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Abstract

This study explores how French firms use artificial intelligence, leveraging a uniquely detailed and representative dataset with information on the use of specific AI technologies and how AI systems are deployed across different business functions within firms, in 2020 and 2022. The use of AI is still rare, amounting to 6% of firms, and varies by technology, with sectors often specialising in specific technologies and functions. While most firms specialise in a single AI technology applied to a single business function, larger firms adopt multiple technologies for different purposes. Firms adopting AI technologies are generally larger – except for those using natural language-related AI – and tend to be more digitally intensive, though firms leveraging NLG and autonomous movement AI deviate from this pattern. Firm size appears a relevant driver of AI use in business functions requiring integration with tangible processes, while digital capabilities appear particularly relevant for AI applications in business functions more related to intangible ones. AI technologies widely differ in terms of technological interdependencies and applicability, with machine learning for data analysis, automation and data-driven decision making-related AI technologies resulting as being at the core of the AI paradigm.

Keywords: Technology Diffusion, Artificial Intelligence, Business Function, ICT.

JEL Codes: O14, O33.

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1 Introduction

Artificial intelligence (AI) is increasingly at the center of economic debate. On the one hand, key activities and outcomes related to innovation (Cockburn et al., 2018; Agrawal et al., 2018; Besiroglu et al., 2024; Grashof and Kopka, 2023), organisational change (Agrawal et al., 2022; Dell'Acqua et al., 2023), and productivity (Calvino and Fontanelli, 2024; Brynjolfsson et al., 2023; Noy and Zhang, 2023) have already been affected for specific groups of firms and workers, or are expected to be in the near future. On the other hand, many scholars suggest that AI has the potential to become the next general-purpose technology (GPT) (Furman and Seamans, 2019; Trajtenberg, 2019; Goldfarb et al., 2023) and generate a paradigmatic shift (Damioli et al., 2025), implying that its current effects are only a precursor to more profound transformations. As with past GPTs (Bresnahan et al., 2002), AI's full impact will likely take time to materialise due to implementation lags and the presence of complementarities and interdependencies (Brynjolfsson et al., 2018, 2021), particularly with STEM and advanced ICT human capital (Alekseeva et al., 2021; Fontanelli et al., 2024; Babina et al., 2023). Moreover, fully realising AI's potential may require the development of software tailored to the specific needs of organisations (Agrawal et al., 2022).

Despite AI's transformative potential, empirical evidence on how firms use AI remains limited (Acemoglu et al., 2022; McElheran et al., 2023; Calvino and Fontanelli, 2023). While recent measures of AI exposure (see, for instance, Felten et al., 2021; Prytkova et al., 2024; Eloundou et al., 2023; Engberg et al., 2024) provide insights into its sectoral and occupational potential, less is known about how and why firms integrate AI into their operations. The use of different AI technologies – such as natural-language generation and machine learning – may vary in requirements, serve distinct purposes and be applied to different business functions. Understanding such patterns of use is crucial for informing firm strategies and managerial decisions, as well as for assessing the potential for diffusion of specific AI systems across firms and sectors.

In this study, we leverage novel representative data on firm-level technology use in 2020 and 2022 to examine how and for which purposes AI is used by French firms. Our findings are summarised in nine empirical facts, grouped into three key dimensions.

First, we quantify the diffusion of AI technologies and business functions across the French economy. AI adoption remains limited, with approximately 6% of firms using AI systems (see also Calvino and Fontanelli, 2023; Cho et al., 2022; Zolas et al., 2020; Rammer et al., 2022; McElheran et al., 2023). Machine learning, text mining, and automation technologies are the most widely adopted, with AI applications most frequently supporting organisational processes and R&D. Sectoral patterns reveal that firms in ICT services and professional and scientific activities are more likely to use AI, though adoption varies by technology. Sectors tend to specialise in specific AI applications, reflecting complementarities between AI capabilities and sectoral core activities. Finally, more than half of AI adopters use a single AI technology for a single business function, though larger firms tend to integrate multiple AI technologies across different functions.

Subsequently, we examine how AI adoption relates to firm characteristics such as size, age, digital infrastructure, and the use of other digital technologies. Their link with AI use is recognised as crucial by previous literature (Calvino and Fontanelli, 2023; McElheran et al., 2023; Zolas et al., 2020; Acemoglu et al., 2022), as it is related to the necessity to overcome fixed costs of adoption and to new managerial and ICT-related capabilities. We extend previous research by showing that these relationships vary across AI technologies and business functions. We find heterogeneous patterns of use in terms of firm characteristics – size, age and use of other digital technologies –, when conditioning on the use of other AI technologies. First, not all AI users are larger than non-users. The use of AI technologies related to natural language – text mining, speech recognition, and natural language generation (NLG) – is not systematically linked to firm size. Younger firms are more likely to use machine learning (ML) for data analysis, while older firms tend to adopt autonomous movement technologies. Second, AI adoption is generally associated with digital intensity, but notable exceptions – such as NLG and autonomous movement AI – suggest some of these technologies can work independently from the other digital technologies considered in the analysis. Third, the adoption of AI across different business functions is not uniformly associated with firm size. The use of AI in business functions related to the presence of physical capital that may embed the technology (production and logistics) are more common in larger firms. Moreover, the use of AI in business functions related to intangibles (commercial activities and organisational processes) is relevantly linked to firms' internal digital architecture. AI applications for digital security are more common among both large and highly digitalised firms.

Finally, we analyse the interdependencies among AI technologies and their applicability across business functions. Technological interdependence has long been recognised as a fundamental force shaping innovation and technological progress, influencing the development, diffusion, and adoption of new technologies (Rosenberg, 1979; Fronzetti Colladon et al., 2025) and describing technological trajectories and hierarchies (Dosi, 2023). These interdependencies create a structured map between technologies and capabilities of firms, shaping what businesses can do (Teece et al., 1994; Dosi et al., 2017; Lybbert and Zolas, 2014). On the one hand, AI technologies exhibit highly heterogeneous combinatorial potential, which can be classified into four categories: foundational (ML for data analysis and automation & Automation and Data-Driven Decision Making – DDDM – related AI technologies), complex (speech recognition and NLG), intermediate (text mining and image recognition), and niche (autonomous movement). Such finding suggests the existence of hyerarchies in the use of AI technologies, with ML for data analysis and automation & DDDM-related AI at the roots of AI systems and complex technologies (speech recognition and NLG) at its end. On the other hand, AI technologies vary in their applicability across business functions. Some (text mining, ML for data analysis and automation & DDDM-related AI), have broad application, while others (NLG, speech recognition, and autonomous movement) are more function-specific. Overall, we find that two technologies – machine learning for data analysis and automation & DDDM-related AI – are at the core of the AI paradigm, displaying the strongest linkages with other AI technologies and business functions.

We contribute to the literature on AI diffusion by offering a detailed investigation of how firms adopt AI. Our analysis draws on comprehensive data from France, providing a richer and complementary perspective on the types of AI technologies used and the business functions they support compared to existing studies (see also McElheran et al., 2023; Acemoglu et al., 2022; Calvino and Fontanelli, 2023). First, we identify distinct industry-specific applications of AI, shedding light on patterns that may shape the future diffusion of AI technologies. This evidence highlights that AI adoption is not uniform but influenced by sectoral needs and complementarities with firms' core activities. Second, contrary to the view that high fixed costs from complementary investments are always a prerequisite for AI adoption, we uncover relevant heterogeneity in the characteristics of AI users. Firm size and the presence of other digital technologies are not uniformly linked with AI use. Instead, their importance varies depending on the specific AI technology considered and the business function they support. Finally, we provide new insights into the interdependencies among AI technologies and their linkages with business functions. Our findings reveal that AI technologies are not all alike. Rather, they exhibit distinct technological patterns and interactions with other digital tools. In particular, machine learning for data analysis and automation & DDDM-related AI emerge as foundational technologies, suggesting their broader applicability across business functions. By contrast, other AI technologies, such as those related to autonomous movement, appear to serve more specialised purposes, suggesting their role in function-specific tasks.

Our findings have several important implications for firms, managers, and policymakers. They suggest that AI adoption is shaped by industry-specific factors, firm capabilities, and technological complementarities, highlighting the limitations of one-size-fits-all approaches to foster AI diffusion. First, recognising sector-specific patterns of AI adoption can help managers and policymakers identify which AI technologies are most relevant to different industries. This understanding can help firms consider the most relevant AI tools and policymakers design relevant measures that can foster AI diffusion across different sectors. Second, our findings somewhat challenge the assumption that larger firms or those with advanced digital infrastructure are always inherently better positioned to adopt AI. While some AI systems may require significant upfront investment, especially in digital capabilities, others less so, suggesting that AI adoption strategies should be adapted to the specific requirements of each technology and its use purpose. Third, the strong interdependencies among AI technologies and their linkages to business functions highlight the importance of interoperability, integration and relevant organisational changes. On the one hand, machine learning and automation & DDDM-related AI, result as core technologies within the AI paradigm, reinforcing their role in enabling broader adoption. Promoting interoperable environments, fostering accessible AI ecosystems, and industry-wide best practices could help firms integrate AI solutions more effectively, reducing adoption barriers and enhancing synergies between different AI applications. On the other hand, some AI technologies exhibit more specialised applications, supporting specific business functions rather than being widely applicable across firms. This suggests the relevance of management capabilities not only to recognise business function and technological specificities, but also to foresee the relevant organisational changes that may be needed to effectively leverage the full potential of AI applications.

The remainder of the paper is structured as follows. In Section 2, we review recent literature on AI use by firms. Section 3 provides a detailed discussion of the data sources used in this study, namely the 2020 and 2022 French ICT surveys, and presents basic summary statistics for the key variables. In Section 4, we present our empirical analysis, focussing on AI diffusion rates, the characteristics of AI users, and the relationships among AI technologies and their application to business functions. Finally, Section 5 provides some concluding remarks and outlines potential directions for future research.

2 A brief overview of related work

Beyond the evidence discussed in the previous section, the literature more closely related to the current analysis on AI use by firms often leverages three different sources of micro-data: firm-level ICT surveys, online job posting data that contain information on AI skills demand, and Intellectual Property (IP) records, in particular patents.[1] Based on these sources, it provides some key insights relevant for the current analysis, briefly discussed below.

Diffusion of AI - The diffusion of AI technologies is still limited and heterogeneous across sectors,

[1]Recent literature on firms' digitalisation frequently employs proxies for digital investments, such as automation shocks or IT expenditures (see e.g. Jin and McElheran, 2018; Acemoglu and Restrepo, 2020; Aghion et al., 2020; Domini et al., 2021, 2022). However, these proxies have not yet been applied specifically to measure AI adoption by firms. While ICT surveys on AI use are typically sourced from official data, the use of ICT survey data collected by other institutions is also common in studies on firm digitalisation (see for instance Cette et al., 2022; Cirillo et al., 2023).

but is growing fast in time. Evidence from several countries shows that the use of AI technologies is still rare (generally below 10%) and concentrated in the ICT and professional services sectors – in the US (Zolas et al., 2020; McElheran et al., 2023), Germany (Rammer et al., 2022), Korea (Cho et al., 2022), the UK (Calvino et al., 2022), and several OECD countries (Calvino and Fontanelli, 2023). Similarly, AI-related innovations are concentrated in high-tech sectors (Santarelli et al., 2022) and the demand for AI-related jobs is prevalent in ICT, consulting and financial/insurance sectors (Alekseeva et al., 2021).[2] However, country-level dynamics of demand for AI-related jobs (Acemoglu et al., 2022; Alekseeva et al., 2021; Babina et al., 2024; Squicciarini and Nachtigall, 2021; Borgonovi et al., 2023) and AI-related patenting activity (Dibiaggio et al., 2022) experienced a surge in the last decade, suggesting how AI technologies are likely to rapidly diffuse in the next decades.

AI and size - Notwithstanding the transformative potential of AI for enterpreneurship activities (Obschonka and Audretsch, 2020), existing evidence highlights a positive relation between AI adoption and firm size. findings from several countries shows that the larger firms are more likely to use AI (Zolas et al., 2020; McElheran et al., 2023; Rammer et al., 2022; Calvino et al., 2022; Calvino and Fontanelli, 2023; Segarra-Blasco et al., 2025). These findings have been explained by the presence of self-selection or an effect of AI on firms' performance. On the one hand, ex-ante larger firms, with higher cash holdings and R&D investments demand more intensively AI skills (Alekseeva et al., 2021; Babina et al., 2024). Indeed, the need for complementary assets (e.g., R&D and ICT capabilities, high computing power and big data) may raise the fixed costs of its adoption and generate scale advantages (Brynjolfsson and McAfee, 2014; Brynjolfsson et al., 2021; Fontanelli et al., 2024). On the other hand, AI-related innovations (Alderucci et al., 2021; Damioli et al., 2023), the use of Big Data analytics (Conti et al., 2024) and investments in AI-related skills (Babina et al., 2024) have a positive effect on firms' size.

AI and age - Some analyses suggest that a wave of high-tech young firms has been driving – at least partly – the development of AI technologies, notwithstanding the role of high entry costs for AI startups (for instance, in terms of proprietary data, see Bessen et al., 2022). Cross-country evidence from 11 OECD countries suggests that older firms tend to be less likely to adopt AI (Calvino and Fontanelli, 2023). Complementary findings for the US show that firms using AI are more likely younger (Acemoglu et al., 2022). Focusing on the UK, Calvino et al. (2022) also show that firms that have AI at the core of their business tend to be young. Relatedly, venture capital investments in AI startups has been significantly growing over time (Tricot, 2021), in line with the existence of a generation of AI start-ups. Furthermore, in the US, AI adoption by young firms is also related to indicators of high-growth entrepreneurship, with few cities and emerging hubs leading AI

[2]See also Calvino et al. (2024) for further analysis leveraging simultaneously the three sources of data mentioned above, uncovering relevant sectoral heterogeneity along different dimensions of AI intensity.

adoption by startups (McElheran et al., 2023).

AI and complementary assets - The literature on the relevance of AI complementary assets is, at our knowledge, still limited (see Brynjolfsson et al., 2021).[3] The conjectures on the existence of firm-level complementarities related to AI is supported by the evidence. Santarelli et al. (2022) highlight how AI-related patents are strongly rooted in ICT and robot knowledge bases. Igna and Venturini (2023) study patent applications filed at the EPO and find that AI innovators have likely developed past innovations in AI or related technology fields such as ICTs. Guarascio et al. (2025) and Guarascio and Reljic (2025) find that positive employment outcomes resulting from AI exposure occurred in countries with strong innovation systems. Furthermore, the literature on AI exposure, albeit preliminary, shows that white-collar workers and knowledge workers could be relatively more affected by AI diffusion (see e.g. Felten et al., 2021, 2023; Montobbio et al., 2024), but remain tacit in distinguishing whether this implies their displacement or reinstatment. In that respect, available empirical evidence shows that advanced ICT workers are necessary for using AI (Fontanelli et al., 2024) and STEM workers' demand correlates with AI use (Alekseeva et al., 2021; Babina et al., 2023). Finally, Calvino and Fontanelli (2023), McElheran et al. (2023), DeStefano et al. (2023), Calvino et al. (2024) and Lo Turco and Sterlacchini (2024) recently showed that firms using AI also employ other digital technologies, suggesting the existence of technological interdependencies between them.

3 Data and summary statistics

Our analysis is based on recent microdata from the 2021 and 2023 French ICT surveys, administered by the French statistical office.[4] These include information related to the use of advanced digital technologies in 2020 and 2022, respectively, and changing on a yearly basis. Each survey provides data for a representative and rotating sample of about 9000 firms with 10 or more persons employed in 2020 and 5 or more in 2022 from manufacturing, utilities, construction and market-services sectors.[5] The sample is exhaustive for firms with more than 500 employees. After accounting for non-responses, we retain information on the AI technologies adopted by 17,816 firms and the AI-driven business functions performed by 17,164 firms.

[3] The absence of complementary assets is often advocated as the reason why AI use has not yet produced an increase in productivity (Brynjolfsson et al., 2018) as done by other ICT (e.g. Brynjolfsson and Hitt, 2003; DeStefano et al., 2023; Jin and McElheran, 2018). Indeed, evidence from empirical studies investigating the relationshiup between AI and productivity offer to this day mixed evidence (see e.g. Babina et al., 2024; Alekseeva et al., 2020; Alderucci et al., 2021; Damioli et al., 2021; Venturini et al., 2024; Calvino and Fontanelli, 2024; Czarnitzki et al., 2022; Dell'Acqua et al., 2023; Kopka and Fornahl, 2024).

[4] *"Enquête sur les Technologies de l'Information et de la Communication (TIC)"*, further information about the survey can be found here and here.

[5] Henceforth, we will refer to persons employed as "employees."

Table 1: The AI technologies included in the ICT survey and their explanations

AI Technology	Definition
Text Mining	Focuses on extracting useful information from unstructured text data.
Speech Recognition	Converts spoken language into machine-readable formats
Natural Language Generation (NLG)	Focuses on generating human-like text from structured or unstructured data.
Image Recognition	Involves identifying objects and people in images.
Machine Learning (ML) for data analysis	Uses machine learning algorithms to analyse data
Automation and Data-Driven Decision Making (DDDM)	Focuses on technologies automating different tasks or assisting in decision-making.
Autonomous Movement	Enables the physical movement of machines through autonomous decisions based on the observation of their surrounding environment.

In particular, firms are asked which AI technologies they used in 2020 and 2022, and for which business functions they used AI tools.[6] The AI technologies surveyed include text mining, speech recognition, natural language generation, image recognition, machine learning for data analysis, automation & DDDM, and autonomous movement (see Table 1). Questions on AI-driven business functions changed over time. In both 2020 and 2022, they include commercial activities, production processes, logistics, and digital security. Additionally, the 2020 survey provides information on functions related to administration, management, and human resources, while the 2022 survey on administration & management, accounting, and research. For consistency, the category "organisational processes" used in the analysis includes administration, management, and human resources in 2020, and administration, and accounting in 2022. The classification of business functions is summarised in Table 2.

The ICT survey also includes questions on the use of various digital technologies and tools, with specific information available on an annual basis. In both 2020 and 2022, firms were asked about their purchase of cloud services, the use of Customer Relationship Management (CRM) software, Enterprise Resource Planning (ERP) software, and the presence of e-commerce activities. These digital technologies are purely software-centric because they operate primarily in the digital realm by focusing on improving digital infrastructure, data management, and business processes without directly interacting with the physical world, differently from other digital technologies such as robots, 3D printers and Internet of Things. We count the number of these business digital technologies to construct the variable "Non-AI digital technologies", which represents the number of technologies used by the firm (ranging from 0 to 4) and serves as a proxy for its level of

[6] The definition of AI and related questions can be found in Section VII of the 2021 survey (questions 1 and 2 of Section VII) and Section VI of 2023 survey (questions 1 to 8 of Section VI).

Table 2: The AI-related business functions included in the survey and examples of applications.

Business Function	Applications
Commercial Activities	AI-powered chatbots for customer service, customer profiling, pricing optimisation strategies, recommender systems, machine learning algorithms for market analysis.
Production Processes	Predictive maintenance, ensuring optimal performance of machinery, computer vision systems to categorize products or detect product defects, autonomous drones for monitoring and inspections, autonomous robots in assembly lines.
Logistics	Autonomous robots for picking and packing, machine learning is used to optimize delivery routes, autonomous drones for package delivery, robots for sending, sorting and tracking.
Digital security	Facial recognition for user authentication, machine learning algorithms to detect and prevent cyberattacks.
Organisational Processes	Machine learning for supporting decision making (e.g. planning, financial, investment decisions), employee performance analysis, automating candidate screening and supporting recruitment, risk analysis, virtual assistants for tasks like document creation or analysis, invoices management and speech-to-text conversion.
R&D	Machine learning data analysis for conducting research, solving research problems by developing a new or significantly improved product/service.

digitalisation.[7]

Additionally, the survey includes a measure of digital infrastructure, with firms asked about the speed of their broadband connection. We create a dummy variable for the presence of a fast broadband connection, which is set to 1 if the connection speed is greater than or equal to 100 Mbit/second. Finally, the ICT survey provides data on firm characteristics notably age and number of employees.

All regressions and summary statistics reported in this work have been weighted using probability weights provided in the ICT survey. As a result, the findings can be considered representative of the population of French firms considered in the sampling structure of the ICT survey.

Based on the database described above, we present a series of summary statistics in Table 3, which provide an initial overview of our data and allow for a comparison between AI users and other firms. The statistics indicate that AI users are, on average and unconditionally, larger and younger. Additionally, AI-using firms are more likely to have a fast broadband connection and demonstrate a higher average use of digital technologies beyond AI.

4 Nine facts about the use of AI in France

In this section we discuss nine key facts about AI use in the French economy which result from our empirical analysis. These are summarised in Table 4 and grouped in three sections. First, we provide descriptive evi-

[7]In 2020, firms are also asked about Internet of Things (IoT) technologies. In 2022, the question regarding IoT usage was replaced with one on the use of business intelligence software (BI). we exclude IoT and BI to make the variable uniform across years and type of technology.

Table 3: Summary statistics.

	All firms	AI Users	Other Firms
Employees	62.78	305.15	46.50
Age	20.08	19.12	20.14
Non-AI Digital Technologies	1.33	2.62	1.24
Fast Broadband	58.23%	71.46%	57.34%
ERP	46.01%	72.60%	44.22%
Cloud	26.40%	65.22%	23.79%
CRM	28.76%	62.28%	26.51%
E-commerce	14.91%	20.72%	14.52%

Notes: Average numer of employees, wage, and number of non-AI digital tecnologies, and share of firms by presence of fast broadband or use of other digital technologies (ERP, Cloud, CRM, E-commerce). Averages and shares are computed using sampling weights. The columns 'All firms', 'AI users' and 'Other Firms' report the startistics computed on the full sample of firms, AI users and non-users, respectively.

dence on the diffusion of AI technologies and the business functions they support in Section 4.1 (**EF1-EF3**). Then, in Section 4.2 we examine key characteristics of AI users (**EF4-EF7**). Finally, in Section 4.3 we estimate the relationships among different AI technologies and explore which AI technologies are related to specific business functions (**EF8-EF9**).

Table 4: Topic and description of key facts about AI use in France.

Fact's topic	**Fact's description – Brief summary of relevant empirical evidence**
EF1 – Which AI technologies are used by firms and for what purpose?	Machine Learning for data analysis, text mining, automation & DDDM-related technologies, are the most commonly used AI technologies, particularly in business functions related to organisational processes and R&D.
EF2 – How do firms in different sectors leverage AI?	The use of AI is higher in ICT and Professional & Scientific services, with different sectors specialising in distinct technologies and applications.
EF3 – How much do firms use AI?	Most firms specialise in a single AI technology or use AI in a single business function; however, the number of adopted AI technologies and the business functions to which AI is applied increase with firm size.
EF4 – What are the characteristics of firms adopting different AI technologies?	Firms adopting AI technologies tend to be larger, except for those using natural language-related AI systems. Firms using ML data analysis tend to be younger while those using autonomous movement technologies older.
EF5 – How the adoption of different AI technologies is linked with digital intensity?	Firms adopting AI technologies are more intensive in their use of other digital technologies, with exceptions of firms leveraging NLG and autonomous movement AI technologies.
EF6 – How the use of AI for different purposes is linked with firm characteristics?	The use of AI to support business functions requiring integration with physical processes (production, logistics) and digital security significantly and positively depends on firm size.
EF7 – How the use of AI for different purposes is linked with digital intensity?	The use of AI for business functions related to intangible processes (commercial activities, organisational processes) and digital security significantly and positively depends on digital intensity.
EF8 – How are AI technologies combined?	AI technologies can be categorised into foundational, complex, intermediate, and niche based on their interlinkages.
EF9 – Which AI technologies support which business functions?	AI technologies can be categorised based on their applicability to business functions, distinguishing between technologies with broad and more limited applicability.

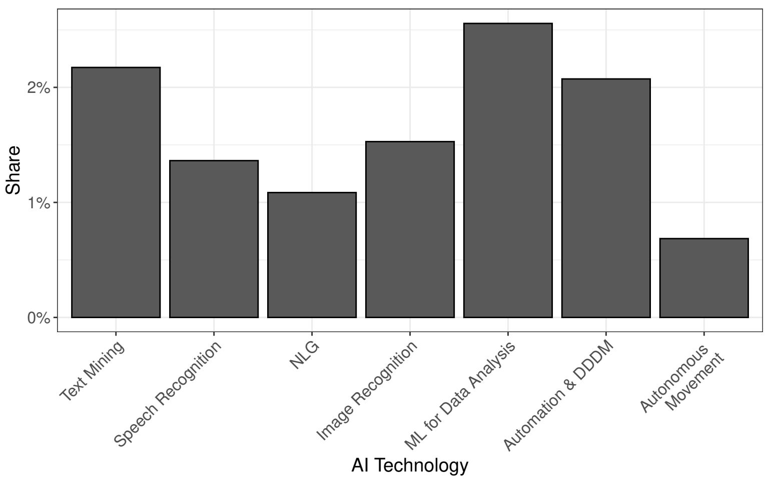
4.1 AI diffusion within firms

In this section we present evidence about AI diffusion within firms in France. We analyse different margins of AI adoption by exploring the heterogeneity in the use of different AI technologies and in the business functions they support. We then explore sectoral patterns of AI use, discussing the extent to which different sectors leverage different AI technologies and the sector-specific business functions supported by AI. We finally present evidence of AI intensity within firms, analysing the extent to which businesses use multiple AI technologies across multiple business functions.

EF1 – Which AI technologies are used by firms and for what purpose?

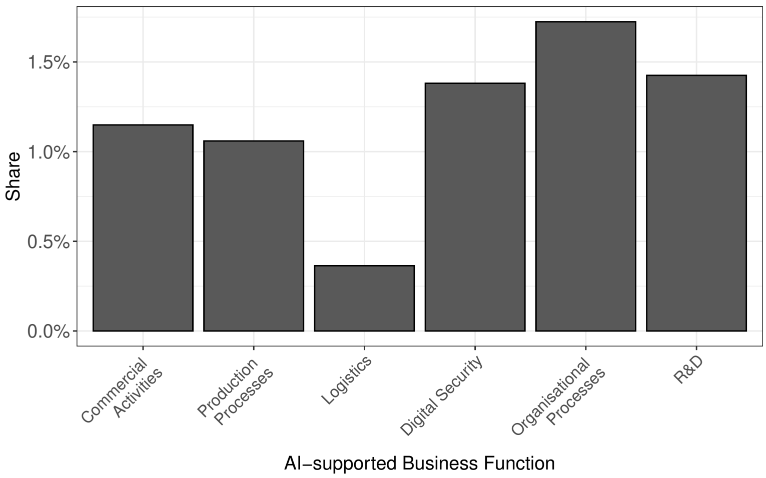
AI technologies exhibit limited use among French firms, with only 6.2% of firms adopting at least one of them, consistent with previous evidence (see e.g. Rammer et al., 2022; Cho et al., 2022; McElheran et al., 2023; Calvino and Fontanelli, 2023, 2024; Calvino et al., 2022). When distinguishing the usage rates of different technologies in Figure 1, we observe substantial heterogeneity. A few technologies (text mining, ML for data analysis, and automation & DDDM-related AI technologies) are more widely used than others, possibly suggesting that their use serves more general purposes across AI systems, and highlights the relevance of predictive analytics (Brynjolfsson et al., 2021) and data-driven applications (Brynjolfsson and McElheran, 2016; Wu et al., 2020). Image recognition, despite its early breakthrough applications (e.g., the AlexNet neural network), is less commonly adopted by firms. The use of NLG was very limited prior to 2023, reflecting patterns to a large extent preceeding the launch of ChatGPT at the end of 2022, and consistently with the evidence showing that the use of LLMs is highly task-specific (Handa et al., 2025). Finally, autonomous movement AI technologies

Figure 1: Share of firms using specific AI technologies.



Notes: Shares are computed using sampling weights.

Figure 2: Share of firms using AI systems for specific business functions.

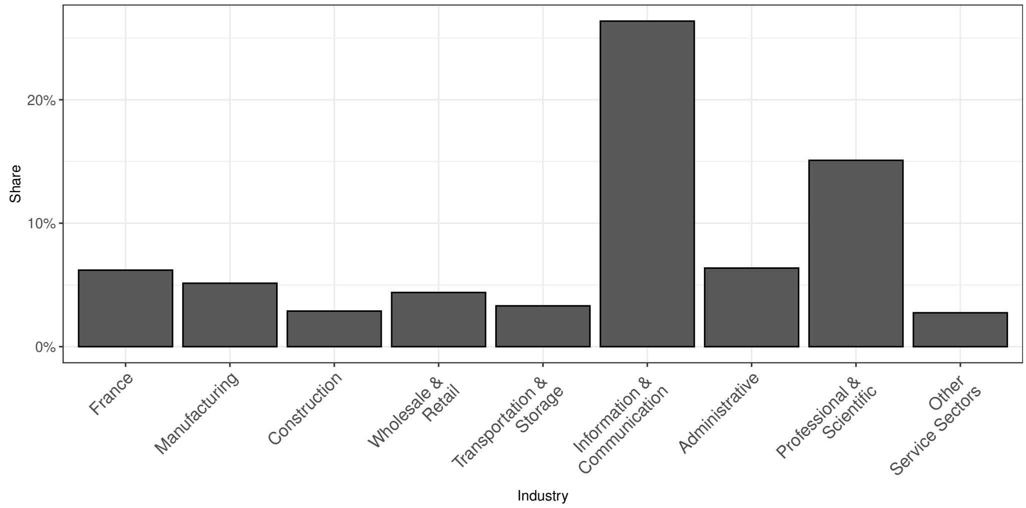


Notes: Shares are computed using sampling weights.

exhibit a particularly low adoption rate, below 1%, possibly due to the nascent stage of these AI systems or their specific purposes.

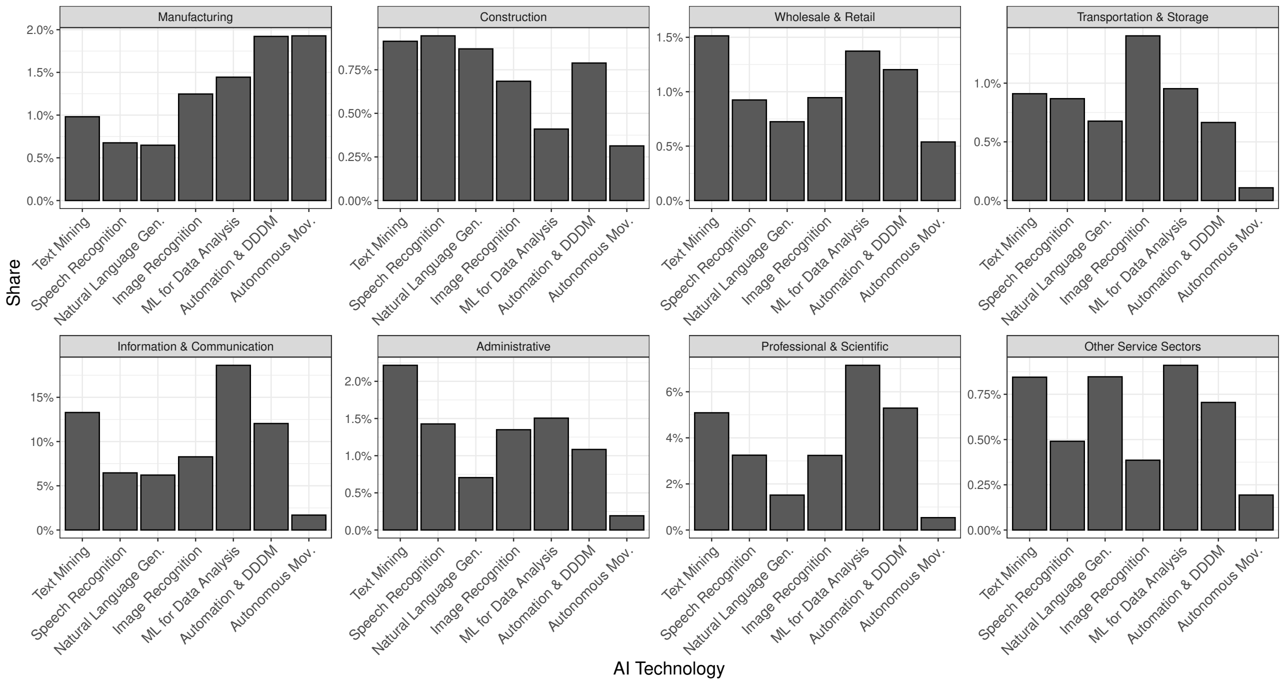
When examining the business function supported by AI system, in Figure 2, the highest rate is found in organisational processes, even before the rise of generative AI. This suggests that AI systems may be relatively more useful in intangible, rather than physical, applications (e.g., decision support systems, see Brynjolfsson and McElheran, 2016). AI applications in R&D show the second highest rate of use, in line with findings that AI systems play a key role in innovation activities (see e.g. Bianchini et al., 2022; Agrawal et al., 2018; Cockburn et al., 2018). AI-powered digital security ranks third in terms of adoption, possibly driven by the rising frequency and severity of cyberattacks and highlighting the increasing threat of cybersecurity for firm performance (see e.g. Jiang et al., 2024). This is especially true for larger firms, because they are more exposed to cyberattacks (see e.g. Florackis et al., 2022), contributing to explaining why are they more likely to adopt AI systems (McElheran et al., 2023; Calvino and Fontanelli, 2023). AI applications related to commercial activities are relatively less common, likely due to the need for customer data, which may only be available in large firms or those operating in the Wholesale & Retail sector, to train AI algorithms. The use of AI is also relatively less frequent when considering production processes, consistent with the lower rate of digitalisation in manufacturing compared to services (Calvino et al., 2018). This is also attributable to the inherent challenges of applying AI in physical processes, a phenomenon long highlighted by arguments such as Moravec's paradox. Finally, AI systems focusing on logistics have the lowest usage rate, suggesting that these applications are still in their infancy or have highly specific scope of applicability, in line with the low adoption rate of AI technologies in autonomous movement (see Figure 1).

Figure 3: Sectoral share of firms using AI systems.



Notes: Shares are computed using sampling weights. Utilities (NACE sectors 35–39) have been excluded to ensure confidentiality.

Figure 4: Sectoral share of firms using specific AI technologies.



Notes: Shares are computed using sampling weights. Utilities (NACE sectors 35–39) have been excluded to ensure confidentiality.

EF2 – How do firms in different sectors leverage AI?

Figure 3 presents the rates of AI technology use across different sectors.[8] The adoption of AI technologies varies considerably across sectors. Consistent with previous literature (e.g., Calvino and Fontanelli, 2023), the

[8]Sectors are categorised as follows: Manufacturing (NACE sectors 10–33), Construction (NACE sectors 41–43), Wholesale & Retail (NACE sectors 45–47), Transport & Storage (NACE sectors 49–53), Professional & Scientific Activities (NACE sectors 69–75), and Administrative (NACE sectors 77–82). Remaining services (Accommodation, food and real estate, i.e., NACE sectors 55, 56 and 68) are classified as the Other Service Sector. Utilities (NACE sectors 35–39) and AI use for R&D in the Other Service Sector have been excluded to ensure confidentiality.

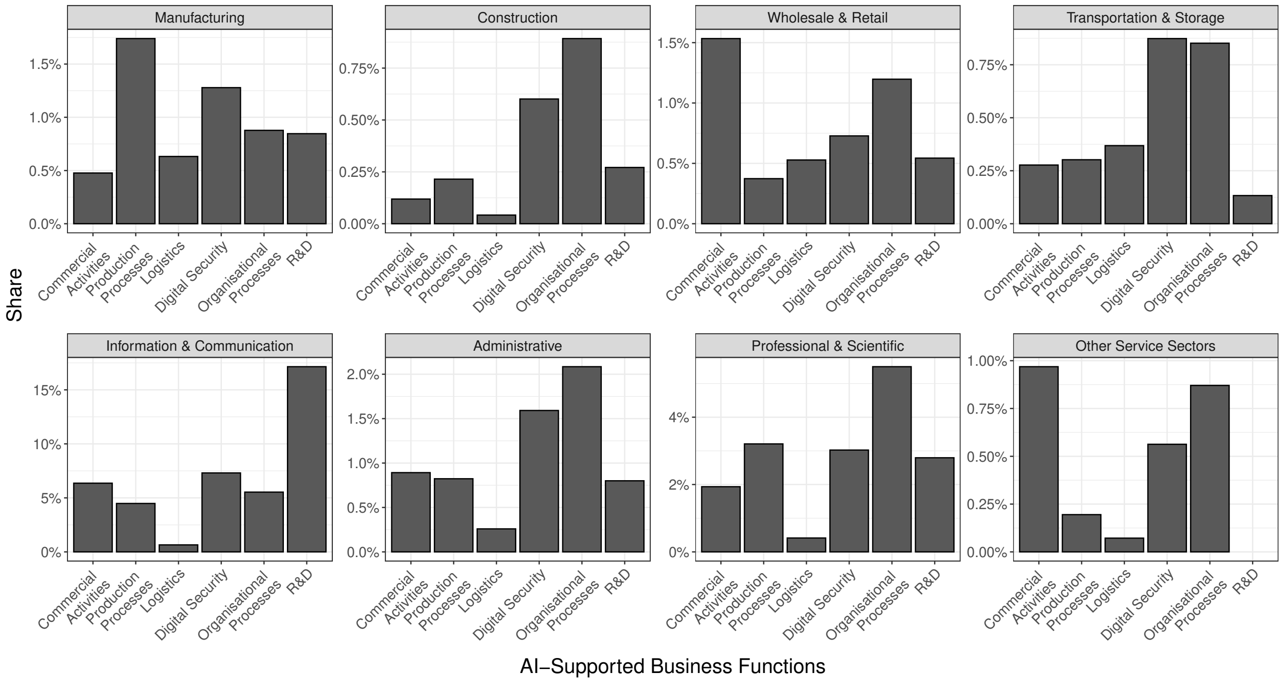
highest adoption rates are observed in the ICT Services and Professional & Scientific sectors, with substantially lower rates in the Administrative and Manufacturing sectors, which rank third and fourth, respectively. This variation suggests that key differences in the core activities of firms across sectors are significant drivers of AI adoption, with firms in the ICT Services and Professional & Scientific sectors more likely to possess the capabilities needed to implement AI in their operations.

Next, we examine the rates of use of specific AI technologies across sectors (Figure 4) and their applications (Figure 5). These figures reveal a tendency toward sectoral specialisation in both technologies and business functions. When focusing on AI technologies (Figure 4), the Manufacturing sector shows higher adoption of technologies related to automation & DDDM and autonomous movement. This may be associated with the robotisation of production systems and findings that highlight overlaps in the knowledge bases of robotics and AI technologies (Santarelli et al., 2022). In contrast, firms in the Wholesale & Retail and Administrative sectors are more frequent users of text mining and ML for data analysis technologies, likely due to the analysis of written language (e.g., documents and product descriptions) and the large volumes of data available to these sectors.

The Transportation & Storage sector exhibits a relative specialisation in image recognition technologies, which are essential for key AI-driven applications in logistics operations, tracking, and monitoring systems. The ICT Services and Professional & Scientific sectors show the highest rates of adoption for ML for data analysis, reflecting the central role of data analytics in most AI systems. Finally, the Construction and Other Service sectors display the lowest rates of AI use, suggesting a less mature technological pattern and indicating that the applicability of AI systems in these areas remains limited (see also Felten et al., 2021).

Similarly, the extent to which AI supports different business functions is sector-specific (see Figure 5). In the Manufacturing sector, firms are more likely to employ AI for functions related to production processes, suggesting that AI systems had already begun to be embedded into physical machinery by the early 2020s. In contrast, AI systems in the Wholesale & Retail sector are more commonly used for functions related to commercial activities, emphasising their possible role in optimising pricing strategies and advertising for firms with large datasets on products and customers. Likewise, the most prevalent AI applications in the Other Services sector are related to commercial activities, reflecting the relevance of sales and marketing in the real estate, accommodation, and food service industries. The ICT sector more frequently uses AI systems for R&D applications, underscoring its critical role in advancing cutting-edge research driven by AI systems. In the Professional & Scientific sector, AI is predominantly adopted for organisational processes, in line with results from Figure 4 showing that the AI technology with the highest rates in this sector are ML for data

Figure 5: Sectoral share of firms using AI systems for specific business functions.



Notes: Shares are computed using sampling weights. Utilities (NACE sectors 35–39) and AI use for R&D in the Other Service Sector have been excluded to ensure confidentiality.

analysis and automation & DDDM. Overall, AI systems related to logistics exhibit limited use across sectors, with the highest adoption rates observed in the Manufacturing, Wholesale & Retail, and Transportation & Storage sectors.

Table 5: AI-supported business functions

Number	AI Technologies 2020-2022	AI-supported business functions 2020	2022
1	56.53%	63.26%	55.93%
2	21.76%	26.45%	26.09%
3	13.18%	6.7%	12.97%
4	3.52%	1.84%	3.88%
5	2.69%	1.74%	0.73%
6	1.19%		0.4%
7	1.14%		

Notes: Share of firms by number of AI technologies or business functions performed with the help of AI systems. We report the share separately across years for business functions supported by AI, as the number increases in 2022. Shares are computed using sampling weights.

EF3 – How much do firms use AI?

We then examine the intensity of AI use in terms of both the number of AI technologies adopted and the business functions supported by them. Table 5 reports the share of firms by number of technologies or supported

Table 6: AI Intensity by Firm Size

Size Class	Number of AI technologies	Number of AI-supported Business Functions
<20	1.616566	1.549407
20-49	1.794975	1.697483
50-249	1.92041	1.725253
250-499	2.143125	1.940289
500-1000	2.206778	1.975082
1000+	2.729337	2.424056

Notes: Average number of AI technologies or business functions performed with the help of AI systems by size class. The size class is based on the number of employees in the firm. Averages are computed using sampling weights.

business functions. These indicate that most firms adopt only a single AI technology, with approximately 44% employing multiple AI technologies simultaneously and fewer than 10% using more than three AI technologies concurrently. Similarly, the majority of firms deploy AI technologies for a single business function (see Table 5).

Table 6 also presents the average number of AI technologies and related business functions adopted by firms using AI systems, categorised by firm size (measured by the number of employees). Larger firms are more likely to adopt multiple AI technologies and use them for various business functions. First, this finding highlights the greater potential of larger firms to implement complex AI systems based on multiple technologies. Second, the shares are consistent with the idea that larger firms are better equipped to overcome the fixed costs associated with adopting multiple AI technologies and supported business functions simultaneously. Third, due to their greater diversification, the range of business functions that can be supported by AI systems is broader.

4.2 The characteristics of AI users

In this section, we analyse the characteristics of AI users in terms of firm size (measured by the number of employees), age, and the use of other digital technologies, while accounting for potential influences of sector, year, and regional composition. To do this, we specify the following regression model:

$$\begin{aligned} \text{AI}^{j}_{i,t} =& \alpha + \beta_1 \text{Log Employees}_{i,t} + \beta_2 \text{Log Age}_{i,t} + \beta_3 \text{Fast Broadband}_{i,t} + \\ &+ \beta_4 \text{Non-AI Digital Technologies}_{i,t} + \beta_5 \text{Other AI}_{i,t} + \text{FE}_{s,t,r} + \epsilon_{i,t} \end{aligned} \tag{1}$$

In this model, the dependent variable $\text{AI}^{j}_{i,t}$ is a binary indicator denoting whether a firm (i) adopts a specific AI technology or uses AI for a specific business function (j) in a given year (t). The independent variables represent firm characteristics such as size (Log Employees$_{i,t}$, the natural logarithm of the number of employees) and age (Log Age$_{i,t}$, the natural logarithm of firm age). The model also includes a measure of broadband quality (Fast Broadband$_{i,t}$, a binary variable indicating the availability of fast broadband) and a count of other digital technologies used by the firm (Non-AI Digital Technologies$_{i,t}$, ranging from 0 to 4). Additionally, the variable Other AI$_{i,t}$ captures the count of other AI technologies (when j refers to a technology) or business functions (when j refers to a business function) adopted by the firm, excluding the dependent variable. This variable is included to isolate the relationship between the dependent and explanatory variables from the broader correlation between size, age, and digital technology adoption linked to the presence of other AI technologies or AI-supported business functions. Sector-year-region fixed effects (FE$_{s,t,r}$) account for variations across 1-digit NACE industries, years, and regions, addressing potential biases, including those introduced by the COVID-19 pandemic. Finally, standard errors are clustered at the 2-digit industry level.

Table 7: AI technologies and firm characteristics

	Text Mining		Speech Recognition		NLG		Image Recognition		ML for Data Analysis		Automation and DDDM		Autonomous Movement	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Log Employees	0.011***	0.001	0.006***	-0.001	0.006***	-0.001	0.012***	0.005***	0.019***	0.009***	0.016***	0.008***	0.009***	0.006***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Log Age	-0.003**	-0.001	-0.003**	-0.001	-0.001	0.001	-0.001	0.001	-0.005***	-0.003**	-0.004**	-0.003*	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Fast Broadband	0.003	0.001	-0.001	-0.002	0.002	0.001	-0.000	-0.002	0.006**	0.004	0.005*	0.003	0.000	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Non-AI Digital Technologies	0.014***	0.006***	0.009***	0.004***	0.008***	0.002	0.009***	0.003**	0.014***	0.005***	0.012***	0.004***	0.002***	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Other AI Technologies		0.148***		0.094***		0.096***		0.102***		0.169***		0.139***		0.040***
		(0.011)		(0.008)		(0.008)		(0.010)		(0.014)		(0.010)		(0.005)
Constant	-0.022***	0.002	-0.010*	0.006	-0.017**	-0.001	-0.029***	-0.014***	-0.041***	-0.017**	-0.035***	-0.015*	-0.027***	-0.021***
	(0.008)	(0.005)	(0.006)	(0.004)	(0.007)	(0.005)	(0.006)	(0.004)	(0.009)	(0.007)	(0.009)	(0.008)	(0.004)	(0.004)
Observations	17,816	17,816	17,816	17,816	17,816	17,816	17,816	17,816	17,816	17,816	17,816	17,816	17,816	17,816
Adj R2	0.0666	0.255	0.0333	0.169	0.0332	0.210	0.0449	0.184	0.0984	0.301	0.0580	0.236	0.0174	0.0730
Industry-Year-Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation results of Equation 1, when the use of a specific AI technology is employed as the dependent variable. 'Log Employees' is the logarithm of the number of employees hired by a firm. 'Log Age' is the logarithm of the age of a firm. 'Fast Broadband' is a dummy variable taking value 1 if a firm has a broadband internat connection with speed equal or greater than 100Mbit/s, and 0 otherwise. 'Non-AI Digital Technologies' is the count of digital technologies adopted by a firm and ranges from 0 to 4. 'Other AI Technologies' is the count of other AI technologies used by a firm, and ranges from from 0 to 6. Industry-Year-Region FE are jointly defined for industry, region and year. Industries correspond to 1-digit NACE codes, and regions to administrative regions of metropolitan France. All the specifications are estimated using survey weights. Standard errors are clustered at the 2-digit industry level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

EF4 – What are the characteristics of firms adopting different AI technologies?

In this and the following section, we discuss the estimation results of Equation 1 when using AI technologies as the dependent variable. The variable Other $\mathrm{AI}_{i,t}$ corresponds to the number of other AI technologies adopted by a firm, excluding the dependent variable.

The regression results are presented in Table 7. Our analysis reveals that firms using AI are, on average, larger than non-users. This finding holds across different AI technologies when the model does not control for the adoption of other AI technologies. However, when controlling for the number of other AI technologies, the relationship becomes not significant for text mining, speech recognition, and NLG technologies. In these cases, the observed relationship between firm size and AI depends on the simultaneous use of other AI technologies. Text mining, speech recognition, and NLG technologies share a strong reliance on natural language processing, distinguishing them from AI technologies that primarily deal with numerical, visual or structured data and automation. Indeed, the AI-size relations remains instead significant for image recognition, automation & DDDM, autonomous movement and ML for Data analysis.

This finding aligns with Brynjolfsson et al. (2021), who suggest that the adoption of AI systems entails large fixed costs of adoption, and at the same time shows that this may not be true for all AI technologies. Indeed, natural language-based AI technologies use may only require the use of a software provided or purchased by third parties and are not likely to be embedded in expensive physical devices. Furthermore, these technologies are based on textual data, whose related analytics is less complex and demanding than images. In other words, this suggests that these AI systems are likely to involve relatively milder fixed costs of use, if compared to other computationally intensive AI technologies such as those dealing with images or computer vision. Furthermore and similarly to ML for data analysis and DDDM, these require substantial IT capabilities (such as developing skills) and rely on large, meaningful datasets. Finally, AI technologies related to autonomous movement are more likely to involve the use of expensive physical devices, such as sensors and robots, and are less scalable due to their tangible nature.

The relationship between AI use and firm age is generally not significant, with three notable exceptions: ML for data analysis, automation & DDDM-related AI and AI technologies related to autonomous movement. In the former case, the negative coefficient suggests that younger firms are more likely to use this technology, in line with the view that a wave of start-ups characterised by innovative technical capabilities is driving the diffusion of this particular AI technology. This finding aligns with existing results on the early period of AI diffusion, wherein ML is was prevalent (Calvino and Fontanelli, 2023). For autonomous movement, the positive coefficient implies that older firms are more likely to use this technology, indicating that established infrastructure and operational experience appear required to integrate and support such advanced technologies.

EF5 – How the adoption of different AI technologies is linked with digital intensity?

Furthermore, firms using AI are generally more digitally intensive, as evidenced by the positive and significant coefficient of the number of non-AI digital technologies across regressions. However, this relationship is not significant for NLG and autonomous movement technologies when controlling for the number of other AI technologies adopted by firms. This suggests that the use of these technologies may not be strongly linked to the adoption of non-AI digital technologies considered in that variable (cloud, CRM, ERP, and e-commerce systems). Nonetheless, the findings imply that firms may first need to establish an internal digital architecture to leverage AI systems effectively. Such an infrastructure is essential for processing and exploiting business data, which supports the successful integration of AI technologies into organisational processes.

In the case of NLG, the lack of a significant relationship with both firm size and the use of other digital technologies suggest relevant implications. Firms do not seem to need to overcome substantial fixed costs or establish a comprehensive internal digital architecture to adopt generative AI systems. This underscores the diffusion potential of this class of AI technologies, and their relevance in terms of economic implications.

Finally, the count of other AI technologies adopted by a firm is positively and significantly associated with AI adoption across all models. This result highlights a tendency among firms to combine multiple AI technologies, underscoring the combinatorial potential of the different AI technologies underlying AI systems. Conversely, the availability of fast broadband is not systematically linked to AI adoption, suggesting that broadband quality may not be a primary determinant in the adoption and diffusion of all AI technologies.

Table 8: AI-supported business functions and firm characteristics

	Commercial Activities		Production Processes		Organisational Processes		Logistics		Digital Security		R&D	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Log Employees	0.009***	0.003*	0.011***	0.005***	0.011***	0.002	0.006***	0.004***	0.017***	0.010***	0.008***	0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Log Age	-0.002***	-0.001	-0.001	0.000	-0.005**	-0.003*	0.000	0.001**	-0.003***	-0.002**	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fast Broadband	0.003**	0.002	0.002	0.001	0.002	0.000	0.002**	0.001	0.002	0.001	0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Non-AI Digital Technologies	0.012***	0.008***	0.006***	0.001	0.013***	0.007***	0.002***	-0.000	0.010***	0.004***	0.009***	0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Other AI-supported Business Functions		0.115***		0.113***		0.185***		0.054***		0.152***		0.144***
		(0.013)		(0.015)		(0.015)		(0.008)		(0.010)		(0.026)
Constant	-0.024***	-0.011*	-0.027***	-0.015***	-0.020***	0.001	-0.021***	-0.015***	-0.041***	-0.026***	-0.017**	-0.001
	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.004)	(0.003)	(0.007)	(0.005)	(0.006)	(0.004)
Observations	17,164	17,164	17,164	17,164	17,164	17,164	17,164	17,164	17,164	17,164	8,892	8,892
Adj R2	0.0411	0.142	0.0305	0.137	0.0418	0.190	0.00817	0.0898	0.0552	0.191	0.0987	0.239
Industry-Year-Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation results of Equation 1, when the presence of AI-supported business functions is used as the dependent variable. 'Log Employees' is the logarithm of the number of employees hired by a firm. 'Log Age' is the logarithm of the age of a firm. 'Fast Broadband' is a dummy variable taking value 1 if a firm has a broadband internat connection with speed equal or greater than 100Mbit/s, and 0 otherwise. 'Non-AI Digital Technologies' is the count of digital technologies adopted by a firm and ranges from 0 to 4. 'Other AI-supported Business Functions' is the count of other AI-supported business functions employed by a firm, and ranges from from 0 to 5. Industry-Year-Region FE are jointly defined for industry, region and year. Industries correspond to 1-digit NACE codes, and regions to administrative regions of metropolitan France. All the specifications are estimated using survey weights. Standard errors are clustered at the 2-digit industry level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

EF6 – How the use of AI for different purposes is linked with firm characteristics?

In this and the following section, we present the estimation results of Equation 1, leveraging the use of AI in specific business functions (AI-supported business functions) as dependent variable. The variable Other $\text{AI}_{i,t}$ represents the number of other AI-supported business functions adopted by a firm, excluding the one specified as the dependent variable.

The results, presented in Table A.1, indicate that larger firms are more likely to use AI across all business functions considered, as reflected by the positive and significant coefficients for firm size when other AI-supported business functions are not included as controls. However, when accounting for the broader AI adoption within firms, firm size remains strongly significant only for AI-supported business functions related to digital security, production processes, and logistics, while its significance weakens for commercial activities.

For digital security, this may be attributed to larger firms being more frequently targeted by cyberattacks (Florackis et al., 2022; Jiang et al., 2024). Conversely, results suggest that AI applications related to production processes and logistics require larger-scale investments and integration with physical processes, making them more relevant for firms more capable of sustaining higher fixed costs. This is not true or less relevant for business functions related to intangible processes, that can be supported by cloud technologies, software purchases with lower expenses or acquisitions through open software.

The relationship between AI-supported business functions and firm age does not exhibit a clear pattern in most cases. However, the results highlight a negative and significant relationship for AI use in organisational processes and digital security, indicating that younger firms may have an advantage in adopting AI for these functions, potentially due to new managerial capabilities and more agile decision-making structures. Conversely, AI use in logistics shows a positive and significant relationship with firm age, suggesting that older firms may be more likely to implement AI solutions in logistics, potentially driven by autonomous movement technologies (see Table 7).

EF7 – How the use of AI for different purposes is linked with digital intensity?

The use of AI across business functions is also linked to firms' internal digital infrastructure. The number of non-AI digital technologies is consistently and positively associated with AI adoption when other AI-supported business functions are not included as controls. However, once controlling for the broader AI adoption within firms, this relationship remains highly significant only for business functions related to intangible processes – commercial activities and organisational processes – highlighting the importance of an internal IT architecture in deploying AI across these functions. This suggests that firms with strong digital capabilities are better positioned to integrate AI into business areas that rely on data and information processing. Conversely, for production processes and logistics, the presence of non-AI digital technologies does not show a significant relationship with AI adoption, suggesting that these functions may rely more on AI integration with physical assets rather than pre-existing digital infrastructure.

This aligns with the idea that AI in logistics and production requires significant upfront investments in hardware and automation, whereas AI applications in more intangible-intensive functions can be supported by software solutions that leverage existing IT infrastructure with lower costs.

For digital security, AI adoption is significantly linked to the number of non-AI digital technologies, reinforcing the idea that digitally advanced firms are more likely to implement AI-powered cybersecurity solutions.

Finally, consistent with findings in Table 7, the number of other AI-supported business functions strongly predicts AI adoption, highlighting already relevant interdependencies among AI technologies, which will be further discussed below. Conversely, the presence of fast broadband does not show a significant relationship with AI adoption in most cases, suggesting that while digital connectivity is essential, it is not the primary determinant of AI across all business functions.

4.3 Interdependencies between AI technologies and their applicability to business functions

In this section, we discuss the findings underlying **EF8** and **EF9** by measuring the intensity of linkages among AI technologies and between these technologies and AI-related business functions.

Results discussed in previous sections shows that a significant proportion of French AI users (approximately 44%, as reported in Table 5) employ multiple AI technologies and that the likelihood of adopting AI technologies and related business functions increases with the number of AI technologies already adopted (see Tables 7 and A.1). To investigate how these technologies are combined, we estimate the probabilities of using a specific AI technology conditional on the use of another AI technology or the application of AI systems in performing a specific business function. Through this approach, we isolate both direct and indirect links, which reveal how AI technologies are combined and how they support various business functions.

Conditional probabilities $P_{i|j}$ are defined as follows:

$$P_{i|j} = n_{i,j}/n_j \tag{2}$$

Where i refers to the use of an AI technology, j either to another AI Technology or an AI-supported business function, $n_{i,j}$ is the weighted number of co-occurrences of i and j at the firm level, and n_j the weigthed number of firms adopting AI technology or business function j. Conditional probabilities can be visualised in an asymmetric matrix, such that:

$$P_{i|j} = n_{i,j}/n_j \quad \neq \quad P_{j|i} = n_{i,j}/n_i$$

Where rows (i) and columns (j) have different meanings. A row i corresponds to an AI technology that supports the remaining AI technologies or the AI-related business functions listed in the columns of the matrix. A column j refers to an AI technology or a related business function that is supported by the AI technologies reported in the rows of the matrix.

Conditional probabilities capture both direct and indirect firm-level linkages between AI technologies. For instance, if technology A supports technology B, which is frequently combined with technology C, then technologies A and C are indirectly linked. These probabilities also account for asymmetries in synergies across technologies, an important consideration given the different adoption rates of AI technologies (Figure 1), which affect the denominator of the conditional probability as defined in 2.

EF8 – How are AI technologies combined?

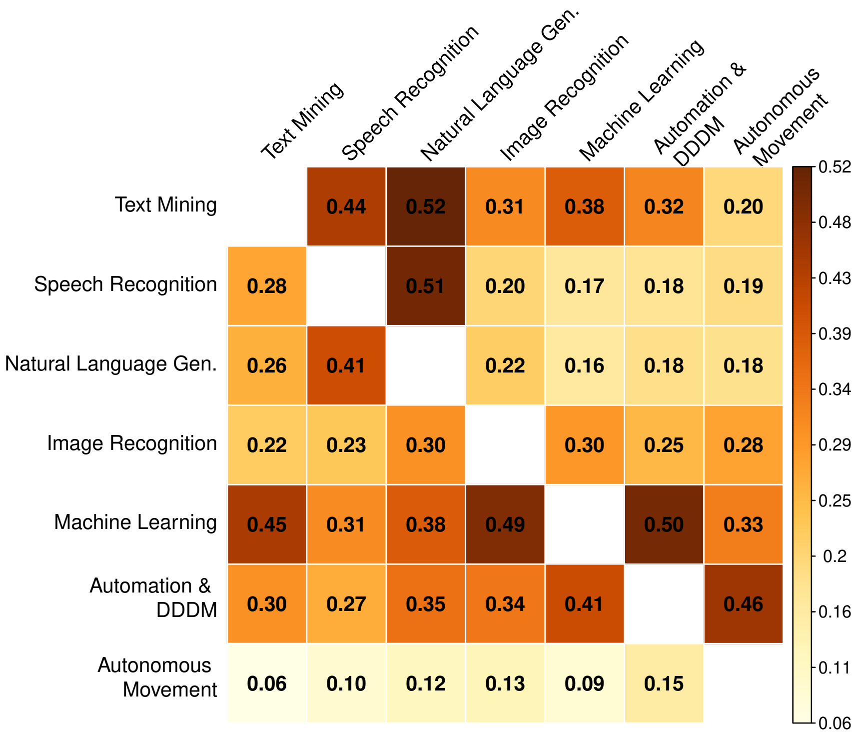
Figure 6 presents the conditional probabilities where both i and j refer to AI technologies, revealing four key patterns:

- **Foundational AI technologies**: ML for data analysis and automation & DDDM emerge as foundational, exhibiting the highest probabilities of supporting other AI technologies. However, they are not complemented by other AI technologies but themselves and – to a lesser extent – image recognition. This implies the critical role of AI-driven data analytics and automation for deploying other AI technologies.

- **Complex AI Technologies**: speech recognition and NLG are more often supported by other technologies. This highlights the complexity of applications, such as Large Language Models, that rely on these as core components. However, they do not support other technologies, with the exception of the clustering observed among themselves and text mining, which suggest the presence of highly complementary functionalities in terms of natural language processing.

- **Intermediate AI Technologies**: text mining and image recognition occupy an intermediate position,

Figure 6: Technological interdependencies between AI technologies.



Notes: Probability of using a technology conditional on using another AI technology. Conditional probabilites are computed using sampling weights.

both supporting and being supported by other technologies. This underscores their importance in data collection and visual pattern recognition but also indicates their reliance on other technologies for effective performance.

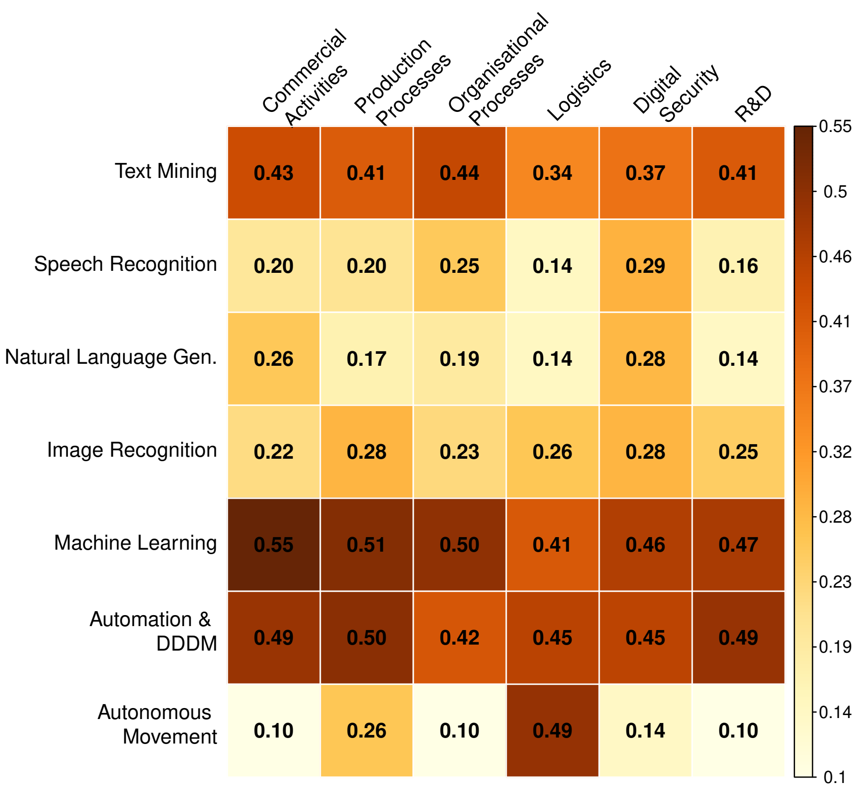
- **Niche AI Technologies**: AI technologies related to autonomous movement represents a niche. While they benefit from the support of automation, machine learning, and image recognition, they do not significantly support other AI technologies.

These findings suggest that AI technologies are not adopted randomly but form part of a coherent technological strategy aimed at building coherent AI systems. Firms often deploy them in bundles, leveraging their synergies. However, the substantial heterogeneity in conditional probabilities highlights that different AI technologies exhibit varying degrees of combinatorial potential, with AI technologies not always supporting other technologies while simultaneously being supported by them. The asymmetries in these relationships emphasise the need for firms and managers to consider the complementary nature of AI technologies when making adoption decisions.

Moreover, the observed interdependencies suggest a hierarchical structure in AI adoption, with machine learning for data analysis and automation & DDDM-related AI forming the foundational layer of AI systems, while more complex technologies, such as speech recognition and NLG, or niche ones (autonomous movement) appear at the upper tiers of this hierarchy.

EF9 – Which AI technologies support which business functions?

Figure 7: Applicability of AI technologies.



Notes: Probability of using AI in support of a business function, conditional on using a specific AI technology. Conditional probabilites are computed using sampling weights.

We now examine the linkages between AI technologies and business functions. Using Equation 2, we estimate conditional probabilities where i refers to an AI technology, and j represents a business function supported by AI systems. Figure 7 displays these conditional probabilities, revealing a heterogeneous mapping between AI technologies and business functions:

- **Broad Applicability**: The support of text mining, ML for data analysis and automation & DDDM is particularly widespread, suggesting that the broad combinatorial potential found in Figure 6 for AI technologies also extends to business functions. Indeed, text mining and ML for data analysis play a critical role in enhancing data collection and analytics, which are at the basis of the training and use of AI systems. The significance of automation and DDDM technologies highlights that applications of AI systems are aimed at extensively supporting production processes and decision making. Although to a lesser extent, image recognition technologies also contribute across all considered business functions, indicating a more limited but still rather general-purpose nature.

- **Business-Function-Specific Technologies**: Certain AI technologies exhibit stronger ties to specific functions. Digital security is widely supported by multiple AI technologies, reflecting the need for diverse functionalities to counter cyberattacks and unauthorised access. NLG is particularly relevant for commercial activities, likely supporting targeted advertising and recommendation systems. Autonomous movement technologies are more often coupled with business functions related to logistics, underpinning innovations in delivery systems and warehouse management. Organisational processes are supported more frequently by speech recognition technologies, which support tasks like drafting and human-machine communication.

These findings suggest that AI technologies are extensively used to enhance business functions, reflecting their combinatorial potential. However, the heterogeneous and often asymmetric relationships between technologies and business functions emphasise the need for tailored adoption strategies to raise their benefits within firms' digital ecosystems.

Overall, the findings suggest that while some AI technologies have broad applicability across various business functions, others are more specialised and tailored to specific areas within business operations. In particular, results highlight the importance of AI systems allowing automation, data collection and analysis, while at the same time also understanding the specific capabilities and applications of different AI technologies when integrating them into business processes.

5 Concluding remarks

This paper provides novel empirical insights on AI use, exploring the diffusion of AI technologies across firms, the characteristics of AI users and how AI systems are implemented and used by firms. Using novel firm-level data from the 2021 and 2023 waves of the French ICT surveys, our findings highlight how firms' use of AI is highly heterogeneous, supported by several AI technologies, with linkages among AI technologies and between these and AI-driven business functions. These findings expand the knowledge of how AI systems are deployed within firms. They may inform managers in their strategic decisions, particularly with respect to the choices of how to implement AI in different business functions, e.g., considering the scope of applicability of text mining, machine learning, and automation technologies for several business functions.

Technology choice decisions related to AI systems are however complex and context-dependent, exhibiting complementarities and specificities. These may be not only related to firm business functions, but also to their organisational structure and human capital. Managerial, technological and organisational capabilities may play an important role in this context, and further research will aim at exploring those further. The findings presented in this study appear also relevant to better understand the implications of AI use by firms. Future analysis can further focus on how different patterns of AI use may be related to firm-level outcomes, such as innovation and firm performance, as more recent data on those become available.

The temporal span of our study, limited to 2020 and 2022, also presents a notable caveat: the absence of reliable evidence on the adoption and impact of generative AI. As generative AI systems rapidly gain relevance across industries, their transformative potential certainly introduces new dynamics in AI adoption that remains unexplored in our current analysis. Future research will be necessary to bridge this gap and to evaluate how the integration of generative AI affects the broader landscape of firm-level AI use.

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A Other Tables

Table A.1: AI intensity and firm's characteristics

AI Intensity and Firm's Characteristics

	Number of AI Technologies	Number of AI Business Functions
	Model 1	Model 2
Log Employees	0.009***	0.017***
	(0.003)	(0.005)
Log Age	-0.003**	-0.002
	(0.002)	(0.002)
Fast Broadband	0.003	0.002
	(0.002)	(0.004)
Non-AI Digital Technologies	0.015***	0.002
	(0.003)	(0.002)
Number of AI Business Functions	0.611***	
	(0.034)	
Number of AI Technologies		1.068***
		(0.059)
Observations	17,164	17,164
Industry-Year-Region FE	Yes	Yes
Adjusted R^2	0.688	0.685

Notes: Estimation results of Equations A.1 (Model 1) and A.2 (Model 2). 'Log Employees' is the logarithm of the number of employees hired by a firm. 'Log Age' is the logarithm of the age of a firm. 'Fast Broadband' is a dummy variable taking value 1 if a firm has a broadband internat connection with speed equal or greater than 100Mbit/s, and 0 otherwise. 'Non-AI Digital Technologies' is the count of digital technologies adopted by a firm and ranges from 0 to 4. 'Number of AI Business Functions' is the count of other AI-supported business functions employes by a firm, and ranges from from 0 to 6. 'Number of AI Technologies' is the count of other AI technologies adopted by a firm, and ranges from from 0 to 6. Industry-Year-Region FE are jointly defined for industry, region and year. Industries correspond to 1-digit NACE codes, and regions to administrative regions of metropolitan France. All the specifications are estimated using survey weights. Standard errors are clustered at the 2-digit industry level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To investigate the factors driving the number of AI technologies adopted and the business functions supported, we estimate the following equations:

$$\text{Number AI Tech.}_{i,t} = \alpha + \beta_1 \text{Number AI Bus. Func.}_{i,t} + \beta_2 \text{Log Employees}_{i,t} + \beta_3 \text{Controls}_{i,t} + FE_{s,r,t} \quad (A.1)$$

$$\text{Number AI Bus. Func.}_{i,t} = \alpha + \beta_1 \text{Number AI Tech.}_{i,t} + \beta_2 \text{Log Employees}_{i,t} + \beta_3 \text{Controls}_{i,t} + FE_{s,r,t} \quad (A.2)$$

Where the dependent variables are either the number of AI technologies adopted (Number AI Tech.$_{i,t}$) or the number of business functions performed with AI systems (Number AI Bus. Func.$_{i,t}$). Log Employees$_{i,t}$ is the measure of size, while Controls$_{i,t}$ encompass age , the count of other non-AI digital technologies (1 to 4) and the presence of a fast broadband connection. The term $\textbf{FE}_{s,r,t}$ represents joint fixed effects for 1-digit NACE industry (s), geographic region (r), and year (t).

The estimation results, presented in Table A.2, indicate a positive and significant relationship between the number of AI technologies adopted and the number of business functions performed using AI. This suggests that a single AI technology may not be sufficient to run all AI-related business functions. Furthermore, firm size, as measured by the number of employees, is significantly and positively associated with both the number of AI technologies and the number of business functions supported by AI, suggesting that larger firms are more likely to adopt multiple AI technologies and use them for various business functions.