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The power of access: international collaboration and the differential adoption of digital technologies

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Abstract

This study examines the association between international collaboration and web technology adoption by companies in Spanish science and technology parks (STPs). Using data from 847 companies and negative binomial regression models, we test three hypotheses regarding participation in European R&D networks and digital technology adoption. Results confirm that international collaboration is significantly associated with higher web technology adoption, with an average difference of €789 monthly in technology spending. Structural access to international networks is more strongly linked to adoption compared to relational intensity, suggesting diversity of connections outweighs relationship depth. These associations are substantially stronger for conventional web technologies than for smart technologies, highlighting the role of technological complexity in shaping diffusion patterns. The study provides new theoretical insights by identifying threshold effects and technological heterogeneity, suggesting that integrative frameworks must incorporate nonlinearities and specific moderators when combining social network theory and innovation diffusion. Practical implications indicate differentiated strategies: international networking for conventional technologies and complementary internal capability development for smart technologies. For STP managers, results support policies facilitating initial access to European networks rather than intensifying existing collaborations. For policymakers, documented technological spillovers justify investments in international collaboration programs, though requiring complementary instruments for complex technologies. Limitations include cross-sectional design and measurement of formal collaborations only, opening opportunities for future longitudinal research with mixed methodologies.

Keywords International collaboration, Technology adoption, Science and technology parks, Innovation networks, Smart technologies

Introduction

Digital transformation has consolidated as a strategic imperative for contemporary enterprises, particularly in the post-pandemic context where the adoption of technologies has experienced unprecedented acceleration. This transformation does not occur in an organizational vacuum but is profoundly influenced by the collaborative networks in which firms are embedded. Science and technology parks (STPs), as innovation ecosystems, provide a privileged context for examining these phenomena by concentrating firms with high propensity for international collaboration and advanced technology adoption [3, 22]. The specific literature on STPs has demonstrated that these organizations facilitate knowledge and technology transfer through dense collaboration networks [20], creating conducive conditions for accelerated adoption of technological innovations.

The literature has consistently established that international collaborations constitute critical mechanisms

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for accessing frontier knowledge and accelerating innovation processes [10]. However, in the era of massive digitalization, there emerges a need to specifically understand how these collaborations influence the adoption of web technologies, which represent the fundamental infrastructure of corporate digital transformation. This understanding is particularly relevant for firms located in STPs, where the density of international collaborations and competitive pressure for technological modernization are especially intense.

Despite widespread recognition of the importance of collaboration networks for innovation, three significant gaps persist in the current literature. First, there exists limited understanding of the specific effects of international collaboration on web technology adoption, with most studies focusing on general innovation or R&D without distinguishing specific technology types [5, 8].

Second, the literature presents contradictory results regarding whether collaboration benefits derive primarily from initial access to international networks or from sustained intensity of these collaborations. While some studies suggest positive linear effects of collaboration numbers [1], others identify diminishing returns or threshold effects [26]. This theoretical and empirical ambiguity limits firms' capacity to optimize their collaboration strategies.

Third, the literature lacks differentiated analyses of how international collaboration affects the adoption of technologies of varying complexity. The distinction between "smart" and "non-smart" technologies has emerged as relevant in the digital transformation context [18], but their interaction with international collaboration patterns remains unexplored. This omission is particularly problematic given that different technology types may require distinct transfer and adoption mechanisms.

This study aims to examine the relationship between international collaboration and web technology adoption by firms located in STPs. Specifically, we seek to: (1) determine whether participation in international collaborations is associated with web technology adoption; (2) evaluate whether access to international networks is more strongly associated with adoption than collaboration intensity; and (3) analyze whether these associations differ between smart and non-smart technologies.

To address these objectives, we ground our analysis in the convergence of social network theory, innovation diffusion theory, and the absorptive capacity perspective as a theoretical lens to interpret how firms assimilate external knowledge. We utilize data from firms located in STPs, which provide an ideal context for examining these phenomena due to their high propensity for international collaboration and technology adoption.

This study makes three main contributions to the literature. Theoretically, we contribute to the debate on differential mechanisms through which international networks are linked to the adoption of distinct technology types. This theoretical integration advances understanding of the conditions under which international collaborations are most effective in supporting corporate digital transformation.

Empirically, we provide evidence on the access versus intensity debate in collaboration networks, demonstrating that threshold effects are more relevant than linear associations in the context of technology adoption. While acknowledging that direct comparisons between these dimensions are subject to differences in model specifications and sample characteristics, our results suggest a prioritized role for network access. Additionally, we document differential adoption patterns between smart and non-smart technologies, contributing to a more nuanced understanding of technological heterogeneity in diffusion processes.

From a practical perspective, our findings inform corporate strategies for optimizing international collaboration portfolios, suggesting that diversification of network access may be more effective than intensification of existing collaborations. For technology park managers, we provide insights on how to facilitate international connections that maximize technology adoption among resident firms.

The article is structured as follows: Section "Background" develops the theoretical framework integrating literature on collaboration networks, innovation diffusion, and technology. Section "Methodology" describes the methodology, including study context, data collection, and analytical strategy. Section "Results" presents empirical results and hypothesis testing. Section "Discussion" discusses theoretical and practical implications of the findings, while Sect. "Conclusions" concludes with limitations and directions for future research.

Background

In this section, we present the theoretical arguments that describe the hypothesized mechanisms through which international collaboration may influence technology adoption. It should be noted that while these theoretical propositions are often directional, our empirical analysis specifically tests associations between these variables, consistent with the study's cross-sectional design.

Collaboration networks in innovation and technology adoption

The adoption of emerging technologies by firms constitutes a complex process that transcends internal organizational capabilities. The literature has converged in recognizing that collaboration networks, particularly those of international character, are linked to critical mechanisms of technological diffusion [10]. However, a fragmented understanding persists regarding how these networks specifically facilitate technology adoption and under what structural conditions they operate most effectively.

Social network theory establishes that a firm's structural position within a network determines its access to resources and knowledge [7, 15]. When firms participate in international collaborations, they embed themselves in network structures that transcend geographical and institutional boundaries, accessing more diverse and advanced knowledge pools [12]. Innovation diffusion theory [30] complements this perspective by explaining that international networks are associated with a faster transmission of information about new technologies, reducing uncertainty associated with their adoption.

From the absorptive capacity perspective [11], interaction with international partners not only provides access to external knowledge but also stimulates the development of internal capabilities to identify, assimilate, and apply new technologies. This perspective suggests that international collaborations are linked to organizational learning, where exposure to heterogeneous technological practices generates the adaptive pressures and knowledge flows required for technological modernization.

However, despite these solid theoretical foundations, specific empirical evidence on the relationship between international collaborations and web technology adoption remains limited. Existing studies have focused primarily on general innovation or R&D [5, 8], without specifically examining how international networks relate to the adoption of digital technologies that constitute the infrastructure of contemporary business transformation.

In the specific context of STPs, where firms operate in ecosystems of high collaborative density and competitive pressure for technological modernization [13, 22], this relationship acquires particular relevance. STPs specifically facilitate access to international knowledge networks, acting as intermediaries that reduce search and connection costs with global partners [3]. Given that web technologies require both specialized technical knowledge and understanding of international standards and practices, we expect that firms located in STPs with access to international collaboration networks will have significant advantages in their adoption. Exposure to international partners should provide both the necessary technical knowledge and competitive pressure to modernize technological infrastructure.

Based on the convergence of social network theory, innovation diffusion theory, and the absorptive capacity perspective, we expect a positive relationship between participation in international collaborations and web technology adoption in STP firms.

Hypothesis 1 Participation in international collaborations is positively associated with web technology adoption in firms located in Science and Technology Parks.

Structural access versus relational intensity in innovation networks

A fundamental theoretical debate in the network literature concerns the relative importance of structural access to the network versus the intensity of relationships within it. Structural social capital theory [7] argues that the primary benefits of networks derive from structural position that enables access to diverse information and resources, rather than from the frequency or intensity of specific interactions.

This perspective finds support in weak ties theory [15], which establishes that less intense but more diverse connections provide access to non-redundant information and novel opportunities. In the context of technology adoption, initial access to international networks may generate the greatest informational impact, while marginal increases in collaboration intensity produce diminishing returns [26].

The knowledge transfer literature suggests that there is a threshold effect in network benefits: once access to international information channels is established, additional benefits from intensifying collaborations tend to be marginal compared to the initial qualitative leap [24]. This threshold mechanism is rooted in the qualitative shift from local isolation to international network embeddedness. The first collaboration provides a firm with the essential architectural knowledge and communication protocols required to access global knowledge pools. From a structural hole perspective [7], the primary benefit lies in the initial bridge to non-redundant information. Once this bridge is built, subsequent collaborations within similar R&D ecosystems, such as European projects, often provide overlapping information and resources, leading to diminishing marginal returns. This process occurs because increasing the number of international partners triggers an attention allocation problem where the marginal gain in novel knowledge decreases while the managerial costs of coordinating and integrating diverse sources escalate [31]. This over-search effect is particularly prevalent when partners share similar institutional backgrounds, as the search space for new technological solutions becomes saturated [25]. However, these diminishing returns are not uniform and can be deferred by high geographic or sectoral diversity. When a portfolio includes partners from distinct knowledge pools, the onset of redundancy is delayed, allowing firms to sustain benefits from a larger number of ties before the costs of complexity outweigh the informational gains. In the context of digital adoption, the first international tie acts as a window of opportunity that exposes the firm to global technological standards, making the mere fact of being in the network more critical than the number of ties maintained.

Nevertheless, empirical evidence on this debate remains mixed, particularly in the specific context of web technology adoption. Some studies have found positive linear effects of collaboration numbers [1], while others identify threshold effects or diminishing returns [14]. In the context of firms located in STPs, where network density and competition for collaboration resources are especially intense [20, 23], this distinction acquires critical practical relevance.

Given that web technologies constitute standardized innovations at the international level, we expect that initial access to international networks provides the fundamental exposure necessary for their adoption, while increases in collaboration intensity generate diminishing marginal benefits. Therefore, we anticipate that the threshold effect will be more pronounced than linear effects in STP firms.

Hypothesis 2 Access to international networks is more strongly associated with web technology adoption than collaboration intensity in firms located in Science and Technology Parks.

Technological heterogeneity and differential diffusion patterns

The technological innovation literature has established that not all technologies diffuse uniformly through organizational networks. The distinction between technologies of different complexity and sophistication is fundamental to understanding adoption patterns. "Smart" technologies (based on artificial intelligence, IoT, and advanced analytics) present distinctive characteristics that affect their diffusion compared to more conventional "non-smart" technologies [18].

Technological complexity theory establishes that less complex technologies diffuse more rapidly through networks due to lower barriers of understanding and implementation [30]. Non-smart technologies typically require less specialized tacit knowledge and present more standardized implementation processes, facilitating their transfer through international collaborations [16]. This is because conventional web technologies are characterized by high codifiability—their features and implementation steps can be easily documented in manuals and standards—which allows them to be transferred efficiently through formal collaboration channels.

In contrast, smart technologies involve greater architectural complexity and require more specialized absorptive capacities for effective implementation [11]. Drawing on tacit knowledge theory [27], these advanced technologies often contain a high degree of sticky, tacit information that is difficult to codify or express in formal documents, which limits their transferability through codified channels. While conventional web technologies have achieved high levels of standardization and codifiability, allowing them to be transferred efficiently through formal channels [16], smart technologies depend more intensively on experiential learning and internal capability development.

The differential diffusion speed also reflects that non-smart technologies have achieved greater maturity and standardization, facilitating their transmission through international network channels [10]. International collaborations, therefore, act as more effective catalysts for the adoption of already consolidated technologies than for emerging high-complexity technologies.

However, empirical evidence on these differential diffusion patterns in the specific context of firms located in STPs remains scarce. Although the parks literature has established their role as technological transfer facilitators [2, 19], few studies have empirically examined how international collaborations are differentially associated with the adoption of web technologies of different complexities in these high innovation density ecosystems.

In the STP context, where firms face intense competitive pressures for technological modernization and have access to international collaboration resources, we expect these differential effects to be particularly pronounced. Specifically, non-smart technologies, characterized by higher knowledge codifiability and lower tacit knowledge requirements, should be more directly linked to access to international networks, whereas smart technologies, due to their lower codifiability and reliance on tacit knowledge, require more complex and sustained transfer processes involving experiential learning and capability building.

Hypothesis 3 International collaboration is more strongly associated with the adoption of non-smart technologies than with the adoption of smart technologies in firms located in Science and Technology Parks.

In summary, the conceptual framework in Fig. 1 integrates these theoretical perspectives into a unified model of international collaboration and web technology adoption. The general association between international participation and adoption (H1) is grounded in innovation

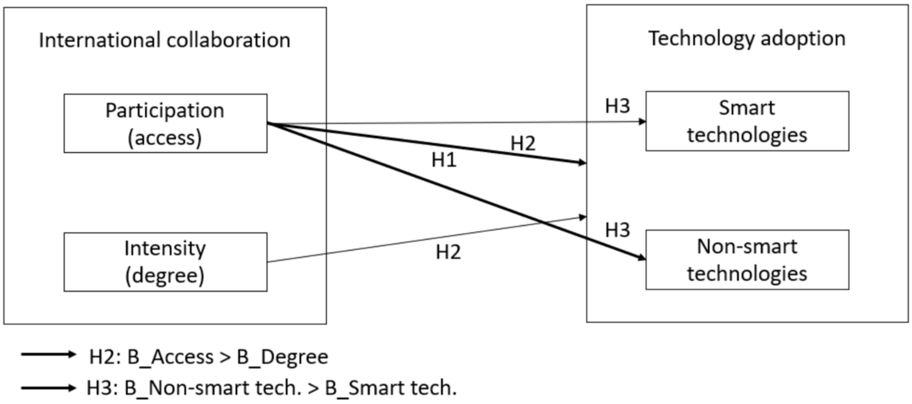

Fig. 1 Conceptual framework of international collaboration and web technology adoption

diffusion theory, where international exposure facilitates awareness of global technological standards. The distinction between structural access and relational intensity (H2) reflects the structural hole perspective [7], suggesting that the initial qualitative leap of entering a network provides greater informational benefits than marginal increases in tie frequency. Finally, the differentiated associations for smart and non-smart technologies (H3) are rooted in absorptive capacity and tacit knowledge theory, proposing that international collaboration is more strongly linked to the adoption of standardized technologies than to complex systems requiring deeper internal organizational adjustments.

Methodology

The study sample comprises 4,086 firms located in 56 STPs in Spain, identified from the official website of APTE (Association of Science and Technology Parks of Spain). Of this total, 450 firms (11% of the sample) have participated in at least one collaboration in European projects.

Information on collaborations was obtained by consulting the CORDIS (Community Research and Development Information Service) database of the European Commission, which records projects funded under European R&D&I programs. A total of 969 unique collaboration pairs between sample firms were identified, corresponding to joint participations in European projects.

From the information extracted from CORDIS, an undirected network was constructed where each node represents a firm, and each edge indicates the existence of at least one collaboration in European projects between two sample firms. For each pair of collaborating firms, the relationship was recorded as a single edge, regardless of the number of shared projects.

The network analysis focused on the 450 firms that have participated in at least one collaboration, generating a total of 969 unique collaboration pairs (edges). The resulting network was analyzed using Python's NetworkX library, enabling calculation of global metrics (number of nodes, number of edges, density, and average degree) as well as centrality metrics (degree, betweenness, eigenvector, and closeness).

From the network analysis, international collaboration variables were constructed. The dichotomous variable *Collab* identifies whether the firm has participated in at least one European collaboration, while *CollabDegree* quantifies the total number of collaborations. Additionally, centrality metrics were calculated to capture different dimensions of each firm's structural positioning in the collaboration network.

Connected components of the network were also identified, and the Louvain algorithm was applied for community detection using the Python NetworkX (version 2.9.1) and python-Louvain (version 0.16) libraries with a resolution parameter of 1.0. To ensure reproducibility, the algorithm was executed with a fixed random seed (seed = 42). This analysis aimed to examine the modular structure and the presence of collaboration subgroups within the STP firm ecosystem.

The web technological profile of each firm was characterized from data obtained through the BuiltWith platform, which enables identification of web technologies implemented in firm domains [28]. The use of BuiltWith provides an objective, non-survey-based assessment of a firm's digital footprint, capturing the organizational learning capacity, and the strategic prioritization of digital capabilities. The total number of web technologies identified (*TechAdoption*) serves as a valid proxy for digital adoption intensity, as it reflects the breadth and complexity of the digital tools, a firm has integrated into its operations—ranging from analytics and hosting to security and marketing automation.

The analysis focused on 2,854 firms with available websites, a necessary condition for technological characterization. However, we acknowledge potential measurement biases inherent in web-scraping tools. First, BuiltWith primarily detects technologies visible on the firm's public-facing website, which may underestimate internal back-end systems. Second, the quality and maintenance of the firm's website could influence the results, as outdated or poorly managed sites might not fully reflect the firm's actual technological capabilities. While this could introduce a systematic bias if poorly maintained websites cluster among smaller or less internationalized firms, we mitigate this risk by explicitly controlling for firm size, age, and high-tech sector membership in all multivariate models. Despite these limitations, BuiltWith remains one of the most reliable and widely used sources for large-scale, cross-sectional studies of digital adoption.

For each firm with an available website, detected technologies were collected and classified into two broad categories: smart technologies and non-smart technologies. To ensure transparency in this classification, we conducted a functional review of the tools identified by BuiltWith. Technologies were classified as smart if they explicitly integrated advanced capabilities such as machine learning, predictive analytics, natural language processing (e.g., chatbots), or complex marketing automation. We acknowledge the existence of borderline cases, such as certain CRM or analytical tools that offer both basic and advanced features. In these instances, we adopted a conservative criterion, classifying them as smart only when their core value proposition was centered on autonomous or intelligent data processing. This manual verification process was intended to minimize misclassification and ensure that the *SmartTech* variable accurately reflects higher levels of technological sophistication.

From this information, the following variables were constructed for analysis: (1) *TechAdoption* (total number of web technologies detected per firm); (2) *SmartTech* (number of smart technologies detected); (3) *NonSmartTech* (number of non-smart technologies detected); (4) *TechSpend* (monthly expenditure on web technologies); and (5) *SmartTechIndex* (proportion of smart technologies over total web technologies detected per firm).

Additionally, control variables were included: firm size (standardized number of employees), age, and membership in high-tech sector. These variables enable analysis of both intensity and technological sophistication of firms, as well as their relationship with collaboration in European projects (see Table 1).

Table 1 Variable names and definitions

Variable	Definition
TechAdoption	Total number of web technologies detected per firm
SmartTech	Number of smart technologies detected
NonSmartTech	Number of non-smart technologies detected
TechSpend	Monthly expenditure on web technologies
SmartTechIndex	Proportion of smart technologies over total web technologies detected per firm
Collab	1 if participates in European collaborations, 0 otherwise
CollabDegree	Total number of collaborations in European projects
FirmSize	Number of firm employees (standardized)
FirmAge	Firm age (years)
HighTechSector	1 if belongs to high-tech sector, 0 otherwise

The statistical analysis was structured in several complementary stages. First, descriptive and exploratory analyses were conducted to characterize the sample and main variables of interest, including distributions, means, medians, and standard deviations. Bivariate correlations were calculated, and scatter plots were developed to explore the relationship between collaboration and different technological indicators.

Subsequently, mean comparisons (*t*-tests) were conducted between collaborating and non-collaborating firms, with the objective of identifying significant differences in technological adoption levels.

To analyze in depth the effect of collaboration on technology adoption and expenditure, various regression models were estimated. Ordinary least squares (OLS) models were employed, both with dependent variables in original scale and logarithmically transformed, as well as count models (Poisson and negative binomial) for discrete variables. Two main approaches for collaboration were considered: a dichotomous variable (participation or not in collaborations, *Collab*) and a continuous variable (number of collaborations, *CollabDegree*).

All models included controls for firm size, age, and membership in high-tech sector. Robustness analyses were conducted, including different specifications, to validate result consistency.

It should be noted that this study adopts an associational approach to analyzing the relationship between international collaboration and technology adoption. Given the cross-sectional nature of the data and the potential for self-selection—where firms with higher latent technological capabilities may be more likely to participate in European projects—we do not claim to establish causal effects. Our econometric strategy, while including key organizational controls, focuses on identifying robust associations while acknowledging the limitations imposed by unobserved firm-level heterogeneity.

Table 2 Descriptive metrics of the collaboration network

Metric	Value
Number of firms (nodes)	450
Number of collaborations (edges)	969
Network density	0.0096
Average degree	4.32
Maximum degree	103
Minimum degree	1
Number of components	20
Main component size	408
Number of communities (Louvain)	31

Results

Collaboration network analysis

Of the 4,086 firms identified in Spanish STPs, 450 firms (11% of the sample) have participated in at least one collaboration in European projects, generating a network of 969 unique collaborations (firm pairs).

To validate the construct of international collaboration and to provide contextual background for the study, we have conducted a network analysis. The resulting network (see Table 2) presents low density (0.0096), indicating that most firms do not collaborate directly with each other. The average degree is 4.32, meaning each collaborating firm maintains, on average, relationships between 4 and 5 firms. Component analysis reveals that the network is composed of 20 connected components, with the main component grouping 408 firms (over 90% of collaborators), suggesting a highly cohesive collaboration ecosystem.

Community detection using the Louvain algorithm identifies 31 communities (see Fig. 2), with sizes ranging from small pairs to groups of 30–80 firms.

Overall, these results evidence the existence of hubs that not only concentrate a high number of collaborations but also play a key role in network integration and cohesion, acting as bridges and facilitators of knowledge and resource diffusion among firms.

Fig. 2 Network of collaborations by community or cluster

Relationship between collaboration and technology adoption

The comparative analysis between collaborating and non-collaborating firms reveals significant differences in web technology adoption and expenditure levels (see Table 3). Firms that have participated in collaborations in European projects present, on average, greater technological intensity (total number of web technologies adopted), higher estimated monthly expenditure on web technologies, and a greater number of smart technologies implemented, compared to those that have not collaborated.

Mean comparison tests (t-tests) confirm that these differences are statistically significant for most technological indicators (see Table 4): *TechIntensity* ($t=-3.56$, $p=0.000$), *TechSpend* ($t=-2.72$, $p=0.007$), *SmartTech* ($t=-2.84$, $p=0.005$), *and NonSmartTech* ($t=-3.61$, $p=0.000$). However, no significant difference is observed for *SmartTechIndex* ($t=-1.75$, $p=0.080$).

The baseline regression models (see Tables 5 and 6) show that collaboration in European projects is associated with greater adoption and expenditure on web technologies. The *Collab* coefficient is positive and significant across all dependent variables: collaborating firms exhibit, on average, 45.5 more web technologies, spend almost €800 more per month on web technologies, and show a higher adoption of both more smart (+4.4) and non-smart (+41.2) technologies, compared to non-collaborators.

The R^2 values are low (0.005–0.010), which is understandable given that technology adoption is a complex organizational behavior influenced by numerous unobserved factors, such as internal culture, managerial preferences, or specific budgetary constraints. However, the focus of this analysis is not to maximize explained variance but to isolate the specific association between international collaboration and adoption. In this sense, the high significance and magnitude of the coefficients reinforce the robustness of the observed associations.

When introducing controls for firm size (standardized employees), age, and membership in high-tech sector

Table 3 Comparison of means and medians of technological indicators by participation in European collaborations

Variable	SmartTech Index	TechAdoption	TechSpend	SmartTech	NonSmartTech
Mean (no collab)	0.046	88.85	996.35	5.82	83.03
Mean (with collab)	0.051	134.36	1785.42	10.18	124.18
Median (no collab)	0.031	54.0	66.0	2.0	52.0
Median (with collab)	0.042	75.0	278.5	3.0	74.5

Table 4 *T*-test results for mean comparison (collaborators vs. non-collaborators)

Variable	Mean (no collab)	Mean (with collab)	*t*
SmartTechIndex	0.05	0.05	−1.75
TechAdoption	88.85	134.36	−3.56***
TechSpend	996.35	1785.42	−2.72**
SmartTech	5.82	10.18	−2.84**
NonSmartTech	83.03	124.18	−3.61***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 5 Models for *TechAdoption* and *TechSpend*

	TechAdoption		TechSpend	
	base (1)	Controls (2)	base (3)	Controls (4)
Collab	45.51*** (8.61)	18.84** (6.40)	789.07*** (202.22)	337.74* (153.57)
FirmSize (std)		14.49*** (2.27)		252.02*** (54.46)
FirmAge		1.50*** (0.16)		35.44*** (3.76)
HighTechSector		19.36*** (4.77)		291.29* (114.36)
Constant	88.85*** (2.44)	50.28*** (4.55)	996.35*** (57.40)	147.49 (109.08)
N	2,855	2,854	2,855	2,854
R^2	0.010	0.057	0.005	0.044

Standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

(see Tables 5 and 6), the collaboration effect remains positive and statistically significant across all dependent variables. For example, in the case of technological intensity, collaborating firms present, on average, 18.8 more web technologies than non-collaborators ($p < 0.01$), after controlling for other factors. Similarly, the link between collaboration and monthly web technology expenditure ($B = 337.7$; $p < 0.05$), number of smart technologies ($B = 2.13$; $p < 0.01$), and non-smart technologies ($B = 16.7$; $p < 0.01$) remains significant.

Table 6 Models for *SmartTech* and *NonSmartTech*

	SmartTech		NonSmartTech	
	base (5)	Controls (6)	base (7)	Controls (8)
Collab	4.35*** (1.00)	2.13** (0.76)	41.15*** (7.82)	16.70** (5.79)
FirmSize (std)		1.05*** (0.27)		13.43*** (2.05)
FirmAge		0.17*** (0.02)		1.32*** (0.14)
HighTechSector		1.17* (0.57)		18.19*** (4.31)
Constant	5.82*** (0.28)	1.72** (0.54)	83.03*** (2.22)	48.55*** (4.11)
N	2,855	2,854	2,855	2,854
R^2	0.007	0.042	0.010	0.057

Standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

The controls included in the models also show positive and significant associations: larger, older firms belonging to high-tech sectors tend to adopt and spend more on web technologies. The inclusion of these controls notably increases the explanatory power of models (R^2 between 0.042 and 0.057), although values remain modest. These values are consistent with empirical benchmarks in firm-level digital adoption, where R^2 often remains limited due to unobserved organizational factors; for instance, Chen et al. [9] and Hanelt et al. [17] report similarly modest explained variance in models of digital transformation and innovation. As previously noted, the contribution of this study lies in identifying specific diffusion mechanisms rather than providing a full explanatory model of adoption behavior.

Overall, these results reinforce the idea that international collaboration is a key factor associated with technological intensification in the STP context, even when considering other relevant firm characteristics.

To further explore the nature of this relationship, we examined whether the intensity of collaboration (number of projects) provides additional benefits beyond mere

Table 7 Robustness models: effect of number of collaborations (*CollabDegree*) on technology adoption

	TechAdoption	TechSpend	SmartTech	NonSmartTech
CollabDegree	0.02	0.63	0.00	0.02
	(0.03)	(0.63)	(0.00)	(0.02)
FirmSize (std)	11.20**	119.22	0.82	10.38**
	(4.03)	(99.14)	(0.49)	(3.60)
FirmAge	3.34***	60.65***	0.38***	2.96***
	(0.47)	(11.46)	(0.06)	(0.42)
HighTechSector	15.84	399.73	1.18	14.65
	(15.29)	(376.53)	(1.87)	(13.65)
Constant	30.19	−153.13	−0.49	30.68*
	(16.17)	(398.40)	(1.98)	(14.45)
N	430	430	430	430
R^2	0.140	0.075	0.109	0.141

Standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

participation (H2). The results, presented in Table 7, show that the *CollabDegree* coefficient is not statistically significant for any of the dependent variables analyzed (technological intensity, expenditure, smart and non-smart technologies) once firm size, age, and sector are controlled for.

These findings suggest that, while participation in international collaborations is associated with higher levels of technology adoption (as shown in Tables 5 and 6), increases in the number of collaborations do not necessarily correlate with additional technological benefits. In other words, the positive association appears to be linked primarily to the fact of participating in the international project network, rather than to the intensity or frequency of such participation.

However, a nuanced interpretation of this threshold effect is required. It is important to note that the models testing the association with *CollabDegree* (Table 7) are estimated on the subsample of collaborating firms ($n = 430$), which is approximately 85% smaller than the full sample used for the binary variable ($n = 2{,}854$). This significant reduction in sample size decreases statistical power and may partly explain the lack of significance for *CollabDegree*, independent of the hypothesized threshold mechanism. Consequently, while these results are relevant from a management perspective suggesting that access to networks may be sufficient to be linked with technology adoption, the evidence for H2 is interpreted as suggestive, acknowledging these power differentials.

Interestingly, the pattern of control variables in the collaborating subsample (Table 7) differs from the full sample models. While *HighTechSector* is a strong predictor in the general population, it becomes non-significant among collaborating firms. Conversely, *FirmAge* remains highly significant across all specifications in Table 7. This suggests that within the restricted group of collaborators—who likely share a high baseline of technological orientation—sectoral differences are less relevant than organizational maturity. For these firms, accumulated experience and established internal routines, captured by firm age, appear to be the primary drivers of technology adoption beyond the initial network access.

To check the robustness of results, additional models were estimated using logarithmic transformation of the dependent variables for technological intensity and web technology expenditure. The results presented in Table 7 confirm the solidity of the main findings.

In the case of technological intensity (*log(TechAdoption)*), the *Collab* variable maintains a positive and significant association ($B = 0.175$; $p = 0.001$), indicating that collaborating firms present, on average, 19% more technological intensity than non-collaborators, after controlling for size, age, and sector. Similarly, for web technology expenditure (*log(TechSpend)*), the *Collab* coefficient is also positive and significant ($B = 0.39$; $p = 0.013$), reflecting an approximate 48% difference in monthly web technology expenditure associated with international collaboration.

The controls included in the models (standardized firm size, age, and high-tech sector) maintain positive and significant links, in line with the main models. The explanatory power of the models ($R^2 \approx 0.045$) is similar to that of models with original variables, reinforcing the robustness of the relationship between collaboration and technology adoption.

These results confirm that the positive association between collaboration and technology adoption does not depend on the measurement scale of dependent variables and is maintained even under logarithmic transformations.

As an additional robustness test, count models (Poisson and Negative Binomial) were estimated for the dependent variables *SmartTech* and *NonSmartTech*. The results presented in Table 8 confirm the solidity of the relationship between international collaboration and technology adoption.

In all models, the *Collab* variable maintains a positive and statistically significant link with the number of smart and non-smart technologies adopted. In the Poisson model for *SmartTech*, the *Collab* coefficient is 0.28 ($p < 0.001$), implying that collaborating firms show, on average, 32% more smart technologies adopted than non-collaborators ($\exp(0.28) \approx 1.32$). This pattern is maintained in the negative binomial model ($B = 0.17$; $p < 0.01$), although with a smaller magnitude ($\exp(0.17) \approx 1.19$).

Similarly, for *NonSmartTech*, the *Collab* coefficient is 0.17 in the Poisson model ($p < 0.001$) and 0.12 in the

Table 8 Robustness models: OLS regression with logarithmic transformation

	log(TechAdoption)	log(TechSpend)
Collab	0.18** (0.06)	0.39* (0.16)
FirmSize (std)	0.10*** (0.02)	0.31*** (0.06)
FirmAge	0.01*** (0.00)	0.03*** (0.00)
HighTechSector	0.22*** (0.04)	0.56*** (0.12)
Constant	3.67*** (0.04)	3.17*** (0.11)
N	2,854	2,854
R^2	0.046	0.045

Standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 9 Robustness models: poisson and negative binomial for smart and non-smart technologies

	SmartTech		NonSmartTech	
	Poisson	Neg. bin	Poisson	Neg. bin
Collab	0.28*** (0.02)	0.17** (0.06)	0.17*** (0.01)	0.12* (0.05)
FirmSize (std)	0.07*** (0.00)	0.30*** (0.02)	0.07*** (0.00)	0.19*** (0.02)
FirmAge	0.02*** (0.00)	0.02*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
HighTechSector	0.19*** (0.02)	0.15*** (0.04)	0.21*** (0.00)	0.19*** (0.04)
Constant	1.23*** (0.01)	1.23*** (0.04)	4.05*** (0.00)	4.09*** (0.04)
N	2,854	2,854	2,854	2,854

Standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

negative binomial model ($p < 0.05$), equivalent to differences of 19% and 13%, respectively, in the number of non-smart technologies adopted by collaborating firms.

The controls included in the models (standardized firm size, age, and high-tech sector) also show positive and significant associations, in line with the OLS model results.

Overall, these robustness analyses reinforce the evidence that international collaboration constitutes a relevant factor linked to the technological intensification of firms, both in the adoption of smart and non-smart technologies, and that this relationship is maintained under different statistical specifications (Table 9).

Discussion

The results reveal a consistent and robust pattern: participation in international collaborations is significantly associated with higher levels of web technology adoption in STP firms. This association is maintained after controlling fundamental organizational characteristics and is especially pronounced for conventional technologies compared to smart technologies.

The results provide strong support for our first hypothesis: participation in international collaborations is significantly linked to web technology adoption in Spanish STP firms. This relationship, which is maintained after controlling for fundamental organizational characteristics such as size, age, and technological sector, provides solid empirical evidence on the role of international networks as technological diffusion mechanisms. The magnitude of the association is considerable: collaborating firms adopt on average 45.5 additional web technologies and spend €789 more per month on technology, representing a substantial difference in their technological capacity.

These findings are consistent with absorptive capacity theory, defined by Cohen and Levinthal [11] as a firm's ability to recognize the value of new external information, assimilate it, and apply it for commercial purposes. Exposure to international partners not only provides access to external knowledge but also may stimulate the development of internal capabilities to identify, assimilate, and apply new web technologies. Our results extend previous evidence on the positive links between international collaboration and innovation to the specific domain of digital technology adoption, complementing studies that have documented these associations in other organizational contexts [4, 29].

In the specific context of STPs, where firms operate in high collaborative density ecosystems, these results are particularly relevant. As established by Löfsten and Lindelöf [22], STPs provide an important resource network for technology-based firms, specifically facilitating access to international knowledge networks and acting as intermediaries that reduce search and connection costs with global partners. The technology parks literature has consistently established their role as technological transfer facilitators [2], and our findings suggest that this relationship extends specifically to web technology adoption through international collaborations.

One of our most revealing findings provides suggestive evidence for the second hypothesis regarding the primacy of structural access over relational intensity. While the dichotomous participation variable shows robust and consistent associations, models based on the number of collaborations (*CollabDegree*) do not reach statistical significance. This potential threshold effect suggests that primary benefits may derive from initial access to diverse information and resources, rather than from the intensification of specific relationships. However, we must interpret this result with caution; the non-significance of intensity could be partially attributed to the reduced statistical power of the collaborating subsample (n = 430). Despite this limitation, the findings point toward a pattern where, once access to European R&D networks is established, marginal associations with additional collaborations appear limited, which has important strategic implications for collaboration portfolio management in STP firms.

This pattern is consistent with structural holes theory developed by [7], which emphasizes how brokerage positions in networks provide competitive advantages through access to non-redundant information. It also aligns with Granovetter's [15] weak ties perspective, who demonstrated that casual connections provide access to non-redundant information and novel opportunities. In the context of our study, international collaborations may function as weak ties that connect firms with knowledge networks external to their local circles, providing critical exposure to new technological paradigms.

The results regarding our third hypothesis provide significant theoretical insights on differential technological diffusion mechanisms. International collaboration is associated differently according to technology type: the association is stronger for non-smart technologies than for smart technologies. This magnitude difference reflects that non-smart technologies presenting lower barriers of understanding and implementation and tend to diffuse more efficiently through international collaboration networks, while smart technologies require greater tacit knowledge and specialized absorptive capacities.

This differential pattern is consistent with the technological complexity literature, which establishes that less complex technologies diffuse more rapidly through networks due to lower barriers of understanding and implementation [30]. Technologies with greater complexity require more intensive learning processes and specialized absorptive capacities, limiting their diffusion through collaboration networks [6, 21]. This differential pattern explains why non-smart technologies, which typically require less specialized tacit knowledge and present more standardized implementation processes, appear to be more easily transferred through international collaborations. In contrast, smart technologies involve greater architectural complexity and depend more intensively on experiential learning, limiting diffusion's effectiveness through collaboration networks.

In the specific context of firms located in STPs, where network density and competition for collaboration resources are especially intense, these results suggest that firms can benefit significantly from international collaborations to adopt conventional web technologies but need to develop more specialized and sustained strategies for advanced smart technologies. As indicated by the STP literature [3], the effectiveness of these ecosystems as innovation policy instruments depends on their capacity to facilitate different types of technological transfer according to the specific characteristics of the technologies involved.

Theoretical and practical implications

This study contributes theoretically to an integrative model combining social network theory, innovation diffusion, and absorptive capacity to explain technology adoption in high-density collaborative ecosystems like STPs. The evidence on threshold effects—where structural access is more closely linked to adoption than relational intensity—reveals that theoretical models must incorporate nonlinearities in network benefits. The empirical distinction between smart and conventional technologies demonstrates that diffusion theories must explicitly consider technological complexity and tacit knowledge requirements as moderators of the relationship between networks and adoption, extending traditional frameworks that assume homogeneous collaboration effects. These theoretical contributions have important implications for developing more precise conceptual frameworks at the intersection between international collaboration networks and digital technology adoption.

These insights have direct practical implications. For business managers, the results suggest that participation in international R&D networks is associated with technological modernization, particularly conventional web technologies. However, smart technology adoption may require complementary strategies focused on internal capability development and more intensive and sustained learning processes. For STP managers, the findings indicate that facilitating initial access to European R&D networks may be more effective than promoting the intensification of existing collaborations. Policies could therefore focus on reducing entry barriers to international programs and facilitating initial connections between resident firms and European networks, leveraging the intermediation role that characterizes STPs as technological transfer facilitators. For policy makers, the evidence suggests that international collaboration promotion programs are linked to significant technological spillovers, justifying public investments in these instruments. However, differential associations between technology types suggest the need for complementary instruments for more complex technologies, including specific programs for developing absorptive capacities for smart technologies.

It is important to note that these recommendations would benefit from further confirmation through experimental or quasi-experimental research designs to establish causal effects.

Limitations

This study presents several limitations that must be considered in the interpretation of results. First, cross-sectional design limits causal inferences. Although the robustness of results under multiple specifications increases confidence in the findings, endogeneity and self-selection remain significant concerns. Firms that participate in international collaborations are not randomly selected; they may possess unobserved characteristics—such as a proactive managerial orientation, strategic vision, or higher baseline R&D intensity—that simultaneously drive both network participation and technology adoption. While we control firm size, age, and sector, these are proxies that cannot fully account for such unobserved heterogeneity. Consequently, our results should be interpreted as associations rather than definitive causal impacts. Second, collaboration measurement is based exclusively on formal European projects identified through the CORDIS database. While this ensures data objectivity and verifiability, it potentially underestimates informal collaborations, local partnerships, or international ties with partners outside the European Union (e.g., USA or Asia) that could also show similar links with technology adoption. Third, the smart/non-smart technology classification, although based on established criteria, may not fully capture heterogeneity within each category and technological complexity. Fourth, the specific context of Spanish STPs may limit generalization to other innovation ecosystems or geographical contexts with different institutional characteristics. Finally, the absence of variables on internal absorptive capacities limits understanding of mediating mechanisms, although the organizational controls included partially mitigate this limitation.

Future research

Future research should adopt longitudinal designs to better understand the direction of the relationship between collaboration and technology adoption. Furthermore, while our models control for key organizational characteristics, we acknowledge that unobserved factors such as managerial quality, strategic orientation toward innovation, or organizational culture could simultaneously drive both the decision to collaborate and the adoption of new technologies. Future studies employing experimental or quasi-experimental designs would be valuable to disentangle these alternative explanations and establish clearer causal pathways.

Analysis of mediating mechanisms, particularly absorptive capacities and knowledge transfer, would provide deeper insights into how network associations operate and explain the differential patterns observed between smart and non-smart technologies.

Extending the analysis to other geographical and institutional contexts, including STPs in different European countries and alternative innovation ecosystems, would allow evaluation of the generalization of findings. Additionally, analysis of heterogeneous effects by firm characteristics (size, sector, and prior capabilities) could identify boundary conditions for the observed effects and develop more precise typologies of beneficiary firms.

Finally, research on informal collaborations and tacit knowledge networks would complement the current understanding based on formal collaborations, providing a more complete perspective on innovation ecosystems and the technological diffusion processes that operate within them. Future studies could benefit from combining formal database records with survey data to capture a broader spectrum of collaborative activities, including partnerships with non-European actors and informal knowledge exchange.

Conclusions

This study has examined the relationship between of international collaboration and web technology adoption by firms located in Spanish STPs, providing empirical evidence on a phenomenon of growing relevance in the digital economy. The findings suggest that participation in international R&D networks is associated with business technological modernization, although with differentiated patterns according to technology type.

The support found for the three main hypotheses provides significant contributions to existing knowledge. First, a positive and robust association is established between international collaboration and technology adoption, where international collaboration is linked to average differences of €789 monthly in technology expenditure. Second, it is observed that structural access to international networks is more strongly associated with adoption than relational intensity, suggesting that diversity of connections may be more relevant than their depth. Third, it is documented that these associations are notably more pronounced for conventional technologies than for smart technologies, suggesting that the effectiveness of international networks as diffusion mechanisms varies significantly depending on the complexity of the technology involved.

From a theoretical perspective, these results contribute to the development of more precise conceptual frameworks that integrate social network theories, innovation diffusion, and absorptive capacity. The evidence on threshold effects and technological heterogeneity suggests the need to incorporate non-linearities and specific moderators in theoretical models of technology adoption.

The practical implications are equally relevant. For business managers, the results suggest differentiated strategies according to technology type: leveraging international networks for conventional technologies and focusing on the development of complementary internal capabilities for smart technologies. For technology park managers, the evidence supports policies focused on facilitating initial access to European networks rather than intensifying existing collaborations. For public policy designers, the documented technological patterns suggest the potential value of investments in international collaboration programs, although they require complementary instruments for more complex technologies.

The specific context of Spanish STP provides a natural laboratory to examine these phenomena, leveraging the high density of innovative firms and active participation in European R&D programs. The results suggest that these ecosystems are positioned effectively as international technological transfer facilitators, consistent with their strategic role in innovation policies.

The identified limitations, particularly the cross-sectional design and measurement of formal collaborations, open opportunities for future research that adopt longitudinal approaches and mixed methodologies. Extension to other geographical and institutional contexts would allow evaluation of the generalization of these findings and development of more comprehensive theories on international collaboration and technology adoption.

In synthesis, this study indicates that international collaboration is a relevant factor associated with web technology adoption, providing empirical evidence that informs both theoretical development and managerial practice and public policy design in the era of digital transformation.

Appendix I: Classification of technology categories: smart vs. non-smart

Category	Smart (n)	Non-smart (n)	% Smart	Representative examples
Analytics	412	355	54%	Smart: Google Analytics 4, Hubspot, Marketo Non-smart: Google Universal Analytics, WordPress Stats
Mapping	14	19	42%	Smart: Google Maps API, Mapbox Non-smart: Leaflet JS, OpenStreetMap, Bing Maps
Robots	13	31	30%	Smart: GPTBot Disallow, Anthropic Claude Bot Disallow, Alexa Bot Disallow Non-smart: Robots Disallow, Googlebot Disallow, Yandex Bot Disallow
Media	32	79	29%	Smart: Brightcove, Vidyard, FreeWheel Non-smart: YouTube, Vimeo, MediaElement.js
Ads	186	641	22%	Smart: DoubleClick Bid Manager, AppNexus Non-smart: Google Adsense, LinkedIn Ads
CDN	16	58	22%	Smart: Cloudflare, Akamai Non-smart: Amazon S3, BootstrapCDN
Payment	19	72	21%	Smart: Stripe v3, Adyen, CyberSource Non-smart: PayPal, Visa, MasterCard
CMS	85	444	16%	Smart: Instapage, Unbounce Non-smart: WordPress, SuccessFactors
MX	24	152	14%	Smart: Proofpoint, Sophos, Mimecast Non-smart: SPF, Google Apps for Business, Mailgun
Widgets	219	2059	10%	Smart: LandBot, reCAPTCHA Enterprise, Cloudflare Bot Manager Non-smart: Font Awesome, Google Tag Manager, Contact Form 7
Agency	6	76	7%	Smart: Beyond Pricing, Scaled Inference Non-smart: Grupo Vansur, donosTIK

Category	Smart (n)	Non-smart (n)	% Smart	Representative examples
NS	10	131	7%	Smart: Amazon Route 53, Cloudflare DNS Non-smart: GoDaddy DNS, DNSSEC, OVH DNS
Shop	25	367	6%	Smart: Shopify, SAP Commerce Cloud, Wix Stores Non-smart: WooCommerce, PrestaShop, Cart Functionality
Web Server	4	86	4%	Smart: BIG-IP, Amazon ALB, Imunify360 Non-smart: Apache, Nginx, IIS
Hosting	19	701	3%	Smart: Amazon Elastic Load Balancing, AWS Global Accelerator Non-smart: Cloudflare Hosting, Google Cloud, DINA Hosting
JavaScript	2	714	0%	Smart: hls.js, annyang Non-smart: jQuery, React, Modernizr
Framework	1	828	0%	Smart: Akamai Bot Manager Non-smart: PHP, Laravel, Organization Schema
SSL	0	98	0%	LetsEncrypt, Comodo PositiveSSL, GoDaddy SSL
Mobile	0	13	0%	Viewport Meta, Apple Mobile Web App Capable, IPhone/Mobile Compatible
Server	0	55	0%	OpenSSL, Parallels Plesk Panel, Ubuntu
Language	0	213	0%	Spanish HREF LANG, English HREF LANG, Portuguese
Feeds	0	10	0%	RSS, Atom
Link	0	96	0%	Google Analytics Opt-Out Privacy, LinkedIn, GitHub
Web master	0	7	0%	Google Webmaster, MSN/Bing Webmaster, Yandex Verification
CDNs	0	110	0%	Amazon CloudFront, KeyCDN
Copyright	0	28	0%	Copyright Year 2021, Copyright Year 2015
Parked	0	38	0%	GoDaddy Parking, Apache2 Ubuntu Default Page, ParkingCrew
Shipping	0	26	0%	UPS, DHL, FedEx
Registrar	0	12	0%	1and1 Internet, OVH Registrar, Google Registrar
Docinfo	0	39	0%	HTML5 DocType, Open Graph Protocol

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Author contributions
S.H. conducted the methodology design, formal analysis, investigation, and wrote the original draft. S.H. also acquired funding for the study. M.P.L.M. contributed to conceptualization, supervised the research, conducted investigation, developed software, and reviewed and edited the manuscript. N.G.C. provided supervision, created visualizations, and reviewed and edited the manuscript. All authors reviewed and approved the final manuscript.

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Data availability
The datasets generated and analyzed during the current study are not publicly available due to confidentiality restrictions imposed by the data providers.

Declarations

Ethical approval and consent to participate
Not applicable.

Consent for publication
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Competing interests
The authors declare no competing interests.

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References

1. Ahuja G (2000) The duality of collaboration: inducements and opportunities in the formation of interfirm linkages. Strateg Manag J 21(3):317–343. https://doi.org/10.1002/(SICI)1097-0266(200003)21:3%3c317::AID-SMJ90%3e3.0.CO;2-B
2. Albahari A, Catalano G, Landoni P (2013) Evaluation of national science park systems: a theoretical framework and its application to the Italian and Spanish systems. Technol Anal Strateg Manag 25(5):599–614. https://doi.org/10.1080/09537325.2013.785508
3. Albahari A, Pérez-Canto S, Barge-Gil A, Modrego A (2017) Technology parks versus science parks: does the university make the difference?

Technol Forecast Soc Change 116:13–28. https://doi.org/10.1016/j.techfore.2016.11.012

4. Audretsch DB, Belitski M (2024) Knowledge collaboration, firm productivity and innovation: a critical assessment. J Bus Res 172:114412. https://doi.org/10.1016/j.jbusres.2023.114412
5. Belderbos R, Carree M, Lokshin B (2004) Cooperative R&D and firm performance. Res Policy 33(10):1477–1492. https://doi.org/10.1016/j.respol.2004.07.003
6. Broekel T (2019) Using structural diversity to measure the complexity of technologies. PLoS ONE 14(5):e0216856. https://doi.org/10.1371/journal.pone.0216856
7. Burt RS (1992) Structural holes: the social structure of competition. Harvard University Press.
8. Cassiman B, Veugelers R (2002) R&D cooperation and spillovers: some empirical evidence from Belgium. Am Econ Rev 92(4):1169–1184
9. Chen QA, Zhao X, Zhang X, Jiang Z, Wang Y (2024) Driving forces of digital transformation in Chinese enterprises based on machine learning. Sci Rep 14(1):6177. https://doi.org/10.1038/s41598-024-56448-w
10. Chesbrough HW (2003) Open innovation: the new imperative for creating and profiting from technology. Harvard Business Press.
11. Cohen WM, Levinthal DA (1990) Absorptive capacity: a new perspective on learning and innovation. Adm Sci Q 35(1):128–152. https://doi.org/10.2307/2393553
12. Criscuolo P, Narula R, Verspagen B (2005) Role of home and host country innovation systems in R&D internationalization: a patent citation analysis. Econ Innov New Technol 14(5):417–433. https://doi.org/10.1080/1043859042000315285
13. Díez-Vial I, Montoro-Sánchez Á (2016) How knowledge links with universities may foster innovation: the case of a science park. Technovation 50:41–52. https://doi.org/10.1016/j.technovation.2015.09.001
14. Gilsing V, Nooteboom B, Vanhaverbeke W, Duysters G, van den Oord A (2008) Network embeddedness and the exploration of novel technologies: technological distance, betweenness centrality and density. Res Policy 37(10):1717–1731. https://doi.org/10.1016/j.respol.2008.08.010
15. Granovetter MS (1973) The strength of weak ties. Am J Sociol 78(6):1360–1380. https://doi.org/10.2307/202051
16. Hall BH, Khan B (2003). Adoption of new technology. https://doi.org/10.3386/w9730
17. Hanelt A, Firk S, Hildebrandt B, Kolbe LM (2021) Digital M&A, digital innovation, and firm performance: an empirical investigation. Eur J Inf Syst 30(1):3–26. https://doi.org/10.1080/0960085x.2020.1747365
18. Hildebrandt M (2020) Smart technologies. Internet Policy Review 9(4):1–16. https://doi.org/10.14763/2020.4.1531
19. Klofsten M, Jones-Evans D (2000) Comparing academic entrepreneurship in Europe–the case of Sweden and Ireland. Small Bus Econ 14(4):299–309. https://doi.org/10.1023/A:1008184601282
20. Klofsten M, Fayolle A, Guerrero M, Mian S, Urbano D, Wright M (2015) The entrepreneurial university as driver for economic growth and social change-key strategic challenges. Technol Forecast Soc Chang 141:149–158. https://doi.org/10.1016/j.techfore.2018.12.004
21. Laursen K, Salter AJ (2014) The paradox of openness: appropriability, external search and collaboration. Res Policy 43(5):867–878. https://doi.org/10.1016/j.respol.2013.10.004
22. Löfsten H, Lindelöf P (2002) Science parks and the growth of new technology-based firms—academic-industry links, innovation and markets. Res Policy 31(6):859–876. https://doi.org/10.1016/S0048-7333(01)00153-6
23. Löfsten H, Lindelöf P (2005) R&D networks and product innovation patterns—academic and non-academic new technology-based firms on Science Parks. Technovation 25(9):1025–1037. https://doi.org/10.1016/j.technovation.2004.02.007
24. Love JH, Roper S (2009) Organizing innovation: complementarities between cross-functional teams. Technovation 29(3):192–203. https://doi.org/10.1016/j.technovation.2008.07.008
25. Martínez-Noya A, Narula R (2018) What more can we learn from R&D alliances? A review and research agenda. BRQ Bus Res Q 21(3):195–212. https://doi.org/10.1016/j.brq.2018.04.001
26. McFadyen MA, Cannella AA Jr (2004) Social capital and knowledge creation: diminishing returns of the number and strength of exchange relationships. Acad Manag J 47(5):735–746. https://doi.org/10.5465/20159615
27. Nonaka I (1994) A dynamic theory of organizational knowledge creation. Organ Sci 5(1):14–37. https://doi.org/10.1504/IJTM.1996.025472
28. Roche MP, Oettl A, Catalini C (2024) Proximate (co-) working: knowledge spillovers and social interactions. Manag Sci 70(12):8245–8264. https://doi.org/10.1287/mnsc.2022.03555
29. Rodríguez A, Nieto MJ, Santamaría L (2018) International collaboration and innovation in professional and technological knowledge-intensive services. Ind Innov 25(4):408–431. https://doi.org/10.1080/13662716.2017.1414752
30. Rogers EM (1962) Diffusion of innovations the free Press of Glencoe. NY, 32, 891–937.
31. Santamaría L, Nieto MJ, Rodríguez A (2021) Failed and successful innovations: the role of geographic proximity and international diversity of partners in technological collaboration. Technol Forecast Soc Change 166:120575. https://doi.org/10.1016/j.techfore.2021.120575

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