Artificial Intelligence and Labour: theory, empirics and challenges ahead

Dario Guarascio and Jelena Reljic

Sapienza University of Rome

Political Economy of Production and Labour

Scuola Normale Superiore, Florence - 20 March 2026

Context

- The **labour–technology nexus** is as old as economics itself
- Rapid advancements in AI and its diffusion have revived concerns about **technological unemployment** (Ernst et al., 2019; Felten et al., 2021)
- **AI systems increasingly perform** a wide range of tasks—from routine (e.g., data entry) to complex cognitive ones (e.g., writing, legal or medical advice)—**blurring traditional boundaries between human and machine capabilities**
- Yet, **empirical evidence on employment (and income) effects remains mixed**: some point to neutral or even positive outcomes (Albanesi et al., 2025; Damioli et al., 2024), others point to disruptive impacts (Bonfiglioli et al., 2025; Hui et al., 2024)
- **For the EU**, empirical evidence is still limited: diffusion is uneven and measurement is challenging (Guarascio et al., 2025)

Numerous research questions still need to be addressed

AI and employment: Guiding Questions

If some **benefits**—such as higher productivity or increased labour demand—are about to emerge, these are likely to be **asymmetrically distributed** (Guarascio et al., 2025)

- Which activities can (and cannot) be performed by AI? Are these primarily **cognitive** or **manual**?
- Which occupations are most exposed? Are they **high- or low-skilled**, **routine** or **non-routine**?
- Which countries or regions are likely to be most affected? What roles do **structural characteristics** and **innovation capabilities** play?
- Which sectors are poised for transformation—**services**, **manufacturing**, or both?
- How do different forms of AI shape outcomes? **Generative AI** (e.g. ChatGPT) vs **specialised AI systems** (e.g. medical image interpretation)

Theoretical expectations

Negative ΔEMP < 0

- **Substitution**: automation to save labour costs (e.g., after-sales services)
- **Labour fragmentation**: algorithmic management weakens bargaining power and job quality
- **Market concentration**: AI-intensive products foster concentration and monopsony, with second order negative impact on jobs

Positive ΔEMP ≥ 0

- **Price-based compensation**: efficiency lowers prices, expands demand/market size
- **Tech-competitiveness**: new AI-driven products increase demand and market shares
- **New jobs/tasks effect**: AI enables new tasks and roles (absent strong SBTC/RBTC effect)

Difficult to establish ex-ante as these channels are not mutually exclusive and heterogeneity matters $\Rightarrow$ Either a **complementarity** or a **substitution** effect may prevail

Empirical evidence so far

Table 1: List of selected studies

Study	Indicator	Coverage	Result
Acemoglu et al. (2022)	AI vacancies/exposure	US 2010–2018	No effects
Squicciarini and Nachtigall (2021)	AI vacancies	CA, SG, UK, US	Growing demand for AI jobs
Felten et al. (2021)	AI exposure	US 2010–2016	No effects
Bonfiglioli et al. (2025)	AI exposure	US 2000–2020	Negative, esp. low-skilled
Guarascio et al. (2023)	AI exposure	EU 2011–2019	Positive
Albanesi et al. (2025)	AI exposure	EU 2011–2019	Positive, small
Webb (2020)	O*NET/AI patents	US 2000–2018	High-skilled more exposed
Yang (2022)	AI patents	Taiwan 2002–2018	Positive
Damioli et al. (2024)	AI patents	Global 2000–2016	Positive
Hui et al. (2024)	Gen-AI (Upwork)	2022–2023	Negative

Indicators: issues and limitations

- **Online vacancies**: not representative of total labour demand: occupation/industry/country biased
- **Patents**: imprecise proxy of *innovation*, not adoption; partial coverage
- **Occupation-based indices**: measure *exposure*, not adoption; limited information regarding industry/firm heterogeneity (Felten et al., 2021); some indicators rely on expert opinions and/or LLM-based scoring (Gmyrek et al., 2023; Eloundou et al., 2023)
- **AI patents + O*NET tasks**: *exposure* not adoption; keyword selection and title-based mapping are fragile (Webb, 2020)

AI and Employment in Europe (Guarascio and Reljic, 2025):

- We examine the **employment impact of AI** in the EU over the period **2012–2022**
- Our contribution extends the literature in several ways:
  - We analyse the **mediating role of task routinisation**, distinguishing between routine and non-routine cognitive occupations
  - We investigate **cross-country heterogeneity** in the labour–AI nexus, assessing how **R&D intensity, human capital, and absorptive capacity** shape countries' ability to benefit from AI

AI occupation exposure index (Felten et al., 2021)

AI exposure is defined as follows:

$$\mathrm{AIOE}_j = \frac{\sum_{k1}^{52} A_k \, L_{jk} \, I_{jk}}{\sum_{k=1}^{52} L_{jk} \, I_{jk}}. \tag{1}$$

where A_k denotes ability-level AI exposure, computed as relatedness scores between ten AI applications (e.g., translation, image generation, reading comprehension) for each of 52 abilities k (e.g, oral comprehension, speech recognition), while L_{jk} and I_{jk} are **prevalence** and **importance** of ability k in occupation j

- This methodology remains neutral regarding whether AI substitutes or complements occupations (Felten et al., 2021)

Descriptive evidence (1)

Table 2: Top 10 most AI-exposed occupations

#	ISCO-3 label	AIOE
1	Mathematicians, Actuaries and Statisticians (212)	1.66
2	Finance Professionals (241)	1.63
3	Legal Professionals (261)	1.63
4	Administration Professionals (242)	1.46
5	Numerical Clerks (431)	1.45
6	University and Higher Education Teachers (231)	1.44
7	General Office Clerks (411)	1.44
8	Sales, Marketing and Development Managers (122)	1.42
9	Software and Applications Developers and Analysts (251)	1.40
10	Secondary Education Teachers (233)	1.38

Descriptive evidence (2)

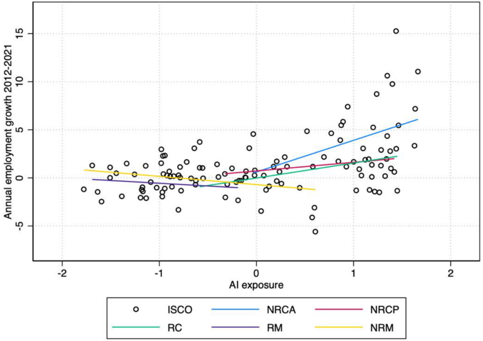
Table 3: Bottom 10 least AI-exposed occupations

#	ISCO-3 label	AIOE
126	Mining and Construction Labourers (931)	-1.78
125	Subsistence Crop Farmers (631)	-1.74
124	Vehicle, Window, Laundry and Other Hand Cleaning Workers (912)	-1.69
123	Domestic, Hotel and Office Cleaners and Helpers (911)	-1.64
122	Painters, Building Structure Cleaners and Related Workers (713)	-1.60
121	Subsistence Fishers, Hunters, Trappers and Gatherers (634)	-1.53
120	Manufacturing Labourers (932)	-1.51
119	Agricultural, Forestry and Fishery Labourers (921)	-1.51
118	Subsistence Mixed Crop and Livestock Farmers (633)	-1.47
117	Building Finishers and Related Trades Workers (712)	-1.44

Descriptive evidence (3)

- Positive correlation between AI exposure and employment growth $\Rightarrow \rho \approx 0.46$
- Driven by non-routine cognitive analytical occupations $\Rightarrow$ **possible complementarity**
- **Manual occupations**, regardless of routineness, appear **less susceptible**

Figure 1: Employment growth and AI exposure



Notes: NRCA (blue) - Non-Routine Cognitive Analytical; NRCP (red) - Non-Routine Cognitive Personal; RC (green) - Routine Cognitive; RM (purple) - Routine Manual; NRM (yellow): Non-Routine Manual occupations; The annual employment growth rate was calculated using the EU27 data.
Source: Authors' elaboration

Descriptive evidence (4)

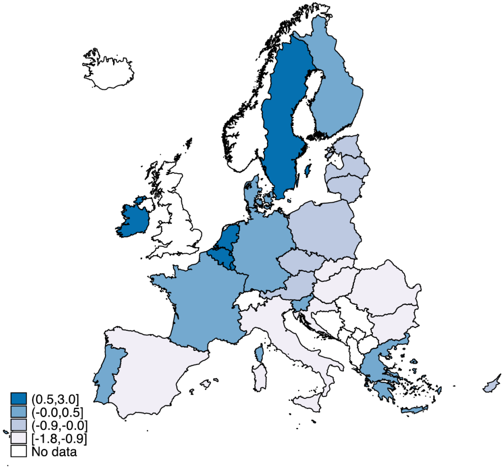
Table 4: Workforce characteristics in the EU27

	Total	Top AI	TOP AI & NRC	TOP AI & RC
Gender				
Female	46,8%	**54,3%**	46,3%	**75,7%**
Age				
20to34	27,9%	27,1%	27,6%	25,8%
35to49	38,8%	41,2%	42,1%	38,7%
50to64	33,3%	31,8%	30,3%	35,6%
Country of birth				
Foreign	14,0%	**10,2%**	10,6%	9,0%
Native	86,0%	89,8%	89,4%	91,0%
Education				
Lower secondary	15,7%	**3,5%**	2,4%	6,6%
Upper secondary	46,6%	29,8%	20,6%	**54,2%**
Tertiary	37,7%	**66,7%**	77,0%	39,2%

Source: Authors' elaboration based on EU LFS data.

Descriptive evidence (5)

Figure 2: AI exposure across the EU27



Source: Authors' elaboration

Econometric strategy

We estimate the following model:

$$Y_{ij} = \alpha + \beta AIOE_j + X_{ij}'\gamma + \tau_i + \varepsilon_{ij}, \tag{2}$$

where Y_{ij} is **annual employment growth** (2012–2022) in country i and occupation j; AIOE measures occupational AI exposure; X_{ij} includes country–occupation controls (share of native, senior, male workers, those with permanent contract, upper secondary, tertiary education); τ_i denotes country fixed effects; and ε_{ij} is the error term

To allow for heterogeneity by task content, augment it with an interaction:

$$Y_{ij} = \alpha + \beta AIOE_j + \delta\left(AIOE_j \times RC_j\right) + X_{ij}'\gamma + \tau_i + \varepsilon_{ij}, \tag{3}$$

where $RC_j = 1$ for routine cognitive occupations

We also estimate (4) separately for four country groups (Innovation Leaders, Strong, Moderate, Emerging) based on the European Innovation Scoreboard

Results (1)

Table 5: Employment growth and AI exposure, 2012–2022

	(1)	(2)	(3)	(4)	(5)
AI exposure	1.359***	0.420*	0.463*	0.703**	0.646**
	(0.193)	(0.237)	(0.266)	(0.271)	(0.251)
AI exposure × RC				-0.552	-0.381
				(0.584)	(0.609)
Routine cognitive (RC)				-0.812*	-0.527
				(0.458)	(0.423)
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	No
Constant	1.994***	4.068***	2.638	2.728	4.604**
	(0.265)	(1.253)	(1.648)	(1.632)	(2.145)
Observations	2,449	2,298	2,298	2,298	2,227

Notes: Robust SE in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In column (5), instead of country FE, we control for public procurement, GVC participation, and public R&D

Results (2)

Table 6: Employment growth and AI exposure by innovation performance

	(1) Innovation Leaders	(2) Strong Innovators	(3) Moderate Innovators	(4) Emerging Inn.
AI exposure	**0.853****	**1.192****	0.143	0.651
	(0.285)	(0.351)	(0.666)	(0.391)
AI exposure × RC	-0.520	0.279	-0.345	-1.627
	(0.761)	(1.282)	(0.719)	(2.079)
Routine cognitive (RC)	-0.911	-2.182	-0.891*	0.990
	(0.468)	(1.128)	(0.450)	(1.287)
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

Notes: Robust SE * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Country groups (EIS): (1) DK, SE, FI, NL, BE; (2) AT, DE, LU, IE, CY, FR; (3) EE, CZ, IT, ES, PT, LT, EL, HU; (4) HR, SK, PL, LV, RO.

Key results and policy implications

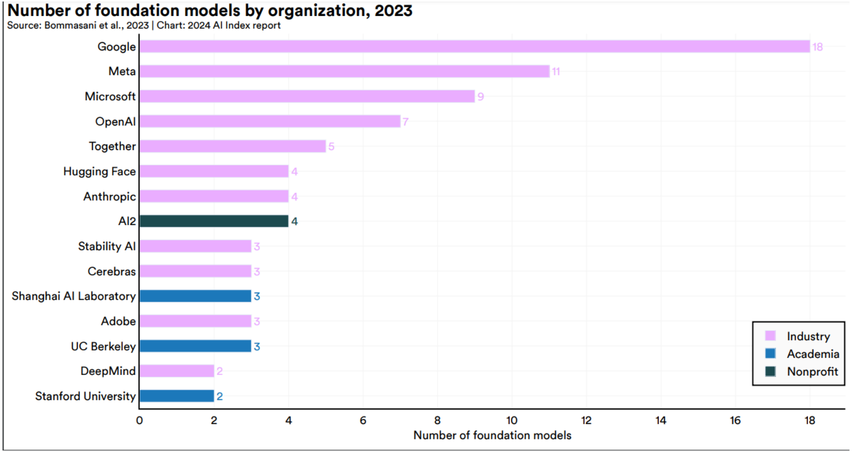
- Occupations most exposed to AI are **high-skilled and cognitive**, mostly in services ⇒ high exposure does not imply a higher substitution risk
- Positive employment effects dominate across the EU ⇒ increases in AI exposure are associated with higher annual employment growth, *ceteris paribus*
- AI may benefit routine cognitive jobs as much as non-routine ones ⇒ no evidence of a labour-saving effect in routine-cognitive occupations
- However, **positive effects concentrate in countries with stronger innovation systems** (higher R&D intensity, patenting, share of innovative firms, KI activities, and more attractive research environments) ⇒ the role of **absorptive capacity**

Caution is needed given the uncertainty surrounding AI's pace and direction

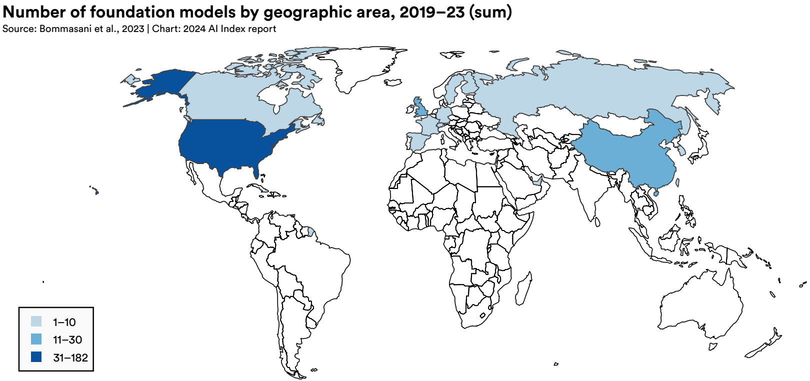
Limitations and other (crucial) issues

- This approach focuses on the **quantity** of jobs associated with AI exposure, but other important aspects of the labour–AI nexus remain underexplored:
  - The development of AI technologies relies on **platform-based micro-work** (e.g., data labelling, content moderation), raising questions about **precarious digital labour** (Casilli, 2020; Greenan et al., 2025)
  - **Algorithmic management** practices may reshape workplace relations, reducing transparency and workers' bargaining power (Prassl, 2018; González-Vázquez et al., 2025)
  - The **intensification of work rhythms and surveillance** can affect well-being and autonomy, with still limited empirical evidence (Staccioli and Virgillito, 2025)
  - The **complementarity between AI and high-skilled jobs** may reinforce existing income inequalities, benefiting those already well-positioned (Cazzaniga et al., 2024)

AI and the concentration of techno-economic power (1)



AI and the concentration of techno-economic power (2)



AI and the capital-labour conflict (fragmentation, surveillance, exploitation)

AI and the capital-labour conflict (fragmentation, surveillance, exploitation)

References I

Daron Acemoglu, David Autor, Jonathon Hazell, and Pascual Restrepo. Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1):S293–S340, 2022.

Stefania Albanesi, António Dias da Silva, Juan F Jimeno, Ana Lamo, and Alena Wabitsch. New technologies and jobs in europe. *Economic Policy*, 40(121):71–139, 2025.

Alessandra Bonfiglioli, Rosario Crinò, Gino Gancia, and Ioannis Papadakis. Artificial intelligence and jobs: evidence from us commuting zones. *Economic Policy*, 40 (121):145–194, 2025.

Antonio A Casilli. *Schiavi del clic: perché lavoriamo tutti per il nuovo capitalismo?* Feltrinelli Editore, 2020.

Mauro Cazzaniga, Ms Florence Jaumotte, Longji Li, Mr Giovanni Melina, Augustus J Panton, Carlo Pizzinelli, Emma J Rockall, and Ms Marina Mendes Tavares. *Gen-AI: Artificial intelligence and the future of work*. International Monetary Fund, 2024.

References II

Giacomo Damioli, Vincent Van Roy, Dániel Vértesy, and Marco Vivarelli. Drivers of employment dynamics of ai innovators. *Technological Forecasting and Social Change*, 201:123249, 2024.

Tyna Eloundou, Sam Manning, Pamela Mishkin, and Daniel Rock. Gpts are gpts: An early look at the labor market impact potential of large language models. *arXiv preprint arXiv:2303.10130*, 10, 2023.

Ekkehard Ernst, Rossana Merola, and Daniel Samaan. The economics of artificial intelligence: Implications for the future of work. *ILO Working Papers*, 2019.

Edward Felten, Manav Raj, and Robert Seamans. Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217, 2021.

Pawel Gmyrek, Janine Berg, and David Bescond. Generative ai and jobs: A global analysis of potential effects on job quantity and quality. *ILO Working paper*, 96, 2023.

References III

Ignacio González-Vázquez, Enrique Fernandez-Macias, Sally Wright, and Davide Villani. Digital monitoring, algorithmic management and the platformisation of work in europe, 2025.

Nathalie Greenan, Dario Guarascio, and Jelena Reljic. Ai and the labour market: Opening the black box. *Eurasian Business Review*, 2025.

Dario Guarascio, Jelena Reljic, and Roman Stöllinger. Artificial intelligence and employment: a look into the crystal ball. Technical report, GLO Discussion Paper, 2023.

Dario Guarascio, Jelena Reljic, and Roman Stöllinger. Diverging paths: Ai exposure and employment across european regions. *Structural Change and Economic Dynamics*, 73:11–24, 2025.

Xiang Hui, Oren Reshef, and Luofeng Zhou. The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market. *Organization Science*, 35(6):1977–1989, 2024.

References IV

Jeremias Prassl. *Humans as a service: The promise and perils of work in the gig economy*. Oxford University Press, 2018.

Mariagrazia Squicciarini and Heike Nachtigall. Demand for ai skills in jobs: Evidence from online job postings. *OECD Science, Technology and Industry Working Papers*, 2021(3):1–74, 2021.

Jacopo Staccioli and Maria Enrica Virgillito. Will your boss be an algorithm? a patent-based analysis of artificial intelligence worker management technologies and labour exposure. *Eurasian Business Review*, pages 1–31, 2025.

Michael Webb. The impact of artificial intelligence on the labor market. *SSRN Working Paper*, 2020.

Chih-Hai Yang. How artificial intelligence technology affects productivity and employment: Firm-level evidence from taiwan. *Research Policy*, 51(6):104536, 2022.