



AI, robots and innovation in European SMEs

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Abstract There is increasing interest in the impact of advanced digital technologies on SMEs, but the determinants of their adoption and their association with multiple innovation outcomes remain unexplored. Based on the Flash Eurobarometer 486, this paper analyses how the adoption of artificial intelligence and robots is related to European SMEs carrying out product, process, organizational and marketing innovations. Our results establish scale-ups and start-ups as the most likely adopters of these technologies and the most innovative firms. Furthermore, internal characteristics, such as internationalization and firm size, and external factors, such as the availability of digital skills and infrastructure, are significant drivers of digitalization at the firm level. In a two-stage approach, we find that the adoption of artificial intelligence and robots is associated with all innovation types, although these technologies serve more specialised objectives in manufacturing rather than in service sectors. Our results confirm a significant variability in the adoption of artificial intelligence and robots, as well as heterogeneous associations with innovation outcomes.

Plain English Summary The digital adoption in European SMEs: how start-ups and scale-ups boost innovation using artificial intelligence and robots. This paper explores what drives SMEs to adopt artificial intelligence and robots, examining the association of these with technological and non-technological innovations. Using the Flash Eurobarometer 486 “SMEs, Start-ups, Scale-ups and Entrepreneurship” we find that, due to their enhanced capabilities and organisational flexibility, start-ups and scale-ups are at the forefront of the digital transformation. This improves their ability to innovate, as these technologies are significantly associated with innovation. However, the relationship between artificial intelligence, robots, and innovation differs between manufacturing and service sectors. In manufactures, digital technologies tend to have more specialised roles, while in services sectors they have a broader application. Our results highlight the importance of fostering a more favourable environment for the development of innovative start-ups and scale-ups to close the digital distance between the European Union and countries at the technological frontier.

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1 Introduction

The integration of advanced digital technologies (ADTs)¹ marks a paradigm shift in corporate innovation strategies, offering new opportunities for growth, efficiency and creativity (Li et al., 2023). Among ADTs, robotics and artificial intelligence (AI)² represent the core of the digital transformation. On the one hand, robotics aims at improving process efficiency by automatising manual tasks. In this sense, a robot is an autonomous machine that does not need a human operator and can be programmed to perform a complex series of actions automatically (Acemoglu & Restrepo, 2019). On the other hand, AI searches for efficiency improvement by automatising cognitive tasks. AI has the potential to disrupt the functioning of all industries and the nature of business processes (Calvino & Fontanelli, 2023).

The versatility of these cross-cutting technologies and their applications across sectors sparks a debate on how they will affect the economy (Makridakis, 2017). Both technologies are characterised by their flexibility and adaptability to a wide variety of tasks, having great potential to generate externalities in multiple scientific and innovative areas, leading to increasing returns of scale. However, the complexity and costs associated with the adoption of AI and robots generate a gap between digitalised and non-digitalised firms that has not been properly addressed in the literature (Skare & Soriano, 2021). The adoption of ADTs for SMEs is more challenging due to their limited resources (Aghion et al., 2021). However, considering the disruptive role that start-ups and scale-ups exert in the market, a group of SMEs might find in digitalisation an opportunity to foster

their innovative potential and close the technological distance (Audretsch et al., 2020; Coad et al., 2024; Veugelers et al., 2019a).

To the best of our knowledge, few comprehensive studies analyse the digital adoption patterns of SMEs and their association with multiple innovation outcomes (Ardito, 2023; Battistoni et al., 2023; Merín-Rodrigáñez et al., 2024). Our paper addresses this gap by determining the internal and external drivers of ADT adoption and their relationship with technological and non-technological innovations for a sample of European SMEs from the Flash Eurobarometer 486 “SMEs, Start-ups, Scale-ups and Entrepreneurship”. We adopt a two-stage residual inclusion strategy to analysing the relationship between the adoption of ADTs and the innovative potential of European SMEs. More concretely, the first stage explores how firm characteristics and country-level digitalisation are associated with the adoption of AI and robots. Then, the second stage addresses the linkages of both technologies with product, process, organisational and marketing innovations. This strategy allows us to control for endogeneity due to reverse causality between innovation and the adoption of digital technologies, as well as the multicollinearity problem due to a multiplicity in the determinants of ADTs and innovation outcomes.

Paying special attention to the differences between start-ups and scale-ups, we observe that these firms have an advantage in the adoption of AI and robots compared to other SMEs, confirming their role as key agents driving the European digital adoption. However, the digital adoption patterns of start-ups and scale-ups differ considerably. While the first are more likely to adopt only robots into their productive structure, scale-ups adopt AI and robots more extensively. Specific firm characteristics such as internationalisation and firm age are tightly related to ADT adoption, confirming self-selection patterns in the digitalisation of firms. Furthermore, the positive and significant impact of digital skills and infrastructure at the country level underscores the role of externalities and knowledge spillovers from the rest of the economy as a key source of incentives for digitalisation.

Overall, in terms of the relationship between artificial intelligence, robots, and innovation, we find a consistent association between both ADTs and all

¹ The European Commission (2021) defines ADTs as recent or future technologies expected to substantially alter the business and social environment. ADTs include AI, big data analysis, Internet of Things, machine learning, 3-D printing, cloud computing services, enterprise resource planning software and robotics.

² AI combines machine learning, deep learning, and language recognition capabilities for structured and unstructured data. In 2019, the World Commission on the Ethics of Scientific Knowledge and Technology (COMEST) of UNESCO defined AI as a field involving machines with the ability to mimic certain functionalities of human intelligence, including features such as perception, learning, reasoning, problem-solving, linguistic interaction and even the production of creative works.

types of innovations. This is despite the relationship being highly industry dependent. In manufactures, the use of technologies is more specialised, driving specific innovation types. Whereas, in service sectors, AI and robots are more extensively integrated into the firm and drive innovation more broadly.

At the academic level, this article contributes to several aspects of the literature. In line with previous works (Blichfeldt & Faullant, 2021), it explores the mechanisms driving the complex relationship between ADTs and innovation processes. Our work emphasizes the importance of AI and robots as the cornerstone of the digital transformation of European SMEs, providing a holistic perspective on how digitalisation is related with the development of complementary technological and non-technological innovations. Among all firms, start-ups and scale-ups lead in the digitalisation of European SMEs, as they take advantage of their more dynamic structure, innovative potential, and market advantages (Piaskowska et al., 2021). Our paper confirms that the current technological wave is driven by heterogenous innovative behaviours of firms and industries and dependent in the technological availability at country level. As a result, an evolutionary (continuous) process of variety generation (innovation) and market selection emerges among SMEs.

At the policy level, we consider that the emergence of studies exploring the links between digital technologies and the innovative capacity of European SMEs is fundamental in addressing the digital distance between the EU and the US (Veugelers et al., 2019b). Our study provides relevant insights for the design of public policies aimed at facilitating the adoption of ADTs. Additionally, we highlight the need to identify start-ups and scale-ups and provide them with incentives to foster their digitalisation and innovation capacities.

The paper is structured as follows. Section 2 provides a literature review providing insights on the determinants of digitalisation, the role of SMEs and the relationship between ADTs and innovation. Section 3 presents the database and provides the main descriptive statistics. Section 4 discusses the econometric strategy, while outcomes are presented and discussed in Sect. 5. Finally, Sect. 6 presents the conclusions of the paper.

2 Literature review

2.1 The adoption of artificial intelligence and robots

The adoption of ADTs is a complex phenomenon, influenced by the intricate nature of modern technologies and the high costs associated with their implementation (Carlaw & Lipsey, 2002; Jovanovic & Rousseau, 2005; Skare & Soriano, 2021). As a result, many firms refrain from major changes, relying on their conventional equipment and processes despite the transformative potential of digitalisation on reshaping their productive structure.

Technologies related to artificial intelligence and robotics range from those based on data, such as machine learning and generative AI, to physical systems such as robots or sensors. Recent advances in communication and machine learning are enabling a more complex and interactive integration of these technologies within firms (Dirican, 2015). The development of task-specific machines and generative AI is reconfiguring workplaces, enhancing the dynamism of innovation processes.

In particular, data-intensive technologies are advancing rapidly, opening new technological scenarios (Ciarli et al., 2021; Lanzolla et al., 2021). The development of AI technologies, in parallel with the emergence of the Internet of Things and sophisticated sensors, is facilitating the way for intelligent computing systems. Furthermore, more sophisticated sensors and wireless communication technologies allow complete mobility on manufacturing floors and self-coordination involving swarms of devices increasing the autonomy of robots, their ability to collaborate with humans, and their precision in various industrial applications (Jaccoud et al., 2024). The emergence of robots with image recognition enables many new applications across industries such as agriculture, manufacturing, and personal services (Autor, 2015). These robots not only perform tasks independently, but also autonomously evaluate and adapt their behaviour. For instance, adaptative robots can interact with customers in personalised ways, learning from each interaction to improve customer services (Bredeche et al., 2018).

The literature identifies several stylised facts that foster the adoption of ADTs. Digital adopters are more competitive in terms of productivity and tend to export more (Camina et al., 2020; Koch et al., 2021;

Añón Higón & Bonvin, 2024). Consequently, firms adopting ADTs are more likely to improve their operations efficiency, productivity and flexibility (Melitz & Redding, 2021; Revoltella et al., 2020). AI and robots require the adaptation of existing IT systems and raise compatibility issues with existing organisational structures (Nolan, 2020). Hence, for successful adoption, firms must develop complementary skills, adapt them to non-digital environments and techniques, train the workforce, align previous production methods and, in essence, modify their organisational culture by developing a whole range of secondary innovations (Ciarli et al., 2021).

However, the nature of the relationship is more intricate and is subject to self-selection patterns. Zeira's (1998) foundational theory posits that only the most successful firms can effectively adopt ADTs and obtain significant returns. Adoption rates of many digital technologies remain relatively low and are biased towards larger firms that are more open to international markets. In particular, Acemoglu et al. (2022) find a pronounced difference in the adoption rates of advanced robots, supporting the idea that ADTs involve major integration costs that limit their adoption to a group of firms.

This underscores the importance of internal capabilities, such as knowledge, skills and human capital, as key enablers of ADTs at the firm level (Soluk et al., 2023). From a technological perspective, there is a hierarchical pattern whereby more sophisticated technologies tend to be adopted only after firms have used and mastered basic applications, and thus have developed basic digital skills (Zolas et al., 2021). This defines part of the heterogeneity in digital adoption, subject to self-selection and path-dependent processes (Montobbio et al., 2022). Among key internal characteristics, the literature identifies firm size, performance and resource availability as relevant variables shaping the adoption of ADTs (Acemoglu et al., 2023; Koch et al., 2021).

In addition to internal factors, firms are subject to competitive forces and other external elements, such as the existence of an adequate digital infrastructure and labour market skills (Agrawal et al., 2019a). The availability of skilled labour is a cornerstone in the effective adoption and use of digital technologies. ADTs require complex, often costly, skills that are scarce in the labour market (Shapiro & Mandelman,

2021). As a result, firms are more likely to adopt ADTs when they operate in a context that ensures the availability of digital skills (Cirillo et al., 2023). Similarly, modern technologies require a more extensive use of physical resources and a better infrastructure to support them, giving firms in more digitalised economies a competitive advantage in the digital transformation (Greenstein, 2019). The combination of internal and external determinants of ADTs adoption leads us to the first set of hypotheses:

Hypothesis 1a. The adoption of AI and robots follows self-selection patterns defined by firm characteristics and other internal capabilities.

Hypothesis 1b. Firms are more likely to adopt AI and robots in highly digitalised economies.

A firm's digital transformation is characterised by interdependencies within a set of emerging technologies causing revolutionary changes at industrial and social levels (Hanelt et al., 2021). Thus, digitalisation is not simply a collection of individual technologies and innovations, it involves a coevolutionary process where reciprocal and dynamic influences—such as in the case of AI and robotics—play a central role (Battaglia et al., 2023). As AI algorithms become more sophisticated, they enable robots to execute increasingly more complex tasks. Alternatively, advancements in robots, such as improved sensors provide richer data leading to better models and solutions.

In essence, this feedback loop creates a self-reinforcing process where the combination of different technologies opens numerous options for achieving tasks more efficiently, enabling the development of new technological trajectories (Ciarli et al., 2021).

However, advancements in digital technologies are not exogenous, as they are shaped by the competitive strategies and challenges faced by innovative firms. As digital technologies evolve, new individual applications emerge, leading to more complex technological interactions that demand new skills and capabilities while offering opportunities to explore novel innovations. The increasingly cross-cutting and interactive nature of ADTs translates into higher degrees of omnipresence and complementarity (Martinelli et al., 2021). Therefore, in addition to internal and external factors driving digitalisation, we propose that AI and robots show a certain degree of complementarity:

Hypothesis 2. The adoption of AI and robots is interdependent.

2.2 Digitalisation in SMEs

Digital technologies facilitate the emergence of new digital business models that are often associated with rapid replication and scalability (Piaskowska et al., 2021). However, the ability to adopt technologies such as AI and robots is strongly related to the internal capabilities and external incentives that are in place prior to the firm's adoption decision (Shahadat et al., 2023). Their internal capabilities allow a rapid identification of opportunities for exploiting short-term benefits, which can potentially become long-term strategic assets due to competitive breakthroughs (Teece, 2007). Therefore, it is crucial to couple the adoption of ADTs with the development of the skills and capabilities required to fully exploit digital technologies (Canhoto et al., 2021).

Among SMEs, start-ups and scale-ups stand out for their dynamic capabilities, which facilitate the adoption of ADTs (Mula et al., 2024). Start-ups, being inherently innovative, possess the capacity to identify, assess and capitalise innovative opportunities in new market niches (Audretsch et al., 2020). Start-ups benefit from their low iteration barriers and a more dynamic workforce ready to adapt to changing technological paradigms (Ghezzi, 2019). This flexibility and responsiveness to market shifts makes them more capable of adopting innovative business models (Hajoary et al., 2024). Additionally, start-ups often have a less entrenched organisational resistance, supporting the adoption of ADT as compared to other SMEs (Aaldering & Song, 2021; Acs et al., 2021). However, their lack of experience moderates their potential to adopt ADTs, as more established firms have a knowledge advantage that allows for a more effective exploitation of digital technologies (Forman & Van Zeebroeck, 2019).

Conversely, scale-ups are characterised by high-growth processes, innovation and the capacity for exploiting economies of scale (Coad et al., 2024). Recently, Mula et al. (2024) show that the development of dynamic capabilities in scale-ups is fundamental to manage the tensions related to rapid growth. These enhanced capabilities have the potential to drive the digital transformation of scale-up

firms. However, scale-ups often face challenges related to managing the pressures of growing early quickly, which can constrain their capacity of AI and robots (Nicholls-Nixon, 2005).

Thus, while start-ups and scale-ups face unique advantages and challenges in adopting ADTs, we expect that these firm types to be more likely to adopt AI and robots compared to other SMEs. This leads to our third hypothesis:

Hypothesis 3. Start-ups and scale-ups are more likely to adopt ADTs than other SMEs.

2.3 The relationship between AI, robots and innovation

Recent empirical studies show that the digital adoption is significantly associated with the development of technological and non-technological innovations (Calvino & Fontanelli, 2023; Cattani et al., 2023; Holl & Rama, 2024; Koch et al., 2021). The extensive applications of AI and robots, along with their interdependencies, offer numerous opportunities to transform business processes. Robotics and AI are the subject of numerous innovations, but they also open new possibilities and facilitate addressing challenges from unexplored perspectives, forming a feedback loop that operates in both directions, generating multiple technological trajectories that evolve over time, at a different pace in different industries (Ciarli et al., 2021). Advances in digital technologies are not completely exogenous, taking into account that innovation is a source as well as an outcome of digital transformations in organizations and industries. Therefore, the use of digital technologies can foster creativity and innovativeness (Blichfeldt & Faullant, 2021; Veugelers et al., 2019a).

AI and robots serve as the outcomes and foundations of innovation due to their inherently knowledge-intensive nature. ADTs significantly foster knowledge spillovers, scalability and collaboration, helping to surpass innovation barriers (Ciriello et al., 2018; Li et al., 2023). Consequently, these technologies spur innovation by allowing a faster accumulation of knowledge and the development of internal capabilities tightly related to innovation (Cockburn et al., 2018). As an example, Igna and Venturini (2023) highlight the strong learning effects from AI

adoption, generating knowledge complementarities across different areas in highly digitalised firms.

ADTs facilitate information storage, data analysis and information transmission, thereby increasing the flexibility of operations and enhancing the interactions within the firm (Blichfeldt & Faullant, 2021). This contributes to a reduction in the costs directly associated with innovation processes, increasing the appeal and demand for existing products or enabling the expansion of product offerings and other organisational changes (Babina et al., 2024). Following Agrawal et al., (2019a, b), AI creates new business opportunities by enabling firms to learn better and faster from big data. Accordingly, Rammer et al. (2022) show a strong association between AI, world-first product innovations and process innovations. Therefore, the adoption of AI and robots is potentially associated with the development of product and process innovations.

Concerning non-technological innovations, digitalised firms have incentives to reallocate their internal resources to knowledge-intensive activities, such as innovation processes, to improve their market position or to close information asymmetries with consumers (Acemoglu & Restrepo, 2018; Rampersad, 2020). This shows that digital adopters have more capacity to explore new market niches and explore new marketing strategies.

Finally, AI and robots drive resource reallocation and human capital adjustments by reducing per-unit labour costs (Agrawal et al., 2019b; Rammer et al., 2022). Analysing the firm as a set of tasks with varying degrees of complexity, the adoption of AI and robots allows the automatization of the relatively less complex tasks (Acemoglu & Autor, 2011).³ Aghion et al. (2017) discuss the possibility that relatively low-skilled tasks, substituted by digital technologies, are replaced by more complex tasks intensive in human capital.

Despite these potential positive linkages, firms must address challenges related to workforce skills and an adaptation of organisational rules in order to obtain returns from ADTs on innovation (Brynjolfsson & McAfee, 2014). Therefore, firms need to

invest in generating learning effects and to train their workforce. These potential barriers can moderate the relationship between digitalisation and innovations. For instance, multiple authors identify insignificant impacts on innovation outcomes from the adoption of artificial intelligence (Babina et al., 2024; Kopka & Fornahl, 2024), making further technological advancements more challenging (Bloom et al., 2020). Despite this, we consider that introducing AI and robots benefits the innovative potential of the firm:

Hypothesis 4. The adoption of AI and robots is positively associated with a firm's innovative capacity.

Regarding specific innovation types, the literature suggests that digital technologies affect differently innovations related to the reorganisation of production methods (i.e. process innovations and organisational innovations) or innovations with a clear market focus (i.e. product and marketing innovations (Ciarli et al., 2021). These differences are tightly related to the specific roles that an advanced digital technology serves and the ability of the firm of generating, integrating and recombining digital knowledge into other organisational dimensions (Colfer & Baldwin, 2016).

As robots become increasingly autonomous, their integration into business processes can drive significant performance gains. However, the integration of smart robots may foster non-technological innovations such as organisational innovations due to the reorganisation of workers and tasks. Additionally, smart robots may also drive marketing innovations when they become an advertising claim for customers.

Concerning artificial intelligence, there are internal and external facts that may affect whether AI promotes the development of innovations. Since AI facilitates the management of big data and information this is technology that can be implemented in different innovation dimensions.⁴ AI is crucial for the development of technological innovations, since the use of AI increases the storage and use of information

³ This leads to a reduction of production costs and generates efficiency gains that lead to a reduction in the price of a product or an enhancement in product quality (Zeira, 1998).

⁴ A recent work from Bahoo et al. (2023) identifies eight fields where AI may promote innovation (business models, product innovation, open innovation, innovation process, innovation structure, firm's knowledge and market performance and supply chain management).

that may improve business processes by increasing their efficiency or reducing time development, while they can also improve the development of more customized products or forecast changes of needs.

Despite the scarce evidence in the literature analysing which specific innovations are more tightly associated with concrete digital technologies, our final hypothesis is the following:

Hypothesis 5. The specific roles of AI and robots associate differently with each specific innovation outcome.

3 The database and descriptive statistics

3.1 The database

Our data belongs to the Flash Eurobarometer 486 “SMEs, Start-ups, Scale-ups and Entrepreneurship” conducted by TNS Political & Social at the request of the European Commission.⁵ The survey was carried out between February 19th and May 5th, 2020, and covers all European countries in addition to Bosnia and Herzegovina, Brazil, Canada, Croatia, Great Britain, Iceland, Japan, Kosovo, Makedonia, Norway, Serbia, Turkey and USA, with a sample of 16,365 firms. The target population includes firms with 1 to 250 employees, but it contains a subsample of larger-sized firms. For the purposes of this analysis, the empirical work primarily focused on the 27 EU member countries.

The cross-sectional nature of the data prevents establishing causality between the variables of interest. Despite this, FL 486 is a relevant dataset for addressing how the adoption of digital technologies affects innovative performance among European firms.⁶ FL 486 asked surveyed firms if they

⁵ European Commission: Flash Eurobarometer 486: SMEs, start-ups, scale-ups and entrepreneurship, February-May 2020. TNS Political & Social [Producer]; GESIS Data Archive: ZA7637, dataset version 2.0.0. (2020), <https://doi.org/10.4232/1.13639>.

⁶ See for instance, Cattani et al. (2023), Ardito (2023) and Holl and Rama (2024). Ardito (2023) reveals that each digital technology has heterogeneous impacts on sustainable innovations. Additionally, Cattani et al. (2023) and Holl and Rama (2024) highlight the role of the geographical environment in adopting ADTs.

had adopted some of the seven ADTs considered: AI and machine learning; cloud computing; robots; smart devices and intelligent sensors; big data analytics; highspeed infrastructure; and blockchain technologies.⁷

To control for country-specific characteristics, we employ the Digital Economy and Society Index (DESI), which reports composite indexes summarizing indicators on the digital performance of EU member states across four main dimensions: human capital, connectivity, integration of digital technologies, and digital public services.⁸ The information in DESI is monitored and published annually since 2014 by the European Commission. Here, we focus on the indexes from 2020, as they match the specific firm information from FL 486.

3.2 Descriptive statistics

Table 1 presents our main variables.⁹ To provide a broad perspective of the relationship between ADTs on innovation, we cover a wide spectrum of potential innovation outcomes. Product innovations refer to the introduction of new products to the market or significantly improving existing ones. Process and organisational innovations respectively focus on increasing the efficiency of operations and the design of more effective managerial practices. Finally, marketing innovations involve the development and implementation of new strategies to promote a firm’s goods or services.

⁷ Other databases are the following. The Survey on Business Strategies (ESEE – Encuesta Sobre Estrategias Empresariales) is an annual survey of 2,000 Spanish manufacturing firms with three decades of coverage. The European Manufacturing Survey (EMS) compiles information about the adoption and impact of robots for manufacturing firms. EMS selects random firms from seven European countries (Austria, France, Germany, Spain, Sweden, Switzerland, and The Netherlands). There are five waves: 2001–02, 2003–04, 2006–07, 2009–10 and 2012–13. However, EMS only includes industrial robots and their application in the manufactures. Finally, the EIB Group Survey on Investment and Investment Finance is an annual survey of 12,800 EU and US firms. It is designed to build a panel of observations to support time series analysis.

⁸ The database is available in <https://digital-strategy.ec.europa.eu/en/policies/desi>

⁹ Tables 6 and 7 show the main descriptive statistics and correlations.

Table 1 Definition of variables

<i>Innovation</i>	<i>Dummy indicating whether the firm has introduced ...</i>
Product	... a product innovation during the last 12 months
Process	... a process innovation during the last 12 months
Organisational	... an organisational innovation during the last 12 months
Marketing	... a marketing innovation during the last 12 months
<i>ADTs</i>	<i>Dummy indicating whether the firm uses...</i>
Artificial intelligence	... Artificial intelligence
Robots	... robots
<i>Firm characteristics</i>	<i>Dummy indicating whether the firm ...</i>
Start-up	...is less than 5 years old, is innovative, and has plans to grow by at least 10%
Scale-up	...has grown by at least 30% int terms of sales or employees during the last three years
Exports	... exports to foreign markets
Global value chain	... belongs to a global value chain
Exports and global value chain	... exports and belongs to a global value chain simultaneously
Firm size	Firm size in terms of the number of employees
Firm age	Number of years
Big city	... is in a big city
Industrial area	... is in an industrial area
Goods	... trades with goods directly
ICT	... belongs to ICT sectors
<i>DESI indicators</i>	<i>Percentage of ...</i>
Internet use	... individuals who use the internet at least once a week
Firms providing ICT training	... firms that provided ICT training to their personnel
ICT specialists	... ICT specialists over total employment
100 Mbps broadband take-up	... households subscribing to a fixed broadband of at least 100 Mbps
VHCN coverage	... households covered by any fixed Very High-Capacity Network
Mobile broadband take-up	... individuals with number of mobile data subscriptions
SMEs selling online	... SMEs selling online
Selling online cross-border	...SMEs that carried out electronic sales to other countries
e-Government users	...internet users with public authorities

As our key explanatory variables, we consider the use of artificial intelligence and robots. AI increases a firm's ability to compute large volumes of information and automatise processes with the use of generative

AI. On the other hand, robots increase the efficiency of relatively simple and repetitive operations. According to Table 6 (Appendix 1), some 6.9% of European SMEs adopt AI, while 8.3% adopt robots. Across sectors,

Table 2 Cross-tabulation showing advanced digital technologies and innovation outcomes

		Innovation outcomes			
		Product	Process	Organisational	Marketing
Advanced digital technologies	Artificial intelligence	0.432 (0.496)	0.301 (0.459)	0.257 (0.437)	0.303 (0.460)
	Robots	0.450 (0.498)	0.450 (0.498)	0.246 (0.431)	0.217 (0.412)

Note: All values show means and standard deviation in brackets

Source: own elaboration from FL 486

manufacturing firms tend to adopt more robots than firms operating in services sectors, which depend more on AI in relative terms. Regarding the distribution of innovation outcomes, product innovations are the most common, being developed by 27.2% of the total sample. Furthermore, 19.9% and 19.5% of firms develop marketing and process innovations, respectively. Finally, organizational innovations are the least common (some 15.6%).

Table 2 cross-tabulates the distribution of ADTs and innovation outcomes. According to our information, firms adopting AI are more likely to develop organisational and marketing innovations on average terms. Alternatively, robot adopters are more likely to introduce product and process innovations. Among AI adopters, product innovations are the most common, followed by marketing and process innovations. For robot adopters, product and process innovations are equally adopted. However, from a descriptive perspective, we cannot identify significant robust associations across groups. These associations will be thoroughly analysed with inference tools.

As additional control variables, we consider whether a firm is a scale-up or a start-up. Scale-ups correspond to firms that grew by at least 30% in terms of sales or employees during the last 3 years. Start-ups are innovative firms that are less than 5 years old and have ambitious growth plans. According to the descriptive statistics, more scale-ups operate in manufactures (20.6%), while more start-ups are in service sectors (6.2%).

Firm size and firm age proxy a firm's resources and experience. On average, firms employ 32 workers and are 23.6 years old. In terms of internationalisation, 30.7% of firms only export, 3.8% only participate in global value chains and 5.1% export and participate in global value chains simultaneously, which shows the limited internationalisation of European SMEs. Regarding firm location, 46.6% of firms locate in big cities, while 16.6% are placed in industrial areas. Finally, a third of the sample is composed of

firms trading directly with goods (38.8%), and a small proportion belongs to ICT industries (3.8%).

Table 8 presents the share of firms adopting AI and robots by sectors and size classes. The overall percentage of firms using AI is 7.2% and using robots is 9.1%. At the sectoral level, there are clear heterogeneous factors. For instance, the ICT sector has the highest percentage of AI users (25%) while robots are adopted more by SMEs in manufactures and those firms operating in the electricity, gas and steam sectors. Similarly, the largest firms have the highest adoption rates for all technologies, while the smallest ones present lower rates of adoption. To sum up, the results provide insights into the heterogeneous pattern across sectors and firm size.¹⁰

Furthermore Tables 9 and 10 provide a breakdown of the adoption of all the digital technologies across European regions. We observe that the most common technology is cloud computing (48%) followed by high-speed infrastructure. Technologies such as blockchain and AI are less common (7.2% and 3.1%, respectively). There is a high divergence in the adoption across regions. SMEs in Northern and Core countries present the higher shares, regardless of the technology. Furthermore, start-ups and scale-ups in general present higher shares of adoption of ADTs. This pattern is particularly high for cloud computing, smart devices and high-speed infrastructure.

In addition to firm characteristics, a set of indicators captures country-specific heterogeneities. These variables refer to the usage of internet and the level of ICT training and specialists in firms, the spread of advanced digital infrastructure and the use of online platforms to conduct trading activities or interaction

¹⁰ Robots are a comparatively well-established technology in manufacturing, but, more recently, have been widely adopted in services. Additionally, the adoption of robotics in manufacturing is highly skewed and mostly adopted by a few large firms. In addition, robot adopters are larger and grow faster than their competitors (Acemoglu et al., 2020).

Table 3 Factorization of DESI indicators

Variable	(1) Digital skills	(2) e-Commerce	(3) Infrastructure
Internet use	0.927	0.236	0.104
Firms providing ICT training	0.630	0.567	-0.261
ICT specialists	0.793	0.295	0.032
100 Mbps broadband take-up	0.126	0.129	0.601
VHCN coverage	0.056	-0.223	0.736
Mobile broadband take-up	0.930	0.300	-0.047
SMEs selling online	0.448	0.768	0.113
Selling online cross-border	0.295	0.763	-0.222
e-Government users	0.817	0.146	0.138

Source: own elaboration from DESI

with public institutions. To properly model the effects of country characteristics, we incorporate them into three factors applying Principal Component Analysis (PCA) to overcome potential multicollinearity issues.¹¹

Table 3 presents the factors. We refer to Factor 1 as *Digital Skills*, as it is characterised by the usage of the internet, the spread of ICT training, the proportion of ICT specialists, the spread of mobile broadband take-up, the share of SMEs selling online and the use of electronic platforms to interact with public institutions. Factor 2 is predominantly composed of ICT training and national or international internet sales. Consequently, we refer to this factor as *e-Commerce*. Finally, Factor 3

mainly comprises the spread of medium and high-speed internet infrastructure. Therefore, we refer to this factor as *Infrastructure*.

4 Methodology

4.1 Econometric strategy

This section presents the econometric strategy applied to explore the factors associated with the decision to adopt AI and robots, as well as their relationship with multiple innovation outcomes. If European SMEs can freely adopt both AI and robots as they become available, our approach considers a sequence of actions in which firms decide to adopt these digital technologies and increase their innovation performance. This two-stage approach allows us to control the endogeneity and multicollinearity problems due to the similarity in the determination of ADTs and the development of innovation activities.

As our endogenous variables in the two stages do not follow a linear distribution, a standard two-stage linear squares assuming a linear distribution of probabilities or, more generally, a two-stage predictor substitution, would provide biased estimates (Blundell & Powell, 2001; Terza et al., 2008). Therefore, we apply a two-stage residual inclusion (2SRI) model following the routinisation proposed by Terza (2017) to asymptotically adjust the estimation in the second stage. 2SRI models allow for non-linearity when the first or second-stage dependent variables are binary. More specifically, our first stage applies a bivariate probit model assuming an interrelationship in the adoption of artificial intelligence and robots:

¹¹ The PCA methodology derives F factors from M variables, providing a linear reconstruction of the variables from the original variance-covariance matrix in the following manner:

$$\theta_{i,m} = \sum_{f=1}^F b_{f,m} \lambda_{i,f} + e_{i,m}$$

where $\theta_{i,m}$ is the value of the firm-year observation i belonging to the variable m ; $b_{f,m}$ are the linear coefficients of variable m on factor f , referred to as factor loadings; $\lambda_{i,f}$ represents a firm-year observation i belonging to factor f ; $e_{i,m}$ is the residual, referred to as unique variance, as it reflects the share of the value not explained by covariances. PCA finds the optimal factor loadings that minimize the residual (unique) variance across all variables. The factors are composed, to a greater or lesser extent, of all the variables introduced in the PCA. Relatively low factor loadings however are not stable. The consensus is that factor loadings higher than 0.4 after orthogonal rotation are considered sufficient to determine a strong association between a variable and a factor (Guadagnoli & Velicer, 1988).

$$Z_{i,m}^* = b_0 + b_1 X_i + b_2 W_i + \epsilon_{i,m} \quad (1)$$

where $Z_{i,m}^*$ is the firm-specific predicted likelihood of adopting an advanced digital technology $m = 1, 2$ referring to AI or robots, respectively. b_0 is the intercept, and b_1 is a vector of parameters determining the effects of the firm-specific controls X_i , which include sector and country fixed effects. Furthermore, b_2 is another vector determining the influence of the matrix of instrumental variables W_i , which corresponds to three factors determining the country-level degree of digitalisation. Finally, ϵ_i are firm-specific errors. This structure explicitly models the interrelation between AI and robots by allowing for correlations between both error terms (Greene, 2000).

After Eq. (1) is estimated, the residuals are defined as:

$$r_{i,m} = Z_{i,m} - Z_{i,m}^* \quad (2)$$

where $Z_{i,m}$ is the observed adoption of AI or robots. Based on these results, our second stage calculates the likelihood of developing product, process, organisational, and marketing innovations,¹² these being $j = 1, 2, 3, 4$, respectively, taking the following form:

$$Y_{i,j}^* = \beta_0 + \beta_1 Z_{i,m} + \beta_2 X_i + \beta_3 r_{i,m} + \epsilon_{i,j} \quad (3)$$

where:

$$Y_{i,j} = \begin{cases} 1 & \text{if } Y_{i,j}^* > 0 \\ 0 & \text{if } Y_{i,j}^* < 0 \end{cases} \quad (4)$$

$Y_{i,j}$ identifies all innovation outcomes. β_0 is the intercept. β_1 determines the effects of adopting AI and robots. β_2 determines the effects of the exogenous variables X_i . β_3 identifies the endogeneity of the relationship between innovation and ADTs defined by $r_{i,m}$ and $\epsilon_{i,j}$ are error terms. Equation (3) is estimated following a multivariate probit structure, which allows for correlations across all innovation outcomes, through the Geweke-Hajivassiliou-Keane method (Cappellari & Jenkins, 2003; Geweke, 1989; Hajivassiliou & McFadden, 1998; Keane, 1994).

¹² Linear distributions of instrumentalized variables provide more robust outcomes in multiple-stage regressions.

However, the results from Eq. (3) cannot be directly interpreted, as the coefficients obtained do not include the relationships established in the first stage. To solve this issue, we obtain the asymptotically correct standard errors (ACSE) for the second stage following Terza (2017).

As both stages are obtained with a maximum likelihood estimator, the ACSE for each element of β is the square root of the same diagonal element in the following matrix:

$$V(\hat{\beta})A'V(\hat{b})A'V(\hat{\beta}) + V(\hat{\beta}) \quad (5)$$

where $V(\hat{b})$ and $V(\hat{\beta})$ are the estimated covariance matrices for the first and second stages, respectively and:

$$A = \sum_{i=1}^n \nabla_{\beta} \ln(\hat{f}_i^{*f}) \nabla_b \ln(\hat{f}_i^{*b}) \quad (6)$$

where $\nabla_{\beta} \ln(\hat{f}_i^{*f})$ and $\nabla_b \ln(\hat{f}_i^{*b})$ are the gradients $f^*(Y|Z, W; \beta, b)$.

As a final note, we remark that continuous variables such as firm size and age were converted into logarithms and that the estimation include sector-specific fixed-effects to capture sectoral heterogeneities and country-specific effects for country heterogeneities.¹³

4.2 Relevance and exogeneity conditions

In a two-stage setting, the instrumental variables utilised must fulfil the relevance and exogeneity conditions, which are defined by $E(Z, W) \neq 0$ and $E(Y, W) = 0$, respectively. In other words, the instruments used must be significantly correlated with a firm's specific level of digitalisation but not with its innovation outcomes.

¹³ Concerning the country-specific effects, countries are grouped into wider geographical clusters to avoid collinearity issues with the factor variables. Here, Western European countries are Austria, Belgium, Germany, France, Ireland, Luxembourg and the Netherlands. Mediterranean countries are Spain, Italy, Portugal and Cyprus. Eastern countries are Bulgaria, Czechia, Croatia, Hungary, Lithuania, Latvia, Poland, Romania, Slovenia and Slovakia. Finally, northern countries are Denmark, Sweden, Finland and Estonia.

According to the correlation matrix Table 7, the relationship between the country-specific level of digitalisation, the firm-specific digitalisation and the innovation outcomes is low in all possible combinations, except for the digital skills factors. While this a strong signal for the exogeneity condition, it hampers the interpretation of the instruments' relevance in the first stage. However, the literature provides strong evidence motivating the relationship between the country and the firm-specific levels of digitalisation.

We define the relevance of the available skills in the labour market and the state of the infrastructure when determining a firm's adoption of digital technologies in Sect. 2 (Cirillo et al., 2023; Greenstein, 2019; Shapiro & Mandelman, 2021). The nature of this relationship is motivated by the needs that digital technologies generate and how easy it is for firms to cover these needs. Additionally, there are relevant digital knowledge spillovers from the rest of the economy that motivate a firm's digitalisation in highly digitalised economies or discourage firms from digitalising if the rest of the economy is poorly digitalised (Gal et al., 2019; Mosiashvili & Pareliussen, 2020).

Therefore, from the combination of the observed correlations in our data and the insights provided by previous research, we consider the factors defining the country-level digitalisation as good instruments, although they are subject to limitations that affect the imputation of direct causality between ADTs and innovations. For this reason, we acknowledge that our IV approach does not completely eliminate endogeneity due to the simultaneity of the digitalisation and innovations decision. Nevertheless, our econometric strategy reduces the multicollinearity problem arising from the adoption of AI and robots, innovation and their determinants.

5 Results

This section presents and discusses the base outcomes from the empirical analysis. Table 4 shows the estimations for the first stage of our 2SRI setting, which explains the adoption of artificial intelligence in Column 1 and robots in Column 2.

We observe that scale-ups and start-ups are more likely to digitalise, but they present different digital

adoption patterns. Scale-ups are associated with the adoption of artificial intelligence and robots, while start-ups are more likely to adopt only robots. On average, both types of SMEs have a great absorptive capacity that makes it easier to adopt the most ADTs and implement different innovative strategies (Zahra & George, 2002). These firms exploit the new knowledge and their existing technological excellence to adapt to demanding market and environmental changes (Camisón & Forés, 2010). Therefore, these firms generate the optimal substrate for the adoption of ADTs.

The internationalisation of the firm also plays a key role in the adoption of artificial intelligence and robots, especially for firms exporting and belonging to global value chains simultaneously. Furthermore, firm size is significantly associated with the adoption of both ADTs. For firm age, we do not observe any significant association. These results remark the role of specific firm characteristics, such as being subject to more competition in international markets and having larger resources, in determining digital adoption patterns, confirming the principles of self-selection in the adoption of ADTs (Montobbio et al., 2022; Soluk et al., 2023). In terms of location, the only significant association is found for robots in industrial areas. Firms trading directly with goods are more likely to adopt robots in their production systems, while firms in ITC sectors are more likely to adopt these technologies.

In terms of the country-specific factors, firms in countries with higher levels of digital skills, e-commerce and a better infrastructure are more likely to adopt artificial intelligence. For robots, we find a significant association with the digital skills present in the country and the infrastructure. It is likely that digital industrialization supports local firms with basic digital equipment and services, resulting in an increased investment in digitalization. Our results contribute to Li et al. (2023), as we find firms more likely to rely on the existing environment created by pioneers' technologies and engage in free-riding behaviours rather than committing to generating breakthroughs on their own, as it is a strategy subject to larger costs and risks. Regarding the interdependencies in the adoption of AI and robots, the

Table 4 First stage bivariate probit determining the adoption of artificial intelligence and robots

	(1) Artificial intelligence	(2) Robots
Firm-specific characteristics		
Scale-up	0.155*** (0.048)	0.176*** (0.047)
Start-up	0.143 (0.093)	0.522*** (0.090)
Exports	0.294*** (0.045)	0.296*** (0.044)
Global value chain	0.275*** (0.092)	0.211** (0.093)
Exports and global value chain	0.534*** (0.075)	0.499*** (0.072)
Size (Logs)	0.114*** (0.014)	0.194*** (0.014)
Age (Logs)	-0.031 (0.029)	0.042 (0.029)
Big city	0.028 (0.041)	0.059 (0.040)
Industrial area	-0.034 (0.059)	0.094* (0.053)
Goods	-0.057 (0.050)	0.206*** (0.047)
ITC	1.057*** (0.092)	0.511*** (0.108)
Country-specific characteristics		
Digital skills	0.132*** (0.040)	0.127*** (0.038)
e-commerce	0.043* (0.025)	0.008 (0.025)
Infrastructure	0.069** (0.030)	0.126*** (0.028)
Geographical cluster fixed-effects	Yes	
Sector fixed-effects	Yes	
Observations	10,626	
Wald test for zero slopes	1,205.92***	
Correlation (AI, Robots)	0.451*** (0.026)	
Log likelihood	-4,849.22	

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients (Std. Err.) reported. Non-exporters and firms not participating in global value chains are the base outcome for internationalisation dummies. Firms located in small or medium cities are the baseline for location dummies. Retail sectors are the base outcomes for the sector fixed-effects. Western European countries are the base outcome for geographical cluster fixed-effects

estimated correlation between the two from the bivariate probit is positive and significant, which highlights the complementary adoption of these two technologies.

The results from the first stage of the 2SRI model support our first three hypotheses. First, we find different adoption patterns depending on a firm's specific internal characteristics and the environment in

which the organisation operates (Hypothesis 1a and Hypothesis 1b). Second, the correlation between the two specifications in the bivariate probit setting, which provides a value of rho of 0.451 significant at $p < 0.01$, confirms the complementarities in the adoption of both AI and robots (Hypothesis 2). Third, scale-ups and start-ups are more likely to digitalise

Table 5 Second stage multivariate probit with residual inclusion and asymptotically adjusted coefficients for the determinants of innovation

	Artificial intelligence				Robots			
	(1) Product	(2) Process	(3) Organisational	(4) Marketing	(1) Product	(2) Process	(3) Organisational	(4) Marketing
Digital technologies – IV								
Artificial intelligence	0.967*** (0.166)	1.297*** (0.180)	0.643*** (0.186)	0.151 (0.172)				
Robots					0.914*** (0.131)	1.297*** (0.142)	0.410*** (0.144)	0.302** (0.135)
Firm-specific characteristics								
Scale-up	0.220*** (0.044)	0.149** (0.001)	0.236*** (0.048)	0.279*** (0.045)	0.208*** (0.042)	0.156*** (0.045)	0.263*** (0.045)	0.219*** (0.043)
Start-up	0.753*** (0.069)	0.680*** (0.074)	0.686*** (0.075)	0.938*** (0.070)	0.510*** (0.091)	0.393*** (0.099)	0.623*** (0.100)	0.793*** (0.093)
Exports	0.086 (0.057)	-0.108* (0.062)	0.035 (0.064)	0.116* (0.060)	0.090* (0.048)	-0.069 (0.053)	0.094* (0.054)	0.013 (0.050)
Global value chain	0.180** (0.084)	-0.023 (0.091)	0.240*** (0.090)	0.239*** (0.086)	0.224*** (0.075)	0.071 (0.082)	0.313*** (0.079)	0.155** (0.076)
Exports and global value chain	0.211* (0.108)	-0.200* (0.117)	0.169 (0.119)	0.294*** (0.112)	0.229** (0.090)	-0.119 (0.098)	0.280*** (0.097)	0.114 (0.092)
Size (Logs)	-0.032 (0.021)	-0.029 (0.023)	0.060** (0.023)	0.017 (0.022)	-0.086*** (0.026)	-0.086*** (0.029)	0.061** (0.029)	-0.043 (0.027)
Age (Logs)	0.089*** (0.021)	0.097*** (0.023)	0.058** (0.023)	0.085*** (0.022)	0.045** (0.021)	0.038* (0.099)	0.037 (0.023)	0.078*** (0.022)
Big city	0.092*** (0.028)	-0.052* (0.031)	-0.014 (0.032)	0.055* (0.029)	0.068** (0.029)	-0.079** (0.032)	-0.018 (0.032)	0.037 (0.030)
Industrial area	0.174*** (0.042)	0.362*** (0.044)	0.110** (0.046)	0.119*** (0.043)	0.088** (0.045)	0.071 (0.048)	0.075 (0.048)	0.090** (0.045)
Goods	0.281*** (0.035)	0.188*** (0.038)	0.007 (0.040)	0.073** (0.036)	0.107** (0.042)	-0.047 (0.073)	-0.071 (0.047)	0.027 (0.043)
ITC	0.020 (0.185)	-0.753*** (0.204)	-0.083 (0.207)	0.590*** (0.192)	0.409*** (0.098)	-0.122 (0.108)	0.274** (0.108)	0.387*** (0.101)
Residuals	-0.614*** (0.160)	-0.909*** (0.175)	-0.404** (0.180)	0.124 (0.166)	-0.615*** (0.125)	-0.756*** (0.136)	-0.216 (0.138)	-0.247* (0.128)
Sector fixed-effects	Yes				Yes			
Country fixed-effects	Yes				Yes			
Observations	10,626				10,626			
Wald test for zero slopes	2,254.61***				2,310.86***			
LR test for no correlation	1,221.37***				1,226.10***			
Log likelihood	-19,283.65				-19,254.05			

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients (Std. Err.) reported. Non-exporters and firms not participating in global value chains are the base outcome for internationalisation dummies. Firms located in small or medium cities are the baseline for location dummies. Retail sectors are the base outcomes for the sector fixed-effects. Western European countries are the base outcome for geographical cluster fixed-effects

than other SMEs (Hypothesis 3). Nevertheless, they differ in their digital adoption patterns, scale-ups being more likely to adopt AI and robots and start-ups more likely to adopt only robots.

Table 5 provides the outcomes from the multivariate probit regression, the second stage of the 2SRI model. Artificial intelligence is significantly associated with product, process and organisational innovations. Similarly, robots are related to all innovation types. On the one hand, the results show the potential interactions between the innovation outcomes and the adoption of ADTs. On the other hand, these positive coefficients are the result of a more effective usage of these new technologies that increases the efficiency of operations, enhances the quality of products, generates new products, improves how firms are organised and how the firm addresses its consumers. To sum up, our results show that more innovative firms are also more likely to have adopted artificial intelligence and robots.

When firms launch new products or expand their product variety, they face uncertainty regarding what customers want and how customer preferences might change. Using AI to analyse customer data can potentially enable firms to overcome this hurdle, providing the right product on a hyper-individualized basis. Furthermore, the availability of resources arising from the adoption of ADTs allow the firm to reallocate resources to more complex tasks, such as innovation activities (Antonoli et al., 2024) (Hypothesis 4). However, the association between ADTs and specific innovation outcomes is heterogeneous. According to our results, both AI and robots are more tightly related to product and process innovations, while to a lower extent with innovations addressing organisational and marketing dimensions (Hypothesis 5). This result is characterised by the fact that the digital transformation is closely linked to technological innovations.

Start-ups and scale-ups are the most innovative firms in our sample, which aligns with previous evidence (Audretsch et al., 2020). Regarding other control variables, the influence of the exporting activity is positive in some cases but is far less consistent than in the adoption decision. This underscores that

exports and internationalisation in European SMEs do not spur innovation directly. Internationalisation forces firms to adopt better strategies, such as becoming more digitalised, which drive innovation extensively.

Firm size is associated with process innovations, but smaller firms are more likely to develop product and process innovations in the robot's specification. As Hottman et al. (2016) suggest, digital technologies such as AI or robots have similar scale advantages and are important drivers of the superstar firm phenomenon. Mature firms have a knowledge advantage that drives innovation more extensively. Furthermore, firm location patterns define a relevant distribution of innovation outcomes, especially for firms in industrial areas. Finally, firms trading directly with goods are more likely to generate product and process innovations, while firms in ITC are more likely to develop all innovations, except process innovations.

5.1 Extension. Manufacturing versus service sectors

A key issue in this digital transformation is the different adoption at multiple sectoral levels. Authors such as Gallouj and Savona (2009) already established that manufacturing firms differ from services since the former focus their innovation efforts on the design, production, and quality of tangible products, aiming to achieve higher efficiency levels, cost reductions, and improvements in the physical attributes of goods. In contrast, service firms emphasize process innovations and customer experience, given the intangible nature of services, which are often produced and consumed simultaneously. This focus leads to innovation that prioritizes enhanced customer interaction, personalization, and service efficiency.

The robustness of the base outcomes across manufacturing and service sectors is tested in Appendix 2. Regarding digital adoption patterns across sectors, we find a lack of significance of the country-level digitalisation in the adoption decision of AI in manufacturing firms. Additionally, service firms located in industrial areas are more likely to adopt robots into their productive

structure. These two differences show two relevant patterns. First, firms in manufacturing sectors seem to be less dependent from the environmental externalities and knowledge spillovers in the short term. A potential explanation is that manufacturing firms usually invest in ADTs which necessitate long-term investments and substantial physical infrastructure developments. Therefore, they require deeper structural changes in the environment. Secondly, firms in service sectors are influenced by the needs of their surroundings. Service firms have more capacity to benefit from environmental changes given the intangible nature of their production.

Regarding the sectoral heterogeneities, AI is more related to product, process, and marketing innovations in manufacturing sectors. However, robots are only significantly associated with product and process innovations. Alternatively, in service sectors, both ADTs are associated with all innovation outcomes significantly. Our results confirm that service firms exhibit greater adaptability, with the ability to scale and modify services rapidly, particularly when leveraging digital platforms or advanced analytics tools. Among service firms, technological innovation primarily revolves around digital tools and information technologies, such as software, digital platforms, and artificial intelligence, which enable flexible, customer-adaptive services with a reduced dependence on physical assets.

This highlights that advanced digital technologies are more broadly integrated in the service sector than in the manufacturing industries, which are more specific in the tasks each digital technology covers. Therefore, digitalisation in European manufactures is used for more specialised purposes than in the rest of the economy, while firms in service sectors exploit artificial intelligence and robots in a broader manner.

6 Conclusions

The cross-cutting nature of robots and artificial intelligence is strongly associated with innovation activities. Despite the potential benefits from digitalisation, European firms, and in particular SMEs, are lagging in the adoption of ADTs due to associated complexity and costs. To provide a better understanding of the topic, this paper explores the determinants of AI and robot adoption and their relationship with multiple innovation outcomes in a sample of European SMEs.

In a two-stage residual inclusion model, our results show that digitalisation is determined by specific firm characteristics, such as internationalisation and firm size, as well as external factors to the firm, more specifically digital skills and infrastructure. Among SMEs, we find start-ups and scale-ups to be the most digitalised and innovative firms, thus taking a leading role in the European digital transition.

Concerning the relationship between artificial intelligence, robots and innovation we emphasize that, on average, both digital technologies are positively associated with all innovation outcomes. However, the relationships vary considerably across industries. Digitalisation in European manufactures is devoted to more specialised needs and drives specific innovation types. Alternatively, in service sectors ADTs are more broadly integrated into the firm, fostering multiple innovation types.

Our paper provides the first comprehensive study analysing simultaneously the digital adoption patterns and their effects on innovation in European SMEs. Firstly, our results disentangle the interlinkages and determinants of the adoption of artificial intelligence and robots. Secondly, while most studies focus solely on individual characteristics, we underscore the importance of territorial factors due to the availability of skills,

infrastructure and other externalities. Thirdly, the motivations for adopting AI and robots stem from the expectation that these will increase the efficiency of production and other internal processes. We discuss and analyse the interactions of these efficiency gains and other factors such as a better use of information linking them to the likelihood of developing product, process, organisational and marketing innovations.

At the policy level, the discrepancy between private and social returns to digitalisation and innovation causes policy intervention to be essential to avoid under-investments in digital technologies, hampering the innovative potential of European firms. Here, our results highlight the importance of fostering a more favourable environment for the development of innovative start-ups and scale-ups, which are often at the forefront of AI adoption and use. This can become a virtuous cycle of innovation and AI development, in which more advanced firms attract highly skilled talent and investment. Laggard firms may take advantage of leaders by having access to specialised resources such as knowledge or human skills. Therefore, to reduce the digital divide between North American and European firms, it is essential to implement policies aimed at fostering a favourable technology ecosystem and business environment, particularly for young SMEs.

As a final remark, our study opens several research lines on the role that digital technologies have in fostering innovation, enhancing the performance of R&D activities and the implementation of technological and non-technological innovations. Thus, the effects of digital applications transcend the limits of technological innovations, creating

novel invention methods. Future research should investigate more deeply the effects that multiple ADTs might have on different typologies of R&D investment and the innovation strategies pursued by firms.

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Author Contribution Agustí Segarra-Blasco conceived and designed the study, supervised the dataset, analysed the data and wrote the manuscript. Josep Tomàs-Porres managed the dataset and wrote the empirical analysis. Mercedes Teruel contributed to the conceptualisation, wrote and supervised.

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Data availability The dataset analysed during the current study belongs to Flash Eurobarometer 486: SMEs, start-ups, scale-ups and entrepreneurship, February-May 2020. TNS Political & Social [Producer]; GESIS Data Archive: ZA7637, dataset version 2.0.0. (2020). The dataset is available in https://search.gesis.org/research_data/ZA7637

Declarations

Competing interests The authors declare no competing interests.

Ethical approval This study was conducted in accordance with the ethical guidelines of COPE.

Appendix 1. Additional descriptive statistics

Table 6 Descriptive statistics

Variable	Full sample	Manufactures	Services
Innovation			
Product	0.272 (0.445)	0.348 (0.476)	0.275 (0.447)
Process	0.195 (0.396)	0.331 (0.471)	0.164 (0.370)
Organisational	0.156 (0.363)	0.160 (0.367)	0.156 (0.363)
Marketing	0.199 (0.399)	0.168 (0.374)	0.222 (0.415)
Advanced digital technologies			
Artificial intelligence	0.072 (0.253)	0.085 (0.269)	0.074 (0.262)
Robots	0.091 (0.457)	0.214 (0.395)	0.060 (0.238)
Firm characteristics			
Scale-up	0.190 (0.392)	0.206 (0.404)	0.184 (0.388)
Start-up	0.060 (0.237)	0.052 (0.223)	0.062 (0.241)
Firm size	32.207 (156.167)	51.923 (145.462)	26.566 (176.069)
Firm age	23.684 (20.571)	27.122 (21.038)	22.595 (19.746)
Exports	0.307 (0.461)	0.520 (0.500)	0.288 (0.453)
Global value chain	0.038 (0.191)	0.013 (0.113)	0.047 (0.211)
Exports and global value chain	0.051 (0.220)	0.103 (0.304)	0.047 (0.211)
Big city	0.466 (0.499)	0.336 (0.472)	0.514 (0.500)
Industrial location	0.122 (0.328)	0.209 (0.407)	0.106 (0.307)
Goods	0.388 (0.487)	0.688 (0.464)	0.386 (0.487)
ICT	0.038 (0.191)	0.0 (0.0)	0.061 (0.240)
DESI indicators			
Internet use	79.262 (9.960)	77.833 (9.752)	79.458 (10.089)
Firms providing ICT training	20.642 (8.593)	19.900 (8.298)	20.817 (8.590)
ICT specialists	3.879 (1.240)	3.741 (1.172)	3.900 (1.258)
100 Mbps broadband take-up	19.097 (13.620)	17.489 (13.527)	19.323 (13.771)
VHCN coverage	37.028 (23.712)	37.060 (23.138)	36.724 (23.935)
Mobile broadband take-up	73.184 (12.153)	71.643 (11.719)	73.548 (12.245)
SMEs selling online	16.976 (6.485)	16.033 (6.041)	17.068 (6.535)
Selling online cross-border	8.480 (3.460)	7.982 (3.133)	8.548 (3.485)
e-Government users	62.707 (19.362)	60.270 (19.539)	63.295 (19.165)
Observations	10,626	2,011	6,624

Note: All values show means and standard deviation in brackets

Source: own elaboration from FL 486 and DESI

Table 7 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	
(1) Product	1.000																			
(2) Process	0.257	1.000																		
(3) Organisational	0.175	0.183	1.000																	
(4) Marketing	0.247	0.165	0.223	1.000																
(5) AI	0.117	0.117	0.090	0.078	1.000															
(6) Robots	0.135	0.204	0.090	0.037	0.230	1.000														
(7) Scale-up	0.103	0.095	0.099	0.056	0.069	0.083	1.000													
(8) Start-up	0.118	0.103	0.102	0.139	0.023	0.040	-0.122	1.000												
(9) Exports	0.102	0.087	0.039	0.015	0.062	0.108	0.089	-0.008	1.000											
(10) Global value chain	0.052	0.031	0.060	0.045	0.028	0.017	0.004	0.044	-0.132	1.000										
(11) Exports and global value chain	0.122	0.097	0.090	0.052	0.093	0.140	0.076	0.014	-0.154	-0.046	1.000									
(12) Firm size	0.102	0.145	0.131	0.019	0.109	0.222	0.204	-0.057	0.144	0.061	0.160	1.000								
(13) Firm age	-0.004	0.014	-0.009	-0.030	0.006	0.049	0.012	-0.498	0.010	-0.003	0.034	0.245	1.000							
(14) Big city	0.038	-0.026	0.012	0.027	0.022	-0.008	0.020	0.041	-0.003	0.010	0.027	-0.002	-0.103	1.000						
(15) Industrial location	0.076	0.087	0.051	0.038	0.021	0.073	0.035	-0.017	0.045	0.034	0.124	0.096	0.074	-0.066	1.000					
(16) Goods	0.131	0.087	0.003	0.045	-0.013	0.115	0.016	-0.024	0.160	0.012	0.081	0.064	0.109	-0.067	0.069	1.000				
(17) ICT	0.071	0.012	0.039	0.041	0.134	0.009	0.027	0.021	0.056	-0.014	0.008	-0.034	-0.035	0.086	-0.028	-0.104	1.000			
(18) Digital skills	0.047	0.056	0.057	0.039	0.089	0.077	0.027	0.026	-0.036	0.087	0.117	0.030	0.082	-0.051	0.100	-0.011	0.011	1.000		
(19) e-Commerce	0.023	0.026	0.051	0.019	0.032	0.003	0.042	-0.007	-0.011	0.060	0.014	0.025	0.082	-0.060	0.029	-0.026	-0.008	0.055	1.000	
(20) Infrastructure	0.033	0.037	0.004	0.036	-0.002	0.031	0.014	0.017	-0.051	0.010	0.044	-0.034	-0.137	0.066	0.000	-0.055	-0.011	-0.017	-0.136	1.000

Source: own elaboration from FLA86 and DESI

Table 8 AI and robot users by sectors and size class (% users)

Sector (NACE rev. 2)	AI	Robots
1. Mining and Quarrying	6.06%	12.12%
2. Manufacturing	8.53%	21.43%
3. Electricity, Gas and Steam	10.16%	15.25%
4. Water Supply and Waste Management	2.70%	7.20%
5. Construction	3.37%	4.25%
6. Wholesale and Retail Trade	5.32%	6.78%
7. Transporting and Storage	4.57%	2.35%
8. Accommodation and Food Service Activities	4.61%	2.86%
9. Information and Communication	25.00%	10.23%
10. Financial and Insurance Activities	11.20%	10.80%
11. Real Estate Activities	6.78%	3.57%
12. Professional, Scientific and Technical Activities	10.90%	8.84%
13. Administrative and Support Service Activities	7.44%	4.89%
14. Education	4.59%	7.06%
15. Human Health and Social Work Activities	5.72%	4.77%
16. Arts, Entertainment and Recreation	7.40%	4.93%
Overall sample	7.24%	9.12%
Size class		
0 to 9 employees	4.88%	4.21%
10 to 49 employees	8.27%	9.59%
50 to 250 employees	10.32%	19.78%
More 250 employees	20.03%	31.72%

% of all surveyed firms

Source: own elaboration from FL486

Table 9 Digital technologies by European regions

Digital technologies	Northern countries	Core countries	Mediterranean countries	Eastern countries
Artificial intelligence	9.32%	9.95%	7.52%	4.56%
Cloud computing	61.04%	56.62%	45.74%	38.07%
Robotics	12.76%	10.08%	8.76%	7.14%
Smart devices	27.23%	32.23%	21.99%	25.30%
Big data analytics	17.03%	15.78%	10.90%	11.33%
High-speed infrastructure	36.56%	46.44%	37.44%	20.00%
Blockchain	2.18%	4.68%	3.63%	2.32%
Not adopting any DT	24.53%	22.84%	36.46%	41.94%
Number of firms	1,920	3,034	1,541	4,730

Note: % of all surveyed firms

Source: own elaboration from FL486

Table 10 Share of adopting digital technologies by types of firms

Digital technologies	Start-ups	Scale-ups	Other SMEs	All sample
Artificial intelligence	9.04%	10.39%	5.72%	7.24%
Cloud computing	55.53%	58.41%	44.09%	48.07%
Robotics	12.79%	12.99%	6.69%	9.12%
Smart devices	32.76%	33.79%	23.70%	27.05%
Big data analytics	19.18%	18.14%	10.42%	13.45%
High-speed infrastructure	36.34%	38.54%	29.64%	32.37%
Blockchain	3.58%	5.05%	2.40%	3.11%
Not adopting any DT	24.80%	23.44%	37.29%	33.05%
Number of firms	641	2,039	8,069	11,225

Note: % of all surveyed firms

Source: own elaboration from FL486

Appendix 2. Sector heterogeneities

Table 11 First stage bivariate probit determining the adoption of artificial intelligence and robots across sector clusters

	Manufactures		Services	
	(1) Artificial intelligence	(2) Robots	(1) Artificial intelligence	(2) Robots
Firm-specific characteristics				
Scale-up	0.251** (0.101)	0.161* (0.085)	0.122** (0.061)	0.227*** (0.063)
Start-up	0.150 (0.232)	0.336* (0.185)	0.084 (0.116)	0.465*** (0.119)
Exports	0.331*** (0.114)	0.389*** (0.090)	0.263*** (0.056)	0.269*** (0.060)
Global value chain	0.535 (0.328)	0.476* (0.283)	0.271** (0.106)	0.176 (0.113)
Exports and global value chain	0.617*** (0.153)	0.539*** (0.128)	0.467*** (0.097)	0.477*** (0.099)
Size (Logs)	0.105*** (0.032)	0.261*** (0.027)	0.139*** (0.018)	0.185*** (0.019)
Age (Logs)	0.021 (0.068)	-0.006 (0.055)	-0.050 (0.035)	0.026 (0.039)
Big city	0.137 (0.091)	0.097 (0.075)	-0.027 (0.051)	0.078 (0.054)
Industrial area	-0.040 (0.108)	-0.060 (0.088)	-0.105 (0.080)	0.189** (0.076)
Goods	-0.049 (0.098)	0.210** (0.082)	-0.137** (0.063)	0.083 (0.065)
ITC			1.090*** (0.117)	0.857*** (0.149)
Country-specific characteristics				
Digital skills	0.063 (0.057)	0.156** (0.069)	0.156*** (0.051)	0.136** (0.054)
e-commerce	0.062 (0.063)	0.060 (0.046)	0.049 (0.032)	0.019 (0.034)
Infrastructure	0.062 (0.063)	0.170*** (0.051)	0.080** (0.037)	0.129*** (0.038)
Sector fixed-effects	Yes		Yes	
Observations	2,011		6,624	
Wald test for zero slopes	295.29***		585.87***	
LR test for no correlation	39.264***		147.809***	
Log likelihood	-1,323.74		-2,791.35	

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients (Std. Err.) reported. Non-exporters and firms not participating in global value chains are the base outcome for internationalisation dummies. Firms located in small or medium cities are the baseline for location dummies. Retail sectors are the base outcomes for the sector fixed-effects. Western European countries are the base outcome for geographical cluster fixed-effects

Table 12 Second stage multivariate probit with residual inclusion and asymptotically adjusted coefficients for the determinants of innovation in manufactures

	Artificial intelligence				Robots			
	(1) Product	(2) Process	(3) Organisational	(4) Marketing	(1) Product	(2) Process	(3) Organisational	(4) Marketing
Digital technologies—IV								
Artificial intelligence	2.203*** (0.519)	1.821*** (0.503)	0.791 (0.543)	1.946*** (0.523)				
Robots					1.049*** (0.219)	1.347*** (0.222)	0.329 (0.241)	0.161 (0.238)
Firm-specific characteristics								
Scale-up	-0.184 (0.152)	-0.139 (0.147)	0.123 (0.158)	-0.317** (0.154)	0.175** (0.086)	0.105 (0.086)	0.277*** (0.092)	0.114 (0.092)
Start-up	0.745*** (0.191)	0.493*** (0.184)	0.592*** (0.198)	0.441** (0.185)	0.744*** (0.180)	0.418** (0.180)	0.634*** (0.195)	0.652*** (0.183)
Exports	-0.415** (0.187)	-0.365** (0.182)	-0.122 (0.199)	-0.631*** (0.190)	-0.116 (0.111)	-0.220** (0.112)	0.048 (0.126)	-0.100 (0.120)
Global value chain	-0.895** (0.426)	-0.660* (0.401)	0.459 (0.402)	-0.693* (0.398)	-0.279 (0.307)	-0.301 (0.301)	0.765*** (0.293)	0.231 (0.298)
Exports and global value chain	-0.761** (0.348)	-0.770** (0.338)	-0.171 (0.363)	-1.060*** (0.350)	-0.046 (0.175)	-0.360** (0.178)	0.177 (0.188)	-0.011 (0.186)
Size (Logs)	-0.190*** (0.058)	-0.052 (0.056)	0.026 (0.060)	-0.219*** (0.058)	-0.229*** (0.059)	-0.145** (0.059)	0.047 (0.065)	-0.087 (0.063)
Age (Logs)	0.068 (0.054)	0.011 (0.052)	0.076 (0.058)	0.026 (0.054)	0.117** (0.050)	0.052 (0.050)	0.092* (0.056)	0.067 (0.053)
Big city	-0.082 (0.098)	-0.264*** (0.085)	-0.080 (0.104)	-0.104 (0.099)	0.102 (0.070)	-0.139* (0.071)	0.003 (0.077)	0.123* (0.074)
Industrial area	0.227** (0.090)	0.253*** (0.085)	0.107 (0.090)	0.193** (0.088)	0.182** (0.082)	0.226*** (0.081)	0.085 (0.086)	0.129 (0.085)
Goods	0.527*** (0.083)	0.347*** (0.079)	-0.081 (0.084)	0.162** (0.081)	0.229*** (0.083)	0.068 (0.083)	-0.164* (0.090)	0.017 (0.088)
Residuals	-1.988*** (0.509)	-1.546*** (0.493)	-0.741 (0.531)	-1.841*** (0.509)	-0.922*** (0.210)	-0.880*** (0.213)	-0.176 (0.233)	-0.248 (0.227)
Sector fixed-effects	Yes				Yes			
Geographical cluster fixed-effects	Yes				Yes			
Observations	2,011				2,012			
Wald test for zero slopes	399.41***				433.18***			
LR test for no correlation	210.17***				211.71***			
Log likelihood	-3,911.11				-3,972.97			

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients (Std. Err.) reported. Non-exporters and firms not participating in global value chains are the base outcome for internationalisation dummies. Firms located in small or medium cities are the baseline for location dummies. Retail sectors are the base outcomes for the sector fixed-effects. Western European countries are the base outcome for geographical cluster fixed-effects

Table 13 Second stage multivariate probit with residual inclusion and asymptotically adjusted coefficients for the determinants of innovation in services

	Artificial intelligence				Robots			
	(1) Product	(2) Process	(3) Organisational	(4) Marketing	(1) Product	(2) Process	(3) Organisational	(4) Marketing
Digital technologies—IV								
Artificial intelligence	0.807*** (0.182)	0.994*** (0.203)	0.683*** (0.206)	0.329* (0.186)				
Robots					0.926*** (0.163)	1.117*** (0.179)	0.511*** (0.181)	0.458*** (0.165)
Firm-specific characteristics								
Scale-up	0.243*** (0.050)	0.226*** (0.055)	0.214*** (0.055)	0.293*** (0.051)	0.170*** (0.057)	0.176*** (0.063)	0.196*** (0.063)	0.229*** (0.058)
Start-up	0.775*** (0.082)	0.748*** (0.089)	0.634*** (0.090)	0.972*** (0.083)	0.554*** (0.107)	0.538*** (0.116)	0.525*** (0.117)	0.836*** (0.107)
Exports	0.171*** (0.062)	-0.008 (0.069)	0.078 (0.070)	0.128** (0.063)	0.143** (0.057)	0.014 (0.064)	0.109* (0.064)	0.062 (0.058)
Global value chain	0.297*** (0.094)	0.034 (0.104)	0.163 (0.103)	0.165* (0.097)	0.319*** (0.085)	0.114 (0.093)	0.223** (0.092)	0.124 (0.087)
Exports and global value chain	0.445*** (0.116)	0.060 (0.128)	0.290** (0.127)	0.306*** (0.119)	0.384*** (0.111)	0.089 (0.120)	0.341*** (0.119)	0.185* (0.111)
Size (Logs)	0.005 (0.027)	-0.012 (0.031)	0.062** (0.031)	0.016 (0.029)	-0.036 (0.031)	-0.029 (0.035)	0.063* (0.035)	-0.031 (0.032)
Age (Logs)	0.081*** (0.027)	0.093*** (0.031)	0.042 (0.030)	0.084*** (0.028)	0.045* (0.026)	0.046 (0.029)	0.014 (0.029)	0.074*** (0.027)
Big city	0.077** (0.036)	0.019 (0.040)	-0.034 (0.040)	-0.009 (0.037)	0.019 (0.038)	-0.048 (0.042)	-0.071* (0.042)	-0.036 (0.038)
Industrial area	0.212*** (0.057)	0.238*** (0.062)	0.137** (0.063)	0.124** (0.058)	0.052 (0.064)	0.056 (0.070)	0.031 (0.070)	0.051 (0.065)
Goods	0.203*** (0.049)	0.086 (0.055)	0.042 (0.055)	0.079 (0.050)	0.094** (0.044)	-0.058 (0.050)	-0.043 (0.050)	0.045 (0.045)
ITC	0.371* (0.210)	-0.264 (0.236)	-0.049 (0.237)	0.477** (0.216)	0.414*** (0.158)	-0.001 (0.176)	0.172 (0.175)	0.308* (0.162)
Residuals	-0.398** (0.174)	-0.612*** (0.196)	-0.388** (0.198)	-0.024 (0.178)	-0.515*** (0.152)	-0.508*** (0.169)	-0.780* (0.409)	-0.287* (0.154)
Sector fixed-effects	Yes				Yes			
Geographical cluster fixed-effects	Yes				Yes			

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Coefficients (Std. Err.) reported. Non-exporters and firms not participating in global value chains are the base outcome for internationalisation dummies. Firms located in small or medium cities are the baseline for location dummies. Retail sectors are the base outcomes for the sector fixed-effects. Western European countries are the base outcome for geographical cluster fixed-effects

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