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REGULAR ARTICLE

Decoding AI: an early look at how French firms use AI

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Abstract

This study investigates *how* French firms use Artificial intelligence (AI), drawing on a uniquely detailed and nationally representative dataset that reports both the specific AI technologies implemented and the business functions in which they are deployed in 2020 and 2022. Evidence on sectoral use rates, the interdependencies between AI technologies, and their applicability across business functions shows that three technologies lie at the core of the AI paradigm and exhibit a more general-purpose nature: Machine Learning Data Analysis, Text Mining, and Automation & Decision Support. This pattern supports the view that AI is not a monolithic technology but a system of heterogeneous technologies with varying degrees of generality. Regression analyses further demonstrate that firms using different AI technologies are far from homogeneous. These results have two important implications. First, diffusion strategies should recognize the distinct characteristics of individual AI technologies. Second, AI use should be treated as part of a broader strategy involving multiple technologies that are interdependent and have different degrees of applicability across business functions.

Keywords Technology diffusion · Artificial Intelligence · Business function · ICT

JEL Classification 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 (Agrawal et al., 2018; Besiroglu et al., 2024; Cockburn et al., 2018; Grashof & Kopka, 2023), organizational change (Agrawal et al., 2022; Dell'Acqua et al., 2023), and productivity (Brynjolfsson et al., 2025; Calvino & Fontanelli, 2024; Noy & Zhang, 2023) have already been affected for specific groups of firms and workers, or are expected to be in the near future.[1] On the other hand, many scholars suggest that AI has the potential to become the next general-purpose technology (GPT, Furman & Seamans 2019; Goldfarb et al. 2023; Trajtenberg 2019) 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 & Trajtenberg, 1995), AI's full impact will likely take time to materialise due to implementation lags and the presence of complementarities (Brynjolfsson et al., 2018, 2021), particularly with STEM and advanced ICT human capital (Alekseeva et al., 2021; Babina et al., 2023; Fontanelli et al., 2025).

Despite AI's transformative potential, empirical evidence on firm-level AI use remains limited in certain respects. Aside from insights derived from measures of sectoral intensity or occupational exposure to AI (see, for instance, Calvino et al., 2024; Eloundou et al., 2024; Engberg et al., 2024; Felten et al., 2021, Prytkova et al., 2024) and the general characteristics of AI users (Acemoglu et al., 2022a; Calvino & Fontanelli, 2023; McElheran et al., 2024), the literature offers limited evidence on *how* firms incorporate AI into their production processes and organizational routines. Yet, understanding this is crucial for assessing the general-purpose potential of these technologies and their role in affecting economic activity.

To address this gap, we draw on novel, nationally representative survey data on firm-level technology use in 2020 and 2022 to provide a detailed mapping of how French firms deploy AI. The dataset allows us to identify both the specific AI technologies used (Machine Learning Data Analysis, Text Mining, Automation & Decision Support, Natural Language Generation, Image Recognition, Speech Recognition, and Autonomous Movement) and the business functions in which they are applied (Organizational Processes, Production Processes, Commercial Activities, Digital Security, Logistics, and R&D). This dual-level information enables us to uncover systematic patterns connecting technologies to functions. Our central hypothesis is that, similarly to non-AI technologies (see e.g. Dosi et al., 2017; Dosi, 2023; Lybbert & Zolas, 2014), different AI technologies serve distinct purposes and therefore exhibit heterogeneous interdependencies between them and applicability across business functions, shaping the general-purpose potential of AI.

The evidence discussed in the paper can be grouped into three sets of results, each highlighting the substantial heterogeneity that characterizes AI technologies.

First, we quantify the diffusion of AI technologies and the business functions supported by them across the French economy and its sectors by estimating their rates of

[1] See also Calvino et al. (2025) for a recent review on the effects of generative AI on productivity, innovation and entrepreneurship.

use. In the period under analysis, AI use remains limited, with approximately 6% of firms using AI systems. Machine Learning Data Analysis, Text Mining, and Automation & Decision Support are the most widely used technologies, with AI applications most frequently supporting Organizational Processes and R&D. Sectoral patterns reveal that firms in ICT services and professional and scientific activities are more likely to use AI, although use varies by technology. With the exception of Construction, each sector tends to specialize in a bundle of one to three AI technologies, which are key for the main activities performed by firms in that sector, and often include Machine Learning Data Analysis, Text Mining, and Automation & Decision Support. We also present evidence showing that the use of AI within sectors tends to specialize in the business functions that best describe the type of activity conducted.

Second, to understand how AI technologies support business functions, we analyse the interdependencies between AI technologies and their patterns of applicability across business functions, using both conditional probabilities and probit models. On the one hand, AI technologies can be classified into four categories based on their link with other AI technologies: foundational (Machine Learning Data Analysis, Text Mining, and Automation & Decision Support), supported (Natural Language Generation), intermediate (Speech and Image Recognition), and specialized (Autonomous Movement). This classification suggests the existence of interdependencies in the use of AI technologies, with Machine Learning Data Analysis, Text Mining and Automation & Decision Support at the roots of AI systems. On the other hand, AI technologies vary in their applicability across business functions. Some (Machine Learning Data Analysis, Text Mining, and Automation & Decision Support) have broad application, while others are more function-specific. Natural Language Generation primarily supports Commercial Activities, Autonomous Movement is significantly related to Production Processes and Logistics, and Image Recognition is deployed across Production Processes and R&D.

Third, to understand how the AI technologies underpinning different business functions diffuse across firms, we examine the characteristics of firms using each AI technology through a set of probit regressions. Our analysis reveals substantial heterogeneity in the characteristics of firms using different AI technologies. The relationship between AI use and firm size is strong for technologies that process numerical, visual, or structured data (Machine Learning Data Analysis, Automation & Decision Support, Image Recognition, and Autonomous Movement) but weak or absent for natural-language-based technologies (Text Mining, Speech Recognition, and Natural Language Generation). Firm age is generally unrelated to AI use, with the notable exception of Machine Learning Data Analysis, which is disproportionately used by younger firms, consistent with the early diffusion of machine-learning-intensive start-ups (Calvino & Fontanelli, 2024; McElheran et al., 2024). AI use is also strongly associated with digital readiness: Cloud Computing and Enterprise Systems significantly predict the use of most AI technologies, reflecting the need for robust data infrastructures, whereas E-commerce is largely irrelevant except for Natural Language Generation, which is closely tied to the use of AI for commercial applications.

Our findings contribute to the emerging evidence of AI as a GPT (see e.g. Bresnahan, 2024; Calvino et al., 2025). Although AI use is still at an early stage and overall diffusion remains limited, the evidence shows that AI is not a monolithic technology but a system of heterogeneous components with distinct levels of generality. Machine Learning Data Analysis, Text Mining, and Automation & Decision Support emerge as the core of the AI paradigm: they lie at the basis of the use of other AI technologies and display broad applicability across business functions. This evidence highlights the importance of AI systems allowing automation, data collection and analysis, and that AI is based on a layered architecture, where a few core technologies shape the trajectory and pace of diffusion. The results therefore support the notion that AI is evolving as a GPT, but with important internal differentiation. General-purpose characteristics arise not from all AI technologies uniformly, but from a subset of them that underpins the broader ecosystem (see also Calvino et al., 2023; Goldfarb et al., 2023). However, despite the heterogeneity across AI technologies, their use remains systematically associated with firm size, age, and digital readiness, indicating that the current generation of AI still requires organizational, technical, and infrastructural capabilities that many firms may not yet possess.

Furthermore, our findings provide the basis for a set of implications that could be useful to both managers and policymakers. First, the findings imply that diffusion strategies should move beyond one-size-fits-all interventions and consider the specific characteristics and requirements associated with individual AI technologies. Second, the evidence suggests that AI use should not be viewed as a single, discrete choice but as a decision involving multiple technologies that are interdependent and have different degrees of applicability across functions.

The remainder of the paper is structured as follows. In Sect. 2, we introduce a conceptual framework that motivates and guides our empirical analysis. In Sect. 3, we review recent literature on AI use by firms. Section 4 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 Sect. 5, 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, Sect. 6 provides some concluding remarks, discussing the managerial and policy implications of our analysis and outlining potential directions for future research.

2 Conceptual framework

GPTs are defined by three core characteristics: their pervasiveness across sectors, their continuous scope for technological improvement, and their ability to generate complementary innovations (Bresnahan & Trajtenberg, 1995). Examples, such as the steam engine, electricity, and ICTs, have profoundly reshaped production processes and organizational structures of firms while considerably affecting the economy more broadly. However, the transformative effects of GPTs do not materialize immediately. Instead, their diffusion unfolds gradually, constrained by implementation lags, learning costs, and the need for co-invention and adaptation of complementary inputs (Bresnahan & Greenstein, 1996).

Existing theoretical work on AI as a GPT has primarily focused on demonstrating that AI exhibits the canonical properties of general-purpose technologies: it can be applied across diverse domains, continues to improve rapidly, and generates complementary innovations in application sectors (Bresnahan, 2024; Calvino et al., 2025; Damioli et al., 2025; Goldfarb et al., 2023; Trajtenberg, 2019). However, this literature has largely treated AI as a monolithic concept, often abstracting from the heterogeneity that exists among different AI applications (Vannuccini & Prytkova, 2024). While this simplification is useful for establishing AI's GPT features, it hides important variation in the extent to which different AI technologies diffuse, the functions they serve, and the complementarities involved in their use. Understanding this heterogeneity is therefore crucial for assessing both the general-purpose potential of AI and the mechanisms driving its diffusion across firms.

This work conceptualizes AI not as a single technology, but as a system composed of heterogeneous technologies with varying degrees of generality, as measured by existing interdependencies among them and by their degree of applicability to different business functions. This perspective draws on research in modularity theory, which emphasizes that complex technological systems can be decomposed into distinct components that interact through standardized interfaces (Baldwin & Clark, 2000; Langlois, 2002). In modular systems, some components serve as platforms or foundations that enable the functionality of other, more specialized components (Gawer & Cusumano, 2014). This architectural logic determines the degree of generality of individual components within a technological system. It creates relationships of interdependence among technologies, where other components leverage core foundational elements, and simultaneously shapes the degree of their applicability to business functions. In the context of complex technological systems such as ones spawning from GPTs, this implies that not all components of a general-purpose system are equally general: some may act as foundational technologies that enable a range of downstream applications.

This perspective suggests that the AI technological system consists of applications operating at different levels of generality. On the one hand, AI technologies vary in the types of tasks they can automate or augment (Gathmann et al., 2024). Indeed, different AI technologies are optimized for processing distinct types of data (e.g., numerical, textual, or visual, see LeCun et al., 2015), creating systematic variation in their applicability across business functions based on the characteristic data types those functions are able to analyze and generate (Brynjolfsson & Mitchell, 2017). This data-task alignment creates a natural match between specific AI technologies and business functions, with business functions leveraging characteristic data types—and hence AI technologies—based on their core activities.

On the other hand, we hypothesize that a subset of foundational technologies can provide core capabilities, more frequently support other AI applications, and exhibit more frequent applicability across business functions. These foundational tools are a prerequisite for leveraging other AI technologies and exhibit broad applicability across business functions because they address fundamental computational tasks, such as extracting patterns from data and processing textual information—which are pervasive—, automating tasks or rule-based decisions. The use of such foundational technologies provides the necessary inputs (processed data, analytical infrastructure, and core algorithmic capabilities) that are at the basis of implementation of AI across business functions.

This framework yields clear, testable hypotheses on the diffusion and use of AI technologies within firms. First, if foundational AI technologies provide leverage for specialized ones, they should be more broadly used. Second, this technological structure implies asymmetric interdependencies among AI technologies and differences in their degree of applicability across business functions of firms. As a consequence, foundational AI technologies will exhibit higher rates of use, stronger support to other AI technologies, and broader applicability across business functions.

In the empirical analysis that follows, we test these hypotheses using detailed survey data on AI technology use and business function deployment among French firms, while providing a broader outlook at how French firms use AI.

3 Literature review

This section summarizes the literature related to our study, dividing it by topic. Namely, we discuss evidence on the diffusion of AI, the relationship between AI and firm characteristics (size, age, and productivity) and one between AI and complementary assets (e.g. digital capabilities, workforce).

Diffusion of AI—Evidence from several countries shows that the use of AI technologies is still limited and highest in the ICT and professional services sectors—in the US (McElheran et al., 2024; Zolas et al., 2020), Germany (Rammer et al., 2022), Korea (Cho et al., 2022), the UK (Calvino et al., 2022), and several OECD countries (Calvino & 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., 2022b; Alekseeva et al., 2021; Babina et al., 2024; Borgonovi et al., 2023; Squicciarini & Nachtigall, 2021) 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. Dahlke et al. (2024) investigates the mechanism of AI diffusion among firms and finds that it is hindered by the presence of localized clusters of AI expertise.

While previous studies often treat AI as a single, aggregate technology, we distinguish the specific AI technologies used by firms. This allows us to offer a more granular view of the early-stage diffusion of AI, complementing and extending prior work by uncovering heterogeneity in the applicability of different AI technologies and identifying which ones form the core of firms' AI systems.

AI and firm characteristics—Existing evidence highlights a positive and robust relation between AI use and firm size (Calvino & Fontanelli, 2023; McElheran et al., 2024; 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-

[2] See also Calvino et al. (2022) for further analysis leveraging simultaneously the three sources of data mentioned above, uncovering relevant sectoral heterogeneity along different dimensions of AI intensity.

ante larger firms 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 use and generate scale advantages (Brynjolfsson & McAfee, 2014; Brynjolfsson et al., 2021; Fontanelli et al., 2025). On the other hand, AI-related patents (Alderucci et al., 2021; Damioli et al., 2023) and product innovations (Babina et al., 2024) have a positive effect on firms' size.

Notwithstanding the positive AI-size relationship and the role of high entry costs for AI startups (for instance, in terms of proprietary data, see Bessen et al., 2022), some analyses suggest that a wave of high-tech young firms has been driving—at least partly—the development of AI technologies (Acemoglu et al., 2022a; Calvino & Fontanelli, 2023; McElheran et al., 2024). This evidence suggests a link between entrepreneurial activities and AI (Obschonka & Audretsch, 2020), linked to the presence of new managerial capabilities.

Evidence on the firm-level relationship between AI use and firm-level productivity remains mixed and mostly focus on predictive AI.[3] Using ICT survey data, Czarnitzki et al. (2023) find a positive impact of AI use on the productivity of German firms. By contrast, Acemoglu et al. (2022a) show that AI use is not significantly associated with labour productivity among U.S. firms. Similarly, Calvino and Fontanelli (2023) report that the productivity advantages of AI users tend to disappear or substantially diminish across several OECD countries once digital capabilities are accounted for. A clearer positive association emerges when focusing on AI-related innovations, such as patents (Alderucci et al., 2021; da Silva Marioni et al., 2024; Damioli et al., 2021; Yang, 2022). In contrast, studies using measures of AI-related skills generally do not identify robust productivity effects (Alekseeva et al., 2020; Babina et al., 2024).

Overall, this mixed evidence contrasts with the well-established positive effects of ICT and digitalization on firm-level productivity (Brynjolfsson & Hitt, 2003). At the same time, it is consistent with the presence of a lag between the early adoption of GPTs and the realization of productivity gains, that may account for the weak or even negative productivity effects observed in the initial stages of diffusion (McElheran et al., 2025). This lag reflects the need for firms to accumulate complementary assets (Brynjolfsson et al., 2021) and to undertake substantial organizational and production restructuring (Agrawal et al., 2022) to effectively implement AI. Indeed, evidence shows that firms possessing internal AI capabilities experience productivity improvements even at early stages of AI diffusion (Calvino & Fontanelli, 2024), whereas firms lacking such capabilities display more volatile productivity growth, with ICT workers playing a stabilizing role (Fontanelli et al., 2025).

Positive effects of AI on size and productivity are often mediated by innovation activities. In this respect, a growing literature investigates the mechanisms through which AI shapes innovation processes (Agrawal et al., 2018; Chugunova et al., 2026;

[3] Recent studies report a positive impact of generative AI on the productivity of certain categories of workers (see also Brynjolfsson et al., 2025; Eloundou et al., 2024; Kreitmeir & Raschky, 2023; Noy & Zhang, 2023; Peng et al., 2023). However, the direction of this effect depend on whether tasks fall within or beyond the capabilities of AI systems (Dell'Acqua et al., 2023). It remains an open question to what extent productivity gains at the worker level translate into overall firm-level productivity improvements (Dell'Acqua et al., 2023).

Haefner et al., 2021; Wang et al., 2023) and suggests that AI technologies may function as an "invention of a method of invention" (IMI) (Griliches, 1957), accelerating the discovery of new products and processes while reducing associated costs (Biggi et al., 2025; Cockburn et al., 2018; Furman & Teodoridis, 2020; Rock, 2019), with relevant implications for aggregate growth (Calvino et al., 2025). Evidence on deep learning shows that both the mean and variance of citations of exposed scientific papers are positively associated with the use of AI (Bianchini et al., 2022). Firm-level studies further indicate that AI use is positively related to innovation activity (Arenas Díaz et al., 2025). Finally, AI-augmented R&D has the potential to accelerate technological change and economic growth (Besiroglu et al., 2024; Bontadini et al., 2025), similarly to earlier GPT (Crafts, 2021). Evidence from Guarascio et al. (2025) and Guarascio and Reljic (2025) further suggests that positive employment effects from AI exposure mainly arise in countries with strong innovation systems.

We connect to the literature on the characteristics of AI users by empirically examining how firm-level characteristics relate to the use of different AI technologies. Unlike previous studies that often focus on general AI use, we explore different AI technologies, providing evidence that users are not all alike.

AI and complementary assets—A central insight from GPT theory is the role of complementarities in determining both the pace and pattern of diffusion (Milgrom & Roberts, 1990, 1995). However, the literature on the relevance of AI complementary assets is, to our knowledge, still limited (see Brynjolfsson et al., 2021). The absence of complementary assets is often cited as a key reason why AI use has not yet produced consistent productivity gains (Brynjolfsson et al., 2018), in contrast with other ICT technologies (e.g. Brynjolfsson and Hitt, 2003, DeStefano et al., 2023; Jin & McElheran, 2025). The existence of firm-level complementarities is particularly supported by evidence on digital capabilities, which are critical not only for AI-related innovations (Igna & Venturini, 2023; Santarelli et al., 2022), but also for the effective use of AI within firms (Calvino & Fontanelli, 2023; DeStefano et al., 2023; Lo Turco & Sterlacchini, 2024; McElheran et al., 2024).

Conversely, the empirical literature on the relationship between AI and workforce characteristics has expanded rapidly in recent years. Yet evidence on aggregate employment effects remains inconclusive, with studies across countries and empirical contexts yielding contrasting results (e.g. Albanesi et al., 2024; Acemoglu et al., 2022b; Bonfiglioli et al., 2024; Damioli et al., 2024).[4] These heterogeneous effects may depend on the predominant role of AI within firms (Agrawal et al., 2019; Jaccoud, 2025; Lábaj et al., 2025; Staccioli & Virgillito, 2025). In this respect, a growing body of research on AI exposure indicates that white-collar and knowledge-intensive occupations are particularly affected by AI use (e.g. Felten et al., 2021; Montobbio et al., 2024), although it remains largely unclear whether these effects reflect displacement or task reinstatement mechanisms (Gathmann et al., 2024).

What is clear is that complementary ICT and STEM capabilities embedded in the workforce are strongly associated with AI use. Empirical evidence shows that advanced ICT workers are necessary for implementing AI (Fontanelli et al., 2025),

[4] Similarly mixed findings emerge in the empirical literature on automation technologies (see Domini et al., 2021; 2022; Jin & McElheran, 2025).

while the demand for STEM workers is positively correlated with AI use (Alekseeva et al., 2021; Babina et al., 2023; Borgonovi et al., 2023; Draca et al., 2024). Workforce skills thus account for a substantial share of cross-country and cross-sector variation in AI uptake (Brey & van der Marel, 2024).

We link to this literature by examining the interplay between the use of different AI technologies and different ICT technologies. Specifically, by distinguishing between different AI technologies and linking them to business functions, we expand the limited evidence on the interdependencies between AI technologies and on their different degrees of applicability across functions (i.e. the complementarities between AI technologies and between them and business functions). Also, our study provides evidence on how the presence of complementary digital technologies shape the use of AI across functions.

4 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.[5] 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.[6] 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 17,170 firms.

In particular, firms are asked which AI technologies they used in 2020 and 2022, and for which business functions they used AI tools.[7] The AI technologies surveyed include Text Mining, Speech Recognition, Natural Language Generation, Image Recognition, Machine Learning Data Analysis, Automation & Decision Support, 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 "Organizational Processes" used in the analysis includes administration, management, and human resources in 2020, and administration/management and accounting in 2022. The classification of business functions is summarized 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

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

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

[7] 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 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	Focuses on generating human-like text from structured or unstructured data
Image Recognition	Involves identifying objects and people in images
Machine Learning Data Analysis	Uses machine learning algorithms to analyse data
Automation & Decision Support	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

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 optimization 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 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
Organizational 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

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 merge ERP and CRM systems into a unique dummy variable (Enterprise Systems).

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.

5 Empirical evidence

In this section we discuss the key empirical facts about AI use in the French economy which result from our empirical analysis. These are summarized in Table 4 and grouped in three sections. First, we provide descriptive evidence on the diffusion of AI technologies and the business functions they support at the aggregate and sectoral level, respectively in Sects. 5.1 and 5.2 (**EF1** and **EF2**). Second, in Sect. 5.3 we analyse the interlinkages among different AI technologies, providing evidence on the existence of interdependencies between them (**EF3**). Third, Sect. 5.4 explores which AI technologies foster specific business functions (**EF4**). Finally, Sect. 5.5 estimates the relationship between distinct AI technologies and firm characteristics (**EF5**).

Table 3 Summary statistics

	All firms	AI Users	Other Firms
Employees	62.78	305.15	46.50
Age	20.08	19.12	20.14
Fast Broadband	58.23%	71.46%	57.34%
Cloud	26.40%	65.22%	23.79%
Enterprise Systems	53.60%	85.92%	51.43%
E-commerce	14.91%	20.72%	14.52%

Average number of employees, wage, and number of non-AI digital technologies, and share of firms by presence of fast broadband or use of Enterprise Systems technologies, purchase of Cloud services, and participation in E-commerce activities. Averages and shares are computed using sampling weights. The columns 'All firms', 'AI users' and 'Other Firms' report the statistics computed on the full sample of firms, AI users and non-users, respectively

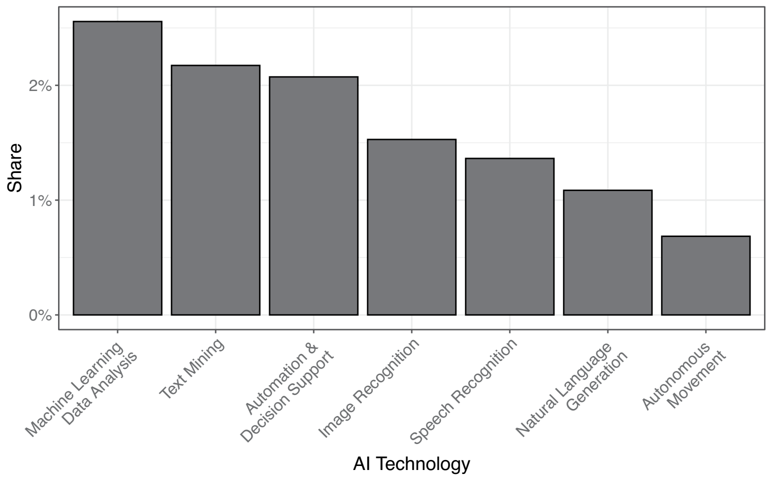
Table 4 Topic and description of key empirical facts about AI use in France

Fact's topic	Fact's description—Brief summary of relevant empirical evidence
EF1—Aggregate patterns of AI diffusion	Machine Learning Data Analysis, Text Mining, Automation & Decision Support-related technologies are the most commonly used AI technologies, particularly in business functions related to Organizational Processes and R&D
EF2—Sectoral patterns of AI diffusion	The use of AI is higher in ICT and Professional & Scientific services, with different sectors specializing in distinct technologies and AI-supported business functions
EF3—Interdependencies between AI technologies	We provide evidence that AI technologies are interdependent, and can be classified as foundational, supported, intermediate, or specialized, based on their linkages
EF4—The applicability of AI technologies	Machine Learning Data Analysis, Text Mining, and Automation & Decision Support broadly support multiple business functions, whereas other AI technologies tend to have more specialized, function-specific applications
EF5—What are the characteristics of AI users?	AI users are larger, younger and have more digital capabilities, but relationships are heterogeneous across AI technologies

5.1 Aggregate patterns of AI diffusion

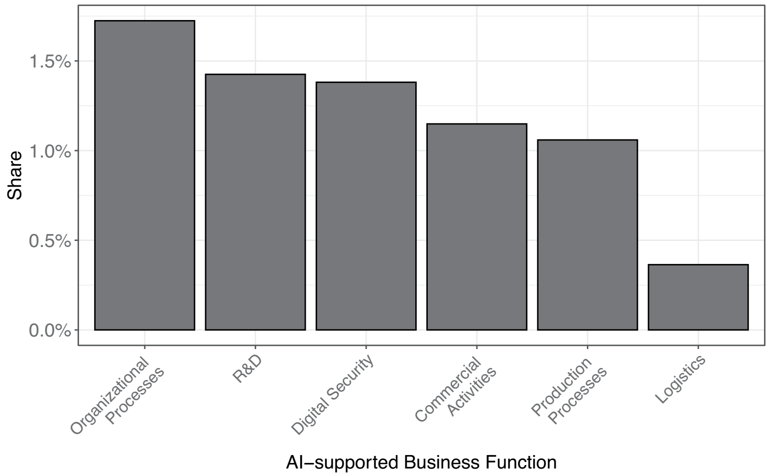
In this section we present aggregate evidence about AI diffusion within firms in France (**EF1**). We analyse the heterogeneity in the use of different AI technologies and in the business functions they support. We then explore sectoral patterns of AI use, discussing the extent to which different sectors leverage different AI technologies and the sector-specific business functions supported by AI.

AI technologies exhibit limited use among French firms in 2020 and 2022, with only approximately 6.2% of firms using at least one of them, consistent with previous evidence (see e.g. Calvino & Fontanelli, 2023, 2024; Calvino et al., 2022; Cho et al., 2022; McElheran et al., 2024; Rammer et al., 2022). When distinguishing the usage rates of different technologies in Fig. 1, we observe substantial heterogeneity. A few technologies (Text Mining, Machine Learning Data Analysis, and Automation & Decision Support) 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), data mining and data-driven applications (Brynjolfsson & McElheran, 2016; Wu et al., 2020). Image Recognition, despite its early breakthrough applications (e.g., the AlexNet neural network), is less commonly used by firms. The use of Natural Language Generation was very limited prior to 2023, reflecting patterns of use 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 exhibits a particularly low usage rate, below 1%, due to the nascent stage of the AI systems based on them.



Notes : Shares are computed using sampling weights.

Fig. 1 Share of firms using specific AI technologies. Shares are computed using sampling weights



Notes: Shares are computed using sampling weights.

Fig. 2 Share of firms using AI systems for specific business functions. Shares are computed using sampling weights

When examining the business function supported by AI system, in Fig. 2, the highest rate is found in Organizational 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 & 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. Agrawal et al., 2018; Bianchini et al., 2022; Cockburn et al., 2018). AI-powered

Digital Security ranks third in terms of use, 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 use AI systems (Calvino & Fontanelli, 2023; McElheran et al., 2024). 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 digitalization 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 usage rate of AI technologies in Autonomous Movement (see Fig. 1).

5.2 Sectoral patterns of AI diffusion

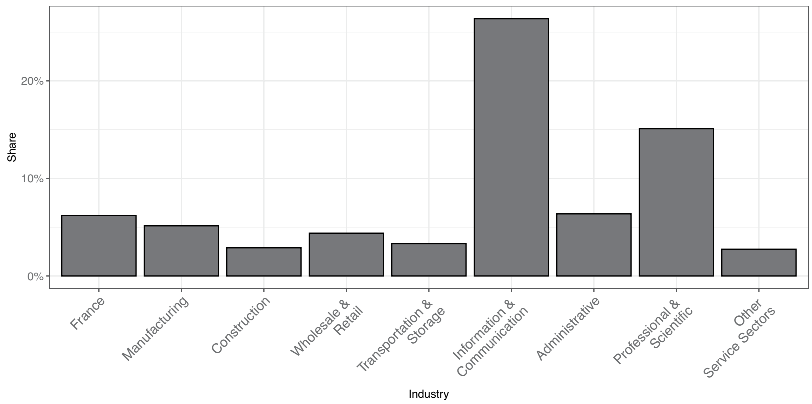
The aggregate patterns of diffusion of AI technologies and the business function they support in firms may depend on the sectoral composition of the French economy. Accordingly, we now report and discuss sectoral rates on AI diffusion (**EF2**).[8]

Figure 3 presents the rates of AI technology use across different sectors. The use of AI technologies varies considerably across sectors. Consistent with previous literature (e.g., Calvino & Fontanelli, 2023), the highest usage 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 use, 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 distinguish the usage rates of individual AI technologies, as reported in Fig. 4. Despite the early stage of diffusion, often reflected in low rates of use, firms within sectors already tend to specialize in relatively narrow bundles of one to three AI technologies. The Manufacturing sector shows higher use of technologies related to Autonomous Movement and Automation & Decision Support. This may be associated with the robotization of production systems and findings that highlight overlaps in the knowledge bases of robotics and AI technologies (Santarelli et al., 2022).

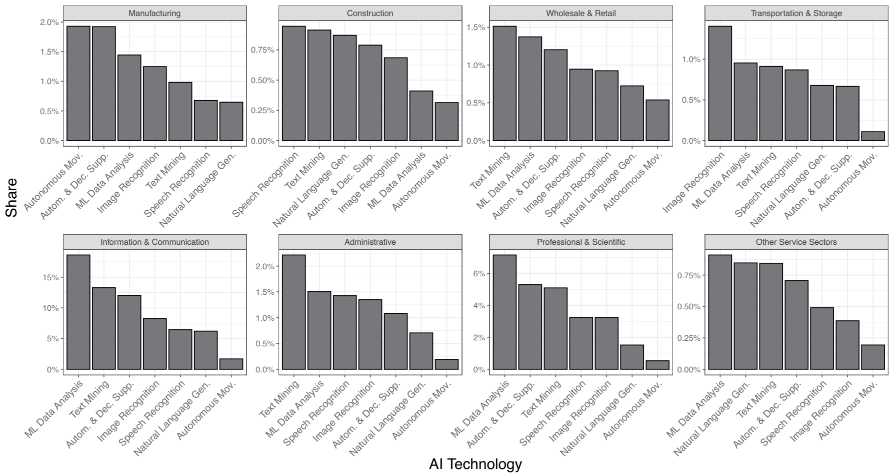
Firms in the Wholesale & Retail sector make comparatively greater use of Text Mining, Machine Learning-based data analysis, and Automation & Decision Sup-

[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.



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

Fig. 3 Sectoral share of firms using AI systems. Shares are computed using sampling weights. Utilities (NACE sectors 35–39) have been excluded to ensure confidentiality



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

Fig. 4 Sectoral share of firms using specific AI technologies. Shares are computed using sampling weights. Utilities (NACE sectors 35–39) have been excluded to ensure confidentiality

port tools. This evidence aligns with the sector's intensive reliance on written language (e.g., product descriptions) and the large volumes of data it generates, which are relevant for tasks such as pricing, inventory management, and storage optimization. Similarly, in the Administrative sector, the use of Text Mining is particularly common, reflecting the importance of processing and analysing written information embedded in documents and records.

The Transportation & Storage sector exhibits a relative specialization in Image Recognition technologies, which are likely essential for key AI-driven applications in operations such as tracking, and monitoring systems.

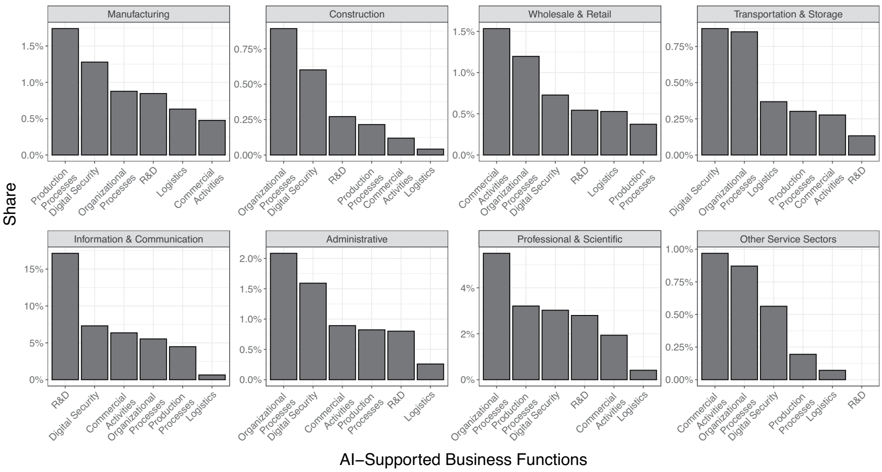
The ICT Services and Professional & Scientific sectors display the highest usage rates of Machine Learning Data Analysis, reflecting the central role of data-driven methods in contemporary AI systems. These sectors also exhibit smaller, yet non-negligible, use of Text Mining and Automation & Decision Support. Conversely, firms in Other Service sectors show very low rates of use—lower even than those observed in manufacturing.

Taken together with the evidence from other parts of the service economy, this suggests that AI diffusion across services is uneven. Traditional service activities, such as accommodation and food services, may have more limited scope for AI applications compared to advanced services, such as Professional & Scientific sectors, where data-intensive processes and knowledge-based tasks make AI adoption more feasible.

Finally, the Construction sector displays 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).

The use of AI technologies across sectors exhibits industry-specific patterns, reflecting the primary activities of each sector. To examine whether similar patterns hold across distinct business functions, Fig. 5 reports the rate of AI usage within these functions. Although use rates remain limited, AI is emerging as a multi-sector technology, with numerous applications across different business functions. 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



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.

Fig. 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 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 used for Organizational Processes, in line with results from Fig. 4 showing that the AI technology with the highest rates in this sector are Machine Learning Data Analysis and Automation & Decision Support.

Overall, AI systems related to Logistics exhibit limited use across sectors, with the highest usage rates observed in the Manufacturing, Wholesale & Retail, and Transportation & Storage sectors.

Although overall usage rates remain limited, AI is emerging as a multi-sectoral technology. Firms within each sector tend to specialize in bundles of one to three AI technologies, with the highest usage observed in business functions closely aligned with the sector's primary activities. This evidence suggests that AI technologies have the potential for cross-sector applications, reflecting their general-purpose nature.

5.3 The interdependence between AI technologies

Aggregate and sectoral results on the use of distinct technologies in ICT services, where frontier AI-based applications are developed, suggest that Machine Learning Data Analysis, Text Mining, and Automation & Decision Support may constitute a core set of foundational technologies that enable and support R&D activities on frontier ICT applications. Furthermore, around 44% of AI users employ multiple AI technologies at once. Building on these insights, in this section we examine the intensity of linkages among AI technologies (**EF3**).

To examine how these technologies are linked, we estimate the conditional probabilities of using a particular AI technology given the use of another AI technology or the deployment of AI systems in a specific business function (also see Santarelli et al., 2022; Teece et al., 1994). This approach allows us to isolate both direct and indirect relationships, revealing technological interdependencies between of AI technologies.

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

$$P_{i|j} = n_{i,j}/n_j, \tag{1}$$

where i refers to the use of a distinct AI technology, j to another AI Technology, $n_{i,j}$ is the weighted number of co-occurrences of i and j at the firm level, and n_j the weigthed number of firms using AI technology j. The conditional probability $P_{i|j}$ is defined as the share of instances in which two AI technologis i and j are used in combination, relative to the total number of instances in which technology j is employed.

Conditional probabilities can be visualised in an asymmetric matrix, where i and j indicate rows and columns respectively, such that:

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

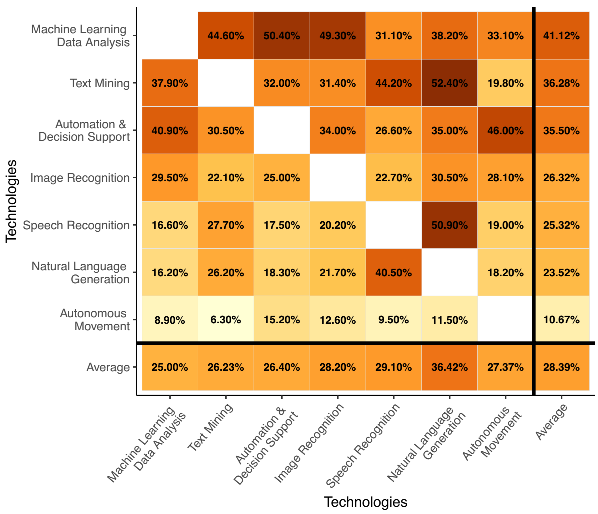
where rows (i) and columns (j) have different meanings:

- A row i corresponds to an AI technology that supports the remaining AI technologies listed in the columns of the matrix;
- A column j refers to an AI technology that is supported by the AI technologies reported in the rows of the matrix.

Differently from standard OLS regression settings, capturing correlational linkages conditional on controls, conditional probabilities estimates both direct and indirect firm-level linkages between AI technologies, and the direction of the link. For instance, if technology A supports technology B, which is frequently combined with technology C, then technologies A and C will likely result to be linked. These probabilities also account for asymmetries in synergies across technologies, an important consideration given the different usage rates of AI technologies (Fig. 1), which affect the denominator of the conditional probability as defined in 1.

Figure 6 presents the conditional probabilities where both i and j refer to AI technologies. The average conditional probability is 28.39%, indicating that an AI technology is combined with another technology roughly one in four times. However, four distinct patterns of heterogeneity emerge when analysing technologies individually:

- **Foundational AI technologies**: Machine Learning Data Analysis, Text Mining, and Automation & Decision Support emerge as foundational, exhibiting the highest probabilities of supporting other AI technologies. The average of their row values is 41.12%, 36.28%, and 35.50%, respectively, all above the overall average of 28.39%. They are also the least likely to be supported by other AI tech-



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

Fig. 6 The interdependencies between AI technologies. Probability of using a technology conditional on using another AI technology. Conditional probabilities are computed using sampling weights nologies, with support rates of 25%, 26.23%, and 26.40%.

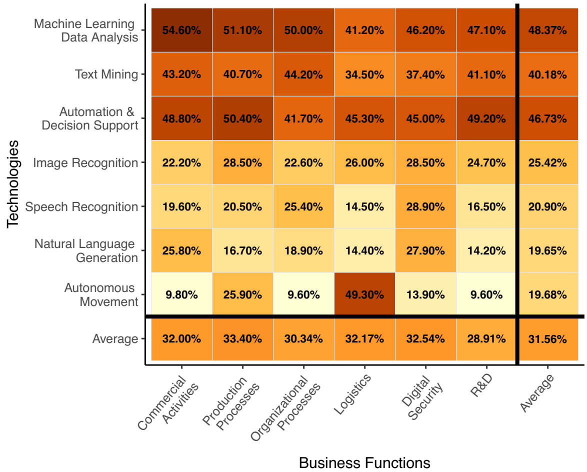
- **Supported AI technologies**: Natural Language Generation is more frequently supported by other AI technologies, particularly Text Mining and Speech Recognition, highlighting the complexity of applications such as Large Language Models that rely on other AI technologies as core components in 36.42% of instances considered. However, it tends not to support other technologies, except for clustering observed among itself, Text Mining, and Speech Recognition (the same technologies it is more frequently supported by), suggesting highly complementary functionalities in natural language processing.
- **Intermediate AI technologies**: Image and Speech Recognition occupy an intermediate position, both supporting and being supported by other technologies with conditional probabilities very close to the mean, but far from the averages of foundational and supported AI technologies. This underscores the importance of visual and audio pattern recognition in AI applications, while also indicating their reliance on Machine Learning Data Analysis and Text Mining for effective performance.
- **Specialized AI technologies**: Technologies related to Autonomous Movement represent a specialized category. While they benefit from the support of Automation & Decision Support, Machine Learning Data Analysis, and Image Recognition, they themselves rarely support other AI technologies, doing so on average only 10.67% of the time.

These findings indicate that AI technologies are not adopted in isolation and are interdependent. At the base of this structure, Machine Learning Data Analysis, Text Mining, and Automation & Decision Support form the foundational layer, underpinning the broader AI system. Natural Language Generation technologies, that have been developing only recently thanks to algorithmic innovations (see Vaswani et al., 2017), appear more likely supported by other AI technologies. This organization of interdependencies highlights that different AI technologies vary in their technological potential: some serve as essential building blocks that support a wide range of applications, whereas others are more specialized and depend on the foundational technologies to be supported. The observed asymmetries in these relationships underscore the importance for firms and managers to account for the structure of interdependencies between AI technologies when designing their AI deployment strategies.

5.4 The applicability of AI technologies

Results on the interdependencies between AI technologies suggest that foundational AI technologies form the architecture of the use of AI by firms. Similarly, AI technologies translates into differentiated patterns of applicability across business functions. Building on this insight, in this section we examine which AI technologies support distinct AI-related business functions (**EF4**).

We now examine how AI technologies are mapped into business functions by firms. Using Eq. 1, we estimate conditional probabilities where i refers to an AI technology and j represents a business function supported by AI systems. Figure 7 presents these conditional probabilities, where each entry estimate the probability that a



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.

Fig. 7 The applicability of AI technologies—Conditional probabilities. Probability of using AI in support of a business function, conditional on using a specific AI technology. Conditional probabilities are computed using sampling weights

technology (rows) supports a business function (columns). On average, an AI technology supports a business function with a probability of 31.56%. Nevertheless, the mapping between AI technologies and business functions is heterogeneous:

- **Broad Applicability**: The support of Text Mining, Machine Learning Data Analysis and Automation & Decision Support is particularly widespread, suggesting that the broad combinatorial potential found in Fig. 6 for AI technologies also extends to business functions. Their average conditional probabilities are 48.37%, 40.18%, and 46.73%, respectively, implying that these technologies support business functions more than 40% of the time on average. Indeed, Text Mining and Machine Learning 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 relevance of Automation & Decision Support technologies highlights that applications of AI systems are aimed at extensively automate and support firms' operations. Although to a much 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. Natural Language Generation 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, and Production Processes, likely due to robotics. Organizational Processes are supported more frequently

by Speech Recognition technologies, which support tasks like drafting and human–machine communication.

Overall, the findings suggest that foundational AI technologies (Text Mining, Machine Learning Data Analysis and Automation & Decision Support) are extensively used by firms to support business functions, while others are more specialized and tailored to specific areas within business operations.

The structure of interdependencies between AI technologies, illustrated in Fig. 6, indicates strong interconnections among them. To assess whether the applicability patterns reported in Fig. 7 persist when accounting for the linkages between AI technologies, we now estimate the relationships shown in Fig. 7 while controlling for firm-level characteristics that may influence the mapping between technologies and business functions. Specifically, we estimate the following Probit model:

$$\begin{aligned} P(\text{AI-supported Business Function}^{j}_{i,t}) = \Phi\{\alpha + \beta_1 \text{AI Technologies}_{\mathbf{i,t}} + \beta_2 \text{Digital Technologies}_{\mathbf{i,t}} + \\ + \beta_3 \text{Fast Broadband}_{i,t} + \beta_4 \text{Log Employees}_{i,t} + \beta_5 \text{Log Age}_{i,t} + \text{FE}_{\mathbf{s,t,r}} + \epsilon_{i,t}\} \ . \end{aligned} \tag{2}$$

The dependent variable $\text{AI-supported Business Function}^{j}_{i,t}$ is a binary indicator equal to 1 if firm *i* uses AI for a specific business function *j* in year *t*. The key explanatory variables are the vectors $\text{AI Technologies}_{\mathbf{i,t}}$, which capture whether the firm use different AI technologies, and $\text{Digital Technologies}_{\mathbf{i,t}}$, which include indicators for the use of Enterprise Systems, Cloud Computing, and E-commerce. The specification further controls for firm characteristics such as $\text{Log Employees}_{i,t}$, the natural logarithm of firm size, and $\text{Log Age}_{i,t}$, the natural logarithm of firm age. We also include a binary indicator for the availability of fast broadband, $\text{Fast Broadband}_{i,t}$. All regressions include sector × year × region fixed effects ($\text{FE}_{\mathbf{s,t,r}}$).

Estimated marginal effects of Probit results are reported in Table 5 and are consistent with the patterns shown in Fig. 7. Text Mining supports all business functions considered. Machine Learning Data Analysis and Automation & Decision Support are generally positive and significant, with the exception of Logistics (Column 4), where the most relevant role is played by Autonomous Movement AI technologies. The latter also supports business functions related to Production Processes. Image and Speech Recognition, as well as Natural Language Generation, support more specific functions, in addition to Digital Security (Column 5). In particular, Image Recognition is used in Production Processes (Column 2)—where operations are tangible—and in R&D activities (Column 6), where this type of technology has been relevant for research on neural networks since the release of AlexNet. Speech Recognition is key for Organizational Processes (Column 3), likely due to its importance in speech-to-text applications and voice-based interfaces embedded in virtual assistants. Finally, Natural Language Generation plays a central role in Commercial Activities (Column 1), as it enables personalised advertising and enhanced customer support.

We report robustness checks of results in Table 5 in Appendix 1. Table 8 uses sales in place of employees and Table 9 includes labour productivity (the ratio of sales to the number of employees). Results are broadly confirmed.

Results presented in this section provide robust evidence that the use of AI technologies translates into clearly differentiated patterns of applicability across busi-

Table 5 The applicability of AI technologies—Probit Eq. 2

	(1) Commercial Activities	(2) Production Processes	(3) Organi-zational Processes	(4) Logistics	(5) Digital Security	(6) R&D
AI—Machine Learning for Data Analysis	0.017*** (0.004)	0.010*** (0.003)	0.020*** (0.004)	0.003 (0.002)	0.012*** (0.003)	0.021*** (0.006)
AI—Text Mining	0.012*** (0.003)	0.014*** (0.003)	0.025*** (0.004)	0.005*** (0.002)	0.009*** (0.003)	0.010*** (0.003)
AI—Automation & Decision Support	0.017*** (0.003)	0.015*** (0.003)	0.023*** (0.005)	0.002 (0.001)	0.019*** (0.004)	0.007*** (0.002)
AI—Image Recognition	0.002 (0.005)	0.007** (0.003)	0.006 (0.006)	0.001 (0.002)	0.011*** (0.004)	0.012*** (0.004)
AI—Speech Recognition	− 0.003 (0.003)	0.001 (0.004)	0.019*** (0.005)	− 0.002 (0.002)	0.014*** (0.005)	0.004 (0.004)
AI—Natural Language Generation	0.011*** (0.003)	− 0.006 (0.005)	− 0.002 (0.007)	− 0.004 (0.003)	0.013** (0.005)	0.000 (0.004)
AI—Autonomous Movement	− 0.001 (0.006)	0.021*** (0.004)	0.003 (0.008)	0.012*** (0.002)	0.007 (0.006)	0.001 (0.005)
Observations	17,170	17,170	17,170	17,170	17,170	8,895
Sector × Year × Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Non-AI Digital Technologies	Yes	Yes	Yes	Yes	Yes	Yes
Fast Broadband	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.501	0.471	0.476	0.473	0.463	0.683

Columns (1)–(6) report marginal effects derived from the coefficients of the Probit model described by Eq. 2, where the dependent variable is a binary indicator indicating AI use for a specific business function. All 1-digit level industry-year-geographic fixed effects are not reported for clarity. All models include unreported coefficients for controls—firm characteristics (size and age), the use of non-AI digital technologies (Cloud, E-commerce and Enterprise Systems) and fast broadband –, whose marginal effects are reported in Table 7. The model is estimated using survey weights. Standard errors of marginal effects in Columns (1)–(6) are reported in parentheses and are estimated using the delta method.

(*significant at 10%, **significant at 5%, ***significant at 1%)

ness functions. Foundational AI technologies—Text Mining, Machine Learning Data Analysis, and Automation & Decision Support—consistently underpin a wide range of business functions, even after conditioning on firm-level digital capabilities and characteristics. By contrast, more specialized technologies, such as Autonomous Movement, Image Recognition, Speech Recognition, and Natural Language Generation, display narrower functional scopes aligned with their technological properties and typical use cases.

5.5 Characterising the users of different AI technologies

Previous sections show that a small set of technologies lies at the core of the AI paradigm and exhibits the highest degrees of diffusion. Examining how these key AI technologies relate to firm characteristics is therefore of substantial research interest, as it may shed light on potential diffusion barriers. The evidence reviewed in Sect. 3

suggests that the AI revolution is currently driven by a narrow group of firms, those that are larger, younger, and more digitally capable. We now assess whether this pattern holds uniformly across the different technologies that underpin the AI paradigm (**EF5**).

We study the characteristics of AI users by estimating the following Probit model:

$$P(\text{AI Technology}^{j}_{i,t}) = \Phi\{\alpha + \beta_1 \text{Log Employees}_{i,t} + \beta_2 \text{Log Age}_{i,t} + \beta_{\mathbf{3}} \text{Digital Technologies}_{\mathbf{i,t}} + \\ + \beta_3 \text{Fast Broadband}_{i,t} + \beta_{\mathbf{X}} \text{Other AI Technologies}_{\mathbf{i,t}} + \text{FE}_{\mathbf{s,t,r}} + \epsilon_{i,t}\} \tag{3}$$

The dependent variable, $\text{AI-Technology}^{j}_{i,t}$, is a binary indicator equal to 1 if firm *i* uses AI or a specific AI technology *j* in year *t*. The key explanatory variables are $\text{Log Employees}_{i,t}$, the natural logarithm of firm size, and $\text{Log Age}_{i,t}$, the natural logarithm of firm age. As explanatory variables, we further include a binary indicator for access to fast broadband, $\text{Fast Broadband}_{i,t}$, and a vector of digital capabilities, $\text{Digital Technologies}_{\mathbf{i,t}}$, which comprises indicators for the use of Enterprise Systems, Cloud Computing, and E-commerce. When the dependent variable refers to a specific AI technology rather than overall AI use, we additionally include the vector $\text{Other AI Technologies}_{\mathbf{i,t}}$ as a control. This accounts for the use of other AI technologies and helps isolate the relationship between the firm characteristics and the specific technology of interest, mitigating concerns related to multi-technology usage. All regressions include sector × year × region fixed effects ($\text{FE}_{\mathbf{s,t,r}}$), controlling for geography-sector-year level unobserved heterogeneity.

The estimated marginal effects of Probit results results are presented in Table 6. In general, AI users tend to be larger, younger, and more likely to employ other digital technologies (with the exception of E-commerce), as well as fast broadband (Column 1). These patterns are consistent with previous evidence (Calvino & Fontanelli, 2023; McElheran et al., 2024). We extend this literature by examining the drivers of use for different AI technologies in Columns (2)–(8).

The AI-size relationship is only weakly significant for Text Mining and not significant for Speech Recognition and Natural Language Generation. These technologies rely heavily on natural language processing, distinguishing them from AI technologies that primarily process numerical, visual, or structured data, or support automation. Indeed, by contrast, the AI-size relationship remains significant for Machine Learning Data Analysis (Column 2), Automation & Decision Support (Column 4), Image Recognition (Column 5), and Autonomous Movement (Column 8).

The relationship between AI use and firm age is generally not significant, with the notable exception of Machine Learning Data Analysis (Column 2). The negative coefficient indicates that younger firms are more likely to use this technology, consistent with the view that a wave of start-ups is driving the diffusion of Machine Learning. This result aligns with evidence from the early stages of AI diffusion, when Machine Learning was the most prevalent technology (Calvino & Fontanelli, 2023).

Furthermore, firms using AI tend to be more digitally intensive, as reflected in the positive and significant coefficients for Cloud and Enterprise Systems. This finding highlights the importance of scalable computing infrastructure and internal digital architectures that facilitate data flows and storage. By contrast, E-commerce is generally not associated with AI use, with the exception of Natural Language Generation,

Table 6 The characteristics of AI users—Probit Eq. 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AI Use	Machine Learning for Data Analysis	Text Mining	Automation & Decision Support	Image Recognition	Speech Recognition	Natural Language Generation	Autonomous Movement
Log Employees	0.014*** (0.002)	0.002*** (0.001)	0.001* (0.001)	0.002*** (0.001)	0.002*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.002*** (0.000)
Log Age	− 0.008*** (0.003)	− 0.003*** (0.001)	− 0.001 (0.001)	− 0.002 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.000 (0.001)	0.001 (0.001)
Cloud	0.049*** (0.008)	0.012*** (0.003)	0.009*** (0.003)	0.008*** (0.002)	0.005*** (0.002)	0.005*** (0.001)	0.003** (0.001)	− 0.000 (0.001)
Enterprise Systems	0.042*** (0.006)	0.011*** (0.003)	0.006** (0.002)	0.009*** (0.002)	0.005** (0.002)	0.006** (0.003)	0.006*** (0.002)	0.003 (0.002)
E-commerce	0.006 (0.004)	− 0.000 (0.002)	0.003 (0.003)	0.003 (0.002)	− 0.003 (0.002)	− 0.001 (0.001)	0.002** (0.001)	− 0.001 (0.001)
Fast Broadband	0.012** (0.006)	0.008*** (0.003)	− 0.001 (0.002)	0.004** (0.002)	− 0.001 (0.001)	− 0.002 (0.001)	0.002 (0.001)	− 0.001 (0.001)
Observations	17,170	17,170	17,170	17,170	17,170	17,170	17,170	17,170
Sector × Year × Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other AI technologies		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.181	0.505	0.458	0.442	0.435	0.457	0.508	0.333

Columns (1)–(8) report marginal effects derived from the coefficients of the Probit model described in Eq. 3. The dependent variable is a binary indicator for AI use in Column (1), and for the use of specific AI technologies in Columns (2)–(8), namely: Machine Learning Data Analysis, Text Mining, Automation & Decision Support, Image Recognition, Speech Recognition, Natural Language Generation, and Autonomous Movement. All models, with the exception of Column (1), include unreported coefficients for other AI technologies, whose marginal effects are reported in Table 10. All industry–year–geographic fixed effects at the 1-digit level are included but not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects, reported in parentheses, are estimated using the delta method.

(*significant at 10%, **significant at 5%, ***significant at 1%)

which is closely related to commercial and customer-facing activities. Finally, other digital technologies do not appear to be related to the use of Autonomous Movement technologies, in line with its role of specialized technology.

Fast broadband also emerges as a significant predictor for the use of Machine Learning Data Analysis (Column 2) and Automation & Decision Support (Column 4), suggesting that high-speed connectivity and reliable network capabilities are particularly important for AI technologies that process large amounts of data or support automated decision-making.

We report robustness checks of results in Table 6 in Appendix 1. Table 11 reports the results when firms with unreported applications of AI technologies are includes in the sample, Table 12 includes labour productivity (the ratio of sales to the number of employees) and Table 13 uses sales in place of employees. Results are broadly confirmed.

Overall, these findings suggest that, although AI technologies differ substantially in their requirements, their use remains systematically associated with firm size, age, and digital readiness. This indicates that the current generation of AI relies on organizational, technical, and infrastructural capabilities that many firms may not yet possess. Such capability gaps act as significant barriers to the diffusion of AI, limiting the extent to which its general-purpose potential can be fully realised across the economy. In this respect, natural-language-based AI technologies appear the most accessible, as their adoption is not correlated with firm size. Nonetheless, their use remains strongly linked to the availability of digital capabilities—particularly Enterprise Systems and Cloud Computing—suggesting that even more accessible AI technologies require a solid digital foundation.

6 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 technological interdependencies between AI technologies and varying rates of applicability of these to AI-driven business functions.

First, while overall AI use remains limited (around 6% of firms in both 2020 and 2022) and more prevalent in specific sectors (notably ICT services and professional activities), we observe clear emerging patterns of sectoral specialization. Sectors tend to concentrate their use on a small set of AI technologies and business functions that align more closely with their core activities.

Second, a key finding is the emergence of relevant interdependencies between AI technologies and their applicability across business functions. We identify a set of core technologies—specifically Machine Learning Data Analysis, Text Mining, and Automation & Decision Support—that form the backbone of the AI system. These technologies are deployed across a wide range of business functions. In contrast, other AI technologies occupy intermediate or peripheral positions, exhibiting more function-specific patterns of use (e.g., Natural Language Generation in Commercial Activities).

Third, we document substantial heterogeneity in the characteristics of AI users. The use of data- and automation-intensive technologies (such as Machine Learning and Automation & Decision Support) is strongly associated with firm size, unlike AI technologies that rely on natural-language processing. Crucially, the use of most AI technologies is significantly related to firms' digital capabilities, particularly the implementation of Cloud Computing and Enterprise Systems. This highlights that a solid digital infrastructure is a critical prerequisite for effective AI deployment.

In conclusion, our results contribute to the understanding of AI as a GPT by showing that it is not a single, uniform technology, but a complex system composed of interdependent elements that vary in their degree of generality (see also Dosi, 2023, Vannuccini & Prytkova, 2024). The technological structure we uncover—where Machine Learning for Data Analysis, Text Mining, and Automation & Decision Support form the foundational core—supports the view that AI is indeed evolving as a GPT. Yet its general-purpose properties arise disproportionately from such subset of core technologies, which may affect the development and diffusion of other AI applications. At the same time, gaps in organizational, technical, and infrastructural capabilities may limit the extent to which AI's general-purpose potential can be fully realized across firms and sectors.

Our findings have important implications for firms, managers, and policymakers, emphasizing that AI use is shaped by industry-specific factors, firm characteristics, and technological interdependencies, and highlighting the limitations of one-size-fits-all diffusion strategies.

First, our findings challenge the assumption that larger or younger firms are inherently better positioned to adopt AI, suggesting that AI strategies should consider the requirements of each technology and its purpose. Notably, natural-language-based AI technologies—Text Mining, Speech Recognition, and Natural Language Generation—exhibit limited association with firm size, underscoring the potential of generative AI for small firms and entrepreneurial ventures. Conversely, Cloud Computing and Enterprise Systems facilitate the use of nearly all AI technologies, highlighting the importance of investing in robust digital infrastructure to enable effective data generation, processing and exploitation for effectively using AI.

Second, AI use should be viewed as part of a strategic technological portfolio rather than a single decision. Firms that use foundational AI technologies—Machine Learning, Text Mining, or Automation & Decision Support—position themselves to unlock complementarities across multiple business functions. These technologies can serve as "AI infrastructure," enabling broader downstream applications. In contrast, specialized technologies—such as Image Recognition, Speech Recognition, Natural Language Generation, and Autonomous Movement—tend to support specific functions. Managers should therefore prioritize foundational AI technologies when aiming for broad transformation, while integrating specialized AI systems where a strong business-function fit exists.

A limitation of this study is that we are unable to examine the sequencing of technology adoption due to data constraints.[9] Future research could investigate whether strategic sequencing—first building ICT and then AI capabilities—is essential for effective AI use. Furthermore, such sequencing may depend not only on firms' business functions but also on their organizational structure and human capital, and on the technology-specific complementarities between such human and technological capital. Managerial, technological, and organizational capabilities may play a critical role in this context, and future work will aim to explore these dimensions in greater depth.

The findings presented in this study are also relevant for understanding the implications of AI use by firms. Future analyses could examine how different patterns of AI use relate to firm-level outcomes, such as innovation and performance, as more recent data become available. While doing this, the current analysis could be extended to different contexts beyond France.

Finally, the temporal span of our study, limited to 2020 and 2022, presents an additional caveat: we lack reliable data that can fully capture the more recent use and impact of generative AI. As generative AI systems rapidly gain relevance across industries, their transformative potential introduces new dynamics in AI use that are not entirely captured 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 adoption.

Appendix 1. Additional Tables

See Tables 7, 8, 9, 10, 11, 12, 13.

[9] The sample changes on a yearly basis, making it challenging to construct a panel of firms. Only firms with more than 500 employees are surveyed each year.

Table 7 Baseline results - The applicability of AI technologies—Probit Eq. 2

	(1)	(2)	(3)	(4)	(5)	(6)
	Commercial Activities	Production Processes	Organizational Processes	Logistics	Digital Security	R&D
AI—Machine Learning for Data Analysis	0.017*** (0.004)	0.010*** (0.003)	0.020*** (0.004)	0.003 (0.002)	0.012*** (0.003)	0.021*** (0.006)
AI—Text Mining	0.012*** (0.003)	0.014*** (0.003)	0.025*** (0.004)	0.005*** (0.002)	0.009*** (0.003)	0.010*** (0.003)
AI—Automation & Decision Support	0.017*** (0.003)	0.015*** (0.003)	0.023*** (0.005)	0.002 (0.001)	0.019*** (0.004)	0.007*** (0.002)
AI—Image Recognition	0.002 (0.005)	0.007** (0.003)	0.006 (0.006)	0.001 (0.002)	0.011*** (0.004)	0.012*** (0.004)
AI—Speech Recognition	− 0.003 (0.003)	0.001 (0.004)	0.019*** (0.005)	− 0.002 (0.002)	0.014*** (0.005)	0.004 (0.004)
AI—Natural Language Generation	0.011*** (0.003)	− 0.006 (0.005)	− 0.002 (0.007)	− 0.004 (0.003)	0.013** (0.005)	0.000 (0.004)
AI—Autonomous Movement	− 0.001 (0.006)	0.021*** (0.004)	0.003 (0.008)	0.012*** (0.002)	0.007 (0.006)	0.001 (0.005)
Log Employees	− 0.000 (0.000)	0.001 (0.000)	− 0.000 (0.001)	0.001*** (0.000)	0.003*** (0.000)	0.000 (0.000)
Log Age	0.000 (0.001)	− 0.000 (0.001)	− 0.002 (0.001)	0.001*** (0.000)	− 0.000 (0.001)	− 0.000 (0.001)
Cloud	0.004*** (0.002)	0.005*** (0.001)	0.006** (0.002)	0.001* (0.001)	0.005*** (0.002)	0.005** (0.003)
Enterprise Systems	0.004* (0.002)	0.003** (0.001)	0.011*** (0.003)	0.002* (0.001)	0.009*** (0.002)	0.003 (0.002)
E-commerce	0.013*** (0.002)	− 0.003** (0.002)	− 0.001 (0.002)	0.001 (0.001)	− 0.001 (0.002)	− 0.000 (0.002)
Fast Broadband	0.001 (0.001)	− 0.000 (0.001)	− 0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.002)
Observations	17,170	17,170	17,170	17,170	17,170	8,895
Sector × Year × Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.501	0.471	0.476	0.473	0.463	0.683

Columns (1)–(6) report marginal effects derived from the coefficients of the Probit model described by Eq. 2, where the dependent variable is a binary indicator indicating AI use for a specific business function. All 1-digit level industry-year-geographic fixed effects are not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects in Columns (1)–(6) are reported in parentheses and are estimated using the delta method

Table 8 The applicability of AI technologies—Probit Eq. 2—Sales

	(1)	(2)	(3)	(4)	(5)	(6)
	Commercial Activities	Production Processes	Organizational Processes	Logistics	Digital Security	R&D
AI—Machine Learning for Data Analysis	0.017*** (0.004)	0.010*** (0.004)	0.020*** (0.004)	0.003 (0.002)	0.012*** (0.003)	0.021*** (0.005)
AI—Text Mining	0.012*** (0.003)	0.014*** (0.003)	0.025*** (0.004)	0.005*** (0.002)	0.009*** (0.003)	0.010*** (0.003)
AI—Automation & Decision Support	0.016*** (0.003)	0.015*** (0.003)	0.022*** (0.005)	0.002 (0.001)	0.019*** (0.004)	0.007*** (0.002)
AI—Image Recognition	0.002 (0.005)	0.007** (0.003)	0.006 (0.006)	0.000 (0.001)	0.011*** (0.004)	0.012*** (0.004)
AI—Speech Recognition	− 0.003 (0.003)	0.001 (0.004)	0.019*** (0.005)	− 0.002 (0.002)	0.014*** (0.005)	0.004 (0.004)
AI—Natural Language Generation	0.011*** (0.003)	− 0.006 (0.005)	− 0.001 (0.007)	− 0.004 (0.003)	0.013** (0.005)	0.000 (0.004)
AI—Autonomous Movement	− 0.001 (0.006)	0.021*** (0.004)	0.004 (0.008)	0.012*** (0.002)	0.008 (0.006)	0.001 (0.005)
Log Sales	0.000 (0.000)	0.001* (0.000)	− 0.000 (0.000)	0.001*** (0.000)	0.002*** (0.000)	− 0.000 (0.000)
Log Age	0.000 (0.001)	− 0.000 (0.001)	− 0.001 (0.001)	0.001** (0.000)	− 0.001 (0.001)	− 0.000 (0.001)
Cloud	0.004*** (0.002)	0.005*** (0.001)	0.006*** (0.002)	0.001 (0.001)	0.005*** (0.002)	0.005** (0.002)
Enterprise Systems	0.004 (0.002)	0.003** (0.001)	0.011*** (0.004)	0.002 (0.001)	0.009*** (0.002)	0.003 (0.002)
E-commerce	0.012*** (0.002)	− 0.004** (0.002)	− 0.000 (0.002)	0.001 (0.001)	− 0.002 (0.002)	0.000 (0.002)
Fast Broadband	0.000 (0.001)	− 0.000 (0.001)	− 0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.002)
Observations	17,115	17,115	17,115	17,115	17,115	8,851
Sector × Year × Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.503	0.471	0.475	0.484	0.462	0.682

Columns (1)–(6) report marginal effects derived from the coefficients of the Probit model described by Eq. 2, where the dependent variable is a binary indicator indicating AI use for a specific business function. All 1-digit level industry-year-geographic fixed effects are not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects in Columns (1)–(6) are reported in parentheses and are estimated using the delta method

Table 9 The applicability of AI technologies—Probit Eq. 2—Labour Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Commercial Activities	Production Processes	Organizational Processes	Logistics	Digital Security	R&D
AI—Machine Learning for Data Analysis	0.017*** (0.004)	0.010*** (0.004)	0.020*** (0.004)	0.003 (0.002)	0.012*** (0.003)	0.021*** (0.005)
AI—Text Mining	0.012*** (0.003)	0.014*** (0.003)	0.025*** (0.004)	0.005*** (0.002)	0.009*** (0.003)	0.010*** (0.003)
AI—Automation & Decision Support	0.016*** (0.003)	0.015*** (0.003)	0.022*** (0.005)	0.002 (0.001)	0.019*** (0.004)	0.007*** (0.002)
AI—Image Recognition	0.002 (0.005)	0.007** (0.003)	0.006 (0.006)	0.000 (0.001)	0.011*** (0.004)	0.012*** (0.004)
AI—Speech Recognition	− 0.003 (0.003)	0.001 (0.004)	0.019*** (0.005)	− 0.002 (0.002)	0.014*** (0.005)	0.004 (0.004)
AI—Natural Language Generation	0.011*** (0.003)	− 0.006 (0.005)	− 0.001 (0.007)	− 0.004 (0.003)	0.013** (0.005)	0.000 (0.004)
AI—Autonomous Movement	− 0.001 (0.006)	0.021*** (0.004)	0.004 (0.008)	0.012*** (0.002)	0.008 (0.006)	0.001 (0.005)
Log Labour Productivity	0.001 (0.001)	0.000 (0.000)	− 0.001 (0.001)	0.001*** (0.000)	0.001 (0.001)	− 0.001* (0.001)
Log Employees	− 0.000 (0.000)	0.001 (0.000)	− 0.000 (0.001)	0.001*** (0.000)	0.002*** (0.000)	0.000 (0.000)
Log Age	0.000 (0.001)	− 0.000 (0.001)	− 0.001 (0.001)	0.001** (0.000)	− 0.001 (0.001)	− 0.000 (0.001)
Cloud	0.004*** (0.002)	0.005*** (0.001)	0.006*** (0.002)	0.001 (0.001)	0.005*** (0.002)	0.005** (0.002)
Enterprise Systems	0.004 (0.002)	0.003** (0.001)	0.011*** (0.004)	0.002 (0.001)	0.009*** (0.002)	0.003 (0.002)
E-commerce	0.012*** (0.002)	− 0.004** (0.002)	− 0.000 (0.002)	0.001 (0.001)	− 0.002 (0.002)	0.000 (0.002)
Fast Broadband	0.000 (0.001)	− 0.000 (0.001)	− 0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.002)
Observations	17,115	17,115	17,115	17,115	17,115	8,851
Sector × Year × Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.503	0.471	0.475	0.484	0.462	0.682

Columns (1)–(6) report marginal effects derived from the coefficients of the Probit model described by Eq. 2, where the dependent variable is a binary indicator indicating AI use for a specific business function. All 1-digit level industry-year-geographic fixed effects are not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects in Columns (1)–(6) are reported in parentheses and are estimated using the delta method

Table 10 Baseline results—The characteristics of AI users—Probit Eq. 3

	(1) AI Use	(2) ML Data	(3) Text	(4) Automation &	(5) Image	(6) Speech	(7) NLG	(8) Autonomous
Log Employees	0.014*** (0.002)	0.002*** (0.001)	0.001* (0.001)	0.002*** (0.001)	0.002*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.002*** (0.000)
Log Age	− 0.008*** (0.003)	− 0.003*** (0.001)	− 0.001 (0.001)	− 0.002 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.000 (0.001)	0.001 (0.001)
Cloud	0.049*** (0.008)	0.012*** (0.003)	0.009*** (0.003)	0.008*** (0.002)	0.005*** (0.002)	0.005*** (0.001)	0.003** (0.001)	− 0.000 (0.001)
Enterprise Systems	0.042*** (0.006)	0.011*** (0.003)	0.006** (0.002)	0.009*** (0.002)	0.005** (0.002)	0.006** (0.003)	0.006*** (0.002)	0.003 (0.002)
E-commerce	0.006 (0.004)	− 0.000 (0.002)	0.003 (0.003)	0.003 (0.002)	− 0.003 (0.002)	− 0.001 (0.001)	0.002** (0.001)	− 0.001 (0.001)
Fast Broadband	0.012** (0.006)	0.008*** (0.003)	− 0.001 (0.002)	0.004** (0.002)	− 0.001 (0.001)	− 0.002 (0.001)	0.002 (0.001)	− 0.001 (0.001)
AI—Machine Learning for Data Analysis			0.029*** (0.005)	0.031*** (0.005)	0.019*** (0.003)	0.005 (0.004)	0.001 (0.002)	0.002 (0.003)
AI—Text Mining		0.034*** (0.007)		0.013*** (0.004)	0.003 (0.003)	0.012*** (0.003)	0.011*** (0.002)	− 0.003 (0.002)
AI—Automation & Decision Support		0.033*** (0.007)	0.012*** (0.004)		0.006** (0.002)	0.005* (0.003)	0.005*** (0.002)	0.014*** (0.003)
AI—Image Recognition		0.033*** (0.006)	0.003 (0.004)	0.008 (0.005)		0.006* (0.003)	0.005** (0.002)	0.006*** (0.002)
AI—Speech Recognition		0.009 (0.008)	0.020*** (0.006)	0.007 (0.005)	0.008* (0.004)		0.015*** (0.003)	0.005 (0.004)
AI—Natural Language Generation		− 0.003 (0.007)	0.023*** (0.005)	0.009 (0.005)	0.008*** (0.003)	0.018*** (0.003)		0.002 (0.003)
AI—Autonomous Movement		0.009 (0.008)	− 0.007 (0.005)	0.036*** (0.005)	0.010*** (0.004)	0.004 (0.005)	0.002 (0.003)	
Observations	17,170	17,170	17,170	17,170	17,170	17,170	17,170	17,170

Table 10 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AI Use	ML Data	Text	Automa-tion &	Image	Speech	NLG	Autono-mous
Sector × Year × Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.181	0.505	0.458	0.442	0.435	0.457	0.508	0.333

Columns (1)–(8) report marginal effects derived from the coefficients of the Probit model described in Eq. 3. The dependent variable is a binary indicator for AI use in Column (1), and for the use of specific AI technologies in Columns (2)–(8), namely: Machine Learning Data Analysis, Text Mining, Automation & Decision Support, Image Recognition, Speech Recognition, Natural Language Generation, and Autonomous Movement. All industry–year–geographic fixed effects at the 1-digit level are included but not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects, reported in parentheses, are estimated using the delta method

Table 11 The characteristics of AI users—Probit Eq. 3—Full sample

	(1) AI Use	(2) ML Data Analysis	(3) Text Mining	(4) Automation & Decision Support	(5) Image Recognition	(6) Speech Recognition	(7) NLG	(8) Autonomous Movement
Log Employees	0.017*** (0.002)	0.004*** (0.001)	0.001 (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.000 (0.001)	− 0.000 (0.001)	0.003*** (0.000)
Log Age	− 0.005* (0.003)	− 0.003** (0.001)	− 0.001 (0.001)	− 0.002 (0.001)	0.001 (0.001)	− 0.001 (0.001)	0.000 (0.001)	0.002** (0.001)
Cloud	0.071*** (0.011)	0.018*** (0.004)	0.013*** (0.003)	0.012*** (0.003)	0.007*** (0.003)	0.008*** (0.002)	0.004** (0.002)	− 0.001 (0.001)
Enterprise Systems	0.057*** (0.007)	0.013*** (0.005)	0.013*** (0.003)	0.008*** (0.003)	0.011*** (0.003)	0.009*** (0.003)	0.005** (0.002)	0.004* (0.002)
E-commerce	0.001 (0.006)	− 0.003 (0.003)	0.002 (0.003)	0.003 (0.003)	− 0.003 (0.003)	− 0.001 (0.002)	0.004** (0.001)	− 0.002 (0.002)
Fast Broadband	0.017** (0.007)	0.008*** (0.003)	0.005* (0.003)	0.004 (0.003)	− 0.001 (0.002)	− 0.001 (0.002)	0.001 (0.002)	− 0.002 (0.002)
AI—Text Mining		0.041*** (0.008)		0.016*** (0.005)	0.009** (0.004)	0.023*** (0.004)	0.016*** (0.003)	− 0.005* (0.003)
AI—Automation & Decision Support		0.047*** (0.009)	0.016*** (0.006)		0.011*** (0.004)	0.005 (0.004)	0.008*** (0.002)	0.018*** (0.003)
AI—Image Recognition		0.043*** (0.007)	0.011** (0.005)	0.014** (0.006)		0.005 (0.004)	0.009*** (0.003)	0.008*** (0.003)
AI—Speech Recognition		0.006 (0.008)	0.035*** (0.007)	0.008 (0.005)	0.007 (0.006)		0.025*** (0.003)	0.007* (0.004)
AI—Natural Language Generation		0.000 (0.006)	0.034*** (0.006)	0.013** (0.006)	0.016*** (0.005)	0.036*** (0.005)		0.003 (0.003)

Table 11 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AI Use	ML Data Analysis	Text Mining	Automation & Decision Support	Image Recognition	Speech Recognition	NLG	Autonomous Movement
AI—Autonomous Movement		0.007 (0.009)	− 0.014* (0.008)	0.046*** (0.006)	0.017*** (0.006)	0.010* (0.006)	0.005* (0.003)	
AI—Machine Learning for Data Analysis			0.038*** (0.006)	0.042*** (0.006)	0.030*** (0.004)	0.002 (0.005)	0.001 (0.003)	0.002 (0.003)
Observations	17,822	17,822	17,822	17,822	17,822	17,822	17,822	17,822
Pseudo R^2	0.145	0.429	0.378	0.374	0.325	0.361	0.448	0.272

Notes: Columns (1)–(8) report marginal effects derived from the coefficients of the Probit model described in Eq. 3. The dependent variable is a binary indicator for AI use in Column (1), and for the use of specific AI technologies in Columns (2)–(8), namely: Machine Learning Data Analysis, Text Mining, Automation & Decision Support, Image Recognition, Speech Recognition, Natural Language Generation, and Autonomous Movement. All industry–year–geographic fixed effects at the 1-digit level are included but not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects, reported in parentheses, are estimated using the delta method

Table 12 The characteristics of AI users—Probit Eq. 3—Labour productivity

	(1) AI Use	(2) ML Data Analysis	(3) Text Mining	(4) Automation & Decision Support	(5) Image Recognition	(6) Speech Recognition	(7) NLG	(8) Autonomous Movement
Log Employees	0.014*** (0.002)	0.002*** (0.001)	0.001* (0.001)	0.002*** (0.001)	0.002*** (0.000)	0.000 (0.000)	− 0.000 (0.000)	0.002*** (0.000)
Log Labour Productivity	0.000 (0.002)	0.000 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.000 (0.000)	0.001 (0.001)	0.000 (0.000)	0.001 (0.001)
Log Age	− 0.008*** (0.003)	− 0.003*** (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.000 (0.001)	0.001 (0.001)
Cloud	0.049*** (0.008)	0.012*** (0.003)	0.009*** (0.003)	0.008*** (0.002)	0.005*** (0.002)	0.005*** (0.001)	0.003** (0.001)	− 0.000 (0.001)
Enterprise Systems	0.041*** (0.006)	0.010*** (0.003)	0.006** (0.002)	0.009*** (0.002)	0.005*** (0.002)	0.006** (0.003)	0.006*** (0.002)	0.003 (0.002)
E-commerce	0.006 (0.004)	− 0.000 (0.002)	0.003 (0.003)	0.003 (0.002)	− 0.003 (0.002)	− 0.001 (0.001)	0.002** (0.001)	− 0.001 (0.001)
AI—Machine Learning for Data Analysis			0.029*** (0.005)	0.031*** (0.005)	0.020*** (0.003)	0.005 (0.004)	0.001 (0.002)	0.003 (0.003)
AI—Text Mining		0.034*** (0.007)		0.013*** (0.004)	0.003 (0.003)	0.012*** (0.003)	0.011*** (0.002)	− 0.003 (0.002)
AI—Automation & Decision Support		0.033*** (0.007)	0.012*** (0.004)		0.006** (0.002)	0.005* (0.003)	0.005*** (0.002)	0.014*** (0.003)
AI—Image Recognition		0.033*** (0.006)	0.003 (0.004)	0.008 (0.005)		0.006* (0.003)	0.005** (0.002)	0.006** (0.002)
AI—Speech Recognition		0.008 (0.009)	0.020*** (0.006)	0.007 (0.005)	0.008* (0.004)		0.015*** (0.003)	0.004 (0.004)

Table 12 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AI Use	ML Data Analysis	Text Mining	Automation & Decision Support	Image Recognition	Speech Recognition	NLG	Autonomous Movement
AI—Natural Language Generation		− 0.003 (0.007)	0.023*** (0.005)	0.008 (0.005)	0.008*** (0.003)	0.018*** (0.003)		0.002 (0.003)
AI—Autonomous Movement		0.009 (0.008)	− 0.007 (0.005)	0.036*** (0.005)	0.010*** (0.004)	0.004 (0.005)	0.002 (0.003)	
Fast Broadband	0.012** (0.006)	0.008*** (0.003)	− 0.001 (0.002)	0.004* (0.002)	− 0.001 (0.001)	− 0.002 (0.001)	0.002 (0.001)	− 0.001 (0.001)
Observations	17,115	17,115	17,115	17,115	17,115	17,115	17,115	17,115
pseudo r2	0.181	0.504	0.457	0.446	0.436	0.458	0.508	0.334

Columns (1)–(8) report marginal effects derived from the coefficients of the Probit model described in Eq. 3. The dependent variable is a binary indicator for AI use in Column (1), and for the use of specific AI technologies in Columns (2)–(8), namely: Machine Learning Data Analysis, Text Mining, Automation & Decision Support, Image Recognition, Speech Recognition, Natural Language Generation, and Autonomous Movement. All industry–year–geographic fixed effects at the 1-digit level are included but not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects, reported in parentheses, are estimated using the delta method

Table 13 The characteristics of AI users—Probit Eq. 3—Sales

	(1) AI use	(2) ML Data Analysis	(3) Text Mining	(4) Automation & Decision Support	(5) Image Recognition	(6) Speech Recognition	(7) NLG	(8) Autonomous Movement
Log Sales	0.009*** (0.001)	0.001*** (0.001)	0.000 (0.000)	0.001** (0.000)	0.001*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.001*** (0.000)
Log Age	− 0.009*** (0.003)	− 0.003*** (0.001)	− 0.001 (0.001)	− 0.002 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.000 (0.001)	0.001 (0.001)
Cloud	0.051*** (0.009)	0.012*** (0.003)	0.009*** (0.003)	0.009*** (0.002)	0.005*** (0.002)	0.005*** (0.001)	0.003** (0.001)	− 0.000 (0.001)
Enterprise Systems	0.043*** (0.006)	0.011*** (0.003)	0.006** (0.002)	0.009*** (0.002)	0.006*** (0.002)	0.006** (0.003)	0.006*** (0.002)	0.003 (0.002)
E-commerce	0.006 (0.004)	− 0.000 (0.002)	0.003 (0.003)	0.003 (0.002)	− 0.003 (0.002)	− 0.001 (0.001)	0.002** (0.001)	− 0.001 (0.001)
Fast Broadband	0.013** (0.006)	0.008*** (0.003)	− 0.001 (0.002)	0.004* (0.002)	− 0.001 (0.001)	− 0.002 (0.001)	0.002 (0.001)	− 0.001 (0.001)
AI—Machine Learning for Data Analysis			0.029*** (0.005)	0.032*** (0.005)	0.020*** (0.003)	0.004 (0.004)	0.001 (0.002)	0.003 (0.003)
AI—Text Mining		0.034*** (0.007)		0.014*** (0.004)	0.003 (0.003)	0.012*** (0.003)	0.011*** (0.002)	− 0.003 (0.002)
AI—Automation & Decision Support		0.033*** (0.007)	0.012*** (0.004)		0.006** (0.002)	0.005* (0.003)	0.005*** (0.002)	0.015*** (0.003)
AI—Image Recognition		0.033*** (0.006)	0.003 (0.004)	0.008 (0.005)		0.006* (0.003)	0.005** (0.002)	0.006** (0.002)
AI—Speech Recognition		0.009 (0.009)	0.021*** (0.006)	0.007 (0.005)	0.008* (0.004)		0.015*** (0.003)	0.004 (0.004)

Table 13 (continued)

	(1) AI use	(2) ML Data Analysis	(3) Text Mining	(4) Automation & Decision Support	(5) Image Recognition	(6) Speech Recognition	(7) NLG	(8) Autonomous Movement
AI—Natural Language Generation		− 0.003 (0.007)	0.023*** (0.005)	0.009 (0.005)	0.008*** (0.003)	0.018*** (0.003)		0.002 (0.003)
AI—Autonomous Movement		0.009 (0.008)	− 0.006 (0.005)	0.036*** (0.005)	0.011*** (0.004)	0.004 (0.005)	0.002 (0.003)	
Observations	17,115	17,115	17,115	17,115	17,115	17,115	17,115	17,115
pseudo r2	0.173	0.503	0.456	0.443	0.432	0.458	0.508	0.332

Columns (1)–(8) report marginal effects derived from the coefficients of the Probit model described in Eq. 3. The dependent variable is a binary indicator for AI use in Column (1), and for the use of specific AI technologies in Columns (2)–(8), namely: Machine Learning Data Analysis, Text Mining, Automation & Decision Support, Image Recognition, Speech Recognition, Natural Language Generation, and Autonomous Movement. All industry–year–geographic fixed effects at the 1-digit level are included but not reported for clarity. The model is estimated using survey weights. Standard errors of marginal effects, reported in parentheses, are estimated using the delta method

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