AI-Complementary Skills: Real-Time Evidence from Italian Job Postings

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Motvation & Research question

Artificial intelligence is reshaping labour markets, not only by changing the demand for jobs, but also by reshaping the tasks performed within occupations and the demand for complementary human skills.
This project uses Italian online job vacancies from Lightcast to study whether greater exposure to AI is associated with changes in the demand for different groups of skills, distinguishing technical AI-related skills and broader human competences.

Research question:
Which human skills become more or less demanded as AI exposure increases across occupations and local labour markets?

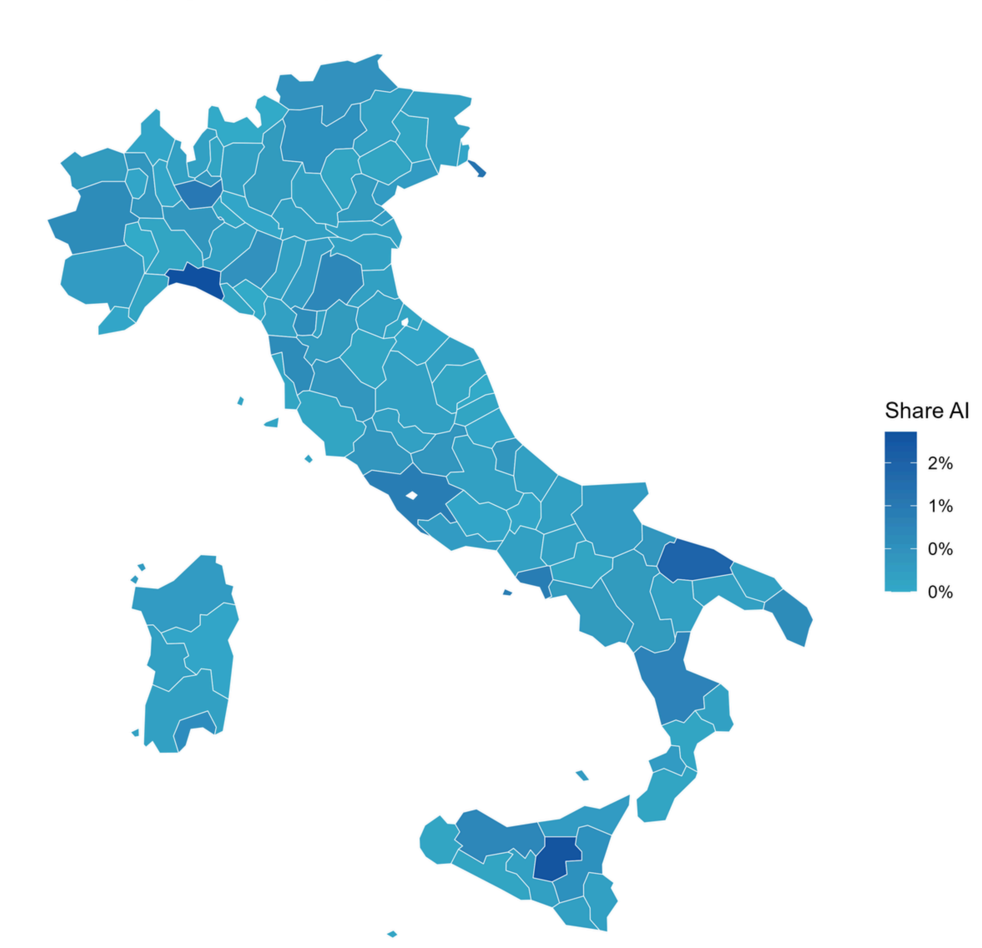
Data

- Online job vacancies | ~ 15,5 M postings, Italy, 2018-2024
- ESCO 4-digit occupations, NUTS-3 provinces
- ESCO skill classification and Lightcast AI skill taxonomy
- Unit of analysis: 3-digit occupation x province x year cell, weighted by geo-coverage

AI postings over time and location

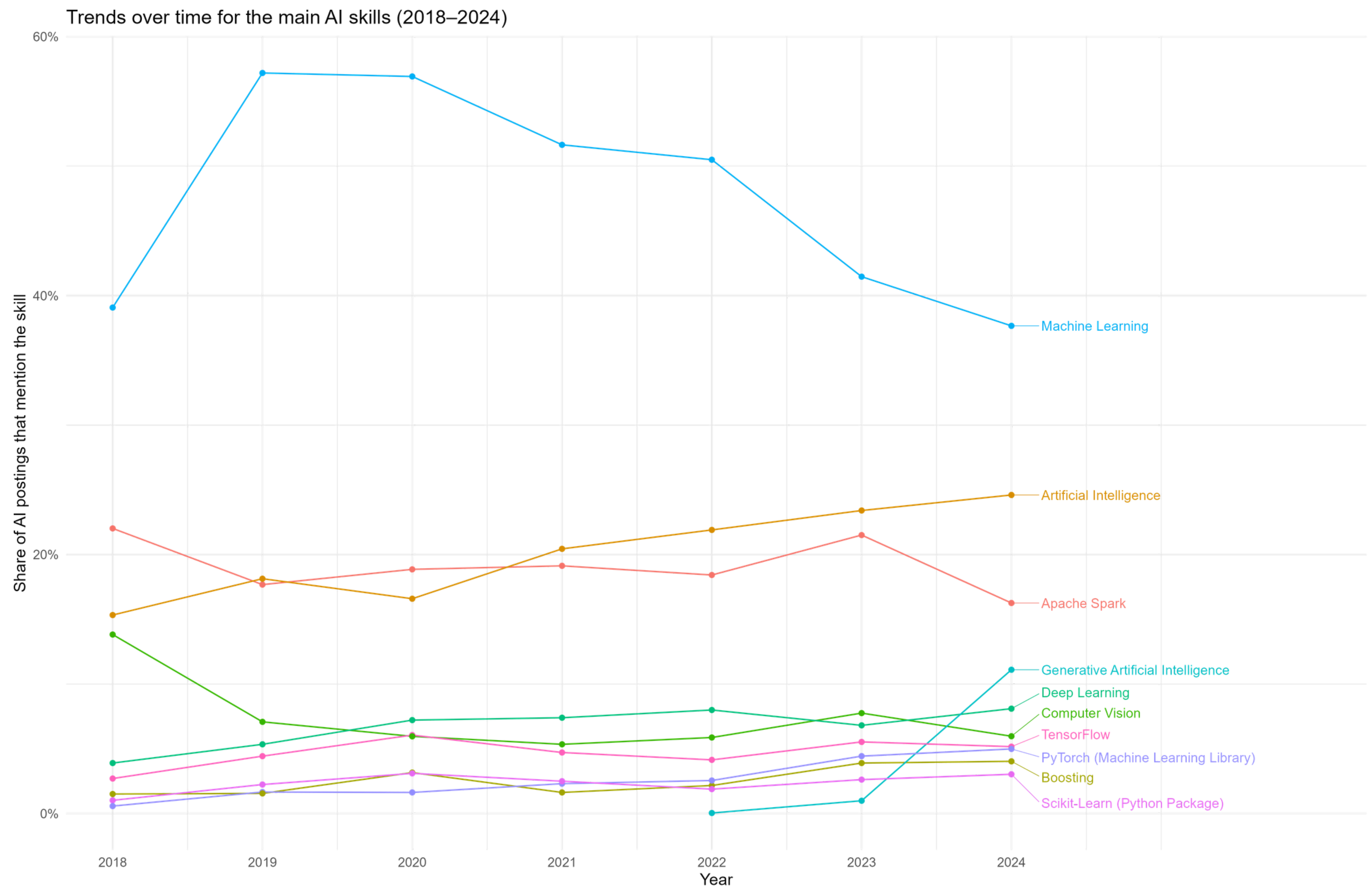
Year	Postings (total)	AI postings	Share AI
2018	858,746	2,363	0.3%
2019	1,259,049	6,775	0.5%
2020	1,485,169	8,464	0.6%
2021	1,919,623	11,362	0.6%
2022	2,797,980	20,625	0.7%
2023	3,942,017	18,123	0.5%
2024	3,321,541	16,926	0.5%

AI exposure by province (2023-2024)
Share of AI postings out of total postings in province

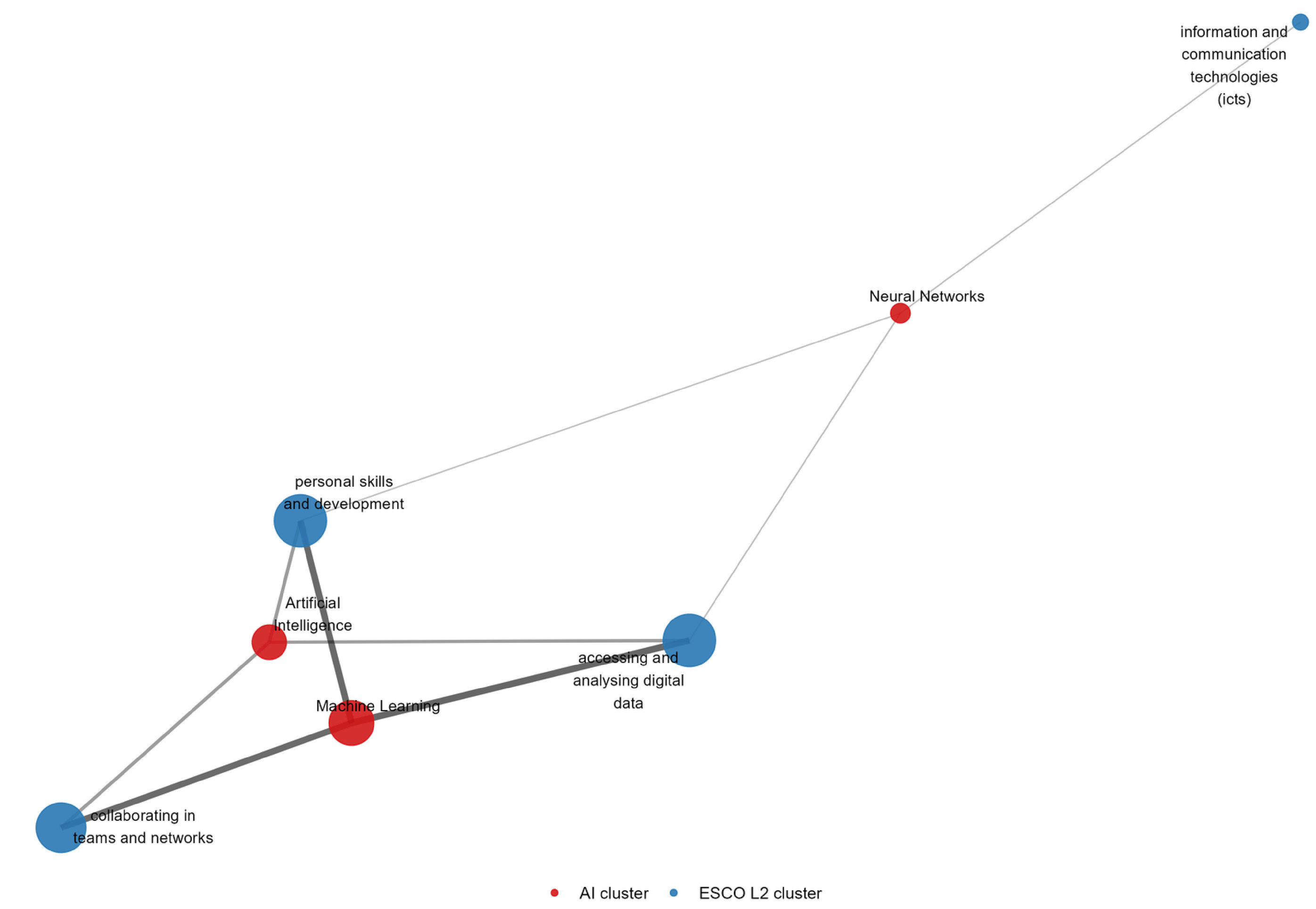


Skill demand

Trends over time for the main AI skills (2018–2024)

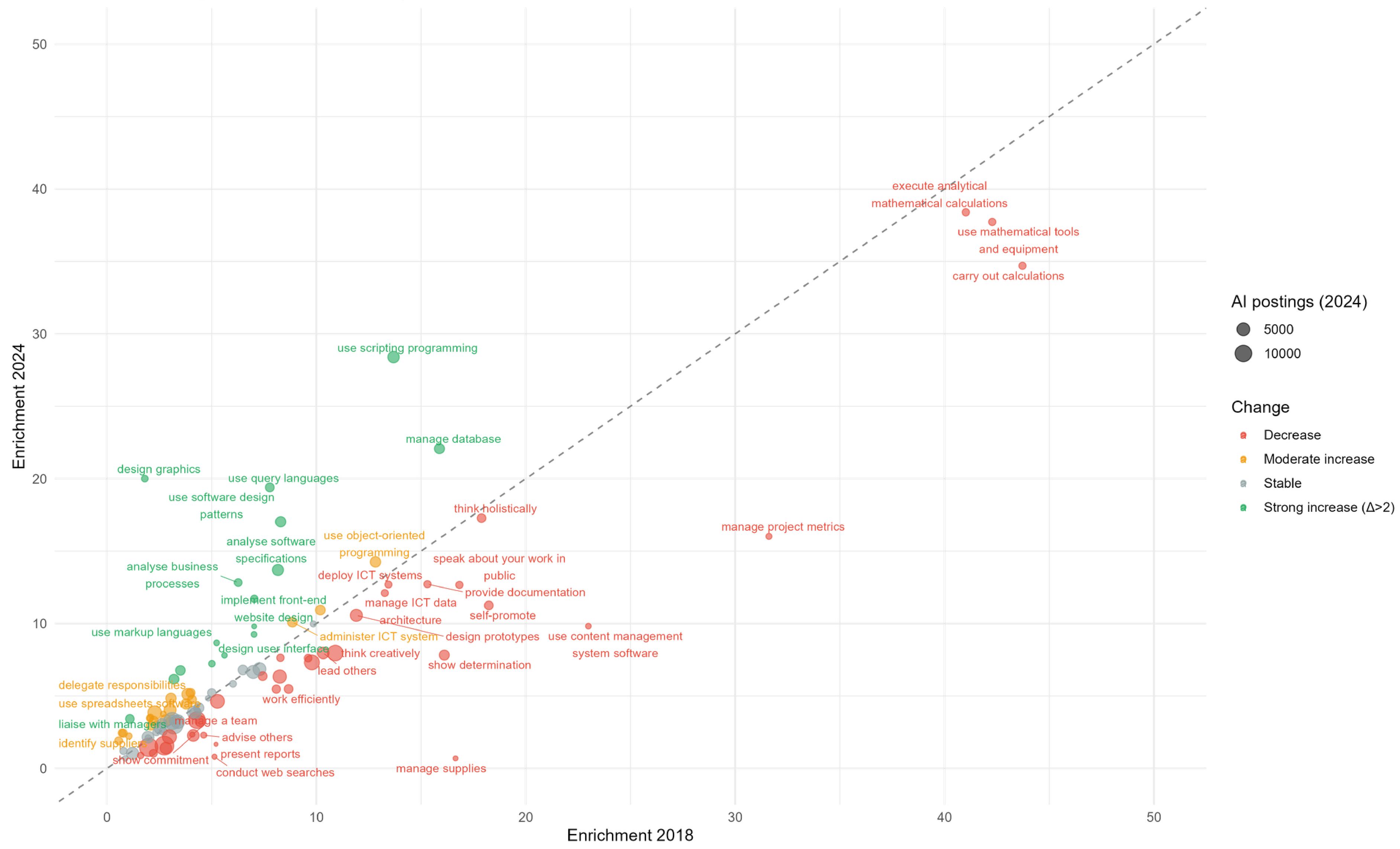


Top 3 AI clusters + top 3 ESCO L2 neighbours, 2023-2024



AI “enrichment” index = share of AI postings mentioning skill k in year t / share of all postings mentioning skill k in year t

Evolution of skill enrichment in AI job market (2018→2024)
Skills above the diagonal have become more specialized in AI roles



Methodology and next steps

The analysis uses an occupation × province × year panel of Italian online vacancies. For each skill cluster k, I estimate whether cells more exposed to AI show different changes in skill demand:

$$y^k_{ort} = \beta AI_{ort} + \alpha_{or} + \lambda_t + \varepsilon_{ort}$$

where y_ort is the share of vacancies demanding skill cluster k, AI_ort is AI exposure, α_or are occupation-province fixed effects, and λ_t are year fixed effects.
To address endogeneity, I use an instrumental-variable strategy based on baseline local occupational structure and national occupation-level AI intensity:

$$Z_{ort} = s_{or,2018} \times g_{ot}$$

where s_or is the baseline share of occupation o in province r in 2018, and g_ot is national AI intensity in occupation o and year t, measured as the share of national vacancies in that occupation mentioning AI skills.

Next steps: refine the outcome varibale using the AI enrichment index, compare alternative fixed-effect, including or+ot+rt FE, use additional data sources to measure occupational exposure, testing instrument strength and pre-trends.

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