The Skill Inside the Task: How AI and Robotics Reshape the Structure of Work.

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The Skill Inside the Task: How AI and Robotics Reshape the Structure of Work*

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Abstract

We examine how exposure to artificial intelligence (AI) and robotics reshapes the skill composition of occupations. Using O*NET data from 2006 to 2019, we construct indicators tracking the importance of seven broad skill categories within each occupation over time. We link these indicators to task-based measures of technological exposure at the occupational level. We then focus on the effect of AI and robotics in altering the skill composition of high-, middle- and low-skilled groups of occupations. We find that AI primarily affects high-skill occupations by increasing the importance of *Technical* and *Resource Management* skills and decreasing that of *Systems* and *Social* skills. Robotics instead boosts *Technical* skills in middle and low-skill occupations and reduces *Process* skills in low-skilled ones. Notably, neither AI nor robots affect the importance of *Complex Problem Solving* skills.

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1 Introduction

The diffusion of AI and robotics is transforming the nature of work, not only by potentially displacing occupations, but also by reshaping their internal skill structure. More specifically, technology might reshape the structure of an occupation as a productive unit, by increasing or reducing the importance of some tasks, and changing the skills required to perform that occupation. Although this possibility is widely acknowledged, to the best of our knowledge no studies systematically analyze how technological exposure alters the skill composition within occupations. This paper aims to fill this gap by focusing on two specific technologies: Robots and AI.

Our contribution is twofold. First, we construct dynamic occupation-level measures of skill content by mapping O*NET Intermediate Work Activities (IWAs) to seven broad skill categories, and link these to consistent measures of AI and robotics exposure. Second, we move beyond aggregate estimates and focus explicitly on heterogeneity across occupational groups, studying how the impact of AI and robotics differs for high-, middle-, and low-skill occupations.

Our work contributes to a growing literature that links technological change to occupational content using task-based methods. Prior studies have developed exposure indices (Webb, 2019; Acemoglu and Restrepo, 2020), and documented shifts in skill demand (Acemoglu, Autor, Hazell, and Restrepo, 2022) and mismatches between individual abilities and occupational skill requirements (Guvenen, Kuruscu, Tanaka, and Wiczer, 2020), but they mostly rely on cross-sectional variation or employment shares. By aligning skill and technology measures within a shared task-based framework, our approach sheds light on how automation transforms work not simply by replacing occupations, but by altering the balance of skills required to perform them, a fundamental dimension of occupational transformation.

2 Data and variables construction

Measuring Technological Exposure: AI and Robotics Share

To measure occupational exposure to robotics, we adopt the task-based measure developed by Cossu, Moro, and Rendall (2024), which captures physical and mechanical automation due to robots but not the role of AI. To fill this gap, we propose a novel AI exposure measure based on the same methodology. Using O*NET data, we map tasks to Intermediate Work Activities (IWAs) and match them to AI applications identified by Rashid and Kausik (2024) through domain-specific text matching. AI exposure is computed annually from 2006 to 2019 as the share of IWAs potentially automatable through AI.

Figure 1 illustrates that AI exposure is large in high-skill occupations, and has increased over time. Interestingly, low-skill occupations exhibit a decline in AI exposure, likely because their task content has shifted over time toward activities such as manual or interpersonal tasks, that possibly remain difficult to automate with current AI technologies. In contrast, exposure to robotics is concentrated in low- and middle-skill occupations.

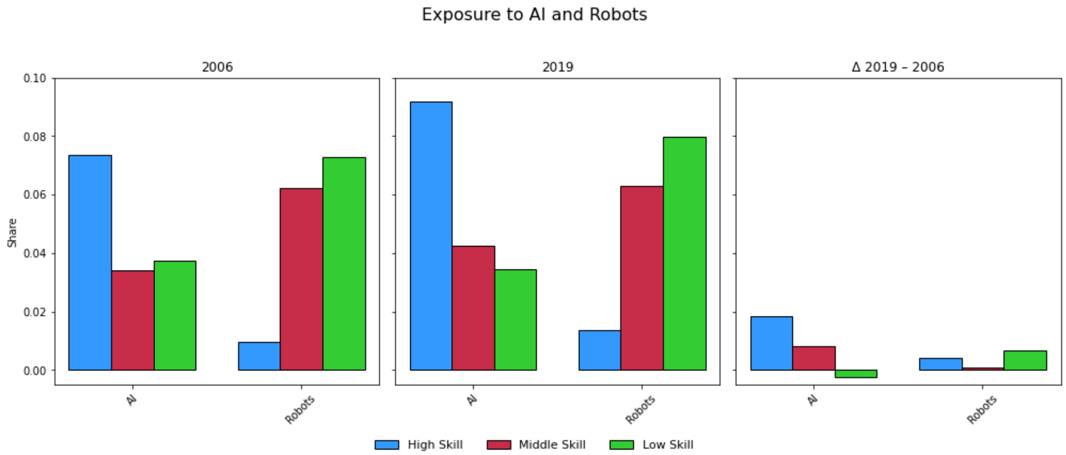

Figure 1: Technological exposure by occupations 2006-2019

Measuring Skill Composition Within Occupations

To investigate how technology reshapes the internal structure of occupations, we construct measures of skill composition based on the Intermediate Work Activities (IWAs) performed in each occupation over time.

We rely on the O*NET mapping between Work Activities (WAs) and skills. Following O*NET's taxonomy, we define seven broad skill categories: 1) *Content*; 2) *Process*; 3) *Social;* 4) *Complex Problem Solving;* 5) *Technical;* 6) *Systems*; 7) *Resource Management*. An IWA is considered to be associated with a given skill if it maps to at least one Work Activity (WA) that is linked to that skill category in the Skills-to-WA mapping.[1]

Figure 2 provides a visual representation of the relationship skills-WA-IWA-occupations.[2] For each occupation j and year t, we compute the share of each skill category s as the number of IWAs linked to that skill divided by the total number of IWAs, resulting in a seven-dimensional skill vector per occupation-year. These measures are calculated annually from 2006 to 2019, forming a dynamic panel that tracks within-occupation changes in skill content.

Figure 3 illustrates how the internal skill composition of occupations varies across skill groups and evolves over time.[3] Low-skill occupations are consistently dominated by Technical skills, while Content and Process skills prevail in high-skill. Over time, Process skills increase in all groups, while Social and Systems skills decline. The figure reflects shifts in skill

[1]While O*NET provides direct ratings of skill importance at the occupation level, we construct our measure of skill composition from Intermediate Work Activities (IWAs). This choice ensures consistency with our technological exposure measures, also defined at the IWA level, and allows us to capture a finer and more task-based representation of the internal structure of occupations.

[2]The blue-colored node represents AI and Robots applications. While not part of the original O*NET taxonomy, it is included in Figure 2 to visualize the mapping we construct between technological applications and tasks performed in occupations.

[3]The methodology used to construct the skills share aggregated by the three occupations is exactly the same used for the AI measure.

composition within occupations. In the next section, we investigate whether technological exposure may be one of the drivers of these transformations.

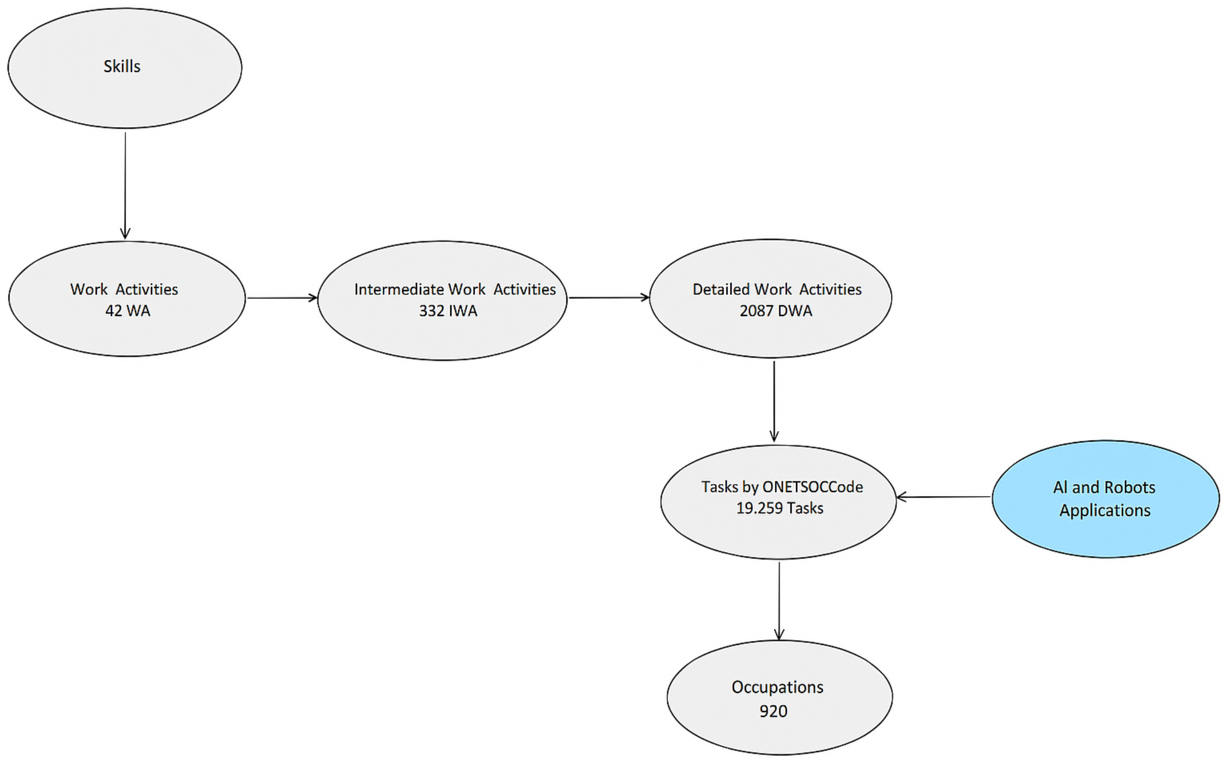

Figure 2: Map skills-activities-tasks-occupations

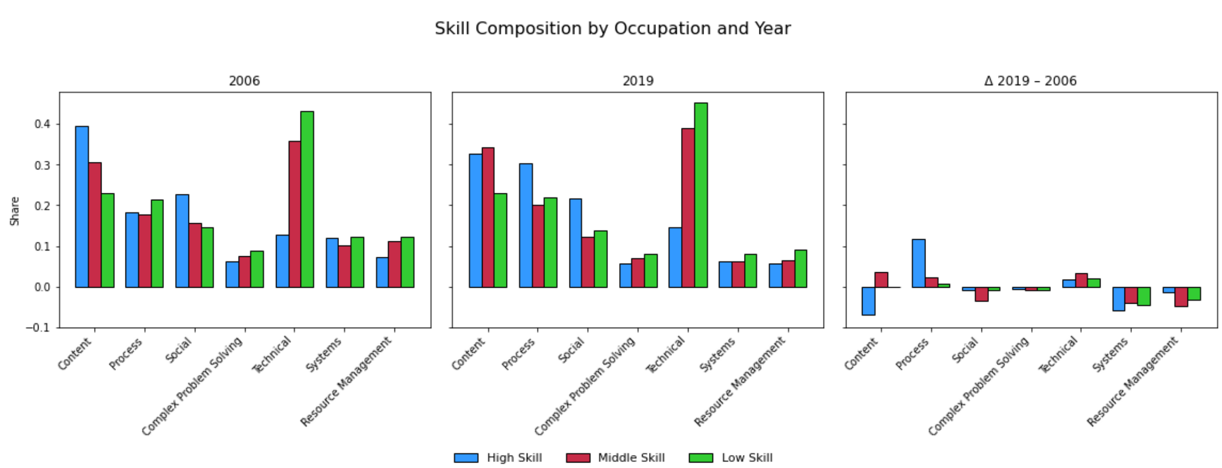

Figure 3: Skill composition by occupation 2006-2019

3 The Effect of Technological Exposure on Task-Skill Composition

To quantify the impact of technological exposure on occupational skill composition, we implement a two-stage least squares (2SLS) strategy. The dependent variable is the share of each of the seven broad skill categories within occupation j and year t, and the endogenous regressors are AI and robotics exposure measures. We address potential endogeneity of the regressors by constructing shift-share style instruments interacting each occupation's baseline exposure in 2006 with the aggregate annual trend in AI and robotics diffusion.

Formally, the instruments are defined as follows:

$$AI\,IV_{j,t} = AI\,baseline_j \times AI\,trend_t$$

$$Robots\,IV_{j,t} = Robots\,baseline_j \times Robots\,trend_t$$

This approach builds on Bartik (1991) and is consistent with a large literature that uses shift-share designs to isolate exogenous variation in local or occupational exposure to aggregate shocks (Goldsmith-Pinkham, Sorkin, and Swift 2020; Borusyak, Hull, and Jaravel 2022). The identifying assumption is that the baseline exposure is uncorrelated with other unobserved determinants of skill composition, conditional on fixed effects.

The second-stage regression is:

$$skill^s_{j,t} = \alpha + \beta_1 \widehat{AI}_{j,t} + \beta_2 \widehat{Robots}_{j,t} + \gamma_j + \delta_t + \varepsilon_{j,t}$$

In this specification, $skill^s_{j,t}$ denotes the share of skill category s in occupation j at year t. The variables $\widehat{AI}_{j,t}$ and $\widehat{Robots}_{j,t}$ are the predicted values of AI and robotics exposure obtained from the first-stage regressions. The specification includes occupation fixed effects γ_j and year fixed effects δ_t.[4]

Table 1 reports the results, AI exposure is significantly associated with an increase in Process skills and a decline in Content, Social and Systems skills. For instance, a one percentage point increase in AI exposure is associated with a 0.93 percentage point rise in Process skills, and a 0.73 percentage point decline in Content skills. In contrast, robotics is linked to a positive effect on Technical skills and a reduction in Content and Social skills.

[4] First-stage results confirm that the instruments are strong predictors of technological exposure, with F-statistics well above conventional thresholds for weak instrument concerns.

Table 1: Second stage results

	(1) Content skills	(2) Process skills	(3) Social skills	(4) Complex Problem Solving skills	(5) Technical skills	(6) Systems skills	(7) Resource Management skills
$\widehat{AI}_{j,t}$	-0.734**	0.930***	-0.707**	0.0461	0.216	-0.412**	0.306
	(0.325)	(0.330)	(0.280)	(0.159)	(0.222)	(0.199)	(0.232)
$\widehat{Robots}_{j,t}$	-0.580**	0.502*	-0.470**	-0.172	0.429*	0.169	0.0864
	(0.232)	(0.292)	(0.185)	(0.126)	(0.233)	(0.156)	(0.158)
Constant	0.315***	0.183***	0.281***	0.0427***	0.0599***	0.0751***	0.111***
	(0.0154)	(0.0216)	(0.0360)	(0.00895)	(0.0137)	(0.0115)	(0.0236)
Observations	3,812	3,812	3,812	3,812	3,812	3,812	3,812
R-squared	0.829	0.530	0.684	0.451	0.967	0.524	0.567
Occupations FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Note: * p<0.1; ** p<0.05; *** p<0.01. Standard errors are in parentheses below coefficients.
The Kleibergen–Paap F-statistics is 30.850.

To explore heterogeneity across skills, we estimate the IV model by occupational group. The results, reported in Table 2, show that AI primarily affects high-skill occupations, boosting Technical and Resource Management skills while reducing Social and Systems skills. In middle-skill occupations, AI increases Process skills but lowers Content skills. Robotics mainly impacts low-skill occupations, raising Technical skills but displacing process components. Overall, AI reshapes the skill composition of high-skill occupations by strengthening individual expertise, while robotics transforms the skill profiles of lower-skill occupations by reinforcing technical aspects, highlighting the distinct and occupation-specific impact of each technology.

Interestingly, we found that neither AI nor robotics appears to have any statistically significant effect on Complex Problem Solving skills. This result suggests that these higher-order cognitive abilities may remain unaffected by current technological advances. Recently, the economic and policy debate raised growing concerns about the potential cognitive effects of widespread generative AI use (The Economist, 2025). In particular, it is questioned whether the use of AI impairs neural and behavioral abilities (Kosmyna, Hauptmann, Yuan, Situ, Liao, Beresnitzky, Braunstein, and Maes, 2025). While answering this question is beyond the scope of our paper, our empirical findings offer an indirect contribution to this debate. The absence of measurable changes in Complex Problem Solving skills may indicate that existing AI technologies are not yet capable of replicating or replacing these advanced mental processes. Alternatively, it may reflect a subtler shift: problem-solving is increasingly delegated to machines, but not to a degree that significantly alters the observable skill composition of occupations. In this sense, our findings suggest that Complex Problem Solving remains, for now, largely insulated from the effects of AI-driven automation.

Table 2: Impact of AI and Robotics on Skills, by Occupational Group

Skill Category	Technology	High-Skill	Middle-Skill	Low-Skill
Content	$\widehat{AI}_{j,t}$	0.203	-3.045*	1.147
		(0.274)	(1.599)	(0.934)
	$\widehat{Robots}_{j,t}$	-0.0243	-0.612	-0.886
		(0.314)	(0.395)	(1.290)
Process	$\widehat{AI}_{j,t}$	0.194	3.216**	0.0898
		(0.277)	(1.526)	(1.060)
	$\widehat{Robots}_{j,t}$	0.557	-0.0855	-2.097*
		(0.479)	(0.431)	(1.267)
Social	$\widehat{AI}_{j,t}$	-0.939***	-1.015	-1.713*
		(0.251)	(0.904)	(0.981)
	$\widehat{Robots}_{j,t}$	-0.601**	-0.108	-0.499
		(0.277)	(0.262)	(1.066)
Complex Problem Solving	$\widehat{AI}_{j,t}$	-0.0305	-0.585	0.482
		(0.131)	(0.568)	(0.466)
	$\widehat{Robots}_{j,t}$	-0.0954	-0.00141	0.364
		(0.125)	(0.210)	(0.600)
Technical	$\widehat{AI}_{j,t}$	0.466**	0.801	0.569
		(0.186)	(0.802)	(0.979)
	$\widehat{Robots}_{j,t}$	-0.491	0.995***	3.545***
		(0.386)	(0.298)	(1.029)
Systems	$\widehat{AI}_{j,t}$	-0.445**	-0.786	-0.812
		(0.175)	(0.629)	(0.496)
	$\widehat{Robots}_{j,t}$	0.319	0.136	0.622
		(0.219)	(0.239)	(0.712)
Resource Management	$\widehat{AI}_{j,t}$	0.359**	0.626	-0.850
		(0.182)	(0.726)	(0.824)
	$\widehat{Robots}_{j,t}$	0.0608	0.0801	-0.403
		(0.213)	(0.240)	(0.922)
Observations		1,134	2,218	460
Occupations FE		YES	YES	YES
Year FE		YES	YES	YES

Note: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Standard errors are in parentheses below coefficients.

4 Conclusion

This paper examines how exposure to AI and robotics reshapes the internal skill composition of occupations. We develop a novel measure of AI exposure and track changes in the share of seven broad skill categories within occupations over time. Our findings reveal that AI and robotics exert distinct effects: AI increases Process skills while reducing Content, Systems, and Social skills; robotics boosts Technical skills while displacing Social and content-related components. These patterns vary across occupational groups, with AI affecting high-skill jobs more strongly, and robotics impacting middle- and low-skill roles. Overall, our results highlight that automation transforms work not only by potentially displacing jobs, but by reconfiguring the mix of skills within occupations, a critical yet often overlooked dimension of technological change.

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