Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Domestic versus Foreign R&D Collaboration and Technology Transfer Performance: Does Technology Field Matter?

Jung Han

hjh0037@gmail.com

Hongik University

Research Article

Keywords: technology transfer, university–industry and international collaboration, technology field, moderation effect, open innovation, log-linear regression

Posted Date: October 26th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10933063/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Few studies examine how domestic versus foreign partnerships differentially affect technology transfer performance across technological fields, despite growing interest in R&D collaboration. Using large-scale data from Korea's National Science and Technology Information System (NTIS) on government-funded R&D projects, this study examines (i) whether domestic and foreign co-research enhance technology transfer performance, measured as royalty income, and (ii) whether these effects are moderated by technology field (IT, BT, NT, ET). Results show that both domestic and foreign collaboration positively predict royalty income at the pooled-sample level, confirming that proximity-based and internationally networked partnerships each generate commercializable value. However, moderation analyses reveal no statistically significant field-contingent variation in these effects. Although raw means suggest a numerically larger foreign-collaboration effect in BT and ET, we interpret this cautiously given the small foreign-collaboration subsample and limited statistical power. Theoretically, this study repositions the partner-geography–technology-field interaction as a substantive object of inquiry rather than a control variable, challenging Pavitt-style assumptions that sector-contingent collaboration effects transfer uniformly from innovation counts to licensing outcomes. We propose that partner geography shapes the qualitative character of collaborative value more than its quantitative monetary yield. Theoretically, this study repositions the partner-geography–technology-field interaction as a substantive object of inquiry rather than a control variable, and proposes that partner geography may shape the qualitative character of collaborative value more than its quantitative monetary yield. Practically, the null moderation finding provides an empirically defensible basis for field-agnostic collaboration-promotion policy, no single technology field is systematically under- or over-served by uniform partner-geography targeting, so R&D funding agencies need not default to sector-differentiated collaboration strategies without first testing for them in their own data.

1. Introduction

Numerous prior studies shows that collaborative partnership research is one of the most effective mechanisms for narrowing the gap between technology suppliers and technology users (Bekkers, and Bodas Freitas, 2008; Al- Harrasi and Al- Subhi, 2024), because it allows firms to internalize external knowledge while it is still being generated rather than acquiring it after the fact through arm's length licensing alone (Cohen and Levinthal, 1990; Chesbrough, 2003; Perkmann et al., 2021).

Yet, two essence questions that underpin the effective design of interorganizational collaboration remain theoretically and empirically underexplored. The first concerns partner geography e.g., does it matter, for technology transfer performance, whether the co-research partner is domestic or foreign? Domestic partners offer institutional and geographic proximity that speeds up tacit-knowledge exchange and coordination (Boschma, 2005; Chetty and Michailova, 2011; Lu, et al, 2024; Usai, et al., 2017), whereas foreign partners provide access to heterogeneous knowledge pools and international networks that are unavailable at home (Keller, 2004; Annique and Alicia, 2018; Eric; 2011; Kang and Park, 2012; Radici, 2026).

According to recent studies regarding ambidextrous partnerships, using large-sample evidence, these two channels are not interchangeable. For example, Nieto et al (2024) show in a panel of manufacturing firms that international R&D coopetition disproportionately drives new-to-the-market innovation, while domestic coopetition is more strongly associated with new-to-the-firm innovation, a result that implies the two partner types generate qualitatively different value, not merely different magnitudes of the same value. A second, and comparatively underexplored, question concerns whether the relationship between partnership and performance is itself moderated by technology field.

Technology fields differ systematically along several dimensions relevant to this relationship e.g., the tacitness and codifiability of their underlying knowledge base, the duration and capital intensity of their commercialization cycles, and the extent to which international research networks are already institutionalized within the field.

Biotechnology (BT), for instance, is described in the literature as a canonically science-based field in Pavitt's (1984) sectoral taxonomy, characterized by science-driven, cumulative, and highly internationalized research practices (Ervits, 2024; Cantabene and Grassi, 2024), whereas information technology (IT) tends to rely on modular, platform-based knowledge that diffuses rapidly through domestic industrial ecosystems and standards bodies. If the knowledge structure of a field shapes how readily external knowledge obtained through collaboration can be absorbed and commercialized, then the marginal value of a domestic versus a foreign partner should not be constant across fields, implying a moderation effect that pooled, field-agnostic models cannot detect.

Consistent with this reasoning, recent sector-heterogeneity studies of university–industry and international R&D collaboration report substantial cross-sector variation in the strength of the collaboration performance link (Lin and Yang, 2020; Belderbos et al., 2006; García-Vega and Vicente-Chirivella, 2024), even though few of these studies test the interaction directly using government technology transfer outcome data.

This study addresses both gaps using a single, purpose-built dataset: 3,096 technology-licensing records generated by government-funded R&D projects, spanning four major technology fields under Korea's 6T classification, IT (Information Technology), BT (Bio Technology), NT (Nanotechnology), and ET (Environmental technology). We have two research questions. First, does co-research with a domestic partner and, separately, with a foreign partner improve technology transfer performance, measured as royalty income? Second, is this collaboration effect systematically moderated by technology field that is, is domestic or foreign collaboration relatively more effective for royalty generation in some fields than in others? We test these questions using log-linear regression, an interaction-term moderation specification, heteroscedasticity-robust (HC3) inference, and joint Wald tests on sets of interaction terms, which allow us to assess the interaction hypotheses independent of the significance pattern of any single coefficient.

The study makes three contributions. Theoretically, it introduces an explicit partner-type and technology-field interaction framework to the technology-transfer literature, treating technology field as a boundary

condition on the absorptive-capacity mechanism rather than as a control variable to be partial led out. Empirically, it provides one of the few direct tests of this interaction using administrative, contract-level technology-transfer outcome data rather than firm-level innovation surveys. Practically, the findings give directly to a policy question that R&D funding agencies face routinely: whether collaboration-promotion programs should be designed uniformly across technology fields or tailored to each field's collaboration profile.

The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature and develops four hypotheses. Section 3 describes the data, variables, and empirical models, including the estimating equations. Section 4 reports the results. Section 5 discusses the summary, implication, and directions for future research.

2. Literature Review and Hypothesis

2.1 Collaborative Partnerships and Technology Transfer Performance

The Open Innovation (OI) paradigm holds that firms and public research organizations increasingly rely on external knowledge flows, both inbound and outbound, to accelerate commercialization and reduce the cost and risk of internal R&D (Chesbrough, 2003; Thursby and Thursby, 2004; Bogers et al. 2018; Koo and Cho, 2021; Kim et al., 2021). The central value of OI-based collaboration in R&D lies in its ability to enable the seamless mobilization, integration, and application of heterogeneous knowledge resources, spanning technological expertise, codified knowledge, and experience-based tacit knowledge. (Terhorst et al., 2018; Caccamo et al., 2023; West and Bogers, 2014).

A central mechanism underlying this paradigm is absorptive capacity, thus the capability of an organization to recognize, assimilate, and commercially exploit external knowledge (Cohen and Levinthal, 1990; Kashan et al., 2025; Hoch et al., 2026). Collaborative research, as opposed to arm's-length technology licensing after invention, allows this absorptive process to begin while the technology is still under development, so that tacit know-how, not only codified patent claims, is transferred alongside the formal output (Hagedoorn et al., 2009; Zahra and George, 2002; Mowery et al., 1996).

Recent University–Industry Collaboration (UIC) research reinforces this channel. García-Vega and Vicente-Chirivella (2024) and Escribano et al (2009) find that external knowledge obtained from public research organizations and universities raises firm-level innovativeness, and that this effect is stronger for firms with lower absorptive capacity, implying that collaboration substitutes, in part, for capabilities the firm does not yet possess internally.

Similarly, a systematic synthesis of UIC determinants identifies joint and contract research as one of the most consistently reported antecedents of successful technology transfer output, alongside patenting, licensing, and spin-off formation (Hojnik et al., 2026). Within this general logic, domestic and foreign

partnerships are expected to operate through complementary but distinct channels. Geographic and institutional proximity to a domestic partner shared language, legal system, funding agency, and physical distance lowers the transaction costs of coordinating joint research and facilitates the exchange of tacit, uncodified knowledge that is difficult to transfer over distance (Boschma, 2005; Lee and Kim, 2016).

Domestic collaboration networks built around government R&D programs also tend to be denser and more repeat-based, which supports trust-based knowledge sharing (Roesler and Broekel, 2017; Lee and Kim, 2016; Hojinik et al., 2026). Foreign partnerships, by contrast, are theorized to matter primarily because they expose the domestic research team to heterogeneous knowledge bases and international technology networks that are structurally unavailable within the domestic system (Keller, 2004; Ervits, 2024).

International co-patenting and co-publication studies consistently find that cross-border collaboration is associated with higher-novelty, more internationally cited output, consistent with a knowledge-recombination mechanism rather than a pure knowledge-diffusion mechanism (Ervits, 2024; Cantabene and Grassi, 2024). At the firm level, Nieto et al (2024) show that international R&D coopetition produces a significantly larger effect on new-to-the-market (radical) innovation than domestic coopetition does, while domestic coopetition is comparatively more effective for new-to-the-firm (incremental, imitative) innovation, direct evidence that the two partnership types are not interchangeable substitutes but generate different kinds of market value. Because both mechanisms, proximity-based tacit-knowledge exchange for domestic partners, and heterogeneous-knowledge access for foreign partners are expected to raise the commercial value of the resulting technology and therefore its licensing (royalty) value, we hypothesize a positive main effect for each partnership type. Domestic R&D collaborations can benefit from geographic and social proximity, as repeated interactions facilitate trust formation and reduce barriers to the exchange of tacit knowledge (Cantabene and Grassi, 2024; Alpaydın et al., 2021; Nast et al., 2025).

This complementary channel view is also consistent with a broader trend documented in the recent university-industry engagement literature, which finds that collaboration governance is becoming more heterogeneous as institutions increasingly combine flexible, project-based joint research with formal licensing and, increasingly, digitally mediated knowledge exchange (Mascarenhas et al., 2024; O'Dwyer et al., 2023). This reasoning applies with essentially equal force to domestic and foreign collaboration, because both are channels through which additional, non-redundant technical knowledge and, often, a more clearly identified downstream commercialization partner becomes embedded in the licensed technology before the contract is signed. Based on literature review, we make research hypothesis as follows:

Hypothesis 1

(H1). *Co-research with a domestic partner has a positive effect on technology transfer performance (royalty income).*

Hypothesis 2

(H2). *Co-research with a foreign partner has a positive effect on technology transfer performance (royalty income).*

2.2 The moderating role of technological filed Specific Knowledge Structure

The utmost output of research and development activities is the marketization through the technology transfer as a central pillar of national innovation policy in most advanced and emerging countries. This is why Open innovation (OI) has been attracted for scholars. Because universities and public research institutes rarely possess the complementary assets (Teece, 2006; Rothaermel and Hill, 2005) thus, manufacturing capacity, market access, distribution channels required to bring an invention to market, technology transfer typically proceeds through licensing agreements with private firms, and the resulting royalty income is one of the most direct and widely used indicators of technology transfer performance (Thursby et al., 2001; Thursby and Kemp, 2002; Siegel et al., 2003).

Absorptive capacity theory implies that the value of externally sourced knowledge depends not only on the collaboration channel through which it arrives but also on how well that knowledge fits the recipient field's existing knowledge base and commercialization pathway (Cohen and Levinthal, 1990; Kobarg, 2018; Biedenbach et al., 2018; Hou et al.,2017). Pavitt's (1984) sectoral taxonomy of technical change, still a foundational reference in recent sectoral-innovation research (Castellacci, 2008) classifies industries into supplier-dominated, scale-intensive, specialized-supplier, and science-based groups that differ systematically in the source, cumulativeness, and appropriability of their technological knowledge.

Science-based fields such as biotechnology draw heavily on codified scientific knowledge generated in university and public research settings, have long and capital-intensive commercialization cycles subject to regulatory approval, and importantly for this study have historically developed dense international research networks, because frontier scientific knowledge in these fields is itself internationally distributed rather than concentrated in any one national system (Ervits, 2024; Cantabene and Grassi, 2024).

Information technology, in contrast, is built on modular, platform-based, and rapidly standardizing knowledge that diffuses quickly through domestic supply chains, industry consortia, and user communities, so that a very large share of commercially relevant knowledge recombination can occur without crossing a national border (Tilson, 2010; Gawer, 2014; Barile and Secundo, 2026). These field-level differences in knowledge structure give rise to a straightforward moderation logic: because the marginal informational value of a domestic versus a foreign partner depends on how internationally distributed a field's relevant knowledge already is, the effect of domestic and foreign collaboration on technology transfer performance should not be homogeneous across technology fields.

Recent sector-heterogeneity evidence supports the plausibility of this mechanism outside the technology-transfer context specifically. Lin and Yang (2020) boosts substantial heterogeneity in the strength of the industry–university R&D collaboration innovation performance link across industries, tracing the variation to differences in technological opportunity and appropriability regimes consistent with Pavitt-type sectoral classifications. Belderbos et al. (2006) similarly show that the propensity and productivity impact of R&D cooperation strategies vary by cooperation-partner type and by sector, rather than following a single uniform pattern. In the specific context of international collaboration, Nieto, Rodríguez, and Santamaría (2024) and the broader coopetition literature they build on emphasize that the innovation payoff to crossing a national border is conditional on the technological regime in which the firm operates, rather than a constant premium.

Extending this logic to technology transfer performance from government R&D where BT and ET projects are, on average, closer to the science-based end of Pavitt's spectrum and IT projects closer to the specialized-supplier or information-intensive end, we expect the effect of both domestic and foreign collaboration on royalty income to differ across the four fields examined here (IT, BT, NT, ET), even though the direction of the difference is an open empirical question given the countervailing forces at work e.g., BT's stronger international networks versus its longer, more uncertain commercialization cycle. Based on literature review, we make research hypothesis as follows:

Hypothesis 3

(H3). *The effect of domestic collaboration on technology transfer performance differs across technology fields (IT, BT, NT, ET).*

Hypothesis 4

(H4). *The effect of foreign collaboration on technology transfer performance differs across technology fields (IT, BT, NT, ET).*

Determinant-focused syntheses of successful university–industry and public–private technology transfer identify strategic alignment between the research partner's objectives and the recipient field's commercialization pathway, along with the maturity of intellectual-property support and industry-expertise integration, as key enablers of technology-transfer success (Hojnik et al., 2026). These enabling conditions are themselves field-specific e.g., BT commercialization typically requires regulatory-science expertise and long-horizon capital that is more readily available through internationally networked partners with prior experience navigating comparable regulatory regimes abroad, whereas IT commercialization can often proceed through faster, more standardized domestic contracting because the relevant complementary assets (software integration, platform compatibility, distribution) are concentrated in the domestic digital economy (Teece 1986; Ceccagnoli, 2013). To the extent that these institutional-fit conditions vary by field in ways correlated with, but conceptually distinct from, the pure knowledge-recombination mechanism discussed above, they provide an additional, non-mutually-exclusive theoretical route by which the collaboration–performance relationship could be field-

contingent, strengthening the case for testing H3 and H4 empirically rather than assuming a uniform effect a priori.

Figure 1 summarizes the conceptual model: domestic and foreign collaboration are modeled as two parallel, partially independent paths to royalty income, each of which is hypothesized to be moderated by technology field, net of research-scale, patenting, research-stage, and time controls.

3. Data and Methods

As we above shown Fig. 1, this paper utilizes the log regression analysis methods to catch research objectives. Namely the empirical strategy is designed to answer the two research questions in a way that is transparent about statistical power, since as later results show one of the two collaboration channels (foreign partnership) is rare by nature in this policy setting. Rather than relying solely on a series of separate subgroup regressions, whose individual coefficients can appear inconsistent purely because of sampling variability, the design combines (i) descriptive field-by-field comparisons, (ii) field-specific regressions with full controls, and (iii) a single pooled interaction model tested with a joint Wald statistic, so that the moderation hypotheses (H3, H4) are evaluated at the level at which they are actually stated as claims about a set of field-specific differences taken together, not about any single coefficient in isolation.

3.1 Data and Sample

For the purpose of it, in this study, data was obtained from the NTIS (national Science and Technology information system), which is the service platform providing government-funded R&D information on topics such as programs, projects, human resources, equipment/facilities, and outcomes. In fact, NTIS is a platform not only open innovation dynamics which, offering numerous chances to find external knowledge (e.g., patents, research partners, technology life cycle) but an underpin of national innovation system in Korea.

The analysis uses 3,096 technology-licensing (execution-contract) performance records drawn from government-funded R&D projects completed between 2017 and 2019. Each record corresponds to a single technology-licensing agreement and reports the associated royalty payment, the characteristics of the underlying R&D project, and whether the project involved collaborative research with a domestic partner (firm, university, or public research institute) and/or a foreign research organization. Following Korea's 6T technology classification, projects are coded into six broad fields; this study focuses on the four largest fields for which the moderation model is estimable, IT (n = 1,118), BT (n = 581), NT (n = 178), and ET (n = 375), for a moderation-model estimation sample of 2,252, and excludes 844 records in residual fields (e.g., ST, CT) that are too sparse to support field-specific estimation.

An administrative dataset of this kind offers two advantages over the firm-level innovation surveys that dominate the sectoral-heterogeneity literature cited in Section 2. First, because every record corresponds to an actual, executed licensing contract rather than a self-reported innovation outcome, the dependent

variable is a market-validated, arm's-length measure of commercial value rather than a perceptual or count-based proxy. Second, because the underlying R&D projects were all funded through the same government program architecture, the sample holds broadly constant a range of institutional factors, funding-agency review standards, eligibility criteria, and reporting requirements that would otherwise vary substantially across firms drawn from heterogeneous industries and ownership structures, thereby sharpening the comparison of technology-field effects net of that source of confounding.

3.2 Variables and Empirical Models

The dependent variable, ln_royalty, is the natural logarithm of the royalty amount received under the licensing (execution) contract, which log-transforms the strongly right-skewed distribution typical of technology-licensing income (a small number of high-value licenses alongside many modest agreements). The two focal independent variables are co_do, a binary indicator equal to 1 if the underlying R&D project involved collaborative research with a domestic partner, and co_fr, a binary indicator equal to 1 if the project involved collaborative research with a foreign research organization. Technology field is captured by three dummy variables for BT, NT, and ET, with IT as the reference category. Control variables include ln_rd (the natural logarithm of total research funding, capturing project scale), pat_d (a binary indicator for whether the underlying invention was patented), two research-stage dummies (applied research and development research, relative to basic research), rde (the number of participating researchers), and a full set of year dummies to absorb macro-level and policy-cycle variation in licensing activity.

To test H1 and H2 while controlling for observable project characteristics, we estimate the following field-specific and pooled log-linear regression model separately for each technology field f:

$$ln_royalty_i = \beta_0 + \beta_1\, co_do_i + \beta_2\, co_fr_i + \beta_3\, ln_rd_i + \beta_4\, pat_d_i + \Sigma_k\, \gamma_k\, Stage_{ki} + \Sigma_t\, \delta_t\, Year_{ti} + \beta_5\, rde_i + \varepsilon_i \quad (1)$$

where i indexes technology-licensing records. Estimating Eq. (1) separately within each field (IT, BT, NT, ET) yields four field-specific estimates of β1 and β2, which provide a first, purely descriptive check on whether the net collaboration effect (after controlling for project scale, patenting, research stage, and year) survives within each field. To test H3 and H4 directly, we pool all four fields (N = 2,252) and estimate a single interaction model with IT as the reference field:

$$ln_royalty_i = \beta_0 + \beta_1\, co_do_i + \beta_2\, co_fr_i + \Sigma_f\, \lambda_f\, Field_{fi}$$

$$+ \Sigma_f\, \theta_f\, (co_do_i \times Field_{fi}) + \Sigma_f\, \varphi_f\, (co_fr_i \times Field_{fi}) + Controls_i + \varepsilon_i \quad f \in \{BT, NT, ET\} \quad (2)$$

In Eq. (2), β_1 and β_2 capture the collaboration effect within the IT reference field, θf captures how much the domestic-collaboration effect differs in field f relative to IT, and φf captures the corresponding difference for foreign collaboration. H1 and H2 correspond to $\beta_1 > 0$ and $\beta_2 > 0$; H3 and H4 correspond to the joint hypotheses θBT = θNT = θET = 0 and φBT = φNT = φET = 0 being rejected.

We adopted robust inference and joint significant testing. Because royalty income is heavily right-skewed even after the log transformation, and because project characteristics such as research funding vary substantially in scale across fields, ordinary least-squares residuals are likely to be heteroscedastic. All models are therefore estimated with heteroscedasticity-consistent HC3 standard errors (MacKinnon and White, 1985), which weight each observation's contribution to the variance-covariance matrix by its leverage:

$$Var\text{HC3}(\beta) = (X'X)^{-1} X' \, diag[\hat{e}_i^2 / (1 - h_{ii})^2] \, X \, (X'X)^{-1} \quad (3)$$

where êi is the OLS residual for observation i and hii is its leverage (the i-th diagonal element of the hat matrix X(X'X)⁻¹X'). HC3 up-weights high-leverage observations relative to the simpler HC1 estimator and is preferred in samples, such as this one, where a subgroup (foreign collaboration) is small and potentially influential.

Because the significance of a single interaction coefficient (e.g., co_do × BT) is a weak test of an overall moderation hypothesis that concerns three interaction terms simultaneously, H3 and H4 are each tested using a joint Wald test on the full set of relevant interaction coefficients. For a restriction matrix R and hypothesized value r = 0 (e.g., R selecting θBT, θNT, θET), the Wald statistic is:

$$W = (R\beta - r)' \, [R \, Var\text{HC3}(\beta) \, R']^{-1} \, (R\beta - r) \sim \chi^2(q), \text{ or equivalently } F = W / q \sim F(q, n - k) \quad (4)$$

where q is the number of restrictions (q = 3 for each hypothesis, corresponding to the BT, NT, and ET interaction terms), n is the sample size, and k is the number of estimated parameters. Rejecting the null of Eq. (4) at conventional significance levels would support H3 (for the domestic-collaboration interaction set) or H4 (for the foreign-collaboration interaction set); failing to reject implies that the data do not provide evidence of field-contingent moderation, independent of whether any individual interaction term happens to be significant. All analyses were conducted with heteroscedasticity-robust (HC3) covariance estimation implemented in standard statistical software, independent-samples t-tests (assuming unequal variances) were used for the preliminary mean-comparison analysis reported in Section 4.

4. Results

4.1 Sample Composition and Collaboration Patterns by Technology Field

Table 1 reports the sample composition and collaboration rates across the four technology fields. The domestic-collaboration rate is highest in IT (53.8%) and lowest in BT (16.2%), with NT (30.9%) and ET (43.2%) falling in between. Foreign collaboration is rare across all fields (39 of 2,252 records, 1.7%) and is heavily concentrated in IT, which accounts for 25 of the 39 foreign-collaboration cases (64%) despite

representing only about half of the pooled sample a pattern consistent with IT's comparatively open, internationally networked collaboration structure.

Table 1
Sample Distribution and Collaboration Status by Technology Field

Field	No	Domestic collab., n (%)	Foreign collab., n (%)	Mean royalty (KRW mil.)	Mean ln(royalty)
IT	1,118	601 (53.8%)	25 (2.2%)	32.0	16.51
BT	581	94 (16.2%)	6 (1.0%)	47.8	16.22
NT	178	55 (30.9%)	1 (0.6%)	39.0	16.71
ET	375	162 (43.2%)	7 (1.9%)	41.0	16.70
Total (4 fields)	2,252	912 (40.5%)	39 (1.7%)	37.5	16.53

Note. "Total (4 fields)" sums IT, BT, NT, and ET; 844 records in residual fields are excluded from the moderation analysis.

Table 2 reports independent-samples t-tests comparing ln(royalty) between projects with and without domestic collaboration, separately by field. Domestic collaboration is associated with significantly higher mean royalty income in all four fields (all $p < .05$), providing initial support for H1.

Table 2
a. Mean ln (Royalty) by Domestic Collaboration Status, by Field

Tech field	With domestic collab., mean (n)	Without, mean (n)	t	p	Results
IT	16.75 (601)	16.23 (517)	5.86	< .001	Supported
BT	16.70 (94)	16.12 (487)	3.49	.001	Supported
NT	17.05 (55)	16.56 (123)	2.61	.011	Supported
ET	17.02 (162)	16.45 (213)	4.16	< .001	Supported

For foreign collaboration (Table 2b), the collaborating group shows significantly higher mean royalty income in IT ($p < .001$) and ET ($p = .037$), a non-significant difference in BT ($p = .216$), and a case in NT where the test is not computable because only one foreign-collaboration observation exists. Overall, the raw mean comparisons point in the hypothesized direction for foreign collaboration as well, offering partial support for H2, though the extremely small foreign-collaboration subsamples in BT and NT substantially limit the interpretability of these comparisons.

Table 2
b. Mean ln (Royalty) by Foreign Collaboration Status, by Field

Tech Field	With foreign collab., mean (n)	Without, mean (n)	t	p	Results
IT	17.40 (25)	16.49 (1,093)	4.15	< .001	Supported
BT	17.32 (6)	16.21 (575)	1.41	.216	Not supported
NT	17.22 (1)	16.56 (177)	n.a.	—	Not testable
ET	17.86 (7)	16.68 (368)	2.64	.037	Supported

4.2 Technology- field Specific Regression Results (Net Collaboration Effects)

Table 3 reports the coefficients on co_do and co_fr from Eq. (1), estimated separately within each field with full controls (ln_rd, pat_d, research-stage dummies, rde, and year dummies) and HC3 standard errors. Once project-scale and other controls are introduced, the net effect of domestic collaboration remains statistically significant only in IT (β = 0.193, p = .031); the BT, NT, and ET coefficients, while still positive in three of four fields, lose statistical significance. This indicates that a substantial share of the raw mean-difference advantage documented in Table 2a reflects differences in project scale and other observable characteristics between collaborating and non-collaborating projects, rather than an independent effect of collaboration per standard error (SE), and that the independent domestic-collaboration effect is most robust in IT. The net effect of foreign collaboration is not statistically significant in any field once controls are added (ET shows a marginal trend at p = .088), consistent with the very small foreign-collaboration cell sizes inflating standard errors.

Table 3
Technology field-Specific Regression Results: Collaboration Coefficients (HC3 SE)

Collaboration types	IT (N = 1,118)	BT (N = 581)	NT (N = 178)	ET (N = 375)	Note
Domestic collaboration. (co_do)	0.193* (.031)	0.289 (.233)	0.080 (.793)	0.358 (.113)	Significant in IT only
Foreign collaboration. (co_fr)	0.258 (.237)	0.435 (.659)	-0.078 (.964)	0.888+ (.088)	Not significant overall
R^2	0.137	0.064	0.135	0.119	

*Note. Cell values are regression coefficients with p-values in parentheses; dependent variable = ln_royalty; controls = ln_rd, pat_d, research-stage dummies, rde, year dummies. *p < .05, +p < .10.*

4.3 Collaboration multiply Technology-Field Interaction Model (Tests of H3 and H4)

To test H3 and H4 directly, Eq. (2) was estimated on the pooled four-field sample (N = 2,252). Table 4 reports the full interaction model. The main effects of domestic and foreign collaboration, evaluated at

the IT reference category, are both statistically significant and positive (domestic: *β = 0.216, p = .014;* foreign: *β = 0.531, p = .022*). However, none of the six interaction terms, domestic collaboration × BT, × NT, × ET, and foreign collaboration × BT, × NT, × ET reaches conventional statistical significance individually.

Table 4
Collaboration multiply Technology-field interaction Model

Variable	**β**	**Robust SE (HC3)**	**p**
Domestic collab. (co_do) [ref. = IT]	0.216*	0.088	.014
Domestic collab. × BT	-0.185	0.194	.340
Domestic collab. × NT	-0.323	0.210	.124
Domestic collab. × ET	-0.215	0.168	.201
Foreign collab. (co_fr) [ref. = IT]	0.531*	0.231	.022
Foreign collab. × BT	0.202	0.989	.838
Foreign collab. × NT	-0.792	160.00	.996
Foreign collab. × ET	0.385	0.510	.450
Ln (research funding)	0.202***	0.035	< .001
Patent applied/registered	-0.070	0.099	.481
Research-stage and year dummies	Included	—	—

*Note. Dependent variable = ln_royalty; reference field = IT; HC3 robust standard errors. N = 2,252; R^2 = .087. *p < .05, ***p < .001.*

Because individual-coefficient non-significance does not, by itself, rule out overall moderation, we conducted joint Wald tests on each set of three interaction terms (Table 5). The domestic-collaboration × field interaction set is jointly non-significant, F(3, 2233) = 1.147, p = .329, and the foreign-collaboration × field interaction set is likewise jointly non-significant, F(3, 2233) = 0.195, p = .900. Both H3 and H4 are therefore not supported by the pooled interaction model: within the resolution of this dataset, the effect of domestic and foreign collaboration on royalty income is statistically indistinguishable across the four technology fields examined.

Table 5
Joint Wald Tests of Moderation (H3, H4)

Test (moderation hypothesis)	**F**	**df**	**p**	**Result**
H3: Domestic collab. × field (3 interaction terms, joint)	1.147	(3, 2233)	.329	Not supported
H4: Foreign collab. × field (3 interaction terms, joint)	0.195	(3, 2233)	.900	Not supported

Taken together, the results support H1 and H2, both domestic and foreign collaboration raise royalty income at the pooled level, and domestic collaboration's net effect is particularly robust in IT but do not support H3 and H4: the collaboration–performance relationship does not differ significantly across IT, BT, NT, and ET once tested with an appropriately powered joint test. The numerically larger raw effect of foreign collaboration in BT and ET observed in Table 2b should accordingly be interpreted as suggestive rather than confirmatory, given the low statistical power created by a foreign-collaboration subsample of only 48 cases (1.6% of the pooled sample).

4.4 Robustness Considerations and summary of hypothesis

Several features of the results merit closer interpretation before turning to their implications. First, the pattern across Tables 2–4 is internally consistent: the raw, control-free mean differences in Table 2a are considerably larger than the control-adjusted coefficients in Table 3, indicating that project scale (ln_rd) and related observable characteristics account for a meaningful share of the simple collaboration–performance association, particularly outside IT.

This is corroborated by the large and highly significant coefficient on ln (research funding) in Table 4 ($\beta = 0.202$, $p < .001$), which is, in absolute magnitude, comparable to or larger than the domestic-collaboration main effect itself. Second, the extremely large standard error on the foreign collaboration × NT interaction (160.00) in Table 4 is a direct artifact of NT having only one foreign-collaboration observation in the entire pooled sample; this coefficient should not be interpreted substantively, and its presence is itself evidence for why a joint Wald test which does not depend on any single, potentially degenerate coefficient behaving well is the appropriate test of H3 and H4 rather than a term-by-term reading of Table 4. Third, the R^2 of the pooled interaction model (.087) is modest by cross-sectional standards but is not unusual for licensing-royalty regressions, where outcome variance is driven substantially by technology-specific and negotiation-specific factors not captured in an administrative dataset of this kind (e.g., the identity and market power of the licensee, the exclusivity terms of the license, and unobserved technology quality); this limits the share of variance explained without necessarily biasing the sign or relative significance of the coefficients of theoretical interest.

Table 6
Summary of Hypotheses and Findings

Hypothesis	Statement (abbreviated)	Statistic	Result
H1	Domestic collaboration → royalty income (+)	β = 0.216, p = .014 (pooled model)	Supported
H2	Foreign collaboration → royalty income (+)	β = 0.531, p = .022 (pooled model)	Supported
H3	Domestic collaboration effect differs by field	F (3, 2233) = 1.147, p = .329	Not supported
H4	Foreign collaboration effect differs by field	F (3, 2233) = 0.195, p = .900	Not supported

Table 6 consolidates the four hypothesis tests reported across Sections 4.2 and 4.4. The pattern supported main effects alongside a non-significant joint interaction is consistent across both the field-level mean comparisons and the pooled interaction model, reinforcing the paper's central empirical claim: collaboration matters for technology transfer performance, but its marginal value, at least as measured through royalty income in this dataset, does not depend systematically on which of the four technology fields (IT, BT, NT, ET) the underlying project belongs to.

5. Discussion and Conclusion

Beyond the statistical results reported in Section 4, it is worth situating this study's contribution relative to the broader R&D management literature on collaboration governance. Whereas prior work has often treated "collaboration" as a single construct whose effect is assumed (or found) to be homogeneous, and separately treated "technology field" or "sector" as a control variable to be absorbed by fixed effects, this study's interaction design treats the combination of partner geography and technology field as the theoretical object of interest in its own right. That the joint tests in Table 5 return null results does not diminish the value of this design; rather, it demonstrates that an a priori theoretically plausible moderation hypothesis, grounded in well-established sectoral-innovation theory (Pavitt, 1984; Castellacci, 2008) and supported by adjacent empirical findings in other performance domains (Lin and Yang, 2020; Nieto et al., 2024), need not hold for every outcome variable or every institutional setting, and that R&D managers and policymakers should treat sector-differentiated collaboration strategies as an empirical question to be tested in their own data rather than a default assumption.

5.1 Summary of Findings and Theoretical Contributions

This study examined whether the effect of collaborative research on government-funded technology transfer performance depends on the geographic origin of the partner (domestic vs. foreign) and, further, whether either effect is contingent on technology field. Three main findings emerge. First, both domestic and foreign collaboration are positively associated with royalty income at the pooled-sample level, supporting the general open-innovation and absorptive-capacity logic that external research partnerships

whether proximity-based or internationally networked add commercializable value to publicly funded R&D (Cohen and Levinthal, 1990; Chesbrough, 2003; García-Vega and Vicente-Chirivella, 2024).

Second, once project scale and other observable characteristics are controlled, the independent (net) effect of domestic collaboration is most robust in IT, suggesting that IT's modular, standards-based knowledge structure may make domestic co-research partnerships an unusually efficient channel for converting collaboration into licensable, royalty-generating output. Third, and most centrally, the hypothesized moderating role of technology field (H3, H4) was not supported by the joint Wald tests: the collaboration–performance relationship, evaluated as a joint restriction across three interaction terms rather than through any single coefficient, does not differ significantly across IT, BT, NT, and ET in this dataset.

The absence of a statistically significant field-contingent moderation effect (H3, H4) should not be read as a weaker or less interesting finding than a confirmed interaction would have been. Two considerations support treating this null result as a genuine contribution rather than an incidental byproduct of the analysis.

First, the hypothesis was strong, not weak. H3 and H4 were derived from a well-established theoretical lineage, Pavitt's (1984) sectoral taxonomy of technical change, its subsequent elaborations (Castellacci, 2008), and directly analogous empirical findings of sector-contingent collaboration effects in adjacent performance domains (Lin and Yang, 2020; Nieto et al., 2024). Second, null moderation results are systematically underreported relative to their true prevalence, which distorts the cumulative evidence base for theory development. Interaction-effects research across the social sciences, including the sectoral-heterogeneity and technology-transfer literatures cited in Section 2 has a well-documented tendency to publish confirmed moderation findings disproportionately relative to disconfirmed ones, whether through outright non-publication of null results or through post hoc respecification of models until an interaction becomes significant. This asymmetry inflates the apparent generality of moderation theories, readers encounter a steady stream of confirmed field-contingent or sector-contingent effects and reasonably infer that such contingency is close to a default expectation, when in fact the universe of tested-but-unpublished null interactions may be considerably larger. By reporting a rigorously tested, theoretically motivated null moderation result alongside two robustly supported main effects (H1, H2), this study contributes a counterweight to that asymmetry and offers other technology-transfer researchers a replicable templated descriptive field-by-field comparison, field-specific regression, and pooled joint Wald testing, for reporting multi-category moderation hypotheses regardless of which way the result turns out.

This last finding is itself a meaningful contribution. Much of the sectoral-heterogeneity literature including Pavitt's (1984) original taxonomy and its various revisions (Castellacci, 2008), as well as recent studies documenting heterogeneous collaboration effects across industries (Lin and Yang, 2020; Belderbos et al., 2006; Nieto et al., 2024) provides strong theoretical grounds to expect field-contingent collaboration effects. Our results indicate that this expectation, while theoretically well-motivated, does

not automatically transfer to every empirical setting: at the level of technology-transfer royalty outcomes from government R&D, and within the specific IT/BT/NT/ET classification used here, the pooled interaction model and joint significance test could not statistically distinguish the fields.

Reporting this null moderation result alongside supported main effects is itself informative for the technology-transfer literature, which like much of the interaction-effects literature more broadly has tended to publish confirmed moderation findings disproportionately relative to disconfirmed ones; the joint Wald-test design used here offers a template for testing multi-category moderation hypotheses that other technology-transfer studies with categorical field or sector variables can adopt.

It is also useful to relate this study's field-level null-moderation finding to Nieto et al (2024) firm-level distinction between new-to-the-market and new-to-the-firm innovation outcomes under domestic versus international coopetition. Their finding that partner geography shapes the type of innovation value created, even when the overall performance level is comparable, suggests one plausible reconciliation of the present results: technology field may moderate what kind of value collaboration creates (e.g., more radical versus more incremental improvements to the licensed technology) without necessarily moderating how much royalty income that value ultimately commands once it reaches the licensing stage, since royalty negotiations compress heterogeneous technical value into a single monetary figure that also reflects licensee bargaining power, market size, and exclusivity terms. Future research that observes both the innovation-novelty characteristics of a licensed technology and its royalty value simultaneously would be well positioned to test this reconciliation directly.

5.2 Policy Implications

Two implications follow for the design of open-innovation and technology-commercialization policy. First, because the collaboration performance relationship does not differ significantly across technology fields in this sample, policies that promote collaborative research broadly rather than being narrowly tailored to a single field appear reasonably justified: both domestic and foreign co-research partnerships raise expected royalty income across the technology portfolio, not only in specific favored fields. Second, the raw pattern in which foreign collaboration shows a numerically larger association with royalty income in BT and ET, even though this difference is not statistically confirmed, combined with the fact that foreign collaboration is rare precisely in these fields (1.0% in BT, 1.9% in ET, versus 2.2% in IT), suggests that there may be untapped potential from expanding international co-research opportunities in fields where such partnerships are currently scarce.

Funding agencies could treat this as a hypothesis-generating basis for pilot programs for example, targeted international-partnership matching or co-licensing support in BT and ET whose outcomes should then be evaluated with adequately powered follow-up studies rather than assumed on the basis of the present, likely underpowered, comparison. For managers of publicly funded R&D portfolios and technology transfer offices, three practical takeaways follow. First, because both domestic and foreign collaboration are positively associated with royalty income at the portfolio level, R&D managers evaluating which projects to prioritize for external co-research funding need not treat partner geography

as a primary screening criterion; project-level fit with an appropriate partner, of either type, appears to matter more than partner nationality per se.

Second, because the domestic-collaboration effect is most robust, net of controls, in IT, technology transfer offices managing IT-field portfolios can reasonably expect measurable royalty gains from actively brokering domestic co-research partnerships, and may wish to invest disproportionately in domestic partner-matching services for this field. Third, the absence of confirmed field-level moderation should temper any managerial tendency to conclude, from a handful of high-profile foreign-partnered BT or ET licenses, that international collaboration is systematically more lucrative in science-based fields; managers should treat such anecdotes as hypotheses for portfolio-level tracking rather than as an established basis for reallocating collaboration-support budgets away from other fields.

5.3 Limitations and Future Research

Several limitations qualify these conclusions and point to directions for future research. First, the data are cross-sectional and cover a single three-year window (2017–2019); causal interpretation of the collaboration–performance relationship should therefore be made cautiously, and replication with more recent and longer panel data is needed to assess whether the patterns are stable over time. Second, the foreign-collaboration subsample is very small (48 of 3,096 records, 1.6%), which as reflected in the extremely large standard error on the foreign collaboration multiply by NT interaction in Table 4 limits the statistical power available to detect a true moderation effect, if one exists; the failure to reject H3/H4 should be read as an absence of evidence rather than confirmed evidence of absence.

Third, both collaboration variables are measured as binary indicators, which cannot capture the intensity, duration, number of partners, or network centrality of a given collaboration, dimensions that recent international-collaboration research suggests matter independently of the partner's mere presence (Ervits, 2024; Netieto et al, 2024). Future studies should extend the analysis with more recent and longer panel data, oversample or specifically target foreign-collaboration cases to restore statistical power, and employ continuous measures of collaboration intensity or network centrality, in order to more conclusively determine whether and under what field-specific conditions the marginal value of international research partnerships in technology commercialization differs from that of domestic partnerships.

Fourth, the data originate from a single national R&D funding system (Korea), whose institutional characteristics including the structure of its 6T technology classification, the relative maturity of its domestic industrial base in IT versus its comparatively younger internationally networked BT ecosystem, and country-specific technology transfer regulations may not generalize directly to funding systems in other countries. Cross-national replication, ideally using harmonized technology-field classifications and comparable royalty-income measures across two or more national R&D systems, would help establish whether the null moderation result reported here reflects a genuine absence of field contingency in the collaboration performance relationship or a feature specific to the Korean government R&D context studied.

In sum, this study set out to answer two questions that are of direct interest to R&D management studies and practice: whether partner geography matters for technology transfer performance, and whether that mattering is itself contingent on technology field. The evidence supports the first proposition and does not support the second. Both conclusions carry weight for the design of collaboration-promotion policy and for the future research agenda on the sectoral contingencies of R&D collaboration outcomes.

Declarations

Author Contribution

Junghee Han as the sole author of this paper, conducted the data acquisition, model construction, and manuscript drafting. This empirical study examines the effectiveness of different forms of collaboration on technology transfer, as well as the moderating effects of technology groups.

References

1. Al Harrasi, N., Al Subh, N.: Determinants of effective university–industry collaboration: anempirical study of Oman's Higher Education Institution. Cogent Educ. **2**(1), 2387951 (2024)
2. Alpaydin, U.A.-R., and Fitjar R. D: Proximity across the distant worlds of university–industry collaborations. Reg. Sci. **100**(3), 689–711 (2021)
3. Annique. Un, C., Rodríguez, A.: Local and Global Knowledge Complementarity: R&D Collaborations and Innovation of Foreign and Domestic Firms. J. Int. Manag. **24**(2), 137–152 (2018)
4. AUTM: Statistics Access for Technology Transfer (STATT) Database, Version 4.2. Association of University Technology Managers (2023)
5. Barile, D., Secundo, G.: Digital innovation ecosystem: A systematic mapping to understand how digital technologies are transforming innovation ecosystem. Technovation. **155**, 103573 (2026)
6. Belderbos, R., Carree, M., Diederen, B., Lokshin, B., Veugelers, R.: Heterogeneity in R&D cooperation strategies. Int. J. Ind. Organ. **24**(6), 1237–1263 (2006)
7. Bekkers, R., Bodas Freitas, I.M.: Analysing knowledge transfer channels between universities and industry: To what degree do sectors also matter? Res. Policy. **37**(10), 1837–1853 (2008)
8. Biedenbach, T., Marell, A., Vanyushyn, V.: Industry-university collaboration and absorptive capacity: An empirical study in a Swedish context. Int. J. Technol. Manage. **76**(1/2), 81–103 (2018)
9. Bogers, M., Chesbrough, H., Moedas, C.: Open innovation: Research, practices, and policies. Calif. Manag. Rev. **60**(2), 5–16 (2018)
10. Boschma, R.: Proximity and innovation: A critical assessment. Reg. Stud. **39**(1), 61–74 (2005)
11. Cantabene, S., Grassi, M.: International collaborations and the patenting intensity of US inventors. J. Evol. Econ. **34**, 1–29 (2024)
12. Castellacci, F.: Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. Res. Policy. **37**(6–7), 978–994

(2008)

13. Ceccagnoli, M., Hicks, D.: Complementary Assets and the Choice of Organizational Governance: Empirical Evidence from a Large Sample of U.S. Technology-Based Firms. IEEE Trans. Eng. Manage. **60**(1), 99–110 (2013)
14. Caccamo, M., Pittino, D., Tell, F.: Boundary objects, knowledge integration, and innovation management: A systematic review of the literature. Technovation. **122**, 102645 (2023)
15. Chetty, S., Michailova, S.: Geographical Proximity and Inter-Firm Collaboration: The Role of Knowledge Access and Knowledge Acquisition. J. Gen. Manage. **36**(4), 71–87 (2011)
16. Chesbrough, H.W.: Open Innovation. In: The New Imperative for Creating and Profiting from Technology. Harvard Business School Press, Boston, MA (2003)
17. Cohen, W.M., Levinthal, D.A.: Absorptive capacity: A new perspective on learning and innovation. Adm. Sci. Q. **35**(1), 128–152 (1990)
18. Escribano, A., Fosfuri, A., Tribó, J.A.: Managing External Knowledge Flows: The Moderating Role of Absorptive Capacity. Res. Policy. **38**(1), 96–105 (2009)
19. Ervits, I.: Cross-country co-patenting and international R&D collaboration. Res. Policy. **53**(4), 104940 (2024)
20. Fang, E.: The Effect of Strategic Alliance Knowledge Complementarity on New Product Innovativeness in China. Organ. Sci. **22**(1), 158–172 (2011)
21. García-Vega, M., Vicente-Chirivella, Ó.: External knowledge from public research organizations, universities, and firm innovativeness. (as cited in Hojnik 2026). (2024)
22. Gawer, A.: Bridging differing perspectives on technological platforms: Toward an integrative framework. Res. Policy. **43**(7), 1239–1249 (2014)
23. Hagedoorn, J., Lorenz-Orlean, S., van Kranenburg, H.: Inter-firm Technology Transfer: Partnership-Embedded Licensing or Standard Licensing Agreements? Ind. Corp. Change, **18**(3) (2009)
24. Enhancing Knowledge and Technology Transfer: Determinants and Indicators of Successful University–Industry Collaboration
25. Hojnik, J., Bojnec, Š., Kustec, S., Zemlickiene, V., Turskis, Z.: Enhancing knowledge and technology transfer: Determinants and indicators of successful university–industry collaboration. Corp. Soc. Responsib. Environ. Manag. **33**(4), 5181–5205 (2026)
26. Hoch, F., Röth, T., Kock, A., Backmann, J., Newman, A.: Adaptability in Innovation Management: A Meta-Analysis. J. Prod. Innov. Manage. **43**(5), 746–768 (2026)
27. Hou, J., Chen, H., and Xu. J: External Knowledge Sourcing and Green Innovation Growth with Environmental and Energy Regulations: Evidence from Manufacturing in China. Sustainability. **9**(3), 342 (2017). https://doi.org/10.3390/su9030342
28. Inkpen, A.C.: Learning and knowledge acquisition through international strategic alliances. Academy Manage. Perspectives. **12**(4), 69–80 (1998)

29. Kang, K.N., Park, H.: Influence of government R&D support and inter-firm collaborations on innovation in Korean biotechnology SMEs. Technovation. **32**(1), 68–78 (2012)
30. Keller, W.: International technology diffusion. J. Econ. Lit. **42**(3), 752–782 (2004)
31. Kim, E., Lee, I., Kim, H., Shin, K.: Factors Affecting Outbound Open Innovation Performance in Bio-Pharmaceutical Industry: Focus on Out-Licensing Deals. .Sustainability. **13**(8), 1–17 (2021)
32. Kobarg, S., Stumpf-Wollersheim, J., Welpe, I.M.: University-industry collaborations and product innovation performance: The moderating effects of absorptive capacity and innovation competencies. J. Technol. Transf. **43**(6), 1696–1724 (2018)
33. Koo, Y., Cho, K.: The Relationship between Patents, Technology Transfer and Desorptive Capacity in Korean Universities. Sustainability. **13**(9), 5253 (2021)
34. Lin, J.Y., Yang, C.H.: Heterogeneity in industry–university R&D collaboration and firm innovative performance. Scientometrics. **124**, 1–25 (2020)
35. Lee, Y.H., Kim, Y.J.: Analyzing interaction in R&D networks using the Triple Helix method: Evidence from industrial R&D programs in Korean government. Technol. Forecast. Soc. Chang. **110**, 93–105 (2016)
36. Lu, C., Qi., Y., and Yu. B: Effects of Domestic and International External Collaboration on New Product Development Performance in SMEs: Evidence from China. Sustainability. **16**(1), 400 (2024)
37. MacKinnon, J.G., White, H.: Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. J. Econ. **29**(3), 305–325 (1985)
38. Mascarenhas, C., Mendes, T., Galvão, A.R., Marques, C.S.: Academic researchers' motivations to engage in university–industry collaboration in cross-border regions. J. Technol. Transf. **49**, 2104–2134 (2024)
39. Mowery, D.C., Oxley, J.E., Silverman, B.S.: Strategic Alliances and Interfirm Knowledge Transfer. Strateg. Manag. J. **17**, 77–91 (1996)
40. Nast, C., Yankova, L.O., D., and, E'Este, P.: Sourcing insights elsewhere: The positive influence of academic engagement on scientific impact. Technovation. **139**, 103112 (2025)
41. Nieto, M.J., Rodríguez, A., Santamaría, L.: International and domestic R&D coopetition: The influence of information redundancy on innovation performance. Ind. Innovat. **31**(10), 1324–1349 (2024)
42. O'Dwyer, M., Filieri, R., O'Malley, L.: Establishing successful university–industry collaborations: Barriers and enablers deconstructed. J. Technol. Transf. **48**, 900–931 (2023)
43. Ogink, R., Goossen, M.C., Romme, G., Akkermans, H.: How Do Organizations Turn Jointly-Developed Tacit Knowledge into Explicit Solutions? Academy of Management Proceedings. Vol 1. (2024)
44. Pavitt, K.: Sectoral patterns of technical change: Towards a taxonomy and a theory. Res. Policy. **13**(6), 343–373 (1984)
45. Perkmann, M., Salandra, R., Tartari, V., McKelvey, M., Hughes, A.: Academic engagement: A review of the literature 2011–2019. Res. Policy. **50**(1), 104114 (2021)

46. Radici, A.M.: Knowledge sourcing, geopolitics, and FDI: An empirical analysis on the US green and digital sectors. Strategic Manage. Soc. (2026). 10.1002/gsj.70018
47. Roesler, C., Broekel, T.: The role of universities in a network of subsidized R&D collaboration: The case of the biotechnology-industry in Germany. Reg. Stud. **51**(11), 1667–1679 (2017)
48. Rothaermel, F.T., Hill, C.W.L.: Technological Discontinuities and Complementary Assets: A Longitudinal Study of Industry and Firm Performance. Organ. Sci. **16**(1), 52–70 (2005)
49. Siegel, D.S., Waldman, D., Link, A.: Assessing the Impact of Organizational Practices on the Relative Productivity of University Technology Transfer Offices: An Exploratory Study. Res. Policy. **32**(1), 27–48 (2003)
50. Kashan, A.J., Mohannak, K., de Oliveira, R.T.: Exploring Micro foundations and Multilevel Mechanisms of Absorptive Capacity in an Emerging Economy: Empirical Evidence from a Leading Car Manufacturer. J. Manage. Organ. Camb. Core. **31**(3), 1389–1418 (2025)
51. Siegel, D.S., Wright, M.: *University Technology Transfer Offices, Licensing, and Start-ups*. (in Chicago Handbook of University Technology Transfer and Academic Entrepreneurship (2015)
52. Teece, D.J.: Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. Res. Policy. **15**(6), 285–305 (1986)
53. Teece, D.C.: Reflections on 'Profiting from Innovation'. Res. Policy. **35**(8), 1131–1146 (2006)
54. Terhorst, A., Lusher, D., Bolton, D., Elsum, I., Wang, P.: Tacit Knowledge Sharing in Open Innovation Projects. Project Manage. J. **49**(4), 57–73 (2018)
55. Thursby, J., Jensen, R., Thursby, M.: Objectives, Characteristics and Outcomes of University Licensing: A Survey of Major U.S. Universities. J. Technol. Transfer. **26**(1–2), 59–72 (2001)
56. Thursby, J., Kemp, S.: Growth and Productive Efficiency of University Intellectual Property Licensing. Res. Policy. **31**, 109–124 (2002)
57. Thursby, J.G., Thursby, M.C.: Are Faculty Critical? Their Role in University–Industry Licensing. Contemp. Econ. Policy. **22**(2), 162–178 (2004)
58. Tilson, D., Lyytinen, K., Sørensen, C.: Research Commentary—Digital Infrastructures: The Missing IS Research Agenda. Inform. Syst. Res. **21**(4), 748–759 (2010)
59. Usai, S., Marrocu, E., Paci, R.: Networks, Proximities, and Interfirm Knowledge Exchanges. Ann. Reg. Sci. **58**, 99–121 (2017)
60. West, J., Bogers, M.: Leveraging external sources of innovation: A review of research on open innovation. J. Prod. Innov. Manage. **31**(4), 814–831 (2014)
61. Zahra, S.A., George, G.: Absorptive Capacity: A Review, Reconceptualization, and Extension. Acad. Manage. Rev. **27**(2), 185–203 (2002)

Figures

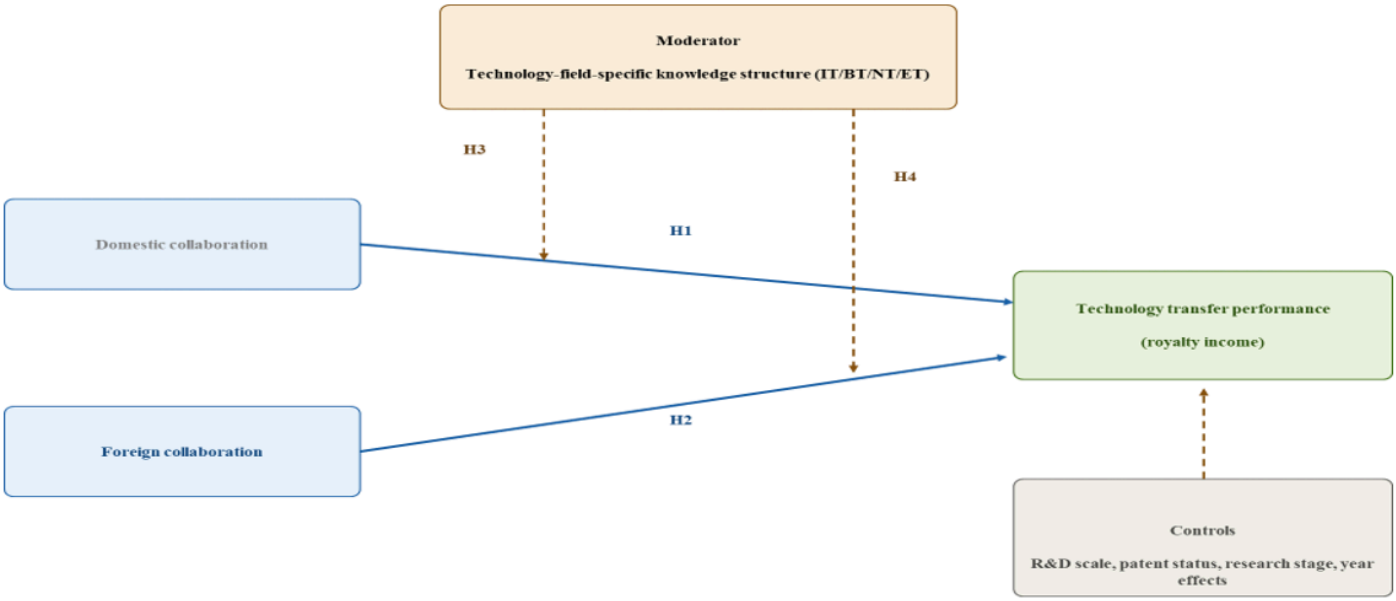

Figure 1

Conceptual research framework