INAPP
ISTITUTO NAZIONALE PER L'ANALISI
DELLE POLITICHE PUBBLICHE

Exposure to Artificial Intelligence and Gender Inequalities in the Italian Labour Market

Marina De Angelis, Silvia Donà and Piero Esposito

SIE, Cagliari

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WHY SHOULD WE CARE?

The effect of AI on wages is an open question not an automatic consequence of technological change

Monitoring AI's impact on the gender pay gap is essential to ensure that technological progress does not reinforce existing gender inequalities in the labour market

WAGE OUTCOMES DEPEND ON SEVERAL INTERRELATED MECHANISMS

TASKS AND JOBS

Are tasks replaced, transformed, or reorganised? Do job content, responsibilities and skill requirements change?

PAY AND BARGAINING

If AI changes output or work organisation, do wages respond—and who captures any gains or bears the costs?

DISTRIBUTION AND GENDER

How do effects vary across workers, firms and occupations? Do occupational segregation and unequal bargaining positions shape women's and men's outcomes?

- **Exposure alone does not tell us whether tasks will be substituted, jobs redesigned, or wage gains realized and shared.**
- **Understanding these channels is essential to assess whether AI may narrow or widen existing gender inequalities in the labour .**

WHAT DOES THE LITERATURE TELL US?

Evidence on wages, gender inequality and job quality—and what remains open

WAGE INEQUALITY	In Italy, wage premiums associated with AI-complementary occupations are concentrated at the top of the wage distribution and weaken around the median. This pattern suggests that AI may widen the wage gap between high- and low-paid workers, potentially reinforcing labour-market polarisation..	**Brunetti & Mussida (2025)**
GENDER PAY GAP	Across six economies, women are more likely than men to work in AI-exposed occupations in most countries. Among jobs at greater risk of substitution, low-paid women show more frequent transitions to inactivity. Women and highly educated workers face greater occupational exposure to AI, while higher-paid workers are more likely to be in occupations where AI has greater potential to complement their work	**Cazzaniga et al. (2025); Pizzinelli et al. (2023)**
JOB QUALITY	AI-related technological change may affect not only wages and employment, but also workers' job satisfaction and broader job quality. These associations can vary across skill levels, occupational groups and gender, suggesting that wage outcomes alone may not capture the full implications of AI exposure for workers.	**Schwabe & Castellacci (2020); De Angelis, Esposito & Scicchitano (2026)**

OUR CONTRIBUTION

We adopt a mixed-methods approach:

I) **We analyse the regulatory framework on the gender pay gap, pay transparency, and the effects of AI on working conditions.**

II) We explore the links between legislation and empirical evidence.

- We examine whether the amendments to the Italian Equal Opportunities Code introduced by Law No. 162/2021 were associated with different outcomes in large firms. We found no statistically significant differences.

III) We describe the situation prior to the introduction of the relevant regulations.

- **Using INAPP-PLUS, we examine the relationship between occupational AI exposure and wages before and after 2022, exploring differences by gender and skill group. We compare Felten's AIOE with an Italian ICP-based measure to assess how the choice of exposure indicator affects the results**.

- We also sought to investigate variable pay, given its potential role in gender pay inequalities. However, the INAPP-PLUS data did not allow us to explore this dimension adequately.

DIRECTIVE (EU) 2023/970

Pay transparency Directive

Before and during work

Pay range in job ads, no questions on pay history, neutral pay criteria and a right to average pay data by sex.

Reporting

Pay gap reports: yearly for 250+ staff, every three years for 100–249, from 2027 (2031 for 100–149).

Enforcement

A gap of 5% or more without justification triggers a joint pay assessment. The burden of proof shifts to the employer.

Member States had to transpose it by 7 June 2026. Italy did so with Legislative Decree 96/2026, in force from 7 June 2026.

ITALIAN AI LAW

Law 132/2025 sets Italy’s national AI framework alongside the EU AI Act

Status

Law of 23 September 2025, Official Gazette No. 223, in force since 10 October 2025. It complements Regulation (EU) 2024/1689.

New rules

Anthropocentric vision of artificial intelligence

Delegation

Arts. 16 and 24 empower the Government to adopt implementing legislative decrees by 10 October 2026.

The approach is innovation within a human-centred framework. The decrees implement the AI Act; they do not replace it.

IMPLEMENTING DECREES

Two decrees put the AI Act into operation

D.Lgs. 160/2026 · art. 18

In force 30 September 2026.

Where the damage results from the breach of one or more obligations laid down in Regulation (EU) 2024/1689, the causal link between the breach and the damage shall be presumed, unless proven otherwise.

D.Lgs. 179/2026 · art. 41

In force 23 October 2026. Final decisions on hiring, changes to or termination of employment, discipline and performance reviews cannot rest solely on automated processing.

D.Lgs. 179/2026 · art. 42

Health and safety: AI affecting work organisation, pace or safety-relevant decisions must be covered by the risk assessment (art. 28, D.Lgs. 81/2008), with worker information and training.

Decree 160: Official Gazette No. 214 of 15 September 2026. Decree 179: No. 234 of 8 October 2026.

QUESTION AND DESIGN

Our aim: To assess the relationship between AI exposure, wages and gender gaps before the new legislation is fully implemented

RQ: Did wages grow less in AI-exposed occupations after 2022, and did women lose more?

Data

INAPP-PLUS cross-sections 2016–2024, employees. Weights W1 raked to official employment by occupation × sex (W_rib).

Exposure

AIOE Felten (SOC → CP2011) and AIOE built on Italian ICP data. Standardised across occupations within skill group.

Estimation

Log wage on exposure × post (2022–24). FE: occupation, skill × wave, sector × wave, region × wave; Mincer controls.

Women vs men: one model fully interacted with gender (FE, controls, exposure). SE clustered by occupation (CP2011 4-digit).

WHO IS EXPOSED

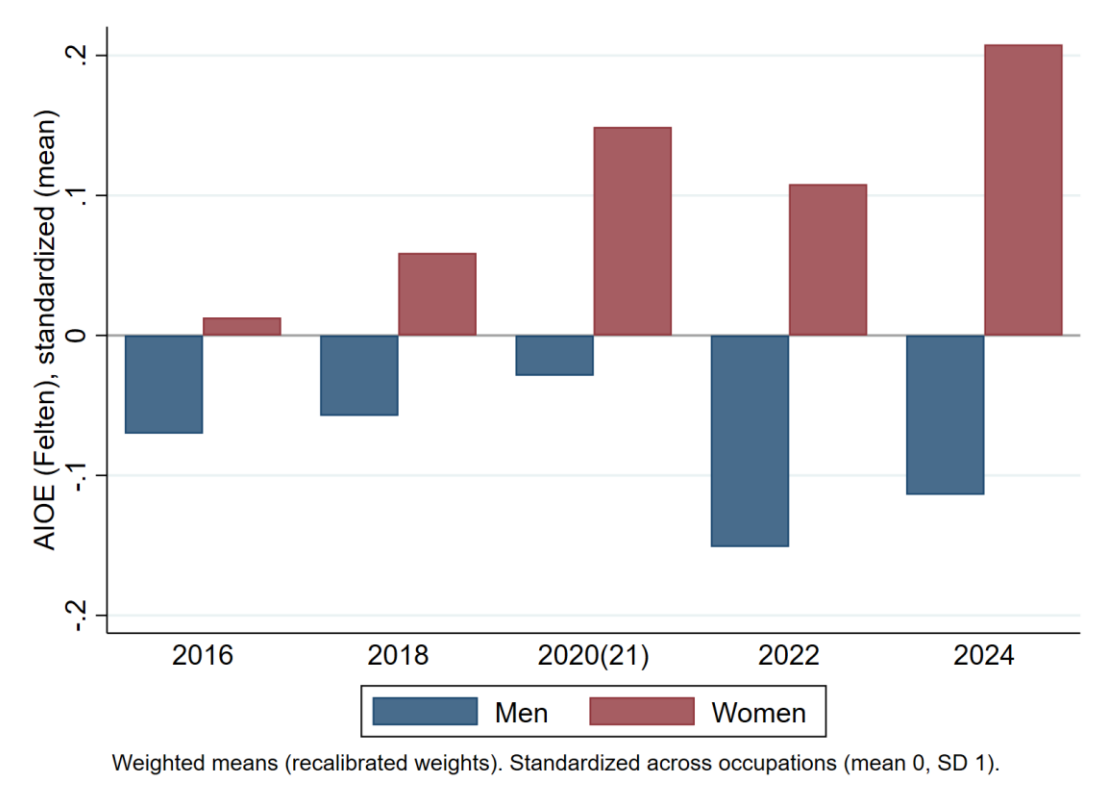
Women are more exposed on both measures, mostly because of the skill mix

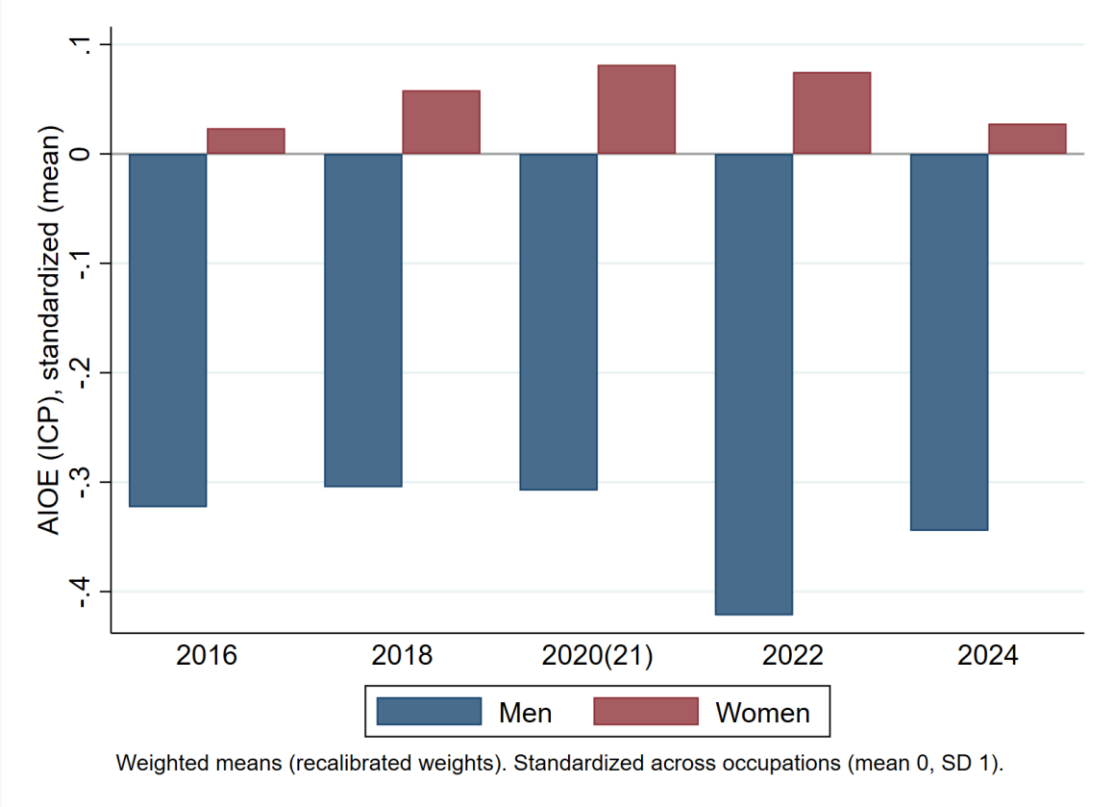
	AIOE Felten			AIOE ICP		
SD units	Women	Men	W – M	Women	Men	W – M
All workers	0.109	−0.078	0.186	0.053	−0.340	0.393**
Pre (2016–2020/21)	0.077	−0.048	0.125	0.054	−0.312	0.366**
Post (2022–2024)	0.162	−0.128	0.290**	0.051	−0.383	0.434***
High skill	0.608	0.861	−0.253***	0.571	0.542	0.029
Medium skill	0.250	0.127	0.122	0.106	0.063	0.044
Low skill	−1.235	−0.882	−0.353**	−1.111	−1.163	0.052
Gap from differences within skill			−0.11			0.04
Gap from skill composition			0.30			0.36

AIOE standardised across occupations; means over waves, weighted (W_rib, normalised within wave). Felten: SE clustered by occupation, * p<0.1, ** p<0.05, *** p<0.01. ICP: descriptive differences. Last two rows: within = Σ s_W (e_W − e_M), composition = Σ (s_W − s_M) e_M over skill groups, averaged across waves.

EXPOSURE OVER TIME

Women are more exposed than men in every wave, with both measures

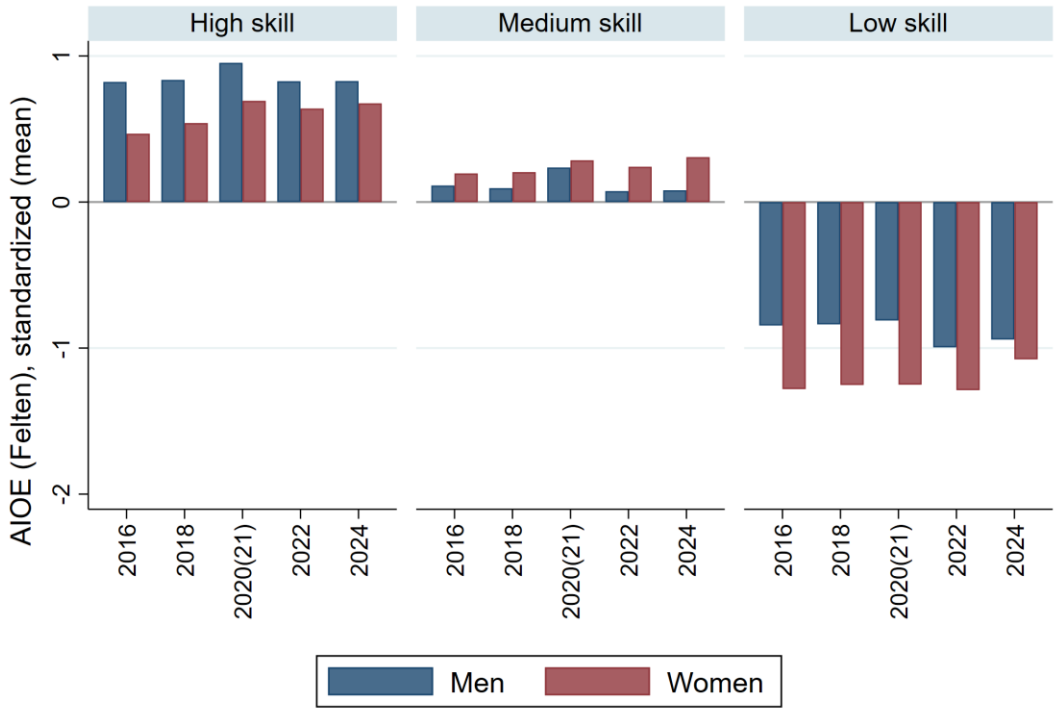


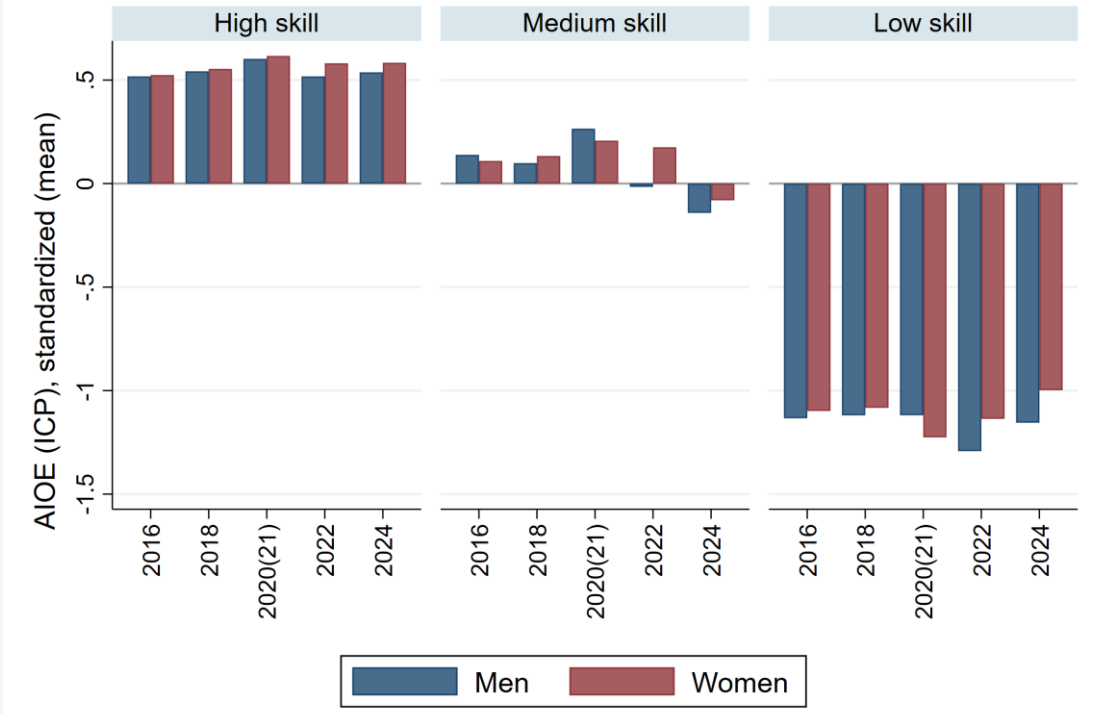


Left: AIOE Felten. Right: AIOE ICP. Mean exposure by wave, standardised across all occupations; W_rib weights.

EXPOSURE BY SKILL GROUP

Within skill groups Felten puts women below men in high and low skill; ICP does not





Left: AIOE Felten. Right: AIOE ICP. Mean exposure by wave and skill group, standardised across all occupations; W_rib weights.

WAGE EFFECTS

One SD of exposure lowers wages by 2–4% after 2022, for women and men alike

Exposure × post	Men	Women	W − M	N (M / W)
AIOE Felten	−0.022**	−0.031**	−0.009	43,307
	(0.011)	(0.014)	(0.019) p=0.64	45,742
AIOE ICP	−0.038***	−0.043***	−0.005	42,517
	(0.013)	(0.016)	(0.021) p=0.81	44,871

Log wage. Exposure standardised within skill. FE and controls (Educational attainment, age group, type of employment contract, job tenure, remote work (yes/no)); W_rib weights; SE clustered by occupation. * p<0.1, ** p<0.05, *** p<0.01.

WAGE EFFECTS BY SKILL

The wage penalty is concentrated in medium-skill jobs

	AIOE Felten			AIOE ICP		
Skill	**Men**	**Women**	**W − M**	**Men**	**Women**	**W − M**
High	−0.024	−0.007	0.017	−0.042**	−0.050*	−0.008
	(0.018)	(0.017)	(0.021) p=0.42	(0.020)	(0.029)	(0.027) p=0.77
Medium	−0.067**	−0.070***	−0.003	−0.064***	−0.043*	0.020
	(0.026)	(0.020)	(0.039) p=0.94	(0.020)	(0.023)	(0.035) p=0.57
Low	−0.010	−0.016	−0.006	−0.020	−0.026	−0.006
	(0.014)	(0.023)	(0.031) p=0.85	(0.021)	(0.037)	(0.044) p=0.89

Exposure × post × skill group, log wage. Skill: High CP 1–3, Medium CP 4–5, Low CP 6–8. * p<0.1, ** p<0.05, *** p<0.01.

HIGH VS LOW EXPOSURE

Wages in exposed occupations fell 5–9% relative to the least exposed

Group × post (ref.: low exposure)	Men	Women	W − M
High exposure, Felten	−0.053**	−0.049	0.004
	(0.025)	(0.031)	(0.041) p=0.92
High exposure, ICP	−0.085***	−0.078***	0.007
	(0.028)	(0.027)	(0.041) p=0.86

High = above the occupational median within skill, same rule for both measures. * p<0.1, ** p<0.05, *** p<0.01.

WOMEN VS MEN

No test rejects an equal wage effect for women and men

	AIOE Felten			AIOE ICP		
Difference W − M in the effect of	**W − M**	**SE**	**p**	**W − M**	**SE**	**p**
Exposure × post	−0.009	0.019	0.64	−0.005	0.021	0.81
… high skill	0.017	0.021	0.42	−0.008	0.027	0.77
… medium skill	−0.003	0.039	0.94	0.020	0.035	0.57
… low skill	−0.006	0.031	0.85	−0.006	0.044	0.89
High vs low exposure	0.004	0.041	0.92	0.007	0.041	0.86
Overall effect (pp)	+0.7	1.8	0.68	−0.3	1.6	0.85

Tests from one model fully interacted with gender (FE, controls, exposure); SE clustered by occupation. Log wage; overall effect from the high/low split.

WHERE THE GENDER GAP COMES FROM

The small gap comes from who is exposed, not from a different response; its sign depends on the measure

AIOE Felten

In high-exposure occupations

Women 39% · Men 50%

Wage effect: women −1.9%, men −2.6%**

Difference **+0.7 pp** (n.s.) = exposure **+0.6 pp**** + response +0.1 pp (n.s.)

AIOE ICP

In high-exposure occupations

Women 43% · Men 36%

Wage effect: women −3.3%***, men −3.0%***

Difference **−0.3 pp** (n.s.) = exposure **−0.6 pp***** + response +0.3 pp (n.s.)

High = above the within-skill median; ref.: low exposure. Exposure part at men's coefficients, response part at women's exposure.

OVERALL EFFECT BY GENDER

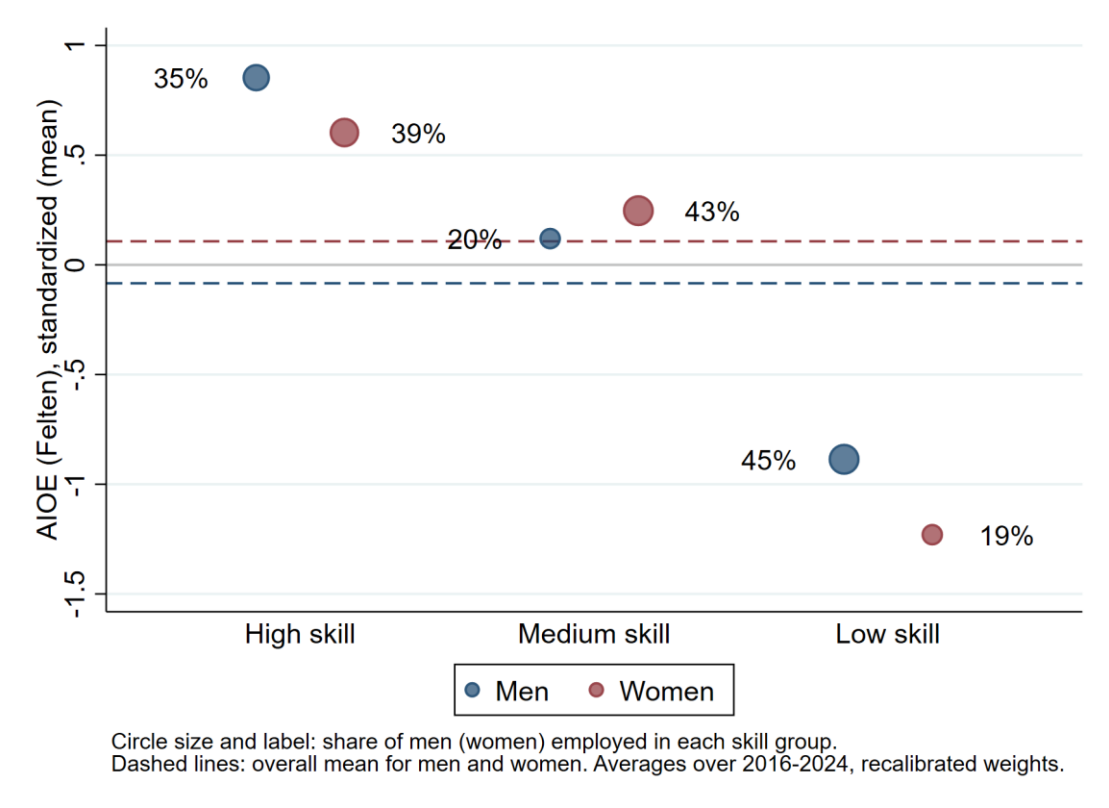
Women and men lose about the same; exposure gaps weigh under one point

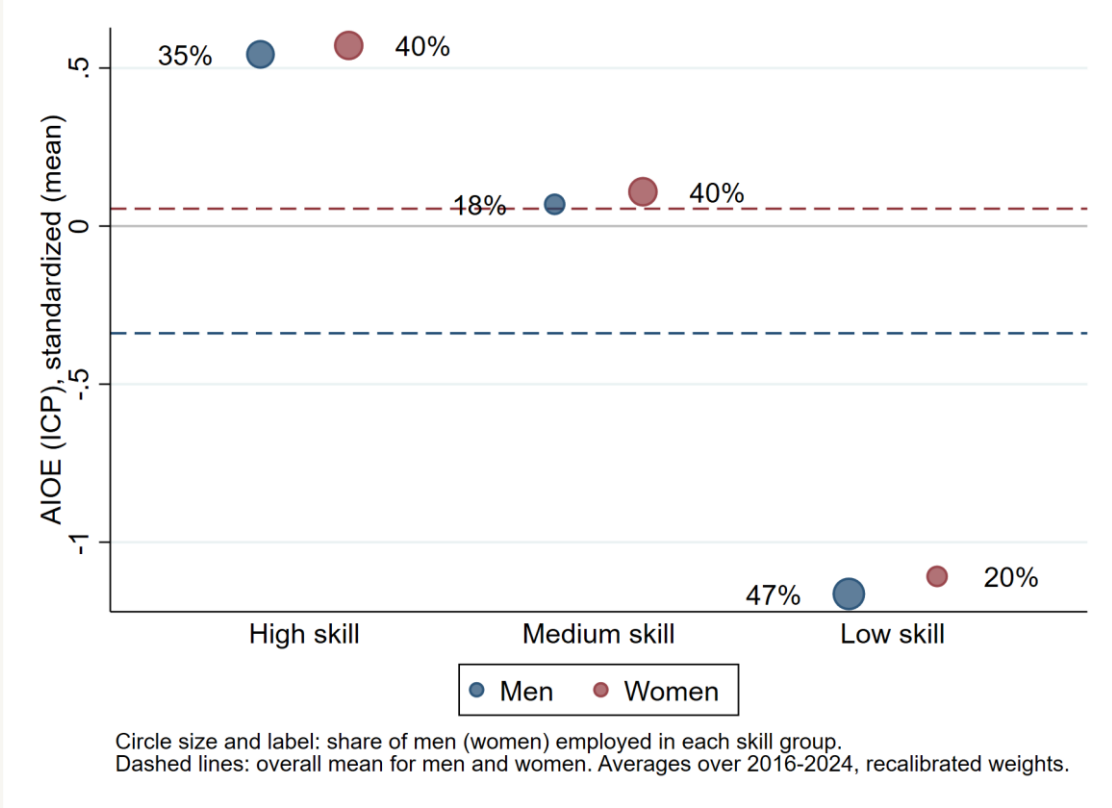
% change in wage	Felten, cont.	ICP, cont.	Felten, high/low	ICP, high/low
Men	−3.3** (1.6)	−4.3*** (1.5)	−2.6** (1.3)	−3.0*** (1.0)
Women	−3.4** (1.5)	−5.2*** (1.9)	−1.9 (1.2)	−3.3*** (1.2)
Difference W − M	−0.1 (2.4)	−0.8 (2.5)	+0.7 (1.8)	−0.3 (1.6)
p-value, difference	0.97	0.74	0.68	0.85
… due to exposure	+0.8** (0.4)	−0.2*** (0.1)	+0.6** (0.3)	−0.6*** (0.2)
… due to response	−0.9 (2.1)	−0.6 (2.6)	+0.1 (1.6)	+0.3 (1.7)
In high exposure, W / M			39% / 50%	43% / 36%

Continuous: vs the 10th percentile occupation within skill. Exposure from the pre period. SE via lincom, exposure means fixed.

EXPOSURE AND COMPOSITION

Men are concentrated in low-skill jobs, and this drives the overall exposure gap





Left: AIOE Felten. Right: AIOE ICP. Circle size and label: share of men (women) in each skill group; dashed: overall mean.

EXPOSURE ACROSS SKILL GROUPS

Women are more exposed overall because they work in more exposed skill groups

Pre period	AIOE Felten	AIOE ICP
Exposure gap W – M (SD)	**+0.12**	**+0.36**
… within skill groups	−0.17	−0.01
… composition across skill groups	+0.29	+0.37
High skill, share of women / men	38% / 34%	40% / 35%
Medium skill, share of women / men	43% / 20%	40% / 18%
Low skill, share of women / men	19% / 45%	20% / 47%
Women more exposed within skill?	No: less exposed	Same exposure

Pre period, wage estimation sample, W_rib weights. Exposure standardised across all occupations. Gap = within skill + composition across skill groups.

TOTAL EFFECT ON THE GENDER PAY GAP

Counting where women work, AI exposure widened the gender pay gap by up to 1.7 points

Percentage points	Felten, V1	Felten, V2	ICP, V1	ICP, V2
Effect on wages, men	−5.2** (2.2)	−1.8 (1.7)	−5.2*** (1.9)	−2.3* (1.4)
Effect on wages, women	−6.8*** (2.5)	−3.8* (2.1)	−8.3*** (3.1)	−5.0** (2.6)
Change in gender pay gap	−1.7 (3.6)	−2.0 (2.8)	−3.1 (3.9)	−2.7 (3.2)
... due to exposure	**−0.50** (0.21)**	**−0.17 (0.16)**	**−1.68*** (0.60)**	**−0.75* (0.45)**
within skill groups	+0.73** (0.30)	+0.25 (0.24)	+0.04*** (0.01)	+0.02* (0.01)
composition across skill groups	−1.23** (0.52)	−0.42 (0.40)	−1.71*** (0.62)	−0.77* (0.46)
... due to response	−1.2 (3.8)	−1.8 (2.9)	−1.4 (4.3)	−1.9 (3.5)

Negative = wider gap against women. V1: skill × wave FE (main); V2: without. Raw gap −29.1 pre, −18.5 post.

TAKEAWAYS

AI exposure cut wage growth, not differently for women

3–5% lower wages

in exposed occupations after 2022, mostly in medium-skill jobs

Robust to the measure

Felten and Italian ICP give the same pattern; effects are larger with ICP

Same response by gender

no significant W – M difference in any of twelve tests

Gap up to 1.7 pp wider

via skill composition: 0.5 pp Felten, 1.7 pp ICP

Thank you for your attention

ma.deangelis@inapp.gov.it
s.dona@inapp.gov.it
piero.esposito@unicas.it

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www.inapp.gov.it