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ABSTRACT

Artificial Intelligence as a Complement to Other Innovation Activities and as a Method of Invention*

This study investigates the relationship between Artificial Intelligence (AI) and innovation inputs in Spanish manufacturing firms. While AI is increasingly recognized as a driver of productivity and economic growth, its role in shaping firms' innovation strategies remains underexplored. Using firm-level data, our analysis focuses on whether AI complements innovation inputs - specifically R&D and Embodied Technological Change (ETC) - and whether AI can be considered as a Method of Invention, able to trigger subsequent innovation investments. Results show a positive association between AI adoption and both internal R&D and ETC, in a static and a dynamic framework. Furtheremore, empirical evidence also highlights heterogeneity, with important peculiarities affecting large vs small firms and high-tech vs low-tech companies. These findings suggest that AI may act as both a complement and a catalyst, depending on firm characteristics.

JEL Classification: O31, O32

Keywords: Artificial Intelligence, method of invention, R&D, innovation inputs, innovative complementarities

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1. Introduction

Artificial Intelligence (AI) is a transformative technology that is reshaping how firms produce and introduce new products to the market. Damioli et al. (2025) argue that AI is emerging as a key driver of economic growth and productivity. However, there is a notable scarcity of empirical research assessing the impact of AI on firms' innovation performance, particularly regarding its role as a complement to other innovation inputs and as a method of invention. While some scholars have examined the role of AI in capability development (e.g., Sjödin et al., 2021), it remains unclear how AI-driven capabilities interact with other types of firm capabilities, such as R&D investments (Mariani et al., 2023).

This study seeks to bridge this gap by addressing two key research questions. First, is AI a complement to R&D and other innovation inputs, such as Embodied Technology Change (ETC)? Second, can AI be considered a method of invention, namely fostering an increase in the subsequent investment in other innovation inputs? The first research question will be investigated trough a contemporaneous correlation analysis, while the second issue will be tested through an econometric specification with a dynamic structure.

The dataset used to address our research questions comes from the ”Encuesta sobre Estrategias Empresariales” (ESEE), a survey of Spanish manufacturing firms covering the period from 1990 to 2022.[1] However, queries specifically related to AI are only available for the years 2018 and 2022, when AI started becoming relevant at the firm-level.[2]

This information first allows us to test the complementarity between AI and other innovation inputs. We follow the methodology proposed by Mohnen and Röller (2005) and Catozzella and Vivarelli (2014), which involves a descriptive analysis of both unconditional and conditional correlations. Then, we assess the impact of AI adoption in 2018 on innovation inputs in 2022, including internal and external R&D expenditure and ETC. All specifications control for firm size and other firm characteristics and include regional and industry fixed effects.

[1] For more information about the SEPI Foundation and ESEE data, please refer to www.fundacionsepi.es

[2] In particular, the ESEE offers insights into AI applications in the following areas: 1) “automatically guided vehicles or systems (self-driving vehicles, drones)”; 2)“machine learning / data driven management / big data”, 3) “computer/machine vision”; and 4) “natural language processing”.

The results from the complementary analysis indicate a certain degree of complementarity between AI and both internal R&D and ETC. These correlations are positive and statistically significant in both the unconditional and conditional analyses. Furthermore, in the econometric analysis, we find a positive impact of AI adoption (in 2018) onto subsequent investments in total R&D, internal R&D and ETC (in 2022), suggesting that AI plays the role of a method of invention, enhancing a firm's innovation capacity in terms of its standard innovation inputs. However, heterogeneity across innovative firms emerge, with these effects mainly driven by large firms and companies operating in the high-tech industries.

The remainder of the paper is structured as follows. Section 2 sets the context and reviews the relevant literature. Section 3 describes the data and the adopted methodology. Section 4 discussess the empirical results and Section 5 concludes.

2 The context and the extant literature

Artificial Intelligence represents a new paradigm that is transforming economic structures and society as a whole, fostering the emergence of intelligent societies (Miller, 2019; Damioli et al., 2025; Lábaj et al., 2025;). Liu et al. (2020) and Yogesh et al. (2021) report that AI is increasingly being applied in the manufacturing, finance, education, healthcare, and logistics sectors. According to Cockburn et al. (2019), Holm et al. (2023), Batabyal et al. (2025), Calvino at al. (2025) AI has the potential to become a powerful driver of innovation, productivity gains, and economic growth.[3]

But what exactly is Artificial Intelligence? According to Aghion et al. (2017), AI refers to "the capability of a machine to imitate intelligent human behaviour" or "an agent's ability to achieve goals in a wide range of environments." Similarly, Liu et al. (2020) highlight a common element across AI definitions: the performance of human-like intelligent activities programmed to accomplish specific

[3] To illustrate this point, one can consider the pharmaceutical sector. When a laboratory seeks to discover and develop a new drug, AI plays an increasingly important role by accelerating the identification of synthesizable molecules, nucleic acid sequences, and proteins with specific structures or functions. In doing so, it enhances both the efficiency (in terms of time and cost) and the effectiveness of drug development (Vert, 2023).

tasks. More precisely, AI systems can mimic human thinking and perform roles and tasks that were previously carried out by people.[4]

In mimic humans, Agrawal et al. (2019) conceptualize AI principally as a tool that dramatically reduces the cost of prediction. This shift has deep implications for firms, as prediction is a fundamental input in decision-making processes, including decisions affecting R&D investment and innovation strategies. In this new framework, AI does not replace judgment; rather, it separates prediction from decision-making, allowing humans to increasingly focus on interpreting and acting on AI-generated forecasts.[5] Moreover, Agrawal et al. (2024), discussing the the impact of AI adoption on organizations, consider how interactions between multiple tasks influence its effectiveness. The study, modelling both modular and non-modular systems, find that AI adoption increases decision variation, posing challenges in organizations with interdependent decisions (as those related to innovation activities).

In such a complex and evolving context, AI encompasses a wide range of technologies, including machine learning, deep learning, natural language processing, computer vision, speech recognition, intelligent decision support systems, intelligent robotic systems, as well as the novel application of these tools across various domains (OECD, 2024). As a initial approach, Cockburn et al. (2019) classified AI into two categories: automation-oriented applications, such as robotics, and emerging developments, including natural language processing (NLP) and deep learning. This distinction is important because AI (particularly with regard to the latter categories) can be considered a "General Purpose Technology (GPT)", and even a "method of invention".

An innovation is considered a General Purpose Technology (GPT) when it satisfies three key characteristics: (1) pervasiveness, (2) innovational complementarities that give rise to increasing returns to scale in innovation and (3) an inherent potential for continuous technological improvement. The first characteristic refers to the innovation's pervasive applicability across multiple sectors. As a GPT evolves and advances, it diffuses throughout the economy, fostering broad-based

[4] Coccia (2019) provides a compelling example of this: the use of AI, particularly deep learning, can assist pathologists in detecting cancer subtypes, gene mutations, and/or metastases, thereby enabling the application of appropriate therapies.

[5] To enhance AI's potential, firms need to understand how quickly AI will impact their sector, recognize its exponential progress, and manage the feedback in a continuous learning loop. However, concerns about negative effects and risks of AI have sparked policy debates, including a 2023 petition calling for a pause in AI research. Goldfarb (2024), analysing those concerns, underlines a long-term optimism about AI's transformative potential while acknowledging short-term risks.

productivity gains (Bresnahan & Trajtenberg, 1995). Obviously enough, this feature fully applies to the case of AI. The second characteristic refers to innovational complementarities (IC), whereby the productivity of R&D and other innovation activities directly benefits from the innovation in the GPT itself (Bresnahan & Trajtenberg, 1995). These complementarities propagate throughout the economy, amplifying the broader impact of technological advancement onto productivity and economic growth. Finally, the third feature of a GPT stems from its role as an enabling technology, one that opens new innovative opportunities rather than providing a final solution. In the particular case of AI, it is enabling role is rooted in the fact that AI tools (particularly deep learning and NLP) can be used as research devices that open new avenues of inquiry and enhances innovation productivity (Cockburn et al., 2019).

The three GPT characteristics (which are so pronounced in the inner nature of AI) open the way to consider AI as a method of invention (MoI). This idea was originally proposed by Griliches (1957) in his seminal study of hybrid corn, where the discovery of double cross hybridization was considered as a MoI. Rather than producing a single new corn variety, the innovation enabled a method that could be applied to generate many new varieties, significantly enhancing agricultural productivity. In other words, an innovation qualifies as a MoI when it constitutes a new way of generating innovations with broad applicability.

Indeed, AI - particularly through deep learning, neural networks and NLP - appears to hold strong potential as a research tool for solving those classification and prediction problems that characterize the innovation activities, so reducing costs and improving performance in R&D projects. Much like hybrid corn, AI expands the “innovation playbook” by enabling the discovery of new ideas and the solution of trade-offs, thereby altering the way scientific research is conducted (Cockburn et al., 2019). Therefore, AI can be seen as a universal technology that can support other innovations.[6] However, AI revolution requires to allow complementary inventions to develop, businesses to be reorganized and workers to upskill in order to diffuse across the economy (Brynjolfsson et al. 2019; Damioli et al., 2021).

[6] One specific case is “Generative AI” which refers to AI models that are specifically designed to produce content, like text, program codes, images, videos, or sounds, in response to human language queries or prompts. This tool utilizes Large Language Models (LLMs) and requires a substantial amount of data, employing algorithms to predict responses. The Generative AI can transform innovation in boosting idea generation, increasing individual creativity and rendering more effective the R&D investments (Calvino et al., 2025).

More in general, when considering the AI role in science, Bianchini et al. (2022) discuss how AI is transforming scientific discovery. Rather than merely accelerating existing research, AI is becoming a tool for generating new hypotheses, designing experiments, and interpreting complex data. By automating and enhancing cognitive tasks, AI enables scientists to uncover patterns and insights that were previously difficult to reach or even to imagine. Therefore, AI has the potential to increase research efficiency and foster interdisciplinarity.

We now turn our attention to those studies that have empirically examined the relationship between AI and innovation performance. We have identified three main groups of contributions: 1) studies that use patents as a proxy for AI; 2) studies that use specific technologies (particularly robots and big data) as a proxy for AI; and 3) studies that rely on survey data, such as the Community Innovation Survey (CIS).

Patents are a widely used instrument for measuring various aspects of innovation. With regard to AI, Cockburn et al. (2019), drawing on data from the USPTO and published articles, examine the changing nature of measurable innovation outputs in AI. The results suggest a shift since 2009 toward the growing importance of application-oriented machine learning research. Similarly, Fujii and Managi (2018), using data from WIPO's PATENTSCOPE from 2000 to 2016, show a transition from biological and knowledge-based models to more specific mathematical models and other AI technologies, particularly in the United States and Japan. More recently, Damioli et al. (2025) – using data from the European Patent Office (EPO) covering the period 2000–2016 - investigate whether AI is initiating a new technological paradigm, using the perspective of evolutionary neo-Schumpeterian economics. Among their findings, one stands out: AI technologies contribute to the generation and acceleration of further innovations.

Another way to assess the impact of AI is using Big Data as a proxy: while Big Data cannot, in a strict sense, be considered AI, it is often regarded as a key component of it. Most studies examining the relationship between Big Data and innovation performance report a positive association, for example, with innovative competitive advantage and with agile product and service co-creation processes (e.g., (Ghasemaghaei & Calic, 2019; Lozada et al., 2019).[7] One interesting study that use Big Data as a proxy of AI is put forward by Niebel et al. (2019). The authors use multiple waves of the German ZEW ICT

[7] Both studies use a survey-based approach, collecting data through questionnaires conducted in the United States and Colombia, respectively.

survey (2000, 2002, 2004, 2007, 2010, and 2015) and find that Big Data is a significant determinant of both the likelihood that a firm becomes a product innovator and of the market success of its product innovations.

Turning our attention to those studies using survey data, Rammer et al. (2022) explicitly adopt a definition of AI in their analysis. Using data from the German component of the 2018 Community Innovation Survey (CIS), which follows the Oslo Manual guidelines, the authors estimate the relationship between AI and innovation outcomes using OLS and Probit models. Their findings reveal a positive association between AI adoption and product innovation (both in binary terms and in terms of sales attributable to new products). In particular, the results indicate that AI use is positively associated with annual sales from radical product innovations. With a slightly different approach, Babina et al. (2024) propose a new measure of firms' investments in AI based on their intensity of AI-skilled hiring. In their study, AI adoption shows an enabling effect shortening experimentation time and increasing product variety thanks to better predictions of demand (while not affecting process innovation).

Based on the literature discussed in this section, we identify a gap in the existing research: while the extant literature provides evidence of a positive relationship between AI adoption and innovation performance (for instance measured in terms of product innovation), the relationship between AI and innovation inputs has never been investigated. Indeed, if AI is a GPT and a MoI, we should expect complementarity and boosting effects onto innovation inputs, as well. In other words, AI adoption should come hand in hand with an increase in expenditures in R&D and other innovation inputs. This gap carries out the two following research questions: 1) Is AI a complement to R&D, and/or to other innovation inputs, such as ETC? Can AI adoption be considered a MoI, so fostering subsequent investments in R&D and other innovation inputs? Indeed, if AI is a MoI, R&D projects and other innovation inputs become more effective in generating innovative outputs and so their expected profitability increases and therefore the incentive to invest in these activities should significantly increase.

3 Data and methodology

To deal with the previous research questions, we use the Survey on Business Strategies (ESEE) conducted by the Ministry of Industry and the SEPI Foundation in Spain. The ESEE survey is representative and provides longitudinal data on firms in Spain's manufacturing sector since 1990. On average, 1,800 companies are surveyed from 1990 to 2023 through a questionnaire with 107 questions that contain information on the company's balance sheet, firm characteristics, markets, technological developments, foreign trade, employment, and so on. The ESEE has been widely used in previous studies. For instance, to analyse the barriers to innovation (González et al., 2005), to assess the persistence of innovation (Triguero et al., 2014), to examine the relationship between R&D drivers and firm's age (García-Quevedo et al., 2014). [8]

3.1 Identification Strategy and descriptive statistics

ESEE has included a question related to the use of Technologies 4.0 every four years[9] since 2018. We use this question to identify AI users and to examine the contemporaneous complementarity between AI and innovation inputs[10] in 2022, as well as the impact of AI adoption in 2018 onto innovation inputs in 2022 (AI as a MoI). The AI indicator in our analysis includes the following four technologies: 1) automatically guided vehicles (e.g., autonomous vehicles, drones); 2) machine learning / data-driven management / big data; 3) computer vision/machine vision; and 4) natural language processing. In particular, our AI indicator is equal to 1 if the firm adopted at least one of the four aforementioned technologies and zero otherwise.

We restrict the sample to firms with non-missing AI information for both 2018 and 2022. Based on this restricted sample, the AI variable indicates that 218 firms (21.5%) used AI in both 2018 and 2022 (always users), while 780 firms (76.9%) did not use AI in either year (never users). 10 firms (0.9%) adopted AI between 2018 and 2022, transitioning from non-use to use (adopters), whereas 7

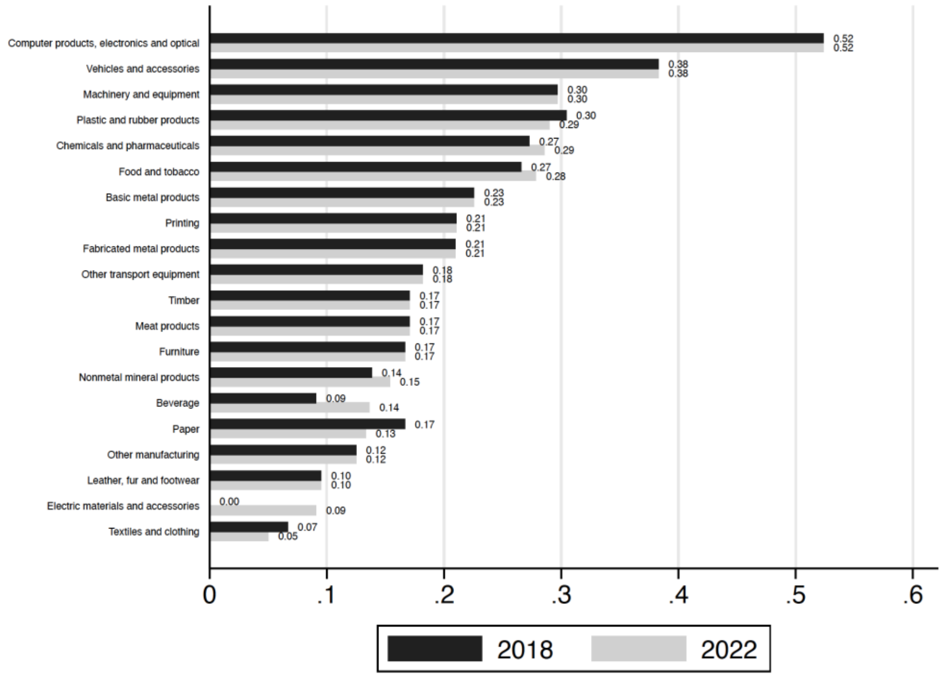
[8] More recently, ESEE data have been used to explore the impact of ETC on employment (Pellegrino et al., 2019), to measure the microeconomic implications of robot adoptions (Koch et al., 2021), and to examine the role of robot adoption on product innovation (Antonioli et al., 2024).

[9] The question asks to the companies in 2018 and 2022: to what extent did your company use the following Industry 4.0 technologies in the production, marketing, or distribution of its products and services? (Select one option for each technology): Augmented/Virtual Reality; Cyber-physical systems; Automatically guided vehicles (e.g., autonomous vehicles, drones); Automated storage and retrieval systems; Machine learning / Data-driven management / Big data; Cloud computing; Computer vision/machine vision; Natural language processing; RFID-based identification and inventory systems; Industrial robotics, Touchscreens/kiosks for client interface; IoT / IIoT (Internet of Things / Industrial IoT); 3D printing / Additive manufacturing

[10] The innovation inputs are: total R&D, internal R&D, external R&D and ETC.

firms (0.7%) discontinued AI use over the same period (stoppers). Based on these classifications, we construct indicators of AI use for 2018 and 2022.[11]

Figure 1: The AI use in 2018 vs 2022 by industries



Note: Figure 1 reports the share of firms using AI in 2018 and 2022, by industry, using the full sample of firms from the ESEE data

Another valuable insight provided by the ESEE is its sectoral-level analysis (NACE classification). Although we do not observe significant changes between 2018 and 2022, Figure 1 reveals substantial heterogeneity across industries in AI adoption, as expected. The figure also shows that the sectors with the highest rates of AI users are “Computer products, electronics and optical” (52%), “Vehicles and accessories” (38%), “Machinery and equipment” (30%) and “Plastic and rubber products” (30% in 2018 and 29% in 2022). In contrast, the sectors with the lowest AI user rates are “Leather, fur and

[11] Specifically, firms classified as stoppers are included among the AI users in 2018, while adopters are included among the AI users in 2022. In 2018, 22.2% of firms used AI, while 77.8% did not. In 2022, the proportion of AI users increased slightly to 22.5%, with non-users accounting for 77.5%. The total sample for the AI variable consists of 1,015 firms. In 2018, 225 firms were classified as AI users and 790 as non-users. In 2022, the number of AI users was 228, while the number of non-users was 787.

footwear" (10%), "Electric materials and accessories" (0% in 2018 and 9% in 2022), and "Textiles and clothing" (7% in 2018 and 5% in2022).

Table 1: Descriptive statistics: Non-AI users vs AI users

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-AI use		AI use		Total	
	mean/sd	obs	mean/sd	obs	mean/sd	obs
R&D	2.83	779	5.759	214	3.461	993
	(5.10)		(6.404)		(5.537)	
Internal R&D	2.24	779	4.945	214	2.823	993
	(4.679)		(6.197)		(5.163)	
External R&D	1.679	779	3.668	214	2.108	993
	(3.963)		(5.450)		(4.401)	
ETC	2.118	750	4.499	203	2.625	953
	(4.640)		(6.348)		(5.142)	
Employment	4.155	790	4.892	225	4.318	1015
	(.838)		(.952)		(.917)	
Collwithuni (Dummy)	0.143	790	0.32	225	0.182	1015
	(.350)		(.468)		(.386)	
% EG	1.891	629	2.306	169	1.979	798
	(1.107)		(.986)		(1.095)	
TCA (Dummy)	0.011	790	0.049	225	0.02	1015
	(.106)		(.216)		(.139)	
Foreign	8.678	779	18.112	214	10.711	993
	(27.310)		(38.030)		(30.175)	
PEURP (Dummy)	0.006	790	0.04	225	0.014	1015
	(.079)		(.196)		(.117)	
R&D (Dummy)	0.24	779	0.458	214	0.287	993
	(.427)		(.499)		(.453)	
Internal R&D (Dummy)	0.19	779	0.397	214	0.235	993
	(.393)		(.490)		(.424)	
External R&D (Dummy)	0.155	779	0.322	214	0.191	993
	(.362)		(.469)		(.394)	
ETC (Dummy)	0.176	750	0.34	203	0.211	953
	(.381)		(.475)		(.408)	

Note: The table reports means and standard deviations (in parentheses) of firm-specific variables for three groups: AI non-users (i.e., firms that never use AI in 2018 (Column 1)), AI users (firms that used AI in 2018 (Column 3)), and the full sample (Column 5)). R&D refers to total research and development expenditure (internal and external, in logs and dummy) in 2022. Internal R&D and External R&D denote internal and external R&D expenditures, respectively (both in logs and dummy) in 2022. Embodied Technological Change (ETC) is measured as the cost of capital goods purchased for product improvement (in logs and dummy) in 2022. Employment is the total number of employees (in logs) in 2022. Collwithuni captures whether the firm collaborates with universities and/or technology centres (dummy variable) in 2022. % EG represents the percentage of engineers and graduates in the workforce in 2022. TCA indicates the existence of a technological cooperation agreement (dummy variable) in 2022. Foreign refers to the share of foreign ownership (in percent) in 2022. Finally, PEURP measures participation in EU research programs (dummy variable) in 2022.

Table 1 shows the descriptive statistics of the main variables used in our analysis. The sample is split into two groups: AI non-users and AI users.[12] As can be seen, the means of the innovation inputs (R&D, internal and external R&D, ETC) are higher for AI users than for AI non-users. This provides preliminary evidence of a positive association between AI adoption and innovation inputs. Another interesting finding is that employment is also higher for AI users than for AI non-users, suggesting that – not surprisingly - large companies are more AI-intensive than their smaller counterparts. Other controls beyond firm's size include (see also Section 4.2): "Collwithuni" that captures whether the firm collaborates with universities and/or technology centres (dummy variable) in 2022; "% EG", that represents the percentage of engineers and graduates in the workforce in 2022; "TCA", that indicates the existence of a technological cooperation agreement (dummy variable) in 2022; "Foreign", that refers to the share of foreign ownership (in percent) in 2022; and "PEURP", that measures participation in EU research programs (dummy variable) in 2022.

3.2 The empirical model

In this section, we present the empirical strategy adopted to assess, on the one hand, the complementarity of AI with other innovation activities (specifically R&D - both internal and external - and ETC[13]) and, on the other hand, the impact of AI adoption onto the subsequent investments in innovation inputs (AI as a MoI).

As far as the complementarity analysis is concerned, we adopt the indirect approach, which assumes that two (or more) activities can be considered complements if their use (or expenditure) tends to move in the same direction, that is, if they are positively correlated. Although this test appears straightforward, the indirect test for complementarity can be biased if the firm's heterogeneity is not adequately considered (Catozzella & Vivarelli, 2014). Indeed, many factors, such as the strategies of the companies, their managerial capabilities and the characteristics of the industries influence the innovation activities. To address this issue, Arora & Gambardella (1990) propose estimating

[12] We focus on AI use in 2018, as our regression analysis examines the impact of AI adoption in 2018 on innovation inputs in 2022. Descriptive statistics for AI users in 2022 yield similar results and are available upon request.

[13] ETC is basically the investment in innovative plants, machinery, and equipment (Catozzella & Vivarelli, 2014) and it is considered a proxy for process innovation (Pellegrino et al., 2019)

conditional rather than unconditional correlations. Specifically, each input is regressed on a set of firm-level and industry-level control variables (Z). The residuals from these regressions are then used to compute the correlation coefficients. A positive and statistically significant correlation among the residuals is interpreted as evidence of complementarity. However, to get consistent estimations, it is required to properly compute residuals. In this respect, since internal and external R&D expenditures and ETC are lower-censored at zero, OLS estimators turn out to be inconsistent in this context. To address this issue, we employ Tobit models for these variables. Since AI is observed as a binary variable, we use a probit model for computing AI residuals. Finally, we also use probit models when innovation activities are measured as dummy variables (see Appendix).

To test the hypothesis of AI as a MoI, we estimate the association between the AI and the innovation inputs using the specification outlined in Equation (1). The dependent variables (y_i) are the innovation inputs in 2022: total R&D, internal and external R&D and ETC. The main independent variable is the AI use in 2018, measured as a binary indicator (AI_i).

$$y_i = \beta_0 + \beta_1 AI_i + \sum_{k=1}^{6} \gamma_k Z_{ik} + \upsilon_j + \upsilon_r + \epsilon_i \qquad (1)$$

We also control for a set of firm-level characteristics (Z_{ik}), including total employment, collaboration with universities and/or technology centers (Collwithuni), the percentage of engineers and graduates in the workforce (% EG), the technological cooperation agreement (TCA), the share of foreign ownership (Foreign) and the participation in EU research programs (PEURP), all measured in 2022. Equation (1) also contains industry (υ_j) and regional (υ_r) fixed effects. Finally, ϵ_i is the stochastic error term.

Finally, we investigate potential heterogeneity with regard to firm's size and sectoral belonging. While the general association between AI and the innovation inputs will be tested through Tobit models when innovation inputs are considered in levels[14] and Probit models when inputs are considered as binary variables, the heterogeneity analysis will use OLS. We opt for OLS in this case because it facilitates the analysis of heterogeneity by firm size and technological intensity (i.e. high-

[14] A Tobit model is used due to the high incidence of zero values in the dependent variables (innovation inputs).

vs. low-tech sectors) through the inclusion of interaction terms and the estimation of marginal effects.[15]

4 Results

4.1 Complementarity analysis

In this subsection, we assess complementarity by examining both unconditional and conditional correlations among five innovation activities: total R&D, internal and external R&D, Embodied Technological Change (ETC) and Artificial Intelligence (AI) in 2022.

Table 2 presents the unconditional correlation results. These preliminary findings indicate positive and statistically significant correlations among the various innovation activities, suggesting potential complementarities. We also estimate unconditional correlations using binary indicators (see Appendix, Table A1), and the results are consistent with those displayed in Table 2. However, as previously noted, to avoid biased estimates of correlation, it is essential to control for firm- and sector-level characteristics.

Table 2: Unconditional correlations (levels)

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.893***	1			
External R&D	0.772***	0.564***	1		
ETC	0.186***	0.190***	0.179***	1	
AI 2022	0.226***	0.217***	0.201***	0.191***	1
Observations	936				

* p<0.10, ** p<0.05, *** p<0.01

[15] To compute the marginal effects, it is necessary to introduce an interaction term in Equation (1): $y_i = \beta_0 + \beta_1 AI_i + \beta_2 Size_i + \emptyset_1(AI_i * Size_i) + \sum_{k=1}^{6} \gamma_k Z_{ik} + \upsilon_j + \upsilon_r + \epsilon_i$ where $Size_i$ is a dummy variable equal to one if the firm is large, and zero otherwise. After estimating the equation, we compute the marginal effect of AI_i as: $\delta y_i/\delta AI_i = \beta_1 + \phi Size_i$. This leads to two cases: if $Size = 1$ (large firms), then $\delta y_i/\delta AI_i = \beta_1 + \phi$ and $Size = 0$ (small firms) then $\delta y_i/\delta AI_i = \beta_1$. The same holds for the case of technological intensity (high and low-tech sectors).

Table 3: Conditional correlations (levels)

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.867***	1			
External R&D	0.662***	0.389***	1		
ETC	0.0809**	0.116***	0.0845**	1	
AI 2022	0.0659*	0.0756**	0.0441	0.120***	1
Observations	748[16]				

* p<0.10, ** p<0.05, *** p<0.01

We then test the conditional correlation analysis. We adopt the following strategy: first, every innovation input is regressed on a selected set of explanatory variables.[17] Second, we predict the residuals and compute the correlations among them. The results are presented in Table 3: we identify a positive and significant correlation between artificial intelligence and, total and internal R&D (at 90% of confidence) and ETC (at 99% of confidence). We also estimate conditional correlations using binary indicators (see Appendix, Table A2), and the results are consistent with those presented in Table 3.[18] These results provide evidence of complementarity between AI and internal R&D, and between AI and ETC. The loss of significance of the conditional correlation between AI and external R&D possibly reflects the (understandable) prevalent use of in-house AI in enhancing in-house innovation activities (such as internal R&D and ETC), rather than supporting innovative activities conducted externally and out of control.

However, while the detected contemporaneous complementarities are a necessary condition to consider AI as an enabling technology, it is not a sufficient condition. To test whether AI is a MoI we

[16] The smaller number of observations in the conditional correlation analysis is attributable to missing values in the control variables.

[17] The control variables are employment, collaboration with universities and/or tech centres, proportion of engineers and graduates, technological cooperation agreements, foreign shareholding, participation in EU research programs, regions, and industry fixed-effects

[18] In both this correlation analysis and in the following regression estimates, we display results using binary indicators (0/1) of the relevant variables with two purposes in mind: 1) to provide a robustness check, to be compared with results based on the tobit methodology; 2) to give account of the relationships which may affect the decisions to invest or not invest in the different innovation inputs.

have to turn our attention to test the impact of AI onto subsequent investments in the various innovative inputs.

4.2 AI as a method of invention

This subsection presents the results of the estimations assessing AI as a MoI. The dependent variables include total R&D, internal and external R&D and ETC. As previously noted, the estimations control for firm-level characteristics: total employment, collaboration with universities and/or technology centres ("Collwithuni"; see Cassiman and Veugelers, 2000; Piga and Vivarelli, 2003), the proportion of engineers and graduates in the workforce ("%EG"; see Cohen and Levinthal, 1990; González et al, 2016), technological cooperation agreements ("TCA"; see Iammarino et al., 2012; Zoia et al., 2018), foreign ownership share ("foreign"; see Kwon and Park, 2018), and participation in EU research programs ("PEURP"; see Gonzáles et al., 2005; Pellegrino and Piva, 2020). We also include regional and industry fixed effects.

Table 4 presents the results from the Tobit estimations for total R&D, internal and external R&D, and ETC. The findings indicate a positive and significant association between AI and both total and internal R&D, as well as ETC (with the strongest association for ETC). In contrast, the relationship between AI and external R&D is not statistically significant. The control variables present the expected significant coefficients in the case of firm's size, scientific collaborations, educated workforce and European programs. While cooperative agreements and foreign ownership fail to be significant.

Table 5 reports the results from the probit estimations, using binary variables for total, internal, and external R&D, as well as for ETC. The association between AI and the decision to engage in R&D is positive and significant, primarily driven by the positive association between AI and the decision to invest in internal R&D. Additionally, the results reveal a positive and significant association between AI and the decision to acquire ETC.

Overall, our results show a positive and significant relationship between AI and most of the innovative inputs (in both continuous and binary variable specifications).

Table 4: The impact of AI on innovation inputs measured in levels- Tobit estimations

VARIABLES	(1) R&D	(2) Internal R&D	(3) External R&D	(4) ETC
AI 2018	2.791**	3.463**	1.912	4.641**
	(1.296)	(1.494)	(1.488)	(1.860)
Employment	1.660***	1.887***	1.395**	3.154***
	(0.629)	(0.719)	(0.710)	(0.919)
Collwithuni	12.989***	12.715***	15.397***	5.068**
	(1.155)	(1.345)	(1.237)	(2.060)
% EG	1.925***	2.280***	1.968***	0.956
	(0.594)	(0.713)	(0.713)	(0.859)
TCA	-0.468	-0.285	3.124	-2.943
	(2.886)	(3.244)	(3.218)	(5.277)
Foreign	-0.012	-0.005	-0.025	-0.066**
	(0.018)	(0.021)	(0.021)	(0.029)
PEURP	5.310**	7.406***	3.477	8.063
	(2.262)	(2.544)	(3.178)	(5.490)
Constant	-22.572***	-25.213***	-33.714***	-33.326***
	(4.300)	(4.845)	(5.472)	(6.729)
Observations	778	778	778	768

Note: All the dependent variables are in logs. AI 2018 is the use of AI in 2018. Employment is the Log of total number of staff in the company. Collwithuni is the collaboration with universities and/or tech centers (dummy variable). % EG captures the proportion of engineers and graduates. TCA is the technological cooperation agreements (dummy variable). Foreign is the foreign shareholding (%). Finally, PEURP is the participation in EU research programs (dummy variable). All specifications include regional and industry-fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reduction in the number of observations in the ETC equation reflects missing values in the dependent variable.

Table 5: The impact of AI on innovation inputs measured as binary variables – Probit estimations

VARIABLES	(1) R&D	(2) Internal R&D	(3) External R&D	(4) ETC
AI 2018	0.098**	0.090**	0.043	0.086**
	(0.046)	(0.040)	(0.035)	(0.038)
Employment	0.045**	0.038**	0.025	0.057***
	(0.022)	(0.019)	(0.017)	(0.019)
Collwithuni	0.464***	0.332***	0.350***	0.095**
	(0.055)	(0.043)	(0.040)	(0.042)
% EG	0.055***	0.051***	0.040***	0.019
	(0.019)	(0.017)	(0.015)	(0.016)
TCA	-0.050	0.002	0.050	-0.067
	(0.154)	(0.122)	(0.103)	(0.112)
Foreign	-0.000	0.000	-0.001	-0.001**
	(0.001)	(0.001)	(0.000)	(0.001)
PEURP	0.396***	0.377***	0.162	0.184
	(0.141)	(0.123)	(0.128)	(0.136)
Observations	774	774	754	744

Note: Marginal Effects. All the dependent variables are dummies (Yes or No). AI 2018 is the use of AI in 2018. Employment is the Log of total number of staff in the company. Collwithuni is the collaboration with universities and/or tech centres (dummy variable). % EG captures the proportion of engineers and graduates. TCA is the technological cooperation agreements (dummy variable). Foreign is the foreign shareholding (%). Finally, PEURP is the participation in EU research programs (dummy variable). All specifications include regional and industry fixed effects. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The slight reduction in observations for external R&D is due to computational issues affecting the maximum likelihood function used in the probit model, while the reduction in observations in the ETC equation reflects missing values in the dependent variable.

In more detail, evidence suggests that AI may favour and accelerate R&D (especially internal one), probably supporting early-stage experimentation, reducing initial research costs, and improving accuracy and forecasting. The emphasis on internal R&D is particularly relevant as AI might enhance relevance and effectiveness of in-house research investments. On the other side, the lack of statistical significance between AI and external R&D is not unexpected: indeed, AI adoption is intended to increase in-house knowledge and internal technological and dynamic capabilities (Teece et al., 1997) and not to support innovation activities developed outside the company.

Turning our attention to ETC, which is typically associated with improving production processes through cost reduction and quality enhancement, AI appears to act as a catalyst, boosting ETC adoption (probably through increasing effectiveness, fostering productivity gains and minimizing technical breakdowns).

4.3 Heterogeneity

In this subsection, we explore the possible heterogeneities in the relationship between firm's AI adoption and the subsequent investments in innovation inputs. In order to insert the relevant interaction variables and to interpret the estimated coefficients, we estimate linear regression models (OLS) and include the interactive terms between AI and size (large *vs* small companies)[19] as well as between AI and technological intensity (high-tech vs low-tech sectors).[20] After estimating the models, we compute the marginal effects to quantify the relationship and assess whether significant differences emerge across firm size and technological level.

Table 6 displays the results for the values in levels of the dependent variables (see Panel A) and their categorical values (see Panel B). The results suggest a positive association between AI and total R&D, primarily driven by internal R&D in large companies. Furthermore, AI is positively associated with ETC in large companies. The results for the categorical values follow the same direction as the previous ones.

Conversely - although the coefficient display the expected signs - our models do not find significant evidence regarding the enhancing role of AI in the case of small companies. These findings have important implications. Large companies mainly drive the revealed association between AI and innovation inputs, and this may be due to different factors. Large companies have the absorptive capacity, the dynamic capabilities and the financial resources to assimilate new AI technologies, while small companies often face major financial constraints and do not have enough capabilities to fully assimilate the latest technologies and get synergies. In contrast, large companies can benefit more from AI adoption since they rely on internal capabilities and organizational structures that enable them to make more value from AI adoption and envisage the possible positive synergy between AI and internal R&D activities. Similarly, ETC is positively associated to AI only in large companies. This

[19] To split the sample, we use the median value of employment, which is 72 employees.

[20] The classification between high- and low-tech sectors is presented in Table A.3 in the Appendix and is based on the OECD classification. For more detail, see Hatzichronoglou (1997)

is likely due to what discussed above and to their large-scale production structures, which are better positioned to exploit AI-driven efficiency gains.[21]

Table 6: The impact of AI on innovation input by size (OLS)

	(1)	(2)	(3)	(4)
Panel (A): Dependent variables in levels				
	R&D	Internal R&D	External R&D	ETC
AI use in Small	0.350	0.624	0.122	0.445
	(0.694)	(0.671)	(0.482)	(0.776)
AI use in Large	1.365**	1.185*	0.627	1.799**
	(0.665)	(0.659)	(0.574)	(0.735)
Observations	778	778	778	768
Panel B: Binary dependent variables				
	R&D	Internal R&D	External R&D	ETC
AI use in Small	0.037	0.069	0.020	0.038
	(0.061)	(0.059)	(0.047)	(0.064)
AI use in Large	0.105**	0.093*	0.053	0.123**
	(0.053)	(0.053)	(0.050)	(0.057)
Observations	778	778	778	768

Note: All the dependent variables are in logs in Panels A, while all in Panel B are dummies (Yes or No). AI is the use of AI in 2018. The specification contains control variables: employment, collaboration with universities and/or tech centers (dummy variable), the proportion of engineers and graduates, technological cooperation agreements (dummy variable), foreign shareholding (%), and participation in EU research programs (dummy variable). All specifications include regional and industry-fixed effects. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, the results for the high- and low-tech industries[22] are put forward in Table 7. The results suggest a positive association of AI with total R&D, internal and external R&D in the high-tech sectors, while the association of AI with ETC is positive and significant in the low-tech industries (while not significant in the other three cases). The consistent positive relationships between AI adoption and R&D in high-tech industries likely reflects these firms' greater propensity to invest in innovation

[21] It is worth remebering that only manufacturing companies are included in our sample.

[22] For more details regarding our classification, see Table A.3.

activities, supported by the presence of R&D departments and the innovative nature of their competitive environment. In this context, AI adoption appears an accelerator of all the knowledge-intensive activities including - in this case - external R&D, as well.

Conversely, firms operating in low-tech sectors appear to significantly benefit from AI through an enhanced access to ETC, which is the dominant channel of technological advancement in the most traditional manufacturing industries. In these sectors, AI adoption is probably conceived as a tool to make technological acquisition more fruitful.

Table 7: The impact of AI on innovation input by technological intensity (OLS)

	(1)	(2)	(3)	(4)
Panel A: Dependent variables in levels				
	R&D	Internal R&D	External R&D	ETC
AI use in Low-tech	0.616	0.660	-0.052	1.933***
	(0.563)	(0.547)	(0.444)	(0.652)
AI use in High-tech	1.949**	1.791*	1.679**	-0.284
	(0.949)	(0.965)	(0.844)	(0.981)
Observations	778	778	778	768
Panel B: Binary dependent variables				
	R&D	Internal R&D	External R&D	ETC
AI use in Low-tech	0.045	0.055	-0.000	0.144***
	(0.046)	(0.045)	(0.039)	(0.051)
AI use in High-tech	0.168**	0.158**	0.142*	-0.040
	(0.077)	(0.078)	(0.075)	(0.077)
Observations	778	778	778	768

Note: All the dependent variables are in logs in Panels A, while all in Panel B are dummies (Yes or No). AI is the use of AI in 2018. The specification contains control variables: employment, collaboration with universities and/or tech centers (dummy variable), the proportion of engineers and graduates, technological cooperation agreements (dummy variable), foreign shareholding (%), and participation in EU research programs (dummy variable). All specifications include regional and industry-fixed effects. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusions

Artificial Intelligence, with its pervasive influence on economies and societies, is reshaping how firms innovate and produce. Its rapid diffusion and large application require attention to fully comprehend risks, effects and consequences. While the existing empirical evidence, using various proxies to operationalize AI, increasingly points to AI as a driver of productivity and economic growth, less is known about how AI affects conventional innovation activities and whether complementarities among AI and innovative inputs exist. However, if AI is to be considered not only a General Purpose Technology, but also a Method of Invention, understanding its interaction with firm's innovation strategies is essential.

This study contributes to this debate by analysing firm-level data from the Spanish manufacturing sector. It explores two key questions: (1) whether AI complements R&D and other innovation inputs, specifically Embodied Technological Change; (2) whether AI can be considered as a MoI, fostering subsequent investments in innovation inputs. Results (1) show a robust correlation between AI adoption and internal R&D and between AI adoption and ETC (both in a conditional and an unconditional framework) suggesting a certain degree of complementarity; (2) highlight, in a dynamic perspective, a general positive and significant impact of AI on internal R&D and ETC, suggesting that AI may trigger and amplify internal innovation investments.

Our findings also reveal heterogeneity across firms. Indeed, our two main results (AI fostering internal R&D and ETC) seem to be driven by larger firms, likely able to better envisage and value the synergic potentialities of AI adoption. Finally, splitting by industries, companies in high-tech sectors seem to benefit more from AI in their R&D departments, while firms in more traditional industries exploit AI in increasing their acquisition of ETC.

These results may have important policy implications: promoting AI adoption might have a booster effect on different innovation activities acting both as a catalyst and an accelerator. Yet, policy makers should also be aware of a significant degree of heterogeneity across industries and across firm's size (implying the need for targeted industrial and innovation policies).

From a managerial perspective, evidence suggests that AI adoption can foster innovation propensity. However, as highlighted by Bianchini et al. (2022) and Antonioli et al. (2024), in-house dynamic capabilities, human capital endowment, and organizational change might be important mediators of what discussed in this study.

The lack of data on these latter dimensions is one of the limitations of this paper; moreover, dealing with contemporaneous correlations and with four-year-span regressions prevents us from inferring any causal effect; finally, while the Spanish case offers valuable insights, country-specific factors may influence the generalizability of our results.

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Appendix

Table A.1: Unconditional correlations (binary variables)

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.867***	1			
External R&D	0.768***	0.557***	1		
ETC	0.168***	0.171***	0.175***	1	
AI 2022	0.206***	0.201***	0.189***	0.164***	1
Observations	936				

* p<0.10, ** p<0.05, *** p<0.01

Table A.2: Conditional correlations (binary variables)

	R&D	Internal R&D	External R&D	ETC	AI 2022
R&D	1				
Internal R&D	0.819***	1			
External R&D	0.686***	0.396***	1		
ETC	0.0842**	0.0890**	0.0846**	1	
AI 2022	0.0636*	0.0655*	0.0466	0.105***	1
Observations	714				

* p<0.10, ** p<0.05, *** p<0.01

Table A.3. Industrial classification: high- and low-tech sectors

Low-tech sector	**High-tech sector**
Meat products	Chemicals and pharmaceutical
Food and tobacco	Machinery and equipment
Beverage	Computer products, electronics and optical
Textiles and clothing	Electric materials and accessories
Leather, fur and footwear	Vehicles and accessories
Timber	Other transport equipment
Paper	
Printing	
Plastic and rubber products	
Non-metal mineral products	
Basic metal products	
Fabricated metal products	
Furniture	
Other manufacturing	

Note: Based on OCDE classification (see Hatzichronoglou, 1997)