The role of human capital for AI adoption: Evidence from French firms

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Introduction

The context

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Human capital is a key asset for technology adoption (Nelson & Phelps, 1966; Benhabib & Spiegel, 2005; Harrigan *et al.*, 2021)

- Particularly for what concerns advanced technologies such as AI (Goos & Savona, 2024)
- The rapid diffusion of AI may restructure the demand for skills and labour markets (Alekseeva *et al.*, 2021; Borgonovi *et al.*, 2023; Albanesi *et al.*, 2023)

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Yet, limited evidence:

- Firm-level studies on the links between AI and workers' characteristics/firms' skills composition/labour demand and mostly focused on the United States (Babina *et al.*, 2023; Alekseeva *et al.*, 2021)
- Exposure of occupations to AI (e.g., among the others Felten *et al.*, 2021; Eloundou *et al.*, 2023; Brynjolfsson *et al.*, 2023; Prytkova *et al.*, 2024)

Our contribution

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We explore which occupations foster the use of AI using Probit and IV Probit models

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- Non-technical **vs** technical non-ICT **vs** ICT human capital

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A nuanced picture of AI-human capital relations emerges from heterogeneity/robustness analysis, beyond ICT engineers

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Data - ICT survey

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- Early period of AI diffusion & Predictive AI (e.g., text mining, ML data analysis)
- AI is a dummy variable Questions from the survey + AI buyers/developers
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Other information on the use of digital complementary assets provided by the ICT survey

- Use of business digital technologies (CRM, ERP, e-commerce); Digital infrastructure (presence of a fast broadband connection)

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- ICT **vs** Non-ICT technical **vs** Non-technical occupations
- Remaining shares (clerical and manual occupations) are not correlated with AI use Regressions

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  Regressions

These occupational classes broadly reflect the level and type of human capital of French firms

	ICT	Technical non-ICT	Non-technical human capital
Higher intellectual occupations	ICT engineers	Non-ICT engineers	Non-technical (e.g., executives)
Intermediate occupations	ICT technicians	Non-ICT technicians	Non-technical (e.g., supervisors)

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We retrieve info on firm characteristics from administrative and business registry data (i.e., tangible and intangible capital, size, age, region, industry, exporter/multiplant status)

Which occupations spur AI use by firms?

The empirical strategy

We explore the human capital of AI users in the following Probit specification using 2018 data:

$$\Pr(\text{AI User}_i) = \Phi(\text{Occupation Share}_i, \text{Firm Characteristics}_i, \text{Digital Controls}_i, \text{Industry}_i, \text{Region}_i)$$

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Industry$_i$ and **Region**$_i$ represent industry and regional fixed effects

The identification strategy

Notwithstanding in early phase of diffusion, AI use may affect the employment of firms

- Endogenous AI-employment relation

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We estimate the following IV probit model:

$$\begin{aligned} \text{AI User}_i^* =& \alpha + \beta_s \text{Occupation Share}_{i,2018} + \beta_{\mathbf{X}} \mathbf{X}_i + \epsilon_i \\ \text{Occupation Share}_{i,2018} =& \gamma + \beta_z \text{Occupation Share}_{i,2011} + \beta_{\mathbf{X}} \mathbf{X}_i + \omega_i \\ \text{AI User}_i =& \begin{cases} 1, & \text{if } \text{AI User}_i^* > 0 \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{1}$$

Where each 2018 share is instrumented with its 2011 value

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2011 shares are very unlikely to be endogenous on AI

- In 2012, machine learning algorithms started to outperform state-of-the-art non-AI techniques in statistical analyses (e.g., AlexNet neural network)
- The boom in AI use by firms very likely started after 2012 in the U.S. (see also here, here and Babina *et al.*, 2021)
- Likely even later in France

Results - Probit & IV Probit Results

	Probit	IV Probit						
		Second Stage	First Stages					
	Margins	Margins	ICT Engineers	Non-ICT Engineers	Non-Technical Higher Intellectual Occ.	ICT Technicians	Non-ICT Technicians	Non-Technical Intermediate Occ.
ICT Engineers 2018	0.170***	0.134**						
	(0.0394)	(0.056)						
Non-ICT Engineers 2018	-0.00777	0.004						
	(0.0430)	(0.076)						
Non-Tech. Higher Intellectual Occ. 2018	0.0218	-0.066						
	(0.0331)	(0.057)						
ICT Technicians 2018	-0.0481	-0.162						
	(0.0743)	(0.105)						
Non-ICT Technicians 2018	(0.0428)	-0.086						
	(0.0428)	(0.072)						
Non-Tech. Intermediate Occ. 2018	0.00198	-0.015						
	(0.0296)	(0.048)						
ICT Engineers 2011			0.808***	0.058***	-0.086***	0.011	0.006	-0.062***
			(0.039)	(0.018)	(0.023)	(0.013)	(0.016)	(0.016)
Non-ICT Engineers 2011			-0.005	0.696***	0.020	-0.007	0.107***	0.005
			(0.008)	(0.040)	(0.033)	(0.006)	(0.028)	(0.023)
Non-Tech. Higher Intellectual Occ. 2011			0.021*	0.027**	0.603***	-0.004	0.001	0.057***
			(0.012)	(0.014)	(0.026)	(0.006)	(0.012)	(0.020)
ICT Technicians 2011			0.046	0.043**	-0.047**	0.646***	0.025	-0.001
			(0.034)	(0.020)	(0.023)	(0.059)	(0.018)	(0.024)
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			(0.004)	(0.019)	(0.013)	(0.009)	(0.038)	(0.014)
Non-Tech. Intermediate Occ. 2011			-0.002	-0.004	0.070***	0.001	0.010	0.664***
			(0.004)	(0.007)	(0.012)	(0.003)	(0.006)	(0.022)
Industry + Region FE + Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,531	7,381	7,381	7,381	7,381	7,381	7,381	7,381

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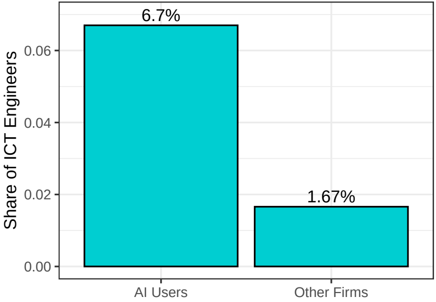
ICT engineers play a key role for AI adoption by firms

Raising the share of ICT engineers of non users to the one of AI users



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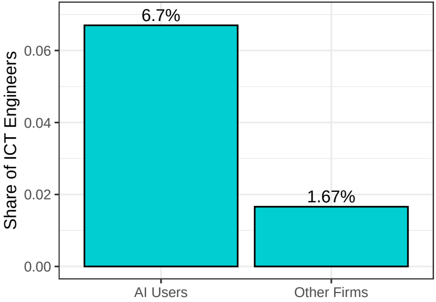

Model	% Change Probability	Additional ICT Engineers
Probit	10.89%	463191.6
IV Probit	8.68%	370484.3

How does the probability to use AI change when the share of ICT engineers of non users (1.67%) is raised to the one of AI users (6.7%)?

We estimate an increase of $\sim$ 10% in the probability to use AI (see Table 12)

But additional $\sim$ 400k of ICT engineers, i.e. $\sim$ 2 times the existing supply of ICT engineers in our sample

Distinguishing ICT engineers by specialisation

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	Model 1
ICT Engineers - R&D	0.186***
	(0.0484)
ICT Engineers - Admin. & Support	0.0139
	(0.166)
ICT Engineers - Manager	0.146*
	(0.0803)
ICT Engineers - Sales	0.229
	(0.145)
ICT Engineers - Telecom.	0.219
	(0.171)
Non-ICT Engineers	-0.00620
	(0.0429)
Non-Tech. Higher Intellectual Occupations	0.0229
	(0.0331)
ICT Technicians	-0.0426
	(0.0741)
Non-ICT Technicians	-0.0186
	(0.0429)
Non-Tech. Intermediate Occupations	0.00180
	(0.0296)
Observations	8,531
Industry + Region FE + Additional controls	Yes
Pseudo R2	.048

We distinguish 5 types of ICT engineers based on their specialisation and estimate the above probit model

- R&D, Administration & Support, Managers, Sales, Telecommunications

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R&D and managerial ICT occupations at the basis of the ICT engineers-AI relation

- Both R&D and specialised managerial capabilities are crucial to use AI

The human capital of AI buyers vs developers

AI buyers and developers

We distinguish between firms sourcing AI from external providers (**AI buyers**) from those developing their own AI systems (**AI developers**)

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Crucial for understanding whether AI is differently implemented by different types of users

- AI developers already experiment significant productivity returns from AI use (Calvino & Fontanelli, 2023a)
- But developing AI systems in-house may require different type of human capital than buying them externally

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- But developing AI systems in-house may require different type of human capital than buying them externally

As buying and developing decisions could be related, we estimate the following biprobit model:

$$\text{AI Buyer} = \begin{cases} 1 & \text{if } \beta_1 X + \varepsilon_1 > 0, \\ 0 & \text{otherwise,} \end{cases} \quad \text{AI Developer} = \begin{cases} 1 & \text{if } \beta_2 X + \varepsilon_2 > 0, \\ 0 & \text{otherwise,} \end{cases} \quad \textbf{Corr}(\varepsilon_1;\ \varepsilon_2) = \rho$$

Where X includes the same controls of previous regressions, and ρ takes into account unobservables' correlation in make-vs-buy choices

AI buyers vs developers

	Model 1		Model 2	
	AI Buyer	AI Developer	AI Buyer	AI Developer
ICT Engineers	0.0741**	0.0869***		
	(0.0376)	(0.0152)		
ICT Engineers - R&D			0.0785*	0.0906***
			(0.0447)	(0.0177)
ICT Engineers - Admin. & Support			-0.00486	0.0549
			(0.186)	(0.0566)
ICT Engineers - Manager			0.129	0.0642**
			(0.0821)	(0.0288)
ICT Engineers - Sales			-0.155	0.136***
			(0.135)	(0.0475)
ICT Engineers - Telecom.			0.254	0.141**
			(0.178)	(0.0583)
Non-ICT Engineers	-0.0724	0.0422***	-0.0735	0.0433***
	(0.0466)	(0.0159)	(0.0469)	(0.0158)
Non-Tech. Higher Intellectual Occupations	-0.00156	0.0348**	-0.00109	0.0351**
	(0.0309)	(0.0144)	(0.0309)	(0.0144)
ICT Technicians	-0.0643	0.0161	-0.0625	0.0172
	(0.0814)	(0.0212)	(0.0820)	(0.0211)
Non-ICT Technicians	-0.0246	0.0283	-0.0236	0.0278
	(0.0415)	(0.0183)	(0.0415)	(0.0184)
Non-Tech. Intermediate Occupations	-0.00307	0.00156	-0.00348	0.00170
	(0.0282)	(0.0148)	(0.0281)	(0.0147)
Observations	8,531	8,531	8,531	8,531
Industry FE + Region FE + Additional Controls	Yes	Yes	Yes	Yes

AI buyers only rely on ICT engineers, and less intensively than developers

AI developers more broadly rely on higher intellectual occupations

- ICT and non-ICT engineers, higher level administrative/managerial occupations

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Key role of R&D-related ICT engineers

- Several types of ICT engineers involved in the development of AI systems

Sectoral analysis

Results

	Manufacturing	Wholesale & Retail	Media & Telecommunications	ICT Business Services	Prof., Scient. And Techn.	Other Service Sectors
ICT Engineers	0.229	0.425**	-0.0478	0.349*	0.280***	0.00827
	(0.204)	(0.194)	(0.164)	(0.202)	(0.0968)	(0.153)
Non-ICT Engineers	-0.0434	0.204**	0.0220	-0.704	-0.00679	0.0414
	(0.0795)	(0.100)	(0.316)	(0.510)	(0.0879)	(0.182)
Non-Tech. Higher Intellectual Occupations	0.167	0.0559	-0.145	0.130	0.00516	-0.00649
	(0.126)	(0.0618)	(0.153)	(0.250)	(0.0782)	(0.0742)
ICT Technicians	-0.251	-0.244	-0.0114	-0.275	-0.537*	0.592***
	(0.308)	(0.266)	(0.170)	(0.255)	(0.313)	(0.174)
Non-ICT Technicians	0.120**	-0.0184	-0.273	-0.188	-0.162	-1.096**
	(0.0581)	(0.0927)	(0.253)	(1.280)	(0.104)	(0.434)
Non-Tech. Intermediate Occupations	-0.167*	0.0116	-0.454*	0.255	-0.0139	0.0842
	(0.0953)	(0.0462)	(0.269)	(0.486)	(0.0831)	(0.0619)
Observations	2,199	2,156	352	233	706	1,821
Pseudo R2	.065	.061	.165	.193	.105	.077
Region FE + Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes

Sector	NACE 2–digit code
Manufacturing	10-33
Wholesale & Retail	45-47
Media & Telecommunications	58-61, 951
ICT Business Services	62-63
Other Services	49-56, 68, 77-82
Professional, Scientific And Technical Activities	69-75

Very nuanced picture at the sectoral level

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Manufacturing on non-ICT technicians

Conclusion

Discussion & Conclusion

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ICT engineers play a key role for the adoption of AI by firms

- Additional 400k ICT engineers are needed to get a 10% raise in the probability to use AI
- R&D capabilities and specialised coordinators are relevant for implementing AI systems

However, very nuanced picture of the human capital of AI users when studying cross users/sectors heterogeneity

- Beyond ICT human capital
- Evidence suggests that these groups of firms use and implement AI differently

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- Beyond ICT human capital
- Evidence suggests that these groups of firms use and implement AI differently

The human capital needed by AI users depends on the use that firms make of AI systems

- Significant investments in ICT/STEM human capital are necessary for fostering the diffusion of AI technologies
- However, these may not be enough, as non-ICT and non-technical skills may be needed for AI applications (see also Borgonovi *et al.*, 2023)

Thank you
for the attention!

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Question on AI use

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Module VI : Utilisation des technologies d'intelligence artificelle

L'**intelligence artificielle** désigne, sous un terme unique, l'ensemble des technologies visant à réaliser par l'informatique des tâches cognitives traditionnellement effectuées par l'humain : reconnaissance vocale, biométrie, reconnaissance d'images, aide à la décision, etc.

➡1. En 2018, votre entreprise a-t-elle eu recours à des logiciels et/ou des équipements intégrant des technologies d'intelligence artificielle ?

Ces logiciels et/ou équipements ont été développés principalement par les employés de votre entreprise (y compris ceux provenant de la maison-mère ou de filiales).	☐ Oui	☐ Non
Ces logiciels et/ou équipements ont été développés principalement par un prestataire externe, pour répondre spécifiquement aux besoins de votre entreprise.	☐ Oui	☐ Non
Ces logiciels et/ou équipements font partie d'offres "sur étagère"* de fournisseurs.	☐ Oui	☐ Non

Figure 1: From 2019 ICT survey.

Artificial intelligence (AI) refers, under a single term, to all technologies aimed at carrying out cognitive tasks traditionally performed by humans using computers: speech recognition, biometrics, image recognition, decision support, etc.

In 2018, did your company use software and/or equipment incorporating AI technologies?

1. These software and/or equipment were primarily developed by employees of your company (including those from the parent company or subsidiaries).
2. These software and/or equipment were primarily developed by an external provider, specifically to meet the needs of your company.
3. These software and/or equipment are part of "off-the-shelf" offerings from suppliers.

Results - Aggregate occupations

	Higher Intellectual Occupations		Intermediate Occupations		Clerical Occupations		Manual Occupations	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Share	0.0784***	0.0579**	-0.0172	-0.0252	-0.0126	-0.00938	-0.0191	-0.00447
	(0.0238)	(0.0246)	(0.0236)	(0.0239)	(0.0195)	(0.0197)	(0.0190)	(0.0193)
Log Sales	0.00908***	-0.00448	0.0125***	-0.00112	0.0120***	-0.00182	0.0117***	-0.00192
	(0.00307)	(0.00685)	(0.00295)	(0.00676)	(0.00297)	(0.00678)	(0.00297)	(0.00683)
Log Age	-0.0112*	-0.0117*	-0.0125*	-0.0127*	-0.0126*	-0.0128*	-0.0123*	-0.0127*
	(0.00643)	(0.00670)	(0.00644)	(0.00669)	(0.00644)	(0.00668)	(0.00645)	(0.00670)
PIK Ratio		-0.00345		-0.00389		-0.00378		-0.00379
		(0.00420)		(0.00419)		(0.00420)		(0.00421)
PKL ratio		-0.00646		-0.00464		-0.00486		-0.00509
		(0.00754)		(0.00747)		(0.00748)		(0.00752)
Log Physical Capital		0.00888		0.00673		0.00715		0.00743
		(0.00774)		(0.00771)		(0.00771)		(0.00778)
Multi Plant		0.00163		0.000557		0.000686		0.000201
		(0.00977)		(0.00979)		(0.00979)		(0.00981)
Exporter		0.00353		0.00756		0.00695		0.00769
		(0.0108)		(0.0106)		(0.0106)		(0.0106)
Fast Broadband		0.0275**		0.0312***		0.0305**		0.0306**
		(0.0120)		(0.0120)		(0.0120)		(0.0120)
CRM		0.0399***		0.0421***		0.0418***		0.0414***
		(0.00988)		(0.00986)		(0.00984)		(0.00984)
ERP		0.0194*		0.0213**		0.0206**		0.0209**
		(0.0102)		(0.0103)		(0.0102)		(0.0102)
E-Commerce		0.00858		0.00616		0.00754		0.00604
		(0.0124)		(0.0124)		(0.0125)		(0.0125)
Observations	8,531	8,531	8,531	8,531	8,531	8,531	8,531	8,531
Industry + Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	.033	.044	.031	.043	.031	.042	.031	.042

Only higher intellectual occupations are significantly related to the use of AI by firms

AI use related to other ICT technologies and fast broadband (Calvino & Fontanelli, 2023a,b)

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