

The Economics of Data and Digital Infrastructures. Evidence and Policy

# AI, human capital and productivity

Flavio Calvino  
OECD

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## Outline: evidence from recent work

- **AI diffusion** across firms and sectors
- **Enablers:** technological interdependencies and the role of **human capital**
- AI use and **productivity**
- **Policy considerations**
  
- **Collaborative work** with several co-authors, references in each slide



# DIFFUSION



# A distributed microdata approach

## AI & Digital Diffuse

- Statistical code developed by the OECD and run by experts that have access to confidential data
- Separate analysis for each country using a harmonised methodology
- Consistency checks and metadata validation in collaboration with experts
- Official ICT surveys – Digital Diffuse: also matching with other sources

## Main outputs

- Summary statistics (shares of adoption, summary, co-occurrences)
- Distributed regressions (adoption regressions, productivity regressions)

Source: based on Calvino and Fontanelli (2023), <https://doi.org/10.1787/0fb79bb9-en> for *AI diffuse* and Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en> for *Digital Diffuse*



## More on data and methodology: Digital Diffuse

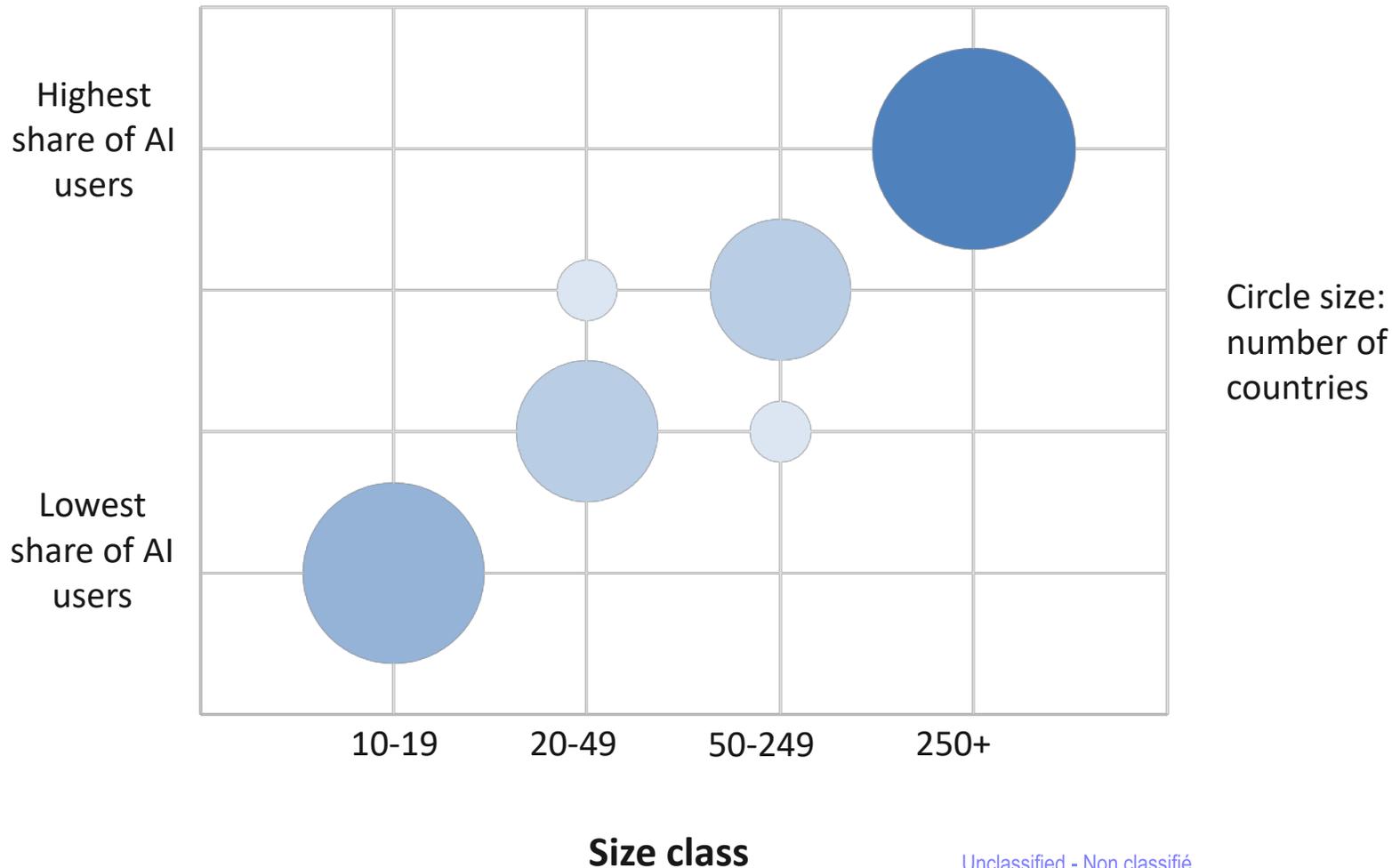
- Main data source: official ICT surveys
  - Representative, providing binary **technology use** information for the five advanced technologies analysed (**AI, big data, IoT, robotics, 3D printing**)
  - Further information e.g. on use of **other digital technologies** (cloud, CRM, etc.) **and firm characteristics** (turnover, employment)
  - Linked with balance sheet data, for additional productivity measures, and linked employer-employee data, providing more details on **human capital**, conditional on availability
  - Country coverage: BEL, CAN, CHE, DEU, DNK, EST, FRA, GBR, IRL, ISR, ITA, JPN, KOR, NLD, PRT

Source: based on Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>



# AI is more widely used across large firms...

## Share of AI users by firm size class: cross-country findings



Notes: based on 10 countries (Belgium, Denmark, France, Germany, Israel, Italy, Japan, Korea, Portugal, and Switzerland). The y-axis shows the ranking for shares of AI users. Circles' size is proportional to the number of countries for which the relation holds. For Korea, the size-class 10-19 is not available (not reported, the 20-49 class is assumed to be the second lowest).

Source: elaborations based on Calvino and Fontanelli (2023), <https://doi.org/10.1787/0fb79bb9-en>



# ...even after accounting for sectoral specificities

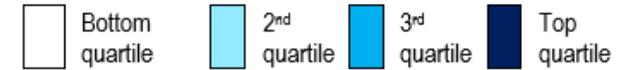
Variables	BEL	CAN	CHE	DEU	DNK	EST	FRA	GBR	IRL	ISR	ITA	JPN	KOR	NLD	PRT
Age: 6-10	0.0093 (0.0251)	-0.0025 (0.0250)	-0.0212 (0.0551)		-0.0248** (0.0106)		0.0240** (0.0097)			0.0119 (0.0245)		0.0162 (0.0183)	-0.0166*** (0.0054)	0.0209*** (0.0070)	-0.0055 (0.0251)
Age: >10	0.0179 (0.0200)	0.0020 (0.0205)	-0.0227 (0.0479)		-0.0412*** (0.0089)		-0.0033 (0.0071)			-0.0116 (0.0160)		0.0226 (0.0155)	-0.0175*** (0.0049)	0.0012 (0.0056)	-0.0041 (0.0228)
Size: 20-49	0.0182 (0.0124)	0.0159 (0.0209)	0.0365** (0.0168)	0.0234 (0.0094)	0.0298*** (0.0063)	0.0001 (0.0099)	0.0142*** (0.0052)	0.0105 (0.0165)	0.0374** (0.0147)	0.0218* (0.0128)	0.0152** (0.0066)	0.0106 (0.0073)	0.0015 (0.0038)	0.0672*** (0.0045)	0.0318*** (0.0109)
Size: 50-249	0.0981*** (0.0137)	0.0243 (0.0174)	0.0448** (0.0180)	0.0518*** (0.0092)	0.0737*** (0.0064)	0.0474 (0.0104)	0.0684*** (0.0072)	0.0192 (0.0160)	0.0855*** (0.0204)	0.0147 (0.0133)	0.0351*** (0.0063)	0.0326*** (0.0064)	0.0128*** (0.0034)	0.1590*** (0.0055)	0.0926*** (0.0143)
Size: 250+	0.3748*** (0.0176)	0.1753*** (0.0219)	0.1820*** (0.0236)	0.1350*** (0.0153)	0.2339*** (0.0108)	0.2125*** (0.0247)	0.2241*** (0.0097)	0.0636*** (0.0223)	0.3285*** (0.0317)	0.0641*** (0.0153)	0.1897*** (0.0082)	0.1720*** (0.0084)	0.0496*** (0.0041)	0.3508*** (0.0079)	0.2566*** (0.0168)
N	5375	3895	4248	6159	15804	5808	17757	11762	2017	1987	32497	20922	38629	30295	8465
R <sup>2</sup>	0.140	0.077	0.121	0.068	0.149	0.137	0.096	0.061	0.185	0.244	0.038	0.069	0.065	0.115	0.092

Notes: This table reports the main estimation results of the baseline adoption regression of AI using a linear probability model. Each regression includes 2-digit NACE rev. 2 sector dummies. Each regression includes year dummies when multiple survey waves are available. All estimated regressions are weighted except for Germany, Ireland and Korea. Robust standard errors in parentheses. Statistical significance is denoted as follows: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

Source: Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>



# AI use tends to be concentrated in some sectors...



- A recent OECD sectoral taxonomy identifies **AI intensive sectors**, based on:
  - AI talent
  - AI innovation
  - AI exposure
  - AI use
- Sectors with **high AI intensity** are also shaping the technology

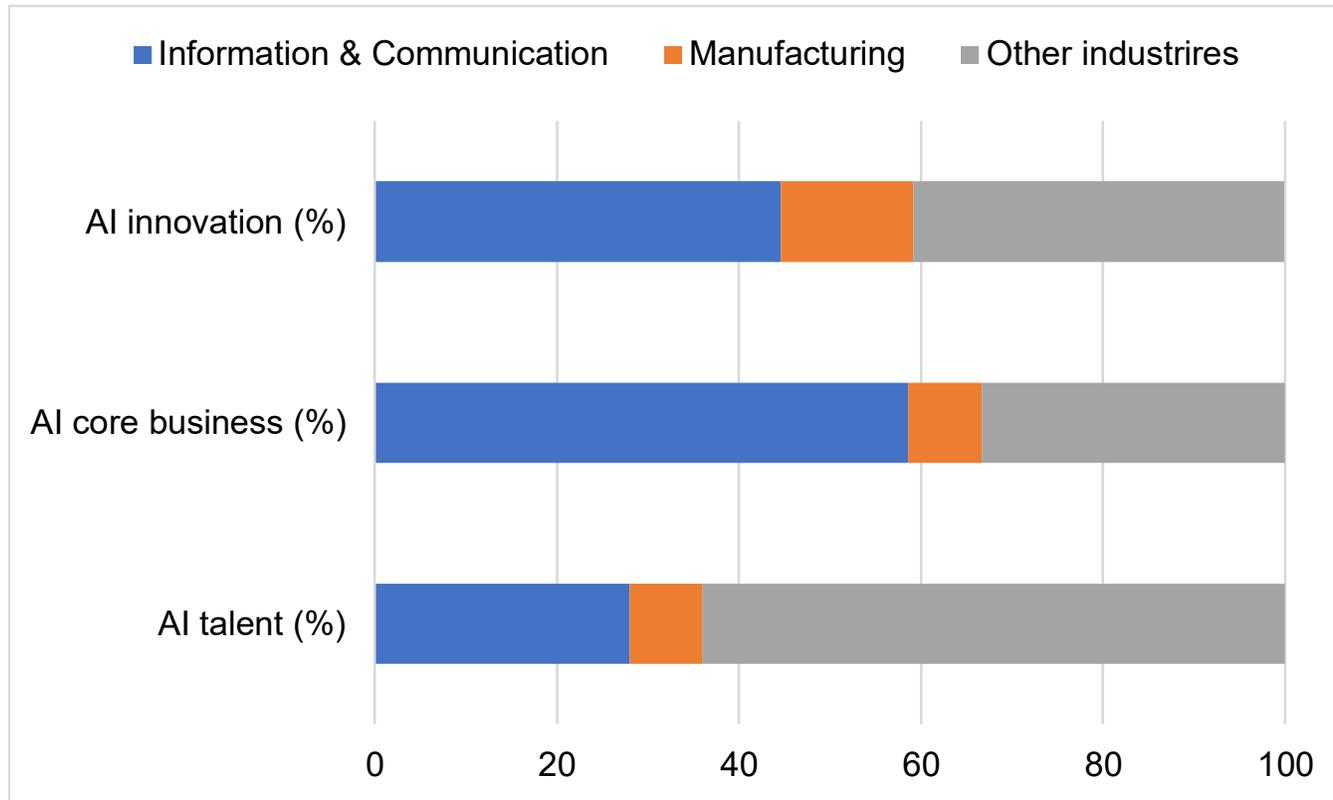
Industry (A38)	AI human capital	AI innovation	AI exposure (barrier-adjusted)	AI use
10-12 Food products				
13-15 Textiles & apparel				
16-18 Wood & paper				
20 Chemicals	2nd quartile		2nd quartile	3rd quartile
21 Pharmaceuticals	Top quartile		3rd quartile	3rd quartile
22-23 Rubber, plastics, minerals	2nd quartile			2nd quartile
24-25 Metal products			2nd quartile	2nd quartile
26 Computer & electronics	Top quartile	Top quartile	Top quartile	3rd quartile
27 Electrical equipment	3rd quartile	3rd quartile	2nd quartile	2nd quartile
28 Machinery & equipment	3rd quartile	2nd quartile		3rd quartile
29-30 Transport equipment	3rd quartile	2nd quartile		3rd quartile
31-33 Other manufactures	2nd quartile	2nd quartile	2nd quartile	
41-43 Construction		2nd quartile		
45-47 Wholesale & retail	2nd quartile	2nd quartile	3rd quartile	2nd quartile
49-53 Transportation & storage	2nd quartile	Top quartile		
55-56 Hotels & food services		3rd quartile		
58-60 Media	Top quartile	Top quartile	Top quartile	Top quartile
61 Telecommunications	Top quartile	Top quartile	Top quartile	Top quartile
62-63 IT services	Top quartile	Top quartile	Top quartile	Top quartile
64-66 Finance & insurance	3rd quartile	3rd quartile	Top quartile	3rd quartile
68 Real estate		2nd quartile	3rd quartile	2nd quartile
69-71 Legal & accounting	3rd quartile	Top quartile	Top quartile	3rd quartile
72 Scientific R&D	Top quartile	3rd quartile	3rd quartile	3rd quartile
73-75 Other business services	3rd quartile	3rd quartile	3rd quartile	3rd quartile
77-82 Admin. & support services	2nd quartile	3rd quartile	3rd quartile	2nd quartile

Source: Calvino, Dennis, Samek and Ughi (2024), <https://doi.org/10.1787/1f6377b5-en>



## ...but there is no such thing as a typical AI adopter

AI adopters by type and broad sector of activity, United Kingdom, 2019



Notes: The figure distinguishes AI adopters that carry out AI innovation (identified through intellectual property rights), have an AI core business (non-innovators mentioning AI-related keywords on their website), and other AI employers (identified through online vacancies). Sectors are constructed using the NACE2 (4-digit level) classification reported in Orbis© for the year 2019. The category "other industries" includes Wholesale and Retail, Finance and Insurance, Professional and Scientific Services, Administrative and Real Estate, Mining and Quarrying, Utilities, Transport and Storage, Accommodation and Food, and Construction.

Source: Author's elaboration based on Calvino et al. (2022), <https://doi.org/10.1787/154981d7-en> Unclassified - Non classifié

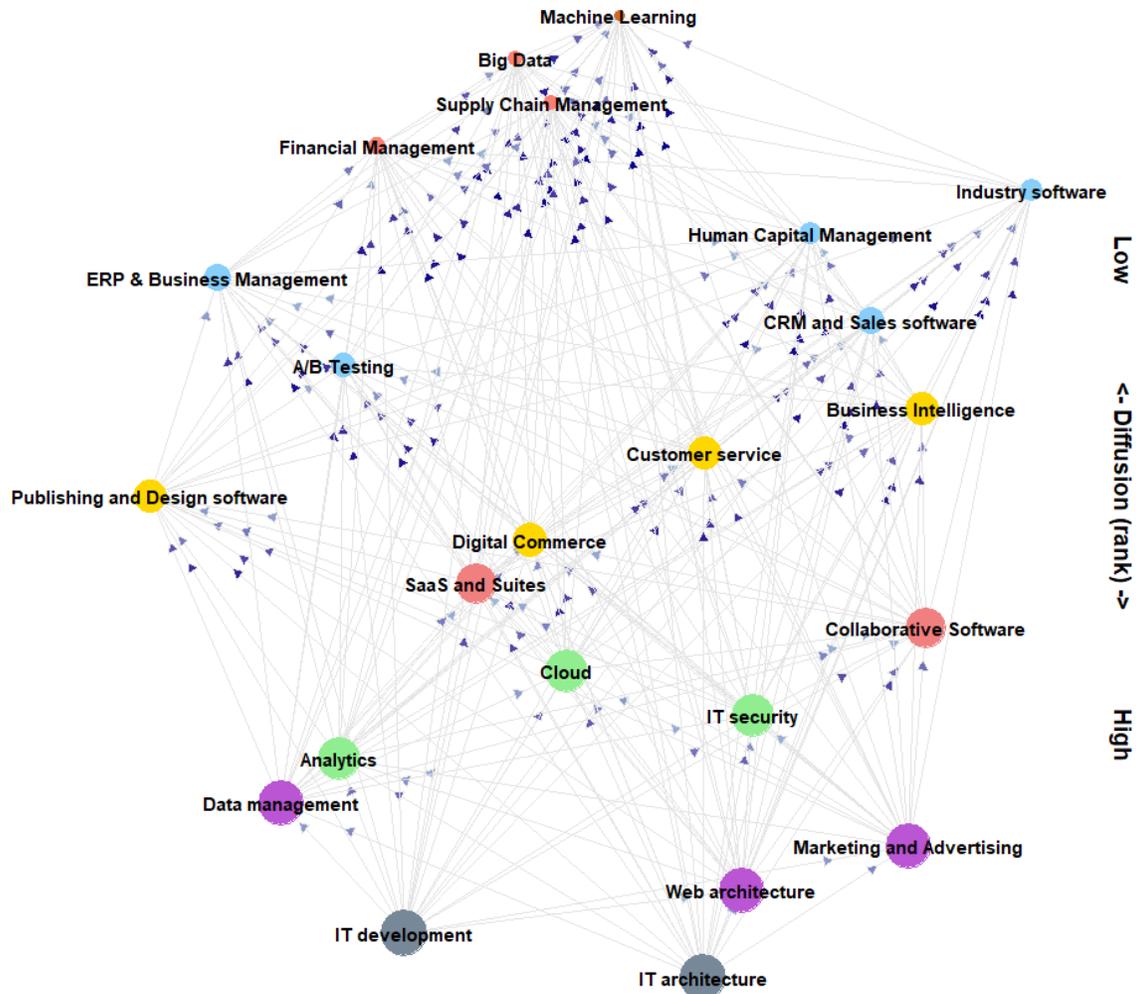
- Matching different sources of microdata for the **UK**
- While **AI innovators** and firms with AI at the **core of their business** are concentrated in the ICT sector, companies **hiring AI talent** are more widespread across industries



# ENABLERS



# The digital transformation is a cumulative process...



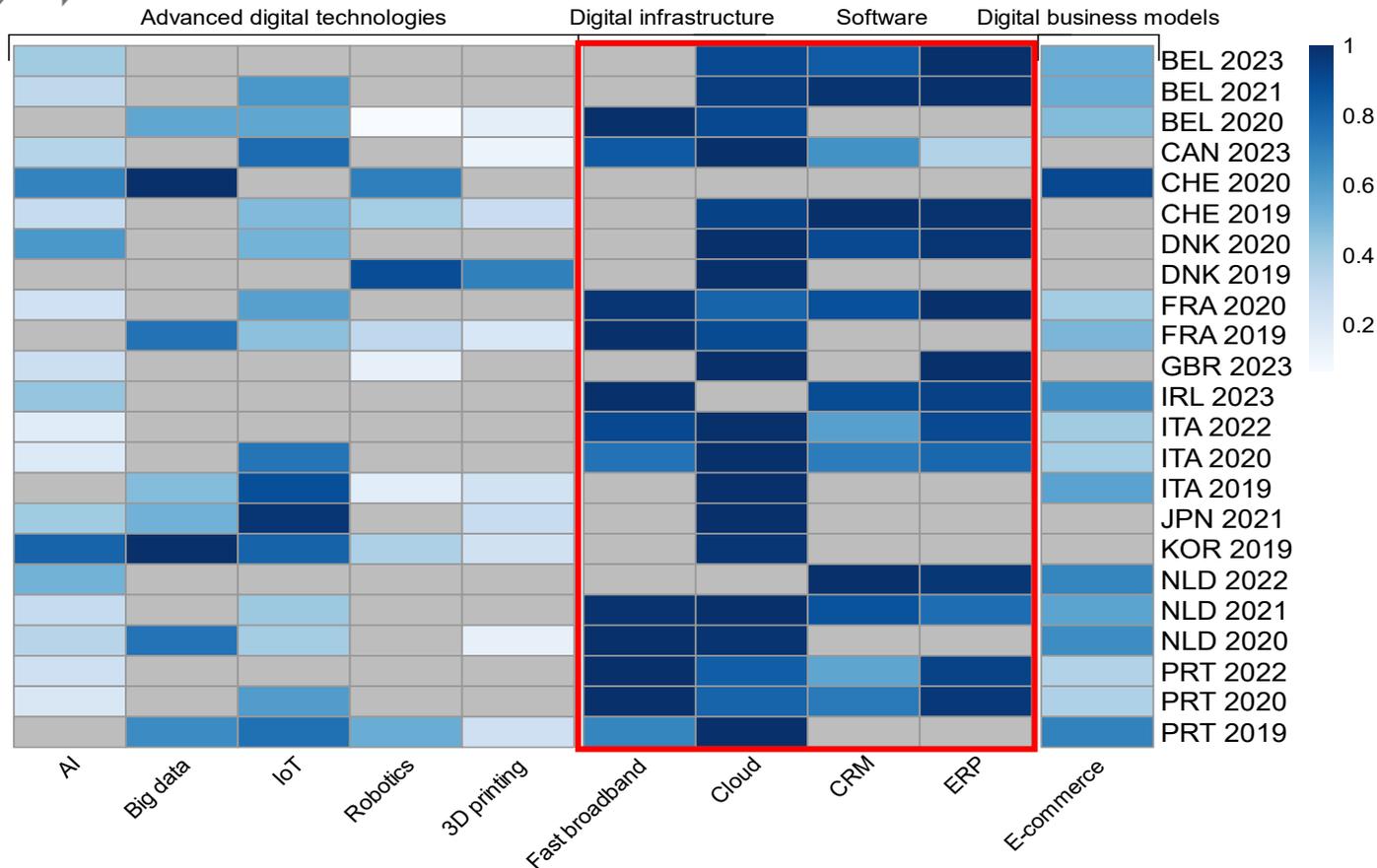
...that is unlikely to happen abruptly, but rather builds upon pre-existing **expertise, infrastructure, and knowledge base**

Notes: the figure displays a network analysis performed on digital technology applications in 2019. Each node corresponds to a given technology application. Nodes are ordered on the vertical axis (from the bottom to the top) according to their (decreasing) absolute level of diffusion in the sample (i.e., less diffused applications are displayed at the top of the graph). An edge between any two nodes is drawn if digital applications co-occur in the sample, i.e., if there are firms that have both digital applications. Edges are directed and weighted based on conditional probabilities of occurrence of each pair of applications. For each given application, inward connected applications are defined as complementary supporting applications. Horizontally complementary applications are defined as applications having similar levels of diffusion across the sample of firms and connected by almost undirected edges. Different groups of horizontal applications are displayed with different node colours. Edges connecting horizontal applications are removed to avoid redundancy.

Source: Calvino, Criscuolo and Ughi (2024), <https://doi.org/10.1787/f63ca261-en>



# There are significant interdependencies among digital technologies



- Network analysis of **co-occurrences**: more advanced technologies tend to build on enablers such as foundational technologies and digital infrastructure.
- Strong **organisational and technological interdependencies**: enablers could reduce adoption costs and help realise productivity benefits of technology adoption.

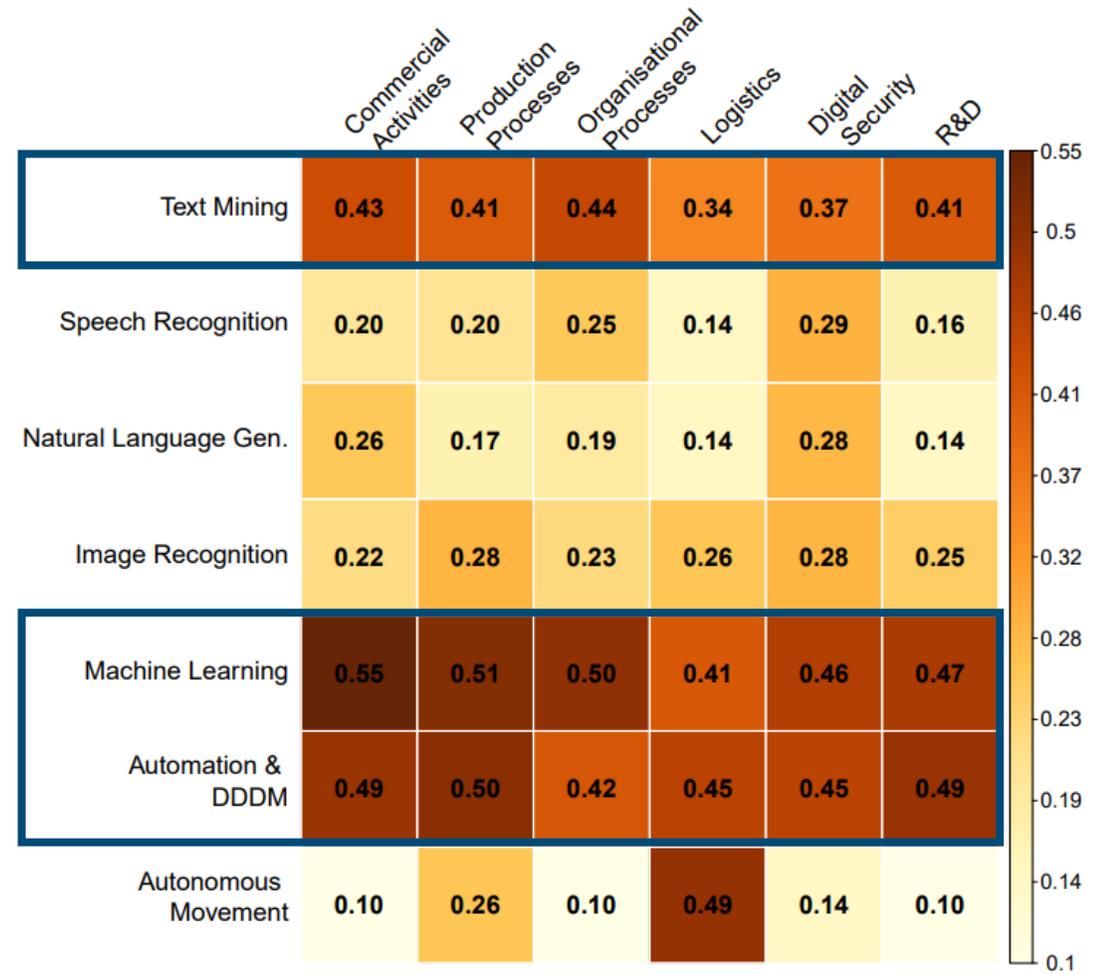
Notes: The colour gradient represents the eigen centrality for each available technology (column) in the network of observed technology co-occurrences for each country-year (row). A high value indicates an influential position of the technology in the network. Greyed out cells correspond to technologies either not surveyed or not available in a given country-year. Networks with blanked co-occurrences due to confidentiality or a low number of available technologies are excluded.

Source: Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>



# Different AI technologies support different business functions

- AI technologies exhibit significant **interdependencies**, both with enabling technologies as well as among them
- Some AI technologies tend to support most business functions (**text mining, ML and DDDM**), while others appear more specific (**autonomous movement**)



Notes: Probability of using AI in support of a business function, conditional on using a specific AI technology. Conditional probabilities are computed using sampling weights. The analysis focuses on France.



# Human and technological capital are key in the age of AI...

## AI use

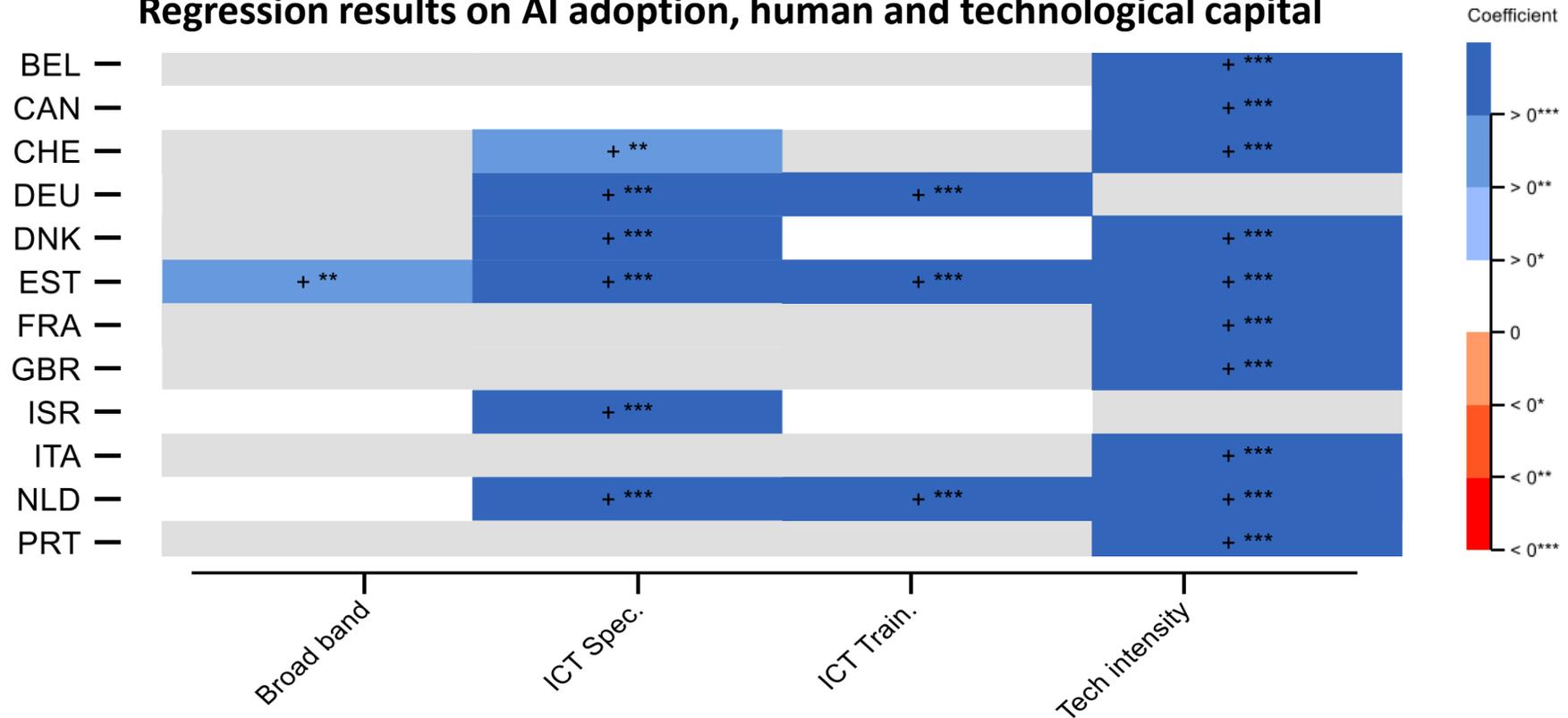
Digital infrastructure	Digital & innovative capabilities	Human capital	Internationalisation
Fast broadband	Other digital technologies	ICT skills	Exporter
Cloud	Innovator	ICT training	

Source: elaborations based on Calvino and Fontanelli (2023), <https://doi.org/10.1787/0fb79bb9-en>



# Human and technological capital are key in the age of AI...

Regression results on AI adoption, human and technological capital



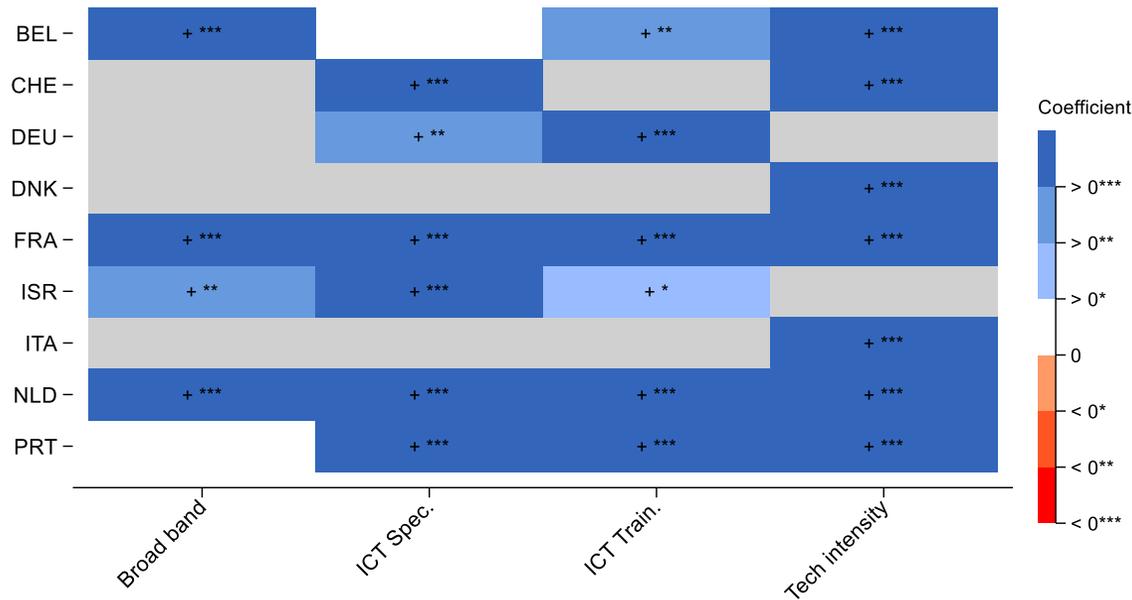
Notes: This figure reports the sign and statistical significance of coefficients from AI adoption regressions. All regressions are weighted except for Germany. For some countries, technologies or cells are omitted due to not being covered. See Table A B.2. for the coverage years of each technology adoption regression. See Table A C.6 – Table A C.10 for the complete list of coefficients. Statistical significance is denoted as follows: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .  
 Source: Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>



# ...even when considering other advanced technologies or human capital proxies

## ICT specialists, training and technological intensity

Big data analysis

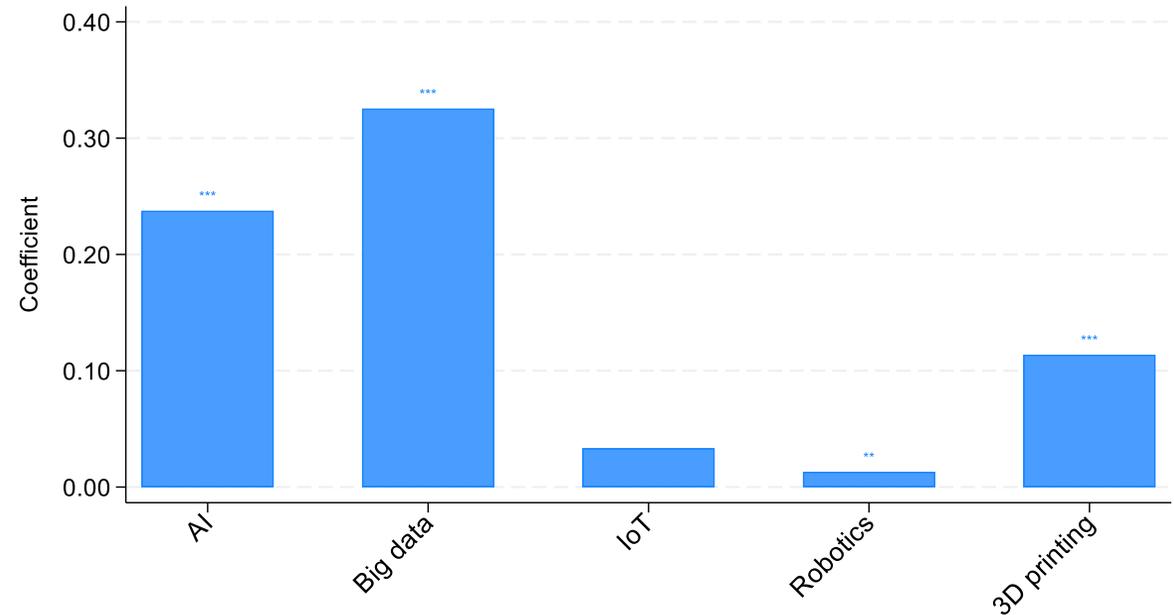


Notes: This figure reports the sign and statistical significance of coefficients from adoption regressions. All regressions are weighted except for Germany. For some countries, technologies or cells are omitted due to not being covered. Statistical significance is denoted as follows: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

Source: Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>

## Tertiary education

Netherlands



Notes: This figure reports the sign and statistical significance of coefficients for the share of workers with tertiary education. All regressions are weighted. The dependent variable is the adoption of an advanced digital technology. All models include size and age classes, and industry and year fixed effects. Statistical significance is denoted as follows: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

Source: Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>



## This includes not only ICT and technical skills...

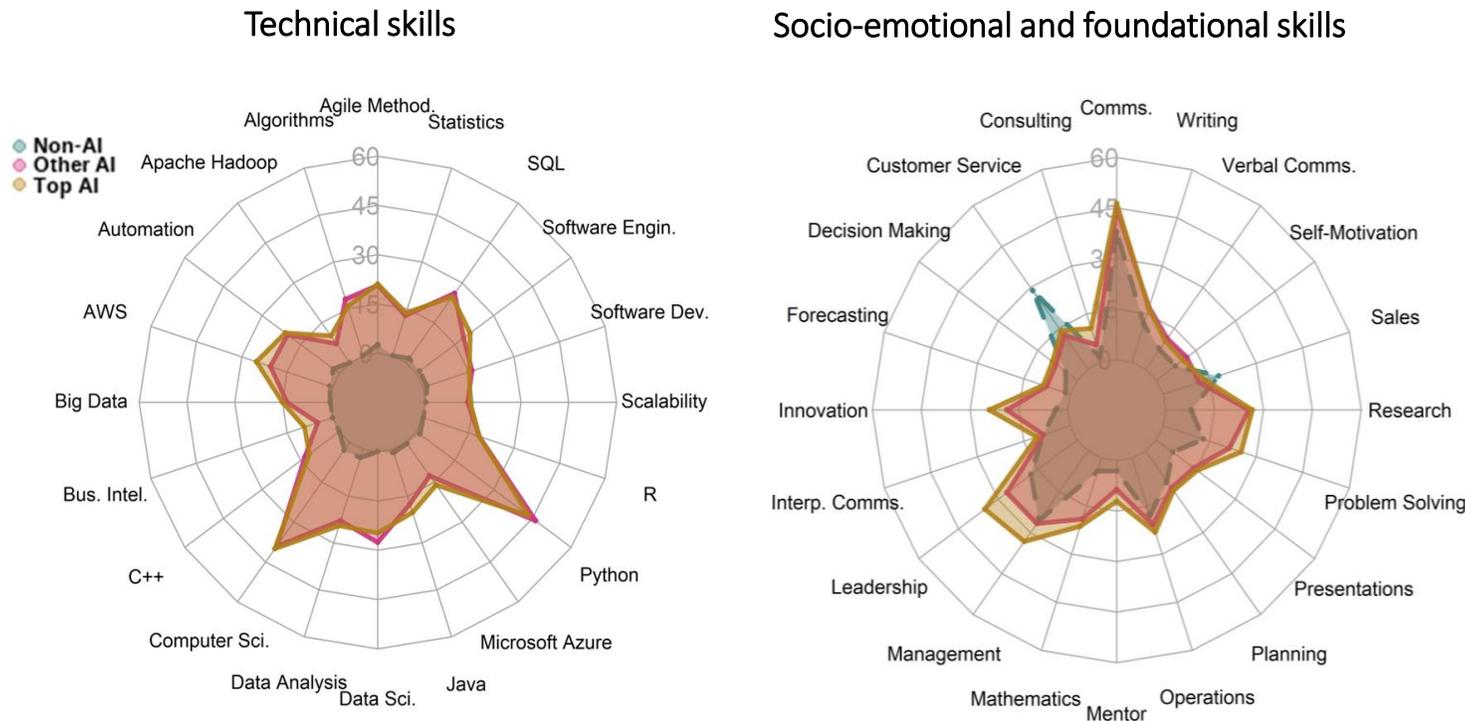
- Analysing comprehensive micro-level data sources on firms and workers in France
  - LEED, ICT survey, balance sheets and business register
- **ICT engineers** are a key driver of predictive AI adoption
  - Not only in ICT services
  - Results of causal estimation
  - Relevant occupational gap between AI adopters and non-adopters
    - Firms that did not adopt AI had significantly lower shares of ICT engineers

Source: discussion based on Fontanelli et al. (2025), <https://doi.org/10.1016/j.labeco.2025.102754>



# ...but also socio-emotional and foundational skills

**Top 3 industries in online vacancies requiring AI skills**  
Percentage of online vacancies advertising positions requiring AI skills



■ **Leading employers have a higher demand for AI professionals combining technical skills with:**

- Innovation
- Problem-solving and
- Leadership

*Notes:* The Figure shows, for the United States, the percentage of AI online vacancies mentioning a specific skill, distinguishing AI vacancies posted by the top ten AI employers from those posted by other AI employers. The top ten AI employers are the ten firms in each industry that posted the largest share of AI vacancies. The Figure also presents the percentage of the remaining online vacancies not requiring AI skills that mention the same specific skill.

*Source:* Borgonovi et al. (2023), <https://doi.org/10.1787/7c691b9a-en>



# PRODUCTIVITY



# AI users are more productive, but premia are linked to human and technological capital

Link with productivity	before accounting for complementary assets		after accounting for complementary assets	
	AI use		AI use	Complementary Assets
Belgium	+	+	+	+
Denmark	+	+	+	+
France	+	+	×	+
Germany	+	+	×	+
Israel	×		×	+
Italy	+	+	×	+
Japan	×		×	+
Korea	+	+	×	+
Switzerland	×		×	+

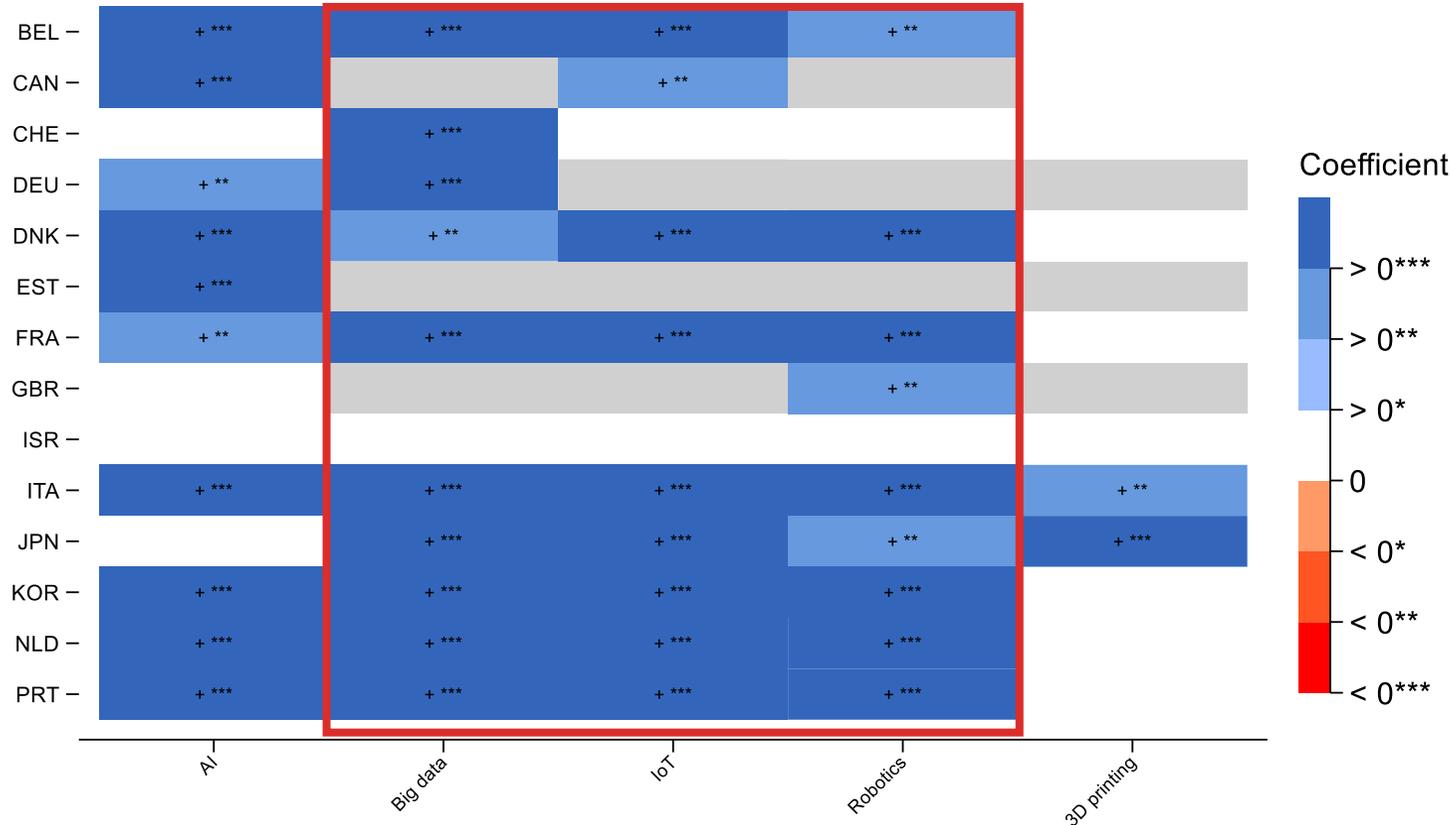
- **Human and technological capital** appear to play a key role: productivity premia significantly reduce when accounting for those **complementary assets**
- Productivity advantages likely related to the **selection** of more digital and competitive firms into AI use
  - This is not the case of developers in France
- Estimates before the boom in generative AI

Notes: the table is based on OLS regressions of labour productivity on AI use, controlling for size class, age class, sector and, upon availability, year fixed effects, while further including proxies of different complementary assets as additional explanatory variables in the right panels.

Source: elaboration based on Calvino and Fontanelli (2023), <https://doi.org/10.1787/0fb79bb9-en>



# This tends to hold also when focusing on a broader set of advanced technologies...



- Firms adopting advanced digital technologies are, on average, **more productive**, except for 3D printing

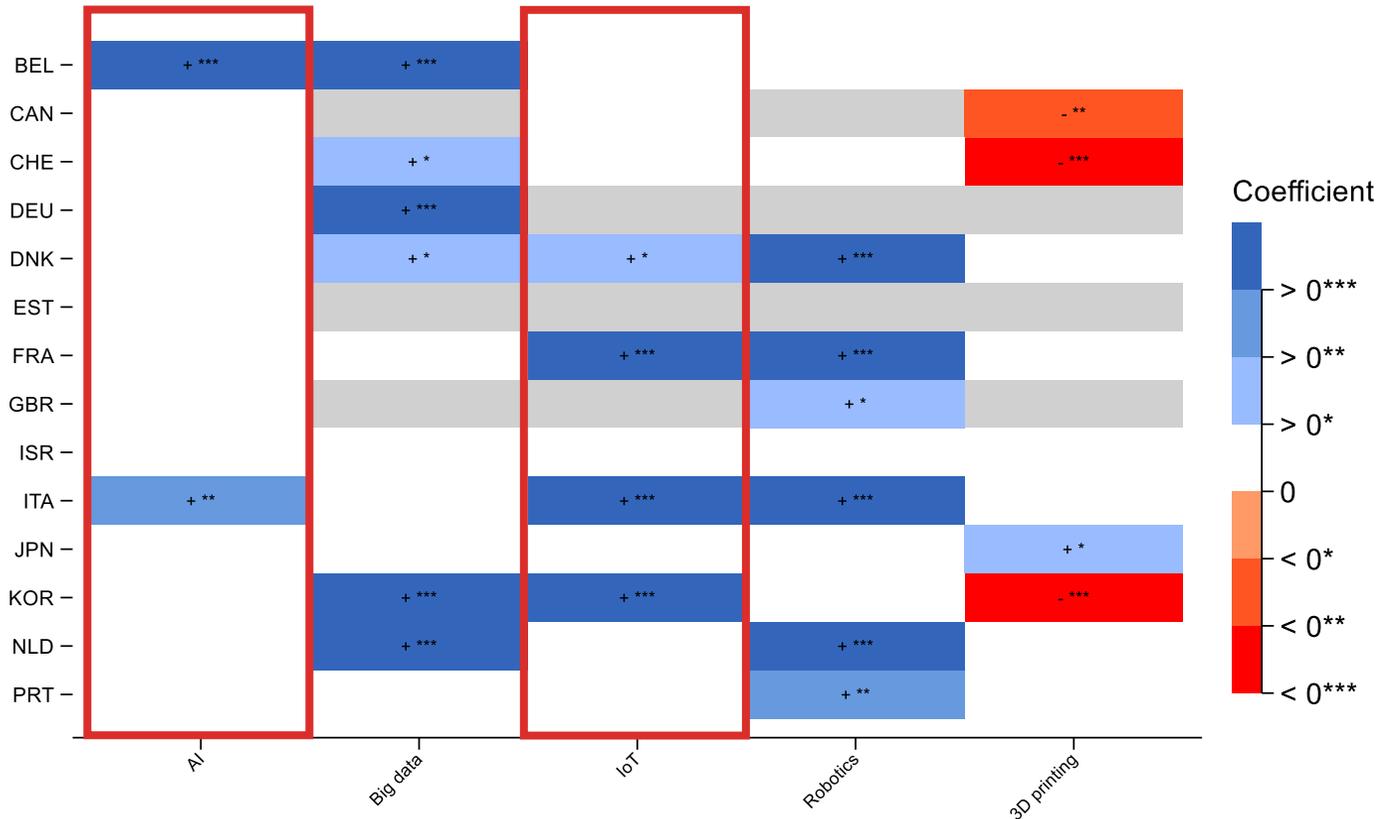
- These productivity advantages are **stronger in large firms**, across all technologies

Notes: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the baseline productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Canada, Germany and Korea. Although not reported, the model includes controls for firm size and age classes, as well as sector and year fixed effects, where available. Statistical significance is denoted as follows: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Source: Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>



# ...with human and technological capital partly explaining the productivity advantages of adopters



- Human and technological capital are **associated with higher productivity**
- These factors contribute to **explaining adopters' productivity advantages**, particularly in the case of AI and IoT
- For instance, when controlling for human and technological capital, only **two countries** retain a significant **AI-related** productivity advantage

Note: This figure presents the sign and statistical significance of the coefficients on technology use indicators in the extended productivity regressions, estimated separately for each country and technology. The dependent variable is the logarithm of firm-level productivity, measured as turnover over employment. The key explanatory variable is a binary indicator for whether a firm uses the relevant advanced digital technology. All regressions are weighted, except for Korea. Although not reported, the model includes controls for firm size and age class, as well as sector and year fixed effects, where available. Statistical significance is denoted as follows: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Source: Calvino, Costa and Haerle (2026), <https://doi.org/10.1787/ebc2debe-en>

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## Beyond firms: experimental evidence on the effects of generative AI

- A recent **literature** review covering 80+ recent experimental studies investigating the effects of generative AI on **productivity, innovation and entrepreneurship**
- **Relevant gains** from generative AI across fields reviewed **but...**
  - ...its impact appears to be highly dependent on **how it is utilised, for which purpose, by whom, on their level of expertise and trust in generative AI...**
  - ...it is important to consider and understand the **fit** between **the task undertaken and AI's capabilities**
- **Critical thinking** remains key to enable workers and organisations to understand when to use generative AI and how to use it in a meaningful way to leverage its full potential

Source: discussion based on Calvino, Reijerink and Samek (2025), <https://doi.org/10.1787/b21df222-en>



# POLICY CONSIDERATIONS



# What can policymakers do?



## Drive AI Innovation and Inclusive Ecosystems

- Facilitate public/private R&D investments
- Cultivate inclusive AI innovation ecosystems



## Support Firm Digitalisation and AI-Enabling Infrastructure

- Strengthen digital capabilities and infrastructure
- Establish mechanisms for AI knowledge/data sharing



## Develop Human Capital for AI Adoption and Use

- Develop technical and non-technical AI skills
- Strengthen managerial capabilities
- Ensure fair labor market transitions



## Cooperate for Trustworthy AI Governance

- Establish interoperable policy/regulation frameworks
- Lower barriers for new firms, facilitate innovation
- Address challenges around IP, data sharing



# AI adoption by small and medium-sized enterprises

- Informing G7 discussions on the proposed Blueprint for SME AI Adoption
- Introducing a taxonomy of SME AI adopters based on digital maturity, complexity of use, and scope of application
- Illustrating diverse adoption pathways through case studies
- Identifying key enablers and discussing recent policy instruments

AI adoption by small and medium-sized enterprises

OECD discussion paper for the G7

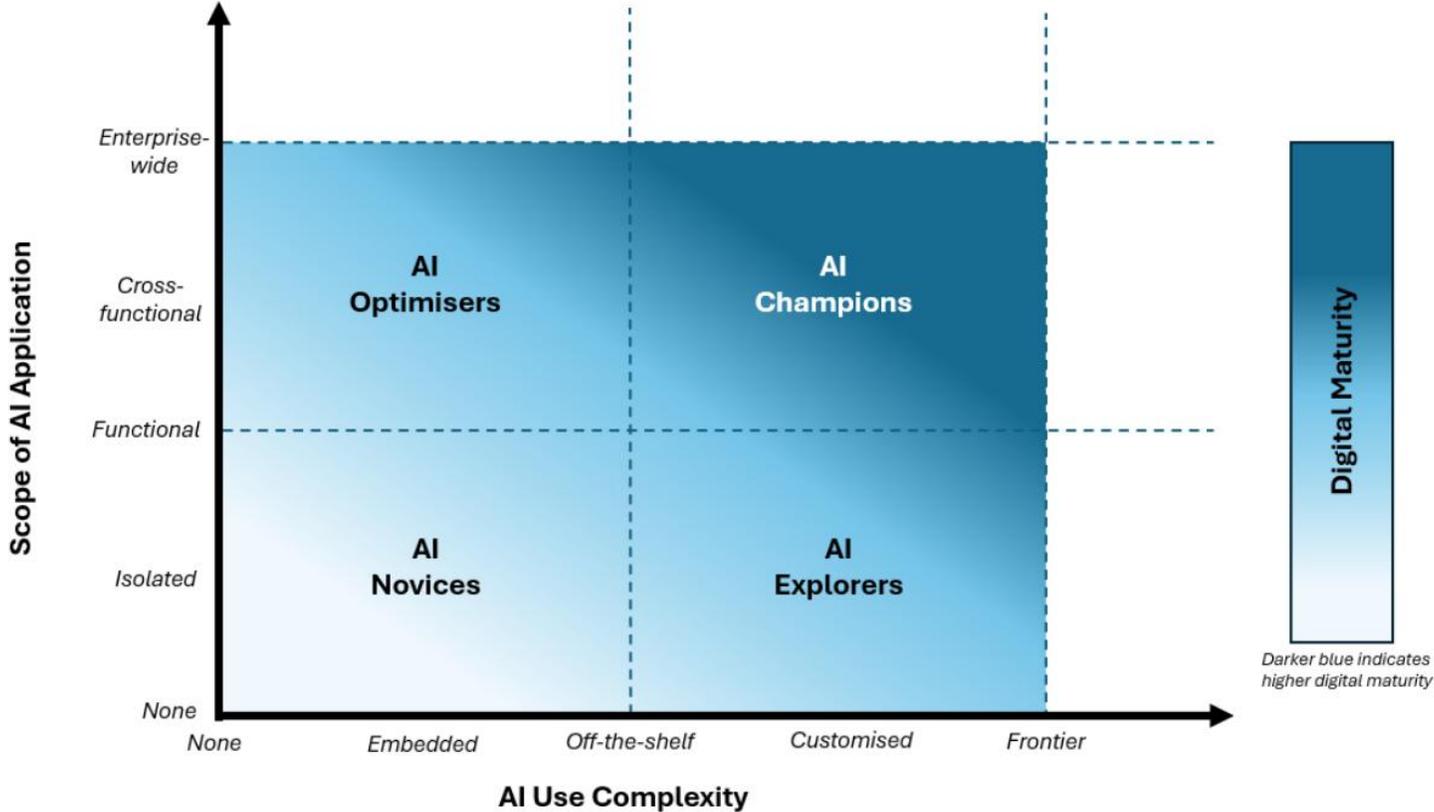


OECD



# Recognising different adoption profiles can help design more targeted policy support

Taxonomy and categories of SME AI adopters



Source: OECD (2025), <https://doi.org/10.1787/426399c1-en>



**Thank you!**

[Flavio.Calvino@oecd.org](mailto:Flavio.Calvino@oecd.org)