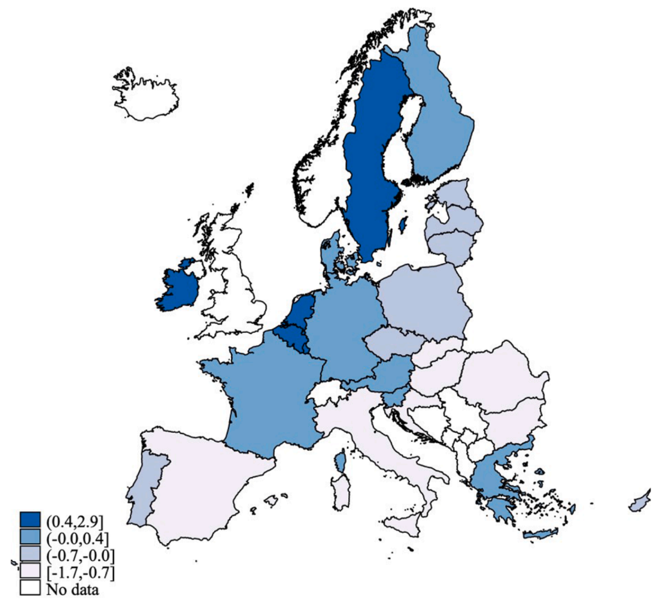

Fig. 1. AI exposure in the EU27, 2022.
Source: Own elaborations based on the EU Labour Force Survey data and Felten et al. (2021).

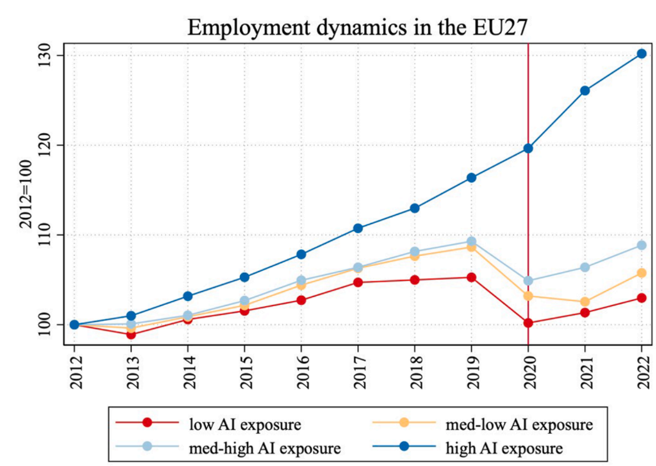

Fig. 2. Employment growth in the EU27 by quartile of AI exposure, 2012–2022.
Source: same as Fig. 1.

3. Empirical strategy and results

To examine the employment impact of AI at the country-occupation level, we estimate the following model:

$$Y_{i,k} = \alpha_0 + \beta_1 AI_k + \gamma * X'_{i,\ k} + \tau_i \ + \ \varepsilon_{i,k} \tag{2}$$

where $Y_{i,j}$ represents the average annual employment growth rate over the period 2012–2022 in country i and occupation k; AI_k denotes occupational AI exposure, X refers to a set of workforce characteristics observed in 2012,[4] while τ_i stands for country fixed effects. To investigate whether the impact of AI varies across occupations, we augment the

[3] Operationally, we use Lewandowski et al.'s (2020) taxonomy, which classifies each 3-digit ISCO occupation into five groups based on the predominant task type: non-routine cognitive analytical, non-routine cognitive personal, routine cognitive, non-routine manual and routine manual.

[4] The variables capturing workforce characteristics were constructed using the EU Labour Force Survey and include the share of males, workers with upper-secondary and tertiary education, permanent employees, individuals aged 50–64 and native citizens for each country-occupation combination.

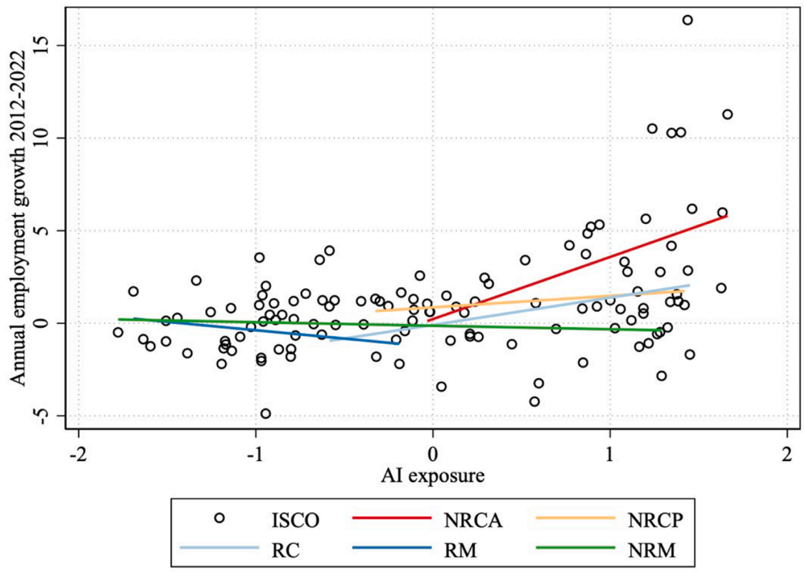

Fig. 3. Employment growth and AI exposure by the type of prevalent task.
Source: Same as Fig. 1; *Notes*: NRCA stands for non-routine cognitive analytical, NRCP for non-routine cognitive interpersonal, RC for routine cognitive, NRM and RM for non-routine and routine manual, respectively.

model with an interaction term between AI exposure and a binary variable RC, which equals one for occupations where routine cognitive tasks prevail and zero otherwise:

$$\Delta Y_{i,k} = \alpha_0 + \beta_1 AI_k + \beta_2 (AI_k * RC_k) + \beta_3 RC_k + \gamma * X'_{i,k} + \tau_i + \varepsilon_{i,k} \quad (3)$$

A significant β_2 would suggest that routine-task intensity mediates AI's impact on employment. The models are estimated using pooled OLS as endogeneity is not a major concern given that AI exposure is constructed using US data, which is plausibly exogenous to EU employment dynamics (Albanesi et al., 2023). Moreover, our indicator captures technological progress in key AI domains, making it unlikely to be directly influenced by past EU employment growth.

Finally, as average estimates may mask important cross-country differences, Eq. (3) is estimated separately for four country-groups based on the European Innovation Scoreboard: *Innovation Leaders* (Belgium, Denmark, Finland, the Netherlands and Sweden), *Strong Innovators* (Austria, Cyprus, France, Germany, Ireland and Luxembourg), *Moderate Innovators* (Czechia, Estonia, Greece, Hungary, Italy, Lithuania, Portugal and Spain) and *Emerging Innovators* (Croatia, Latvia, Poland, Romania and Slovakia). This classification reflects four distinct national innovation systems, highlighting significant cross-country differences in human resources, digitalisation, public and private investment and overall innovation capabilities, all of which could influence the AI-employment nexus.

AI exposure coefficients are consistently positive and significant across all specifications, indicating a positive association between AI exposure and employment (Table 2). However, the magnitude diminishes as workforce characteristics and country fixed effects are controlled for. A one standard deviation increase in AI exposure is associated with a 0.46 percentage point increase in annual employment growth, all else being equal. Moreover, the interaction between AI and routine cognitive tasks is negative but not significant, suggesting AI benefits routine cognitive jobs as much as non-routine ones.

While the positive employment effect of AI prevails in the EU, these gains are asymmetrically distributed. The results reported in Table 3 show that AI has a positive employment impact on employment only among *Innovation Leaders* and *Strong Innovators*. Conversely, the magnitude of the coefficient is markedly lower and statistically insignificant for *Moderate* and *Emerging Innovators*.

These heterogeneous results suggest that the impact of AI is highly context-dependent: a country's innovation capabilities significantly influence how these technologies can be harnessed to drive employment (and economic) growth. The positive employment effects are concentrated in countries with stronger research and innovation systems, characterised by higher R&D expenditures, more patent applications, a higher share of innovative enterprises, greater knowledge-intensive activities and more attractive research environments. In contrast, the potential benefits of AI are less likely to be realised in countries with moderate or emerging innovation systems.

Table 2
AI exposure and employment growth rate, 2012–2022.

	(1)	(2)	(3)	(4)
AI exposure	1.359***	0.420*	0.463*	0.703**
	(0.193)	(0.237)	(0.266)	(0.271)
Routine cognitive (RC)				−0.812*
				(0.458)
AI exposure x RC				−0.552
				(0.584)
Workforce characteristics	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
Constant	1.994***	4.068***	2.638	2.728
	(0.265)	(1.253)	(1.648)	(1.632)
Observations	2449	2298	2298	2298
R-squared	0.041	0.096	0.126	0.129

Notes: Workforce characteristics include share of males, upper-secondary, tertiary, permanent workers, age group 50–64, native citizens. Robust standard errors clustered at country-occupation level in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4. Conclusions

Our analysis points to a positive and significant association between AI exposure and employment growth, consistent with earlier studies (Albanesi et al., 2023; Damioli et al., 2024; Guarascio et al., 2023). However, the impact of AI varies across countries, benefiting only those with robust innovation systems like *Innovation Leaders* and *Strong Innovators*. In contrast, AI-related employment gains fail to materialise in *Moderate* and *Emerging Innovators*. This territorial disparity highlights the asymmetric distribution of innovation capabilities and the importance of their 'absorptive capacity' in fully leveraging AI's potential.

Table 3
AI exposure and employment growth rate by innovation performance groups, 2012–2022.

	(1) DK, SE, FI, NL, BE Innovation Leaders	(2) AT, DE, LU, IE, CY, FR Strong Innovators	(3) EE, CZ, IT, ES, PT, LT, EL, HU Moderate Innovators	(4) HR, SK, PL, LV, RO Emerging Innovators
AI exposure	0.853**	1.192**	0.143	0.651
	(0.285)	(0.351)	(0.666)	(0.391)
AI exposure x RC	−0.520	0.279	−0.345	−1.627
	(0.761)	(1.282)	(0.719)	(2.079)
RC	−0.911	−2.182	−0.891*	0.990
	(0.468)	(1.128)	(0.450)	(1.287)
Workforce characteristics	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Constant	−2.643	2.544	4.653	5.334
	(4.279)	(2.157)	(3.792)	(2.641)
Observations	518	552	783	445
R-squared	0.134	0.169	0.106	0.100

Source: same as Table 2.

These findings do not imply that AI technologies are unlikely to become more disruptive in the future or that they are not already disruptive in specific contexts. Rather, they emphasise the context-dependent and non-neutral nature of technology.

Data availability

Data will be made available on request.

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