

High-tech adoption and innovation in manufacturing firms: Evidence from an Italian industrial area

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ABSTRACT

Objective: The objective of this article is to empirically assess the relationship between firm characteristics, local innovation networks, and the level of high-tech adoption among manufacturing firms located in the Italian provinces of Fermo and Ascoli Piceno, *i.e.*, two territories characterised by long-standing manufacturing traditions but differing sectoral specialisations. It focuses on the role of firm-level characteristics and local innovation ecosystems. I explored how firms in traditional industrial areas engage with new high-tech solutions, and which factors enable or hinder technological upgrading. By providing micro-level evidence from a central Italian economy, the article offers useful insights for industrial areas facing similar structural and technological challenges.

Research Design & Methods: The study adopted a mixed-methods approach combining firm-level financial data for 2022 with a web scraping activity and a cross-sectional survey conducted in December 2023 on manufacturing firms located in Fermo and Ascoli Piceno. The web scraping provided firms' contact information, and the survey yielded 128 valid responses with information on technology adoption, perceived barriers, and innovation behaviour; I used firm-level data for the econometric analysis.

Findings: Results revealed a heterogeneous landscape of high-tech adoption across firms. While some firms, mainly big-sized, were actively implementing these technologies, a large share of small enterprises remained at early stages of high-tech adoption. Barriers included financial constraints, skill shortages, and uncertainty about returns. Conversely, firms operating within technological districts have already implemented, and are further advancing, the integration of several high-tech solutions into their manufacturing processes.

Implications & Recommendations: The findings suggest the need for targeted regional and industrial policies supporting high-tech readiness among firms. Policy actions should focus on enhancing managerial and technical capabilities, facilitating access to financing, and promoting inter-firm collaborations to foster technological diffusion. These recommendations are particularly relevant for traditional manufacturing regions and peripheral industrial areas, where firms face barriers to technological transformation.

Contribution & Value Added: This article contributes to the literature on technological transformation and Industry 4.0 by offering original evidence from a local manufacturing system. The study advances understanding of how territorial, sectoral, and firm-specific characteristics shape high-tech adoption, providing valuable insights for both scholars and policymakers engaged in supporting modernisation in local industries.

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INTRODUCTION

In recent years, the diffusion of new technologies and high-tech innovation has profoundly reshaped the competitive landscape of firms across both advanced and emerging economies. The paradigms of technological transformation and Industry 4.0 have radically changed production processes, organisational structures, and value creation mechanisms (Kiel *et al.*, 2017; Müller *et al.*, 2018; Ancillai *et al.*,

2023). Notably, the paradigms encompass such technologies as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, digital technologies, and additive manufacturing. The introduced transformations exceed technological upgrading, representing a structural shift in how firms design, deliver, and capture value (Teece, 2010; Chesbrough, 2010). Consequently, technological capability has become a key determinant of firms' competitiveness, resilience, and growth potential.

However, despite the growing consensus on the strategic role of technologies, adoption patterns of high-tech remain highly uneven, particularly across territories and firm sizes. Small and medium-sized enterprises (SMEs), which dominate the industrial fabric of most European regions, often approach high-tech adoption cautiously and fragmentarily, owing to limited financial, managerial, and human resources (Cugno *et al.*, 2022; Morais & Ferreira, 2020). These differences raise concerns about potential technological divides within regional production systems. Likewise, all things being equal, smaller economies or contexts may face additional barriers to technological innovation.

The COVID-19 pandemic further accelerated the need for technological adaptation, revealing both the strengths and vulnerabilities of manufacturing ecosystems (Cugno *et al.*, 2022). While advanced technologies ensured business continuity through automation and remote operations, they also exposed persistent structural gaps, particularly in traditional or low-tech sectors. Understanding how regional firms approach high-tech innovation therefore becomes crucial for designing effective industrial and innovation policies.

To achieve this goal, I adopted a strategy that combines balance-sheet information for 2022 with data collected through a survey administered in December 2023. I obtained firms' contact details through a web-based data collection procedure, enabling the administration of the questionnaire, which yielded 128 valid responses on technological adoption, perceived constraints, and innovation practices. Then, I exploited these data within an econometric framework that explores how firms' characteristics, such as size, sector, ownership, and localisation, and the local context shape technological behaviours and innovation readiness.

Empirical evidence reveals a heterogeneous level of high-tech adoption among regional manufacturing firms. While several companies, especially bigger ones, are experimenting with advanced technologies such as cloud systems, IoT, and digital platforms, many smaller firms still rely on traditional production processes and report limited technological readiness. The results confirm a dual structure within the local industrial ecosystem: a minority of technologically advanced firms and a majority lagging in technological upgrading. Furthermore, the analysis highlights that firms' perceived barriers to high-tech adoption relate mainly to financial constraints, lack of skilled personnel, and uncertainty about return on investment. Simultaneously, firms that belong to technological districts have already adopted high-tech solutions and report positive effects in terms of the number of technologies already implemented.

The article contributes to the ongoing debate on technological transformation and regional innovation systems. Indeed, while extensive research has explored national or sectoral drivers of Industry 4.0, fewer studies have focused on territorial-level analyses of technological diffusion, particularly in traditional manufacturing areas. By focusing on a specific regional ecosystem, this research highlights the role of contextual factors, such as local districts and digital innovation hubs, in shaping high-tech adoption pathways, both in the two provinces analysed and in other comparable contexts.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

High-tech transformation is a multifaceted process reshaping how firms generate and capture value through the integration of new technologies into business operations and strategies (Teece, 2010; Foss & Saebi, 2017). The Industry 4.0 framework emphasises the convergence of advanced technologies, including IoT, AI, robotics, digitalisation, and data analytics, as drivers of efficiency, innovation, and competitive advantage (Kiel *et al.*, 2017; Müller *et al.*, 2018). Recent studies highlight that the adoption of these technologies not only enhances productivity but also triggers organisational and strategic renewal, often leading to business model innovation (BMI) (Ancillai *et al.*, 2023; Björkdahl, 2020).

However, empirical evidence shows highly heterogeneous diffusion of these technologies across firms. For example, the literature highlights that firm size plays a crucial role in shaping technological

adoption patterns. Larger enterprises typically benefit from economies of scale, more structured organisational processes, and easier access to financial resources, which facilitate investments in complex digital technologies (Kohtamäki *et al.*, 2019; 2020). In contrast, SMEs face significant barriers to digitalisation, including financial constraints, lack of internal expertise, and uncertainty about the expected returns on investment (Cugno *et al.*, 2022; Morais & Ferreira, 2020). Scholars have conceptualised this imbalance as a ‘digitalisation paradox’ (Gebauer *et al.*, 2020), in which the potential of digital transformation remains underexploited among smaller firms.

In this study, I measured firm size as the number of employees. Building on past literature, I expected that firms with greater organisational and financial resources would be more likely to engage in high-tech adoption.

H1: Larger firms (*i.e.*, firms with more employees) are more likely to adopt high-tech than smaller firms.

Beyond firm-level determinants, the territorial and institutional context also shapes firms’ technological behaviour. Regional innovation systems, industrial districts, and local collaborative networks can provide access to knowledge spillovers, shared resources, and specialised competencies, which can significantly reduce the costs and risks associated with technological upgrading (Asheim & Isaksen, 2002; Belussi & Sedita, 2010). Firms embedded in such innovation networks benefit from proximity to other firms, research institutions, and support organisations, which enhances learning processes and facilitates the diffusion of new technologies. In contrast, firms that are not embedded in these collaborative environments may face greater difficulties in accessing external knowledge and innovation-related resources. In the analysis, I captured this dimension through firms’ participation in technological districts, research centres, and digital innovation hubs. Accordingly, I expected firms integrated within local innovation networks to exhibit higher levels of high-tech adoption.

H2: Firms embedded in technological districts exhibit higher levels of high-tech adoption than firms not involved in such networks.

Finally, internal capabilities shape firms’ ability to adopt and use advanced technologies effectively. Managerial quality, strategic orientation towards innovation, and the availability of skilled human capital can enhance firms’ capacity to identify, evaluate, and implement new technological solutions (Chen & Huang, 2009; Caloghirou *et al.*, 2018).

H3: Firms with greater innovation orientation and managerial capabilities are more likely to overcome barriers to technological transformation.

RESEARCH METHODOLOGY

Sample

I conducted the empirical analysis using a structured data collection process that combined administrative and survey-based information. Firstly, I identified key technological domains and measurable indicators of high-tech development, focusing on the adoption of advanced technologies, software tools, digitalised processes, and e-commerce. Building on these dimensions, I designed a dedicated online survey to collect information on firms’ engagement with high-tech activities, perceived benefits and challenges, collaborative initiatives, and perspectives on future technological development.

Furthermore, I constructed a firm-level dataset using the AIDA database (Bureau van Dijk, 2023), which provided comprehensive financial, registry, and sectoral information on Italian companies. The initial population comprised 16 457 firms located in the provinces of Fermo and Ascoli Piceno. After restricting the sample to active limited liability companies operating in the manufacturing sector and excluding firms without complete financial data for 2022 or those in liquidation, the dataset consisted of 1 383 firms.

To ensure that this dataset remained representative of the overall population, I verified its consistency in firm size, age, and growth dynamics, confirming that the selected firms adequately reflect the structural characteristics of the manufacturing base in the two provinces.

For each firm, I collected detailed information, including structural characteristics, sector, legal status, ownership, district membership, key financial indicators, and employee data.

To facilitate survey administration, I implemented a web scraping procedure to retrieve firms' contact information, which I conducted in full compliance with data protection and privacy regulations.

Specifically, the web scraping targeted firms' official websites as listed in the AIDA database and retrieved publicly available contact information, primarily email addresses used for business communication. The scraping focused on standard website sections (*e.g.*, 'homepage,' 'contacts,' 'about,' 'company information') and did not involve social media platforms or third-party directories. I retained firms if I identified at least one valid and active email address associated with the firm. At that stage, I excluded firms with inactive websites, missing contact pages, or invalid email addresses, thus reducing the sample from 1 383 to 697 eligible firms. While this restriction may introduce a selection bias towards firms with a stronger technological presence, it reflects the practical requirements of online survey administration and the increasing diffusion of corporate websites even among small and medium-sized manufacturing firms. Moreover, the analysis focused on limited liability companies, which are more likely to display a minimum level of high-tech engagement than unipersonal entrepreneurial activities.

I distributed the online survey, implemented via Microsoft Forms, individually to all eligible firms in December 2023. Participation was voluntary and respondents could withdraw at any stage. Of the 697 firms contacted, 141 responded, and 128 firms provided valid consent and completed the questionnaire, resulting in an effective response rate of 18.4%. These 128 firms constituted the final analysed sample.

This final sample was composed predominantly of limited liability companies (S.R.L., 83%), with a substantial presence of family-owned firms (45%). Most firms were Italian-owned (58%), while the remainder was foreign-owned or had undisclosed ownership. Sectoral analysis, based on ATECO classification, showed a diversified manufacturing structure with 19 sectors represented (Table 1).

Table 1. Companies' distribution based on the ATECO code in Fermo and Ascoli Piceno in the year 2022

ATECO description	ATECO code	Freq.	%
Food industries	10	10	7.81%
Beverage industry	11	9	7.03%
Textile industries	13	6	4.69%
Packaging of clothing items; packaging of leather and fur items	14	6	4.69%
Manufacture of leather goods and the like	15	23	17.97%
Wood and wood and cork products industry (excluding furniture); manufacture of articles of straw and plaiting materials	16	2	1.56%
Manufacture of paper and paper products	17	11	8.59%
Printing and reproduction of recorded media	18	4	3.13%
Manufacture of chemical products	20	8	6.25%
Manufacture of articles of rubber and plastics	22	4	3.13%
Manufacture of other non-metallic mineral processing products	23	1	0.78%
Manufacture of metal products (excluding machinery and equipment)	25	13	10.16%
Manufacture of computers and electronic and optical products; electro-medical apparatus, measuring apparatus and clocks	26	4	3.13%
Manufacture of electronic equipment and non-electrical household equipment	27	4	3.13%
Manufacture of NCA machinery and equipment	28	7	5.47%
Manufacture of motor vehicles, trailers and semi-trailers	29	6	4.69%
Furniture manufacturing	31	6	4.69%
Other manufacturing industries	32	2	1.56%
Repair, maintenance and installation of machines and equipment	33	2	1.56%
Total	—	128	100%

Note: distribution of the sample of enterprises responding to the survey.

Source: own study.

The most common sectors were leather and related products (18%), fabricated metal products (10%), and paper and paper products (9%), while several niche sectors were represented by only

one or two firms. Territorial coverage was balanced between the two provinces, with 66 firms in Fermo and 62 in Ascoli Piceno, and more than half of the municipalities across the two provinces included in the survey (see Figure 1 for a geographic distribution).

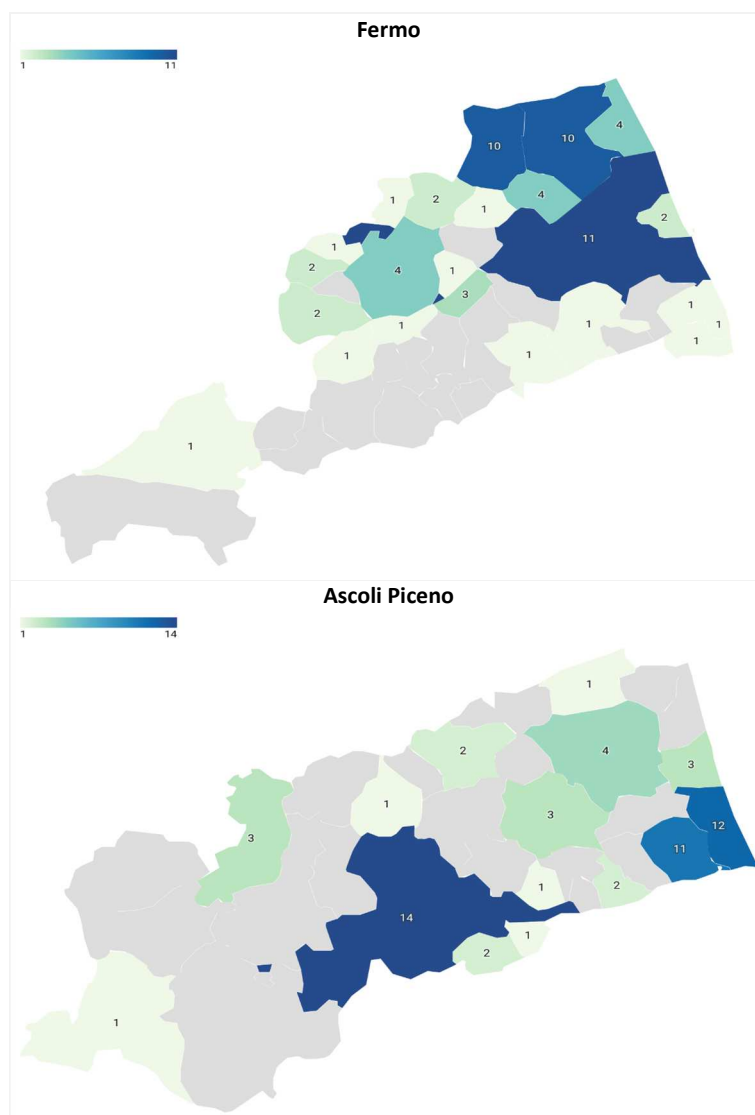


Figure 1. Territorial coverage of the sample surveyed for the two provinces of Fermo and Ascoli Piceno in December 2023

Source: own elaboration.

Overall, the dataset provided a representative and detailed view of manufacturing firms in the two provinces, enabling an in-depth analysis of high-tech adoption patterns and the factors influencing technological engagement at the firm level.

Variables

From the survey, I retrieved the dependent variables that captured the degree of technological adoption within firms. Firstly, I identified a list of fourteen technologies that fell under the category of high-tech and could be relevant to investigate within firms. These technologies were as follows: (1) cloud; (2) industrial Internet or Internet of Things (IoT); (3) simulation; (4) horizontal and vertical integration; (5) cybersecurity systems and cyber-physical systems; (6) additive manufacturing; (7) Big Data analysis; (8) augmented reality; (9) advanced manufacturing solutions and robotics; (10) artificial intelligence

(AI); (11) machine learning; (12) blockchain; (13) wearable, sensors and smart devices; (14) electronic commerce (E-commerce). A detailed description of each technology is provided in Appendix.

In detail, to capture the level of penetration, I formulated a multiple-choice question with four possible answers for each technology. The question ‘According to you, for each of the following high-tech technologies, what is the degree of actual implementation in your company?’ offered the following options, as previously described: (a) not implemented / not of interest; (b) of interest / not yet implemented; (c) planned within the next five years; (d) implemented.

Depending on the answer, the firm was assigned a score ranging from 0 to 3, where 0 corresponded to ‘not implemented/not of interest’ and 3 corresponded to ‘implemented.’ This made it possible to create a quantitative measure that captures, on the one hand, the level of hi-tech penetration and the actual implementation of one or more specific technologies, and on the other, highlights potential delays in adoption or particular technologies of interest, among other aspects.

This synthetic metric allowed me to classify both technologies and firms. In fact, if a technology has been implemented by all 128 firms, the maximum score for that technology would be 384. Conversely, if a firm had already adopted all the technologies, it would obtain a score of 42. Figure 2 presents a summary of the scores received by enterprises by type of technology.

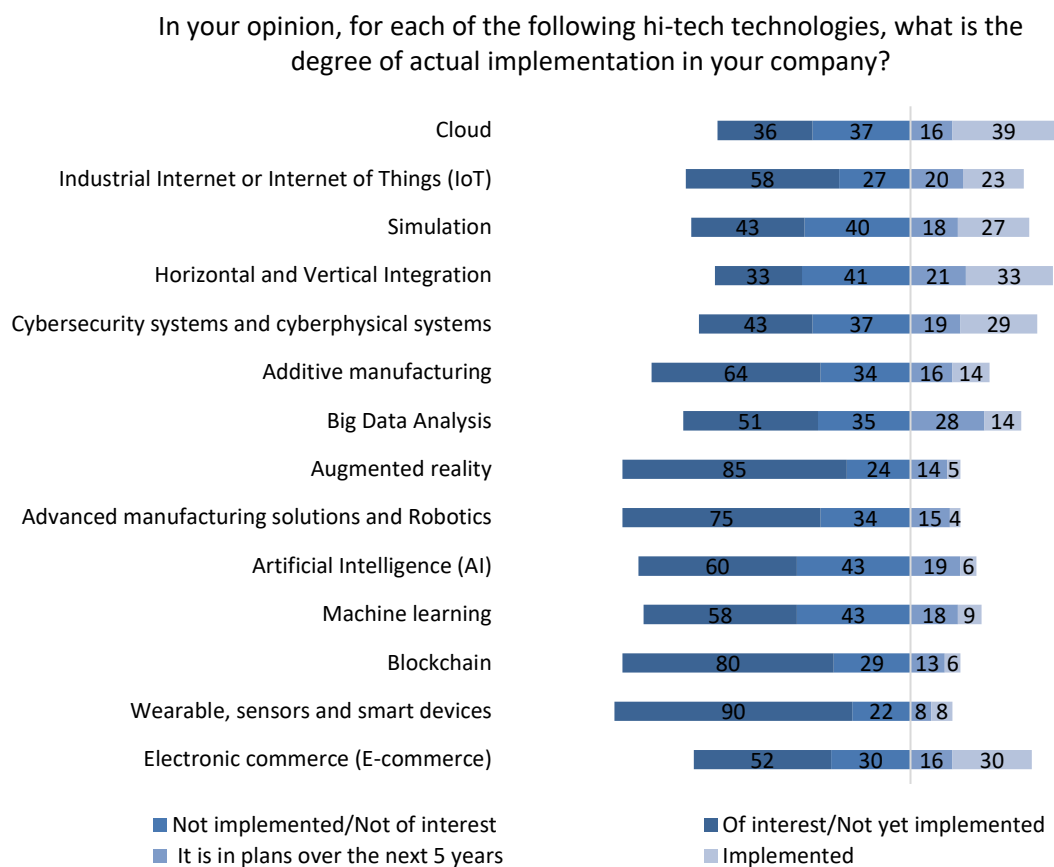


Figure 2. High technologies and penetration level for the surveyed firms in December 2023

Source: own elaboration.

Based on the answer from the survey, HighTech was a discrete variable representing the total score assigned to each firm based on the number of technologies adopted and their level of implementation. Since each technology could take a value ranging from 0, indicating that the technology was not implemented, to 3, denoting full implementation, higher values reflected broader and more advanced technological adoption. WeightedHighTech expressed the same measure in relative terms by dividing the total score by 42, which represents the maximum achievable value if all fourteen technologies were

fully implemented (14×3). This rescaled indicator facilitates comparison across firms of different technological profiles. To capture threshold effects, I also constructed two dummy variables. *D_HighTech* took the value of one if the total technological score (*HighTech*) exceeded the average score achieved by the companies in the sample (i.e., above 13), and zero otherwise. Similarly, *D_WeightedHighTech* equalled one if the weighted score (*WeightedHighTech*) was above 0.5 – corresponding to over 50% of the maximum potential technological adoption level – and zero otherwise.

In the empirical analysis, I controlled for several firm-level characteristics that may influence the outcomes of interest. I measured firm size by the number of employees, capturing differences in scale and organisational capacity (*Size*). I defined liabilities as the ratio of financial debts to total turnover, providing an indication of the firm's financial leverage (*Liabilities*). I measured tangible assets as the share of tangible fixed assets over total assets, reflecting the firm's capital intensity (*Tangible assets*). I calculated firm age as the number of years since the firm's establishment and it served as a proxy for experience and market maturity (*Age*).

In addition to these controls, I included several potential determinants of firm performance and behaviour. The cost per employee variable represented the average labour cost per worker, expressed in thousands of euros, and captures differences in labour quality or intensity (*Cost_employee*). I also considered three dummy indicators capturing firms' participation in innovation-related networks: *Tech_District* equalled one if the firm belonged to a technological district, *Research_Center* equalled one if it was part of a research centre, and *Dig_Inn_Hub* equalled one if it was associated with a digital innovation hub, with all three set to zero otherwise. Furthermore, *Family* was a dummy variable equal to one when the firm's global ultimate owner (GUO) is an individual or family, and zero when ownership was corporate or institutional. Finally, *Foreign* equalled one if the GUO was a foreign entity and zero if it was Italian. Table 2 shows a descriptive summary of these variables.

Table 2. Descriptive statistics of the enterprises in the sample in 2022-2023

Variable	Obs.	Mean	Std. Dev.	Min	Max
Size	128	41.62	89.27	0.00	560.00
Liabilities	128	1.11	1.94	0.00	10.12
Tangible assets	128	0.20	0.20	0.00	0.92
Age	128	25.50	15.87	2.00	93.00
Cost_employee	128	34.41	15.94	0.00	66.85
Tech_District	128	0.12	0.32	0.00	1.00
Research_Center	128	0.12	0.32	0.00	1.00
Dig_Inn_Hub	128	0.07	0.26	0.00	1.00
Family	128	0.45	0.50	0.00	1.00
Foreign	128	0.42	0.50	0.00	1.00
HighTech	128	13.22	7.67	0.00	35.00
WeightedHighTech	128	0.31	0.18	0.00	0.83
D_HighTech	128	0.50	0.50	0.00	1.00
D_WeightedHighTech	128	0.19	0.39	0.00	1.00

Source: own study.

Empirical Strategy

Using this empirical strategy, I tested whether specific firm attributes were more strongly associated than others with the level of high-tech adoption, and whether these characteristics could help explain why some firms adopt these technologies while others do not.

This relationship is inherently complex and multifaceted; theoretically, we may expect a bidirectional interaction. On the one hand, firm characteristics may influence the extent of high-tech adoption: firms investing heavily in research and development or employing highly skilled workers are more likely to implement advanced technologies. On the other hand, the adoption of high-tech solutions may reshape firm characteristics by inducing investments in employee training, organisational

restructuring, or process innovation. Several studies have investigated this interplay between technological adoption and firm attributes. For instance, Spitsin *et al.* (2022) examines how the performance and growth of high-tech firms affect their financial structures, showing that better-performing and faster-growing firms tend to exhibit stronger financial positions. Cavalcante (2013) focuses on how new technologies can reshape business models, highlighting that technological adoption often entails substantial structural and organisational adjustments.

Building on insights from this literature (Cavalcante, 2013; Spitsin *et al.*, 2022) and on the empirical properties of the data, I performed a quantitative analysis to empirically assess the link between high-tech adoption and firm characteristics using two complementary econometric specifications. This dual approach allowed me to capture both the intensity of technology adoption and the likelihood of being a relatively high adopter. I estimated the first model using a linear ordinary least squares (OLS) specification, defined as:

$$HighTech_{i,t} = \alpha_i + \beta_i * D_{i,t} + \gamma_i * C_{i,t} + \alpha_{ateco} + \alpha_{nuts3} + \varepsilon_{i,t} \quad (1)$$

in which $HighTech_{i,t}$ is a discrete index measuring the intensity of high-tech adoption, defined as the sum of fourteen technology-specific scores. Although discrete, this variable exhibits a sufficiently wide support and variability to be treated as approximately continuous, allowing the use of OLS as a parsimonious and easily interpretable benchmark. OLS estimates capture the average marginal effect of firm characteristics on the overall intensity of technology adoption. $D_{i,t}$ is the vector containing the main explanatory variables (or drivers) of interest, while $C_{i,t}$ includes a set of firm-level control variables. The model also includes fixed effects for the 2-digit industry classification (α_{ateco}) and for province (α_{nuts3}), which help control for unobserved heterogeneity across industries and territorial contexts. Finally, $\varepsilon_{i,t}$ denotes the error term. I clustered standard errors at the firm level.

To complement the analysis, I estimated a non-linear Probit model:

$$D\_HighTech_{i,t} = \beta_i * D_{i,t} + \gamma_i * C_{i,t} + \alpha_{ateco} + \alpha_{nuts3} + \varepsilon_{i,t} \quad (2)$$

In this case, the main independent variables, controls, and fixed effects remain the same as in the OLS model. The dependent variable, $D\_HighTech_{i,t}$, corresponds to the probability that a firm, given its characteristics, has a high-tech level equal to or above the observed average score. This specification permits focusing on the extensive margin of adoption by modelling the probability that a firm reaches a relatively high level of technological intensity. Estimating both OLS and Probit models ensured robustness of the results across alternative functional forms and provided complementary insights into the determinants of high-tech adoption. To mitigate potential endogeneity problems, I lagged all independent variables by one year and took them at 2022 values.

RESULTS AND DISCUSSION

Firstly, the results of both the linear and Probit regressions suggest that some firm-level characteristics were clearly associated with a higher high-tech score.

Table 3 reports the results of the OLS regressions investigating the relationship between firm characteristics and the degree of high-tech adoption. Columns (1) to (3) use the total high-tech score as the dependent variable, while Columns (4) to (6) replicate the analysis using the weighted high-tech score, which represents an alternative operationalisation of technological adoption intensity. As expected, rescaling the dependent variable did not alter the qualitative relationships between the regressors and the outcome. Across almost all specifications, the coefficients were consistent in both magnitude and significance, suggesting the consistency of the results even with the inclusion of provincial (NUTS3) and sectoral (ATECO) fixed effects.

Among the control variables, firm size showed a positive and statistically significant association with the level of high-tech adoption in all specifications. Thus, larger firms were more likely to adopt a broader set of advanced technologies. The effect, although modest in magnitude, was highly robust across specifications, implying that scale advantages may facilitate investment in complex technological solutions. Similarly, liabilities, measured as financial debts over turnover, showed a positive and statistically significant coefficient in the baseline OLS specifications: firms with a more leveraged

financial structure were not necessarily constrained in their innovative capacity; rather, they might have used financial leverage strategically to fund technological investments. However, this effect weakens and becomes insignificant once sectoral and provincial fixed effects are included. This pattern suggests that we should interpret the positive association between liabilities and high-tech adoption with caution, as it may reflect unobserved sectoral or territorial characteristics rather than a firm-level driver of technological adoption.

Turning to the determinants, the cost per employee variable was also positive and significant, indicating that firms with higher labour costs – often a proxy for more qualified or specialised workers – were more likely to score higher in high-tech adoption. This finding aligns with the idea that human capital quality is a critical enabler of technological upgrading. Indeed, companies offering higher wages can attract and retain more qualified talent, which in turn can contribute to high-tech development.

I observed the strongest effect for the Tech_District variable. Belonging to a technological district increased the high-tech adoption score by approximately 6 to 8 percentage points, a large and highly significant effect across all model specifications. This result highlights the importance of spatial and network-related factors in fostering technological diffusion. Firms embedded in technological districts likely benefited from knowledge spillovers, local collaboration networks, and institutional support, all of which enhance their probability of adopting advanced technologies. The effect remained significant and stable even after controlling for regional and sectoral heterogeneity, confirming that the impact of local innovation ecosystems operated beyond industry- or region-specific dynamics.

On the other hand, the presence of a Research_Center affiliation exerted a positive and significant influence in the baseline specifications, although its magnitude decreased and became insignificant once fixed effects were introduced. This suggests that while research collaborations can promote technology adoption, their effect may be partially captured by sectoral or regional differences in innovation intensity. In contrast, other variables such as Tangible assets, Age, Family ownership, and Foreign ownership did not display statistically significant relationships with technological adoption. These null results suggest that the firm's asset structure, age profile, and ownership type are less critical in explaining the probability of adopting advanced technologies once other factors are controlled for.

Overall, the results suggest that high-tech adoption is primarily driven by factors related to firm size, financial and human resources, and, most importantly, by the firm's integration within technological districts. These findings support the hypothesis that local innovation ecosystems play a crucial role in shaping firms' technological trajectories, amplifying the benefits of knowledge sharing and collaborative dynamics (Table 3).

Table 4 reports the results of the Probit estimations, where the dependent variable was a dummy indicator equal to one when the firm's high-tech adoption score was above the sample average. Columns (1)–(3) refer to the unweighted version of the dependent variable (D_HighTech), while Columns (4)–(6) use the weighted measure (D_Weighted HighTech). The consistency of the results across the OLS and Probit specifications strengthens the findings' reliability and serves as a meaningful robustness check, indicating that results are not driven by the choice of functional form.

The estimated coefficients confirm that firm size remains a strong and statistically significant determinant of the probability of being classified as a high-tech adopter. Larger firms were significantly more likely to score above the average threshold of technological implementation, underscoring once again the role of firm scale and organisational capacity in enabling the diffusion of advanced technologies.

The Tech_District variable retained its central role and continued to exhibit a positive and significant effect across all model specifications. Belonging to a technological district increased the probability of being a high-tech firm. This result strongly supports the hypothesis that local innovation ecosystems play a crucial role in shaping technological behaviour: firms embedded in such districts are more likely to benefit from proximity to knowledge sources, local collaboration opportunities, and institutional support for innovation.

Moreover, the presence of a Research_Center affiliation was also positively and significantly associated with high-tech adoption, with marginal effects comparable in size to those of technological districts. While research centres do not appear to be significant in increasing the overall high-tech score,

this result suggests that collaboration with research institutions can meaningfully enhance firms' technological capabilities, likely by facilitating access to scientific knowledge and specialised expertise, ultimately improving the likelihood of having more technologies than average.

Table 3. Results from the OLS model for the 128 firms in 2022-2023

Variables	(1) HighTech	(2) HighTech	(3) HighTech	(4) Weighted HighTech	(5) Weighted HighTech	(6) Weighted HighTech
Size	0.0158*** (0.0047)	0.0157*** (0.0047)	0.0140* (0.0072)	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0003* (0.0002)
Liabilities	0.5676** (0.2814)	0.5696** (0.2806)	0.3340 (0.3413)	0.0135** (0.0067)	0.0136** (0.0067)	0.0080 (0.0081)
Tangible assets	0.3214 (3.0158)	0.3469 (3.0228)	2.1191 (3.6635)	0.0077 (0.0718)	0.0083 (0.0720)	0.0505 (0.0872)
Age	-0.0706 (0.0969)	-0.0721 (0.0988)	-0.0678 (0.0958)	-0.0017 (0.0023)	-0.0017 (0.0024)	-0.0016 (0.0023)
Age ²	0.0017 (0.0012)	0.0017 (0.0012)	0.0014 (0.0011)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Cost_employee	0.0880** (0.0435)	0.0883** (0.0436)	0.0961* (0.0516)	0.0021** (0.0010)	0.0021** (0.0010)	0.0023* (0.0012)
Tech_District	7.7416*** (1.8988)	7.7351*** (1.8993)	6.3166*** (2.0092)	0.1843*** (0.0452)	0.1842*** (0.0452)	0.1504*** (0.0478)
Research_Center	2.8794* (1.4982)	2.8743* (1.5114)	1.6678 (1.6802)	0.0686* (0.0357)	0.0684* (0.0360)	0.0397 (0.0400)
Dig_Inn_Hub	2.0812 (1.3561)	2.0687 (1.3829)	2.3612 (1.9640)	0.0496 (0.0323)	0.0493 (0.0329)	0.0562 (0.0468)
Family	-2.3896 (1.6537)	-2.3893 (1.6599)	-1.4750 (1.8925)	-0.0569 (0.0394)	-0.0569 (0.0395)	-0.0351 (0.0451)
Foreign	-1.0605 (1.7052)	-1.0556 (1.7223)	0.1181 (1.9865)	-0.0252 (0.0406)	-0.0251 (0.0410)	0.0028 (0.0473)
Constant	9.2764*** (2.5968)	9.2280*** (2.6338)	4.9152 (4.3762)	0.2209*** (0.0618)	0.2197*** (0.0627)	0.1170 (0.1042)
Observations	128	128	128	128	128	128
R ²	0.2592	0.2592	0.4465	0.2592	0.2592	0.4465
Nuts3 FE	NO	YES	YES	NO	YES	YES
Sector FE	NO	NO	YES	NO	NO	YES

Note: Results from the OLS estimation. Dependent variables: *HighTech* (columns 1-3) and *Weighted HighTech* (columns 4-6). Independent variables are at time $yr=2022$. Provincial and sectoral fixed effects are included in the saturated model (columns 3 and 6).

Source: own study.

Finally, other control variables, such as financial leverage (Liabilities), Tangible assets, Age, and ownership structure (Family, Foreign), remained statistically insignificant. Their lack of significance suggests that once network participation and firm scale are accounted for, these factors do not exert a meaningful marginal effect on the probability of adopting high technologies.

Overall, the Probit model corroborated the main findings from the OLS estimations. The probability of being a high-tech firm increased significantly with firm size, higher-quality human capital, and especially with the firm's integration into innovation-oriented ecosystems such as technological districts and research centres. These results highlight the central role of local knowledge networks and collaborative environments in fostering technological upgrading among firms, confirming that spatial and relational proximity are key drivers of high-technology adoption.

The results are consistent with previous studies highlighting firm size as a key determinant of high-tech adoption (Müller *et al.*, 2018; Kohtamäki *et al.*, 2019). Similar to existing evidence on SMEs, larger firms appeared better equipped to absorb the costs and organisational complexity associated with high-tech. Moreover, the strong effect of technological districts confirmed the relevance of regional

innovation system theories (Asheim & Isaksen, 2002; Belussi & Sedita, 2010), suggesting that local knowledge spillovers and institutional proximity significantly shape firms' technological trajectories. In this respect, the findings extend prior research by providing micro-level evidence on how territorial embeddedness operates even within relatively small and traditional manufacturing contexts. Finally, compared to studies focusing on national or sectoral drivers of high-tech, this article emphasises the importance of place-based factors and district participation, supporting the view that high-tech transformation is not solely a firm-level decision but a context-dependent process.

Table 4. Results from the Probit model for the 128 firms in 2022-2023

Variables	(1) D_HighTech	(2) D_HighTech	(3) D_HighTech	(4) D_Weighted HighTech	(5) D_Weighted HighTech	(6) D_Weighted HighTech
Size	0.0012** (0.0006)	0.0012** (0.0006)	0.0016*** (0.0006)	0.0007*** (0.0003)	0.0007*** (0.0003)	0.0008** (0.0004)
Liabilities	0.0424** (0.0175)	0.0430** (0.0175)	0.0331 (0.0209)	-0.0020 (0.0144)	-0.0029 (0.0137)	-0.0197 (0.0198)
Tangible assets	0.1084 (0.1877)	0.1114 (0.1893)	0.1221 (0.2080)	-0.0410 (0.1518)	-0.0474 (0.1511)	0.1332 (0.1953)
Age	-0.0016 (0.0060)	-0.0020 (0.0061)	-0.0010 (0.0070)	-0.0036 (0.0049)	-0.0033 (0.0051)	-0.0068 (0.0061)
Age ²	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001* (0.0001)
Cost_employee	0.0090*** (0.0025)	0.0091*** (0.0025)	0.0116*** (0.0027)	0.0016 (0.0021)	0.0015 (0.0020)	0.0031 (0.0028)
Tech_District	0.5423*** (0.1548)	0.5388*** (0.1529)	0.2170* (0.1622)	0.1832** (0.0855)	0.1854** (0.0859)	0.3219** (0.1483)
Research_Center	0.2214** (0.1022)	0.2218** (0.1027)	0.2545** (0.1153)	0.1693** (0.0775)	0.1707** (0.0775)	0.3088** (0.1350)
Dig_Inn_Hub	0.2260 (0.1515)	0.2183 (0.1552)	0.1823 (0.1416)	-0.1223 (0.1199)	-0.1243 (0.1179)	-0.3590 (0.1855)
Family	-0.1169 (0.1042)	-0.1179 (0.1044)	-0.0014 (0.1139)	-0.0562 (0.0770)	-0.0563 (0.0764)	-0.0601 (0.1023)
Foreign	0.0155 (0.1053)	0.0148 (0.1053)	0.2124* (0.1167)	-0.0847 (0.0830)	-0.0853 (0.0825)	-0.0215 (0.1043)
Observations	128	128	107	128	128	95
Pseudo R ²	0.2794	0.2797	0.3899	0.1700	0.1710	0.2593
Nuts3 Control	NO	YES	YES	NO	YES	YES
Sector FE	NO	NO	YES	NO	NO	YES

Note: Results from the Probit estimation. Dependent variables: *D_HighTech* (columns 1-3) and *D_Weighted HighTech* (columns 4-6). Independent variables are at time *yr=2022*. Provincial and sectoral fixed effects are included in the saturated model (columns 3 and 6).

Source: own study.

CONCLUSIONS

I analysed the level of high-tech adoption among firms located in the provinces of Fermo and Ascoli Piceno, based on a unique dataset that combines information from the AIDA database and a dedicated survey administered directly to 128 companies. I focused on the implementation of fourteen specific technologies.

The empirical evidence, based on OLS and Probit models, clarified the determinants of high-tech adoption and provided support for all three research hypotheses. Firstly, the results indicate that firm size and human capital intensity emerge as key drivers of high-tech adoption: larger firms and those with higher labour costs per employee, used as a proxy for skilled and qualified personnel, exhibited a significantly higher probability of adopting advanced technologies. Secondly, firms characterised by a stronger innovation orientation and managerial capabilities are better able to overcome barriers to

technological transformation, suggesting that organisational and cognitive resources complement structural factors in shaping adoption behaviour (H1 and H3).

Thirdly, the presence within technological districts and collaboration with research centres emerge as positive and significant determinants of high-tech adoption (H2). These results underscore the importance of spatial and relational proximity: firms embedded in innovation-oriented ecosystems are more likely to access knowledge flows, institutional resources, and collaborative opportunities that foster technological upgrading. Conversely, variables related to firms' financial structure, tangible assets, or ownership type showed no significant relationship with high-tech adoption once network effects and firm size are controlled for.

These findings yield clear policy insights. Firstly, strengthening local innovation ecosystems appears essential: policies should promote the creation and consolidation of technological districts, university-industry collaborations, and applied research networks, which are proven to facilitate technological diffusion. Secondly, public programmes should prioritise human capital development, both by fostering specialised training and by incentivising firms to attract and retain skilled workers. Finally, targeted financial instruments, such as innovation vouchers, tax incentives, and co-funded R&D programmes, could help reduce the cost barriers that currently prevent many firms from adopting advanced technologies.

Overall, the diffusion of high-tech innovation depends on a coordinated, multi-actor strategy. Firms, universities, research centres, and public institutions must act jointly to create an enabling environment for technological upgrading. Only through such an integrated approach, *i.e.*, combining organisational effort, human capital investment, and institutional support, will firms in peripheral regions be able to overcome existing structural constraints and fully exploit the opportunities offered by technological transformation.

Beyond the specific local context analysed, the results offer relevant insights for a broader set of traditional manufacturing regions characterised by similar features, such as fragmented industrial structures, limited technological capabilities, and relatively weak innovation systems. In such contexts, place-based industrial and innovation policies that combine local support, skills upgrading, and inter-firm collaboration are likely to be especially effective in fostering technological upgrading. As a result, the evidence provided in this study can inform policymakers designing strategies to support industrial modernisation in peripheral areas and traditional manufacturing regions, not only in the two provinces but elsewhere as well.

The study is not without limitations. As a survey-based analysis, it may suffer from response bias. Moreover, the relatively small and geographically concentrated sample limited the results' generalisability. Future research should expand the sample to validate these findings across different contexts, assess sector-specific pathways and study the impact of policy interventions on reducing barriers to high-tech. Finally, future research should incorporate longitudinal data to capture dynamic patterns of technological adoption over time.

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Appendix 1: List and description of the main high technologies (high-tech)

List and description of the main high technologies (high-tech)

High-Tech	Description
Cloud	It allows storage and access to computer data and resources via the Internet rather than local devices or physical servers. Resources are hosted and managed by cloud providers and can include storage, computing, software, and more. This allows the management of large amounts of data.
Industrial Internet or Internet of Things (IoT)	It refers to the connection of industrial devices, machinery and systems via the Internet to enable data collection, sharing, and analysis. This allows for more efficient monitoring and control of industrial processes by embedding the internet within 'intelligent' objects.
Simulation	It is the creation of models or representations of real systems in order to study their behaviour or test hypotheses. It is used in particular to simulate processes between connected machines and to optimise processes.
Horizontal and vertical integration	The first refers to the integration of different processes within a company, while the second refers to the integration of processes in different production phases or supply chains.
Cybersecurity systems and cyberphysical systems	The first relates to technologies and practices to protect computer systems from threats and attacks, while the second relates to physical systems integrated with computer components that can be controlled and monitored via digital networks.
Additive manufacturing	Also known as 3D printing, it is a manufacturing process that creates objects by adding material layer by layer, rather than removing it from a solid block. In general, it refers to the use of digital development software for the production of customised objects.
Big Data analysis	It is the process of examining, cleaning, analysing, and interpreting large data sets (big data) to obtain useful information, identify patterns, and support business decisions.
Augmented reality	It overlays digital elements, such as images, onto a real-world view, often through devices such as glasses or viewers, to enrich the user experience.
Advanced manufacturing solutions and robotics	It represents the use of advanced technologies in industrial production, including robotics, automation, intelligent systems and process digitalisation. It mainly refers to the use of interconnected and programmable collaborative robots based on needs.
Artificial intelligence (AI)	It refers to the simulation of human intelligence by computers or computer systems to perform complex tasks such as speech recognition, problem solving and learning to support business.
Machine learning	It is a branch of AI that focuses on the development of algorithms that allow computers to learn from data and improve performance over time without being explicitly programmed.
Blockchain	It is an online recording technology that allows the creation of a public, secure, immutable and decentralised ledger of transactions, often used for financial transactions or smart contracts.
Wearable, sensors and smart devices	It refers to wearable or embedded devices with sensors and connectivity capabilities to collect biometric, environmental or other data and interact with other devices or networks.
Electronic commerce (E-commerce)	Abbreviated as 'electronic commerce,' it refers to the buying and selling of goods and services on the Internet, often through platforms and e-commerce websites.

Source: own elaboration.

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Use of Artificial Intelligence

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Conflict of Interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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