“Perceived external R&D purchases and internal R&D expenditures as innovation drivers in large Ecuadorian firms”

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PERCEIVED EXTERNAL R&D PURCHASES AND INTERNAL R&D EXPENDITURES AS INNOVATION DRIVERS IN LARGE ECUADORIAN FIRMS

Abstract

This study examines the relationship between external R&D purchases and internal R&D expenditure with technological and non-technological innovation in large Ecuadorian companies, using internal R&D expenditure as a mediating variable and company age as a moderating variable. A structured survey was administered in 2024 to the CEOs of 380 large companies in Ecuador's three main business centers: Guayaquil, Quito, and Cuenca. Data were analyzed using PLS-SEM. The results confirmed that internal R&D expenditure is the main driver of reported innovation, with large direct effects on technological ($\beta = 0.545$; $p < 0.001$; $f^2 = 0.434$) and non-technological innovation ($\beta = 0.526$; $p < 0.001$; $f^2 = 0.400$). External R&D purchases directly affect non-technological innovation ($\beta = 0.178$; $p < 0.001$) and internal R&D expenditure ($\beta = 0.308$; $p < 0.001$; $f^2 = 0.105$), with significant indirect effects on both types of innovation ($\beta = 0.168$ and 0.162; $p < 0.001$). The model explains 37.9% of the variance in technological innovation and 37.5% of the variance in non-technological innovation ($Q^2 > 0$). Firm age negatively moderates the external R&D purchases–technological innovation relationship ($\beta = -0.141$; $p = 0.045$), a pattern consistent with younger firms relying more on external R&D purchases for technological innovation, although this interpretation requires caution given the moderate significance of the effect. Therefore, internal R&D expenditure relates to reported outcomes of innovation, while external R&D purchases appear to contribute mainly to the development of internal R&D.

Keywords absorptive capacity, resource-based view, R&D expenditure, technological innovation, firm age

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INTRODUCTION

Innovation stems from the scientific and technological advances of firms, research institutions, and universities (Bianchini et al., 2019), which strengthens the innovation ecosystem (Ramalho et al., 2019), generates economic benefits, and promotes sustainable development (De la Vega, 2018). In competitive economies, innovation is one of the most important factors in the growth of a nation's economy, and it constitutes a primary instrument for increasing value and attaining a durable advantage over competitors (Vîrjan et al., 2023). Innovation allows the transformation of products and processes (Gifford et al., 2022) and the automation of tasks, enhancing decision-making processes, and personalizing marketing efforts, ultimately improving customer experience and driving business growth (Ijomah et al., 2024).

Firms' investment in research and development, whether generated internally or acquired from external sources, constitutes a critical input for innovation. Firms that generate more valuable knowledge will have better financial performance than companies that generate less

valuable knowledge (Chaithanapat et al., 2022). This resource-allocation decision – investing in internal R&D versus purchasing knowledge externally – shapes firms' innovation capacity, both in large firms (Erena et al., 2023) and SMEs (Latifah et al., 2022), and reflects the broader strategic tension between internal knowledge generation and external knowledge acquisition documented in the innovation literature (Cassiman & Veugelers, 2006; Denicolai et al., 2016).

Globally, innovation gaps persist (Kowalski, 2021), primarily affecting emerging economies (Becerra, 2024). Developing economies face socio-political challenges and problems in implementing policies that promote innovation, suggesting an important role for government policies in reducing innovation gaps (Paus & Robinson, 2024). In Ecuador, the creation of new businesses grew by 23% in 2022, but evidence of innovative practices remains limited (Coba, 2022). This gap between business creation and innovative performance points to an underlying resource-allocation question: to what extent do firms' expenditures in R&D, whether internal or external, translate into innovation in emerging economies?

1. LITERATURE REVIEW AND HYPOTHESES

The literature on knowledge management has primarily highlighted absorptive capacity as a central theoretical framework for understanding how firms convert external and internal knowledge into innovation (Cohen & Levinthal, 1990). This theory postulates that knowledge lies at the core of the creation and maintenance of competitive advantage (Ritter-Hayashi et al., 2021), explaining how firms recognize, assimilate, and exploit external knowledge, distinguishing between potential and realized capacity (Zahra & George, 2000), a process shaped by prior knowledge, adequate cognitive structure (Sancho-Zamora et al., 2022), and organizational learning (Ding et al., 2023).

Complementing absorptive capacity theory, the resource-based view (RBV) (Barney, 1991) frames firms' knowledge-related investments as a strategic resource-allocation decision, improving companies' strategic capacity (Lubis, 2022). From this perspective, R&D expenditure has been consistently used as a financial, observable, and comparable proxy for firms' knowledge-sourcing strategy in developing markets (Milojević et al., 2025), regardless of whether that R&D is generated internally or acquired from external sources.

Regarding knowledge, the literature distinguishes between external and internal sources (Aliasghar et al., 2023; Gifford et al., 2022; Hervas-Oliver et al., 2021). External knowledge involves an intensive process of accessing external sources, primarily through the acquisition of embodied knowledge that enables incremental process innovation (Hervas-Oliver et al., 2021). Internal knowledge, in contrast, is shaped by the assets and capabilities a firm builds and finances internally (Hameed et al., 2021). Crucially, the two are not independent: internal knowledge creation capability strengthens a firm's absorptive capacity for external knowledge (Khraishi et al., 2023).

Accordingly, the study operationalizes two variables based on the perceived occurrence of R&D-related financial commitments: internal R&D expenditure, capturing whether the firm reports having made internal R&D-related payments (e.g., to researchers, technicians, or interns), and external R&D purchases, capturing whether the firm reports having purchased R&D from external organizations, nationally or internationally. Under this approach, internal R&D expenditure is operationalized as the firm's expenditure on internally generated R&D activities, while external R&D purchases are operationalized as the firm's expenditure on externally acquired R&D (national and international purchases). This occurrence-based lens allows us to capture firms' reported resource-allocation behavior between internal knowledge generation and external knowledge acquisition, a distinction central to absorptive capacity theory (Cohen & Levinthal, 1990).

Absorbing and applying externally sourced R&D typically requires firms to complement that acquisition with internal investment in technical staff, adaptation routines, and internal validation of the acquired knowledge, in order to build adequate cognitive structures (Sancho-Zamora et al.,

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2022) and promote organizational learning (Ding et al., 2023). In this sense, firms that report allocating financial resources to R&D, skilled technical staff, and codified routines gain an innovation advantage, consistent with the resource-based view (Kero & Bogale, 2023). Li and Gao (2023) reveal that both the acquisition of external market knowledge and the acquisition of external technological knowledge influence the level of opportunity identification and internal R&D activities, allowing the company to update or rebuild its internal knowledge base and ultimately improve innovation performance.

Innovation outcomes follow the Oslo Manual (García et al., 2021), which distinguishes technological from non-technological approaches (Dimakopoulou et al., 2024; Nascimento et al., 2025). Technological innovation outcomes comprise the development of new products and the introduction of new or improved processes and technologies, while non-technological innovation outcomes comprise the re-engineering of organizational practices and procedures (García et al., 2021), within multi-stage processes (Warwick, 2016) and open/closed models (Álvarez-Aros & Bernal-Torres, 2017). Beyond firms' resource-allocation decisions, firm age also shapes how knowledge translates into innovation (Messeni et al., 2018): older firms face path dependence (Chen & Yu, 2022), while younger firms show greater flexibility (Jansen et al., 2023), although outcomes depend on context (Pu & Liu, 2023).

Despite empirical contributions, unresolved gaps remain in the literature. First, within the context of absorptive capacity theory, prior studies have largely treated absorptive capacity as a single, undifferentiated construct (Aliasghar et al., 2023; Fulgence et al., 2023), rarely testing the mechanism by which external R&D acquisition associates with internal R&D expenditure and, in turn, with innovation. Second, the moderation of firm age requires further testing (Pu & Liu, 2023). Third, non-technological innovation is overlooked despite its importance (Dimakopoulou et al., 2024); and fourth, innovation gaps are notable in developing countries, especially in Latin America, due to socio-political challenges, data scarcity, and policy implementation (Paus & Robinson, 2024).

This study contributes to filling that void by providing robust empirical evidence from large, established Ecuadorian firms, thereby testing the boundary conditions of absorptive capacity and RBV theory in this underexplored national context. Therefore, the purpose of this study is to examine the relationship between the perceived occurrence of external R&D purchases and internal R&D expenditures and technological and non-technological innovation outcomes in large firms in Ecuador, using internal R&D expenditure as a mediating variable and firm age as a moderating variable. The conceptual model integrating these relationships is illustrated in Figure 1. To pursue this aim, the study proposes the following hypotheses:

H1: *External R&D purchases have a positive and significant effect on the technological innovation of large firms.*

H2: *External R&D purchases have a positive and significant effect on the non-technological innovation of large firms.*

H3: *External R&D purchases have a positive and significant effect on internal R&D expenditure in large firms.*

H4: *Internal R&D expenditure has a positive and significant effect on the technological innovation of large firms.*

H5: *Internal R&D expenditure has a positive and significant effect on the non-technological innovation of large firms.*

H6: *Firm age negatively moderates the relationship between external R&D purchases and technological innovation.*

H7: *Firm age moderates the relationship between external R&D purchases and non-technological innovation.*

H8: *Firm age moderates the relationship between internal R&D expenditure and technological innovation.*

H9: *Firm age moderates the relationship between internal R&D expenditure and non-technological innovation.*

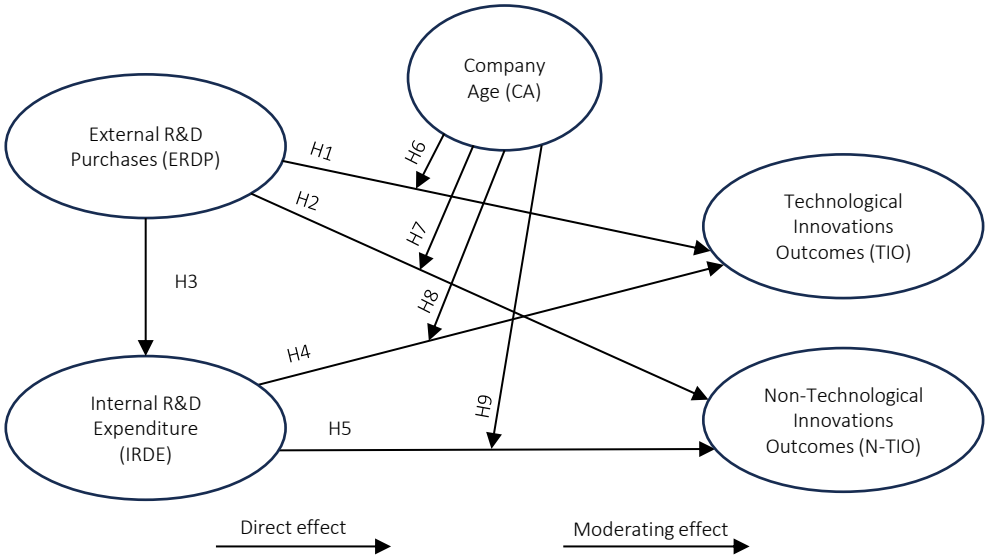


Figure 1. Research model

2. METHOD

2.1. Research design and sample

Based on the research objective, a theoretical research model was developed, grounded in absorptive capacity (Cohen & Levinthal, 1990) and resource-based view (Barney, 1991) theories. The analysis followed a non-experimental, cross-sectional design: variables were observed in their natural context without manipulation, and data were collected at a single point in time.

The data are original and have not been previously used in any other publication. The survey was conducted in 2024, a period that captures the post-pandemic innovation dynamics of Ecuadorian firms, during which business activity had largely stabilized following the disruptions of 2020–2021, making it a particularly relevant moment to examine knowledge-driven innovation behavior. The target population comprised large firms registered in Ecuador's three main business hubs (Guayaquil, Quito, and Cuenca) which collectively concentrate the highest density of large enterprises in the country and are broadly representative of Ecuador's formal business sector (Coba, 2022).

Firms were classified as large based on the criteria established by Ecuador's Superintendencia de Compañías, Valores y Seguros (Andean Community Resolution 1260): 200 or more employees and annual gross sales exceeding USD 5,000,000. While this geographic scope does not allow generalization beyond Ecuador, these three cities concentrate the highest density of large enterprises in the country, making them substantively relevant to the national landscape of large Ecuadorian firms.

Sample size was determined using Monte Carlo simulation criteria, which recommend 10–20 participants per observable variable (Wolf et al., 2013). For 14 observable variables, this yielded a minimum requirement of between 140 and 280 participants, a figure far exceeded by the sample obtained from 380 large Ecuadorian companies. The study adopted non-probability convenience sampling, selecting companies based on their accessibility and willingness to participate. This strategy proved appropriate given the inherent difficulty of accessing large companies and the need to ensure an adequate response rate.

A specialized data collection firm, using its own executive database, administered the survey during 2024, targeting it primarily at CEOs or senior executives, the most qualified informants due to their comprehensive knowledge of their companies' innovation activities and R&D-related payments and purchases. According to information obtained from the consulting firm in charge of collecting the data, the instrument was distributed to 410 large companies in the three cities; 380

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valid responses were retrieved, representing a response rate of 93%. Two of these firms had missing values for firm age; they were retained in the sample for all analyses except the moderation tests, from which they were excluded listwise (H6–H9, $n = 378$).

2.2. Measurement scales

The study employed a structured questionnaire adapted from the Survey of Innovation in Spanish Firms (Instituto Nacional de Estadística, n.d.), an internationally validated instrument aligned with Oslo Manual guidelines. This source was selected for its theoretical alignment with the constructs of interest, its prior validation in a comparable business context, and its cross-national comparability in Spanish-speaking countries. The adapted questionnaire comprises three sections: informed consent, firm characteristics, and items measuring the study variables. From the original instrument, only items directly operationalizing the four theoretical constructs were retained: three items on internal R&D expenditure; three items on reported purchases of national and international R&D; four items on technological innovation; and four items on non-technological innovations (organizational practices, marketing techniques, intellectual property registrations).

Items addressing sources of innovation financing, government support, and barriers to innovation were excluded. All retained items used a 5-point Likert agreement scale, except TIO4 and N-TIO4 (patent and trademark counts), which used a 5-point ordinal scale. The questionnaire was adapted to the Ecuadorian context and administered in Spanish. Content validity was assessed by two innovation management specialists, who recommended no modifications. No pilot testing was conducted, but psychometric properties (reliability, convergent and discriminant validity) were evaluated within the PLS-SEM framework. The full questionnaire is provided in Appendix B.

The Likert agreement scale captures respondents' perceived occurrence of internal R&D expenditures and external R&D purchases – that is, the extent to which the respondent affirms that such expenditures or purchases took place, not their exact volume. This response format was adopted, instead of a direct request for expenditure figures, because of the commercial sensitivity of exact R&D expenditure data in Ecuador. Less threatening, categorical response formats reduce disclosure reluctance in surveys on sensitive topics (McNeeley, 2012), and quantitative items requesting precise financial figures are associated with higher item nonresponse and lower response accuracy in business surveys (Bottone et al., 2021), a defensible trade-off in executive surveys on sensitive financial practices.

2.3. Data analysis method

Internal consistency was assessed using Cronbach's alpha, composite reliability (rho_c), and Dijkstra-Henseler's rho_a, with values > 0.70 considered acceptable. Convergent validity required indicator loadings > 0.708 and average variance extracted (AVE) > 0.50. Discriminant validity was evaluated using the HTMT ratio (< 0.85) (Henseler et al., 2015) and the Fornell-Larcker criterion (√AVE > inter-construct correlations) (Fornell & Larcker, 1981). Indicator-level variance inflation factors (VIF) < 5.0 indicated no multicollinearity issues among the reflective indicators of each construct. Common method bias (CMB) was assessed using two complementary procedures. First, Harman's single-factor test (Podsakoff et al., 2003) was conducted by loading all indicators onto a single unrotated factor, which explained 42.9% of the total variance, below the 50% threshold (Appendix C, Table C1). Second, a full collinearity assessment (Kock, 2015) was performed by regressing each construct against all remaining constructs in the model, yielding full collinearity VIF values ranging from 1.008 to 1.580, well below the 3.3 threshold (Appendix C, Table C2). Both results indicate that common method bias is unlikely to be a significant concern in this study.

The proposed model was analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4.0. PLS-SEM was selected for its suitability in prediction-oriented and theory-developing research, its robustness to non-normal data, and its ability to handle complex models with multiple latent variables (Cheah et al., 2020; Hair et al., 2019a, 2019b). Path coefficients and significance were estimated via bootstrap with 5,000 resamples. Explanatory power was assessed using R^2, predictive relevance using the Stone-Geisser Q^2, and effect sizes using f^2 (Hair et al., 2019b).

2.4. Participants and ethics considerations

This study adheres to the highest ethical standards, following the Declaration of Helsinki and relevant guidelines. The analysis was approved by the Institutional Review Board (IRB) at CENTRUM Graduate Business School, Pontificia Universidad Católica del Perú. A specialized data collection firm obtained informed consent from all participants, ensuring voluntary participation and the right to withdraw without penalty. To guarantee anonymity and confidentiality, responses were coded upon receipt, omitting any identifying information linking individual respondents or firms to their data.

The sample covers 17 economic sectors (ISIC classification), the most important being manufacturing (Section C) and wholesale and retail commerce (Section G), followed by agriculture, forestry, and fishing (Section A) and financial and insurance activities (Section K); all other sectors represent less than 5% of the sample. To verify whether sectoral composition has any effect on innovation reports, the model was re-estimated with three control constructs at the sectoral level (industrial, services, and primary, with trade as the reference category). Geographically, Guayaquil contributes 47.63% of the sample, followed by Quito and Cuenca. The sample is heavily concentrated in the more established age categories. Collectively, 92.63% of the sample comprises firms with more than 10 years of operation, confirming that the sample consists predominantly of consolidated, mature enterprises (Appendix A).

3. RESULTS

Table 1 shows that all factor loadings exceed 0.7, indicating adequate individual reliability. Indicator VIF values range from 1.508 to 2.756, below the 5.0 threshold, confirming no collinearity issues among the reflective indicators of each construct. All constructs have Cronbach's alpha, composite reliability, and Dijkstra-Henseler scores above 0.8, indicating strong internal consistency and convergent validity. The lowest average variance extracted (AVE) is for technological innovation (0.691), still meeting the threshold for acceptable convergent validity.

Table 2 evaluates discriminant validity using two complementary criteria: the HTMT index and the Fornell-Larcker criterion, allowing for a robust analysis of the conceptual differentiation between the constructs.

HTMT values range from 0.366 to 0.681. All are below the conservative threshold of 0.85, indicating adequate discriminant validity between the pairs of constructs evaluated. Regarding the Fornell-Larcker criterion, in all cases the square root of the AVE for each construct is greater than the correlation between the pairs compared. Overall,

Table 1. Convergent validity analysis

Construct	Item	Loading	VIF	Cronbach's Alpha	CR (rho-a)	CR (rho-c)	AVE
ERDP	ERDP1	0.857	1.806	0.820	0.823	0.893	0.735
	ERDP2	0.857	1.956				
	ERDP3	0.858	1.764				
IRDE	IRDE1	0.803	1.698	0.830	0.856	0.898	0.747
	IRDE2	0.919	2.458				
	IRDE3	0.867	2.032				
TIO	TIO1	0.729	1.508	0.850	0.870	0.899	0.691
	TIO2	0.879	2.435				
	TIO3	0.890	2.507				
	TIO4	0.817	1.879				
N-TIO	N-TIO1	0.878	2.756	0.887	0.896	0.922	0.747
	N-TIO2	0.887	2.730				
	N-TIO3	0.811	1.964				
	N-TIO4	0.878	2.375				

Note: ERDP = external R&D purchases; IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.

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Table 2. Discriminant validity analysis

Construct Pair	HTMT	Fornell-Larcker			Overall Assessment
		√AVE Construct 1	√AVE Construct 2	r	
ERDP ↔ TIO	0.366	0.857	0.831	0.303	Pass
ERDP ↔ N-TIO	0.405	0.857	0.864	0.344	Pass
ERDP ↔ IRDE	0.368	0.857	0.864	0.308	Pass
IRDE ↔ TIO	0.681	0.864	0.831	0.583	Pass
IRDE ↔ N-TIO	0.654	0.864	0.864	0.580	Pass
TIO↔N-TIO	0.610	0.864	0.864	0.543	Pass

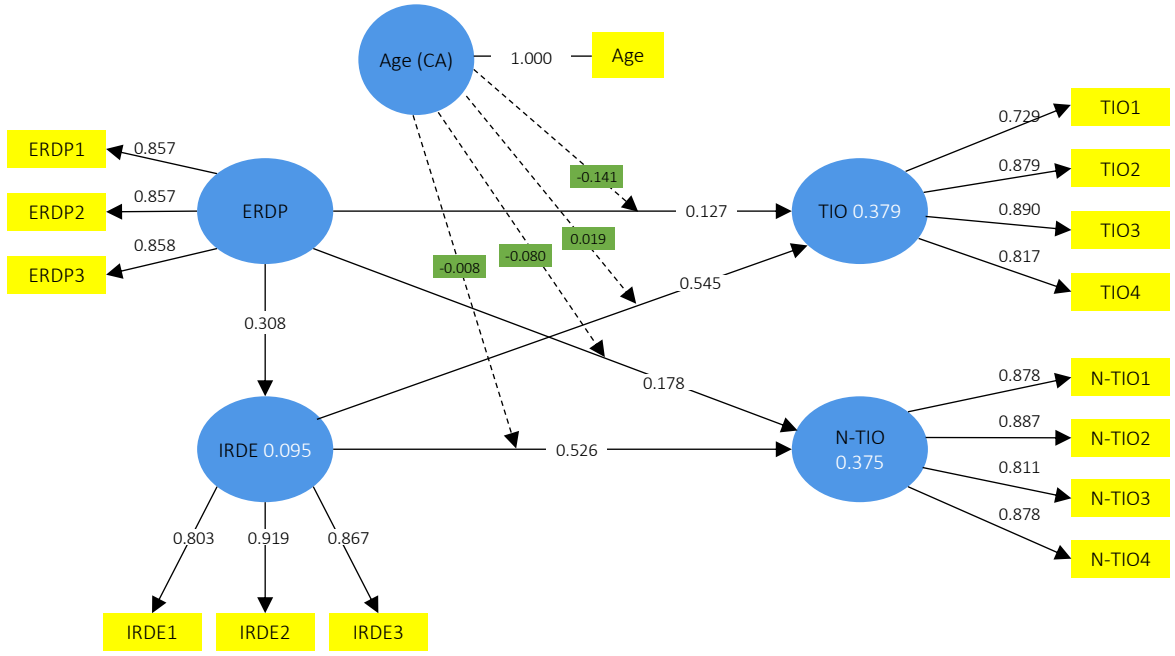
Note: ERDP = external R&D purchases; IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.

the convergence of results between HTMT and Fornell-Larcker reinforces the evidence that the constructs possess adequate discriminant validity.

Figure 2 shows the results of the structural equation modeling in SmartPLS. The model shows theoretical coherence and moderate statistical robustness. Internal R&D expenditure emerges as a central variable in the structural dynamics, acting as a strong predictor of technological innovation and non-technological innovation and as a possible mediator between external R&D purchases and the dependent variables.

Table 3 presents the direct and moderating effects of the structural model. All direct effects are positive and statistically significant; thus, hypotheses H1 to H5 are accepted. External R&D purchases positively affect technological innovation (β = 0.127; p = 0.025), though with a small effect size (f^2 = 0.023). The effect of external R&D purchases on non-technological innovation is stronger (β = 0.178; $p < 0.001$) with a small to medium effect size (f^2 = 0.045). Additionally, external R&D purchases positively impact internal R&D expenditure (β = 0.308; $p < 0.001$), with a small-to-medium effect size (f^2 = 0.105).

Internal R&D expenditure is a robust predictor of both technological innovation (β = 0.545; $p < 0.001$; f^2 = 0.434) and non-technological innovation (β = 0.526; $p < 0.001$; f^2 = 0.400), with



Note: CA = age of the company; ERDP = external R&D purchases; IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.

Figure 2. Analysis of the proposed model after applying partial least squares

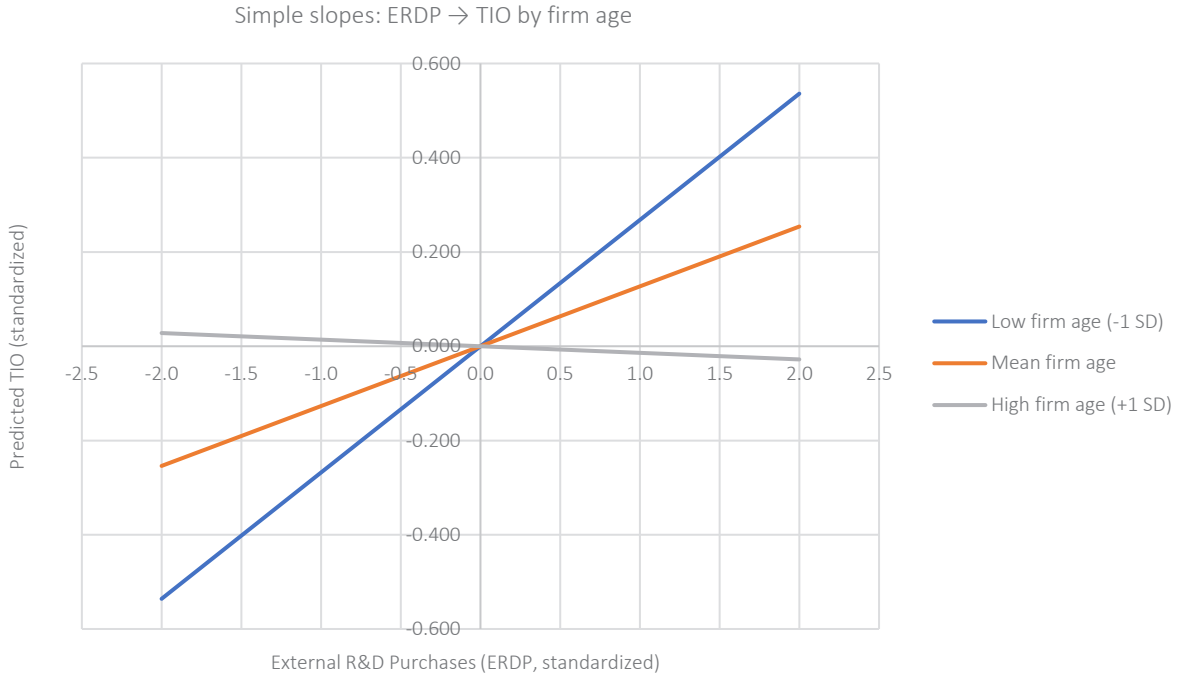
Table 3. Hypothesis testing

Direct effects					
Hyp.	**Relation**	**Path Coef.**	**p-value**	**f^2**	**Results**
H1	ERDP – TIO	0.127	0.025	0.023	Accepted
H2	ERDP – N-TIO	0.178	< 0.001	0.045	Accepted
H3	ERDP – IRDE	0.308	< 0.001	0.105	Accepted
H4	IRDE – TIO	0.545	< 0.001	0.434	Accepted
H5	IRDE – N-TIO	0.526	< 0.001	0.400	Accepted
Moderating effects					
H6	CA (ERDP – TIO)	–0.141	0.045	0.031	Accepted
H7	CA (ERDP – N-TIO)	–0.080	0.172	0.010	Rejected
H8	CA (IRDE – TIO)	0.019	0.800	0.000	Rejected
H9	CA (IRDE – N-TIO)	–0.008	0.898	0.000	Rejected

Note: ERDP = external R&D purchases; IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.

large effect sizes, confirming internal R&D expenditure as the main structural determinant of reported innovation outcomes. Regarding moderating effects of firm age, only H6 is supported: age negatively moderates the external R&D purchases–technological innovation relationship ($\beta = -0.141$; $p = 0.045$; $f^2 = 0.031$). The remaining moderating hypotheses (H7–H9) are not statistically significant ($p > 0.05$) and have negligible effect sizes, thus remaining unconfirmed.

To further examine the significant moderating effect of firm age (H6), a simple slopes analysis was conducted (Aiken et al., 1991). The conditional effect of external R&D purchases on technological innovation was estimated at three levels of firm age: –1 SD ($\beta = 0.268$), the mean ($\beta = 0.127$), and +1 SD ($\beta = -0.014$). As shown in Figure 3, the positive effect of external R&D purchases on technological innovation is stronger among younger firms and weakens progressively with firm age, becom-



Note: Slopes were computed using standardized path coefficients at –1 SD, mean, and +1 SD of firm age. Lines represent conditional effects centered on their respective means.

Figure 3. Simple slopes analysis

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Table 4. Mediating effects

Hypothesis	Beta	p-Value	Result
ERDP → IRDE → TIO	0.168	0.000	Accepted
ERDP → RDE → N-TIO	0.162	0.000	Accepted

Note: ERDP = external R&D purchases; IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.

ing negligible among the most established firms in the sample. These estimates represent point conditional effects derived from the structural model coefficients rather than independently bootstrapped simple slopes.

Table 4 presents the indirect effects, evaluating the mediating role of internal R&D expenditure. The external R&D purchases → internal R&D expenditure → technological innovation pathway shows an indirect coefficient of 0.168 (p = 0.000), indicating a positive and statistically significant mediated effect. Thus, part of the impact of external R&D purchases on technological innovation is channeled through internal R&D expenditure: external R&D purchases not only directly influence technological innovation but also indirectly by strengthening internal R&D expenditure, which in turn increases technological innovation.

Given that the direct external R&D purchases → technological innovation effect was also significant, a partial mediation scenario is established. Likewise, the external R&D purchases→ internal R&D expenditure → non-technological innovation pathway shows an indirect coefficient of 0.162 (p = 0.000), confirming that internal R&D expenditure mediates the transmission of the effect of external R&D purchases to non-technological innovation, again partially.

To assess whether the main structural relationships reflect the sample's industry composition rather than the hypothesized mechanisms, the model was re-estimated with three sector-level control constructs (industrial, services, and primary, with commerce as the reference category) predicting technological and non-technological innovation. All five main paths (external R&D purchases → internal R&D expenditure, external R&D purchases → technological innovation, external R&D purchases → non-technological innovation, internal R&D expenditure → technological innovation, internal R&D expenditure → non-technological innovation) remained virtually unchanged in magnitude and significance (Table 5), indicating that the study's central findings are not an artifact of industry composition. Among the sector controls, only primary → technological innovation was significant (β = 0.342; p = 0.003), suggesting that firms in agriculture, forestry, fishing, and mining report higher technological innovation outcomes than firms in commerce, independent of their R&D purchases or expenditure.

Table 6 presents the model's overall evaluation. Coefficients of determination (R^2) range from 0.095 to 0.379. Following Hair et al. (2019b), the R^2 values for technological innovation (0.379) and non-technological innovation (0.375) fall between the weak and moderate thresholds, approaching a moderate level of explanatory power, while the R^2 for internal R&D expenditure (0.095) is weak. The model explains 37.9% of variance in technological innovation and 37.5% in non-technological innovation, indicating acceptable explanatory power. The weak R^2 for internal R&D expenditure (0.095) suggests other unmodeled variables influence it, pointing to future research avenues.

All Q^2 values exceed zero, indicating the model's predictive relevance (Geisser, 1974; Hair et al., 2019b; Stone, 1974). Non-technological innovation shows the highest value (Q^2 = 0.108), followed by technological innovation (0.088) and internal R&D expenditure (0.086). Following conventional Q^2 thresholds (Hair et al., 2019b), these values fall in the small range; though modest in absolute terms, they are meaningful given the model's exploratory nature. Overall, the structural model demonstrates useful explanatory power and predictive relevance. The consistency between R^2 and Q^2 for technological and non-technological innovation supports the model's validity and utility for understanding how firms' reported R&D expenditure and purchases relate to innovation outcomes.

Table 5. Structural path estimates with industry-sector controls

Path	Beta (Original model)	Beta (Control)	p-value (Control)
ERDP → IRDE	0.308	0.303	<0.001
ERDP → TIO	0.127	0.128	0.026
ERDP → N-TIO	0.178	0.173	<0.001
IRDE → TIO	0.545	0.579	<0.001
IRDE → N-TIO	0.526	0.550	<0.001
CA × ERDP → TIO	−0.141	−0.125	0.083
CA × ERDP → N-TIO	−0.080	−0.081	0.152
CA × IRDE → TIO	0.019	−0.020	0.772
CA × IRDE → N-TIO	−0.008	−0.004	0.938
Industrial → TIO	–	0.103	0.303
Industrial → N-TIO	–	−0.095	0.363
Services → TIO	–	0.191	0.079
Services → N-TIO	–	−0.024	0.821
Primary → TIO	–	0.342	0.003
Primary → N-TIO	–	−0.188	0.221

Note: ERDP = external R&D purchases; IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.

Table 6. PLS-SEM model goodness of fit indicators

Assessment Dimension	PLS-SEM Indicators	Value	Interpretation
Explanatory Power	R^2 IRDE	0.095	Weak
	R^2 TIO	0.379	Weak-to-moderate
	R^2 N-TIO	0.375	Weak-to-moderate
Predictive Relevance	Q^2 IRDE	0.086	Small
	Q^2 TIO	0.088	Small
	Q^2 N-TIO	0.108	Small

Note: IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.

4. DISCUSSION

The findings strongly support the central role of internal R&D expenditure in reported innovation outcomes among large Ecuadorian firms. Internal R&D expenditure emerged as the primary predictor of both technological ($\beta = 0.545$; $f^2 = 0.434$) and non-technological innovation ($\beta = 0.526$; $f^2 = 0.400$). These results align with and extend prior evidence: Khraishi et al. (2023) found that internal knowledge creation capability is positively associated with absorptive capacity for external knowledge. This finding may reflect a contextual dynamic: internal R&D expenditure enables large Ecuadorian firms to convert knowledge, whether generated internally or acquired externally, as reflected in the mediating role of internal R&D expenditure, into concrete innovation outcomes.

Even when large firms can access external knowledge and technology abroad, translating that knowledge into product, process, or organizational innovation requires sustained internal R&D capacity. Developing research infrastructure provides a substantial driver to expand the R&D base in the economy and increases innovation (Kowalski, 2021). Firms that develop internal R&D, skilled technical staff, and codified routines gain a competitive innovation advantage, consistent with the resource-based view (Kero & Bogale, 2023).

External R&D purchases exhibited a differentiated pattern of effects across innovation types. Their direct effect on technological innovation was small ($\beta = 0.127$; $f^2 = 0.023$), while the effect on non-technological innovation was modestly larger ($\beta = 0.178$; $f^2 = 0.045$). This distinction is consistent with prior research linking external R&D investment to innovation performance (Milojević et al., 2025). This finding is further explained by Aliasghar et al. (2023), who demonstrated that the breadth, rather than the depth, of external knowledge seeking is associated with

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process and organizational innovation. These results suggest that wide-ranging external exposure more readily translates into non-technological innovation outcomes than into formal technological development.

This differential effect likely stems from the nature of each innovation type. Technological innovation requires technical absorptive capacity to transform external knowledge into new products or processes, a demanding conversion constrained by the firm's existing R&D infrastructure. Non-technological innovation, being less codified and more dependent on organizational practices and relational learning, is more directly actionable from external inputs (Dimakopoulou et al., 2024; Nascimento et al., 2025). In this research, reported expenditures on external knowledge are expressed primarily in organizational and commercial adaptations rather than formal technological development, which explains both the modest external R&D purchases–technological innovation effect and the larger external R&D purchases–non-technological innovation effect.

The positive external R&D purchases–internal R&D expenditure relationship (β = 0.308; f^2 = 0.105) confirms the absorption logic of absorptive capacity theory. Thus, converting externally purchased R&D into usable knowledge requires firms to build an adequate cognitive structure and to engage in organizational learning (Sancho-Zamora et al., 2022; Ding et al., 2023), a requirement that, in this study, materializes as firms' internal R&D expenditure. This finding is particularly meaningful for emerging economies. As Kowalski (2021) argues, development success depends on closing the technological gap through the absorption of external technology and the deliberate creation of internal capabilities to utilize and build upon it, precisely the dynamic captured by the external R&D purchases → internal R&D expenditure pathway confirmed in this study.

In contrast, Gifford et al. (2022) found substitution rather than complementarity effects between external and internal knowledge search channels in their influence on innovation performance, a divergent finding that may reflect differences in industry context or the type of innovation examined. The small-to-medium effect size (f^2 = 0.105) indicates that reported external R&D purchases alone do not fully explain firms' reported internal R&D expenditure. This study deliberately emphasizes firms' reported R&D-related payments and purchases, understood as a measurable financial commitment rather than an intangible or relational asset. Consistent with the resource-based view (Barney, 1991; Lubis, 2022), this occurrence-based emphasis captures firms' reported resource-allocation behavior, internal versus external R&D, a dimension that is more readily observable, comparable across firms, and actionable for managerial and policy purposes.

Mediation analysis confirmed that internal R&D expenditure partially mediates both the external R&D purchases → technological innovation (β_indirect = 0.168; $p < 0.001$) and external R&D purchases → non-technological innovation pathways (β_indirect = 0.162; $p < 0.001$). This partial mediation indicates that external R&D purchases contribute to innovation both directly and indirectly through firms' reported internal R&D expenditure. This finding is consistent with Li and Gao (2023), who argue that external knowledge acquisition enhances a firm's ability to intensify internal R&D efforts and reconfigure its internal knowledge base, thereby improving innovation performance. While this pattern is consistent with a complementary relationship between external and internal R&D channels, establishing complementarity versus substitution formally would require an interaction-based test that this cross-sectional design does not provide; this interpretation may require future verification.

Regarding firm age as a moderator, only H6 was confirmed: age negatively moderates the external R&D purchases–technological innovation relationship (β = −0.141; p = 0.045). The observed pattern shows a weaker external R&D purchases–technological innovation effect among more established firms, which is consistent with the risk of knowledge obsolescence and path dependence in older firms (Chen & Yu, 2022). Moreover, Jansen et al. (2023) argue that younger firms tend to exhibit greater organizational flexibility and a stronger orientation toward acquiring external knowledge. However, Pu and Liu (2023) point out that the moderating effects of firm size and age require evaluation under more rigorous conditions, and

that mature firms often have a reputational advantage in acquiring external knowledge, a pattern that, in principle, could counteract the negative moderation by age observed in this study.

Provided the limited representation of young firms in this sample, this study cannot resolve between these opposing explanations, and the finding should be interpreted as a tentative pattern rather than a robust comparison between groups of firms by age. In line with this caution, the sensitivity analysis presented in Table 5 shows that the external R&D purchases×Age on technological innovation interaction loses statistical significance (p = 0.083) once controls for industry sector are added, reinforcing the conclusion that H6 should not be considered definitive.

Hypotheses H7, H8, and H9 were not confirmed: firm age does not moderate the external R&D purchases–non-technological innovation, internal R&D expenditure–technological innovation, or internal R&D expenditure–non-technological innovation relationships. This selective pattern is revealing: once internalized, knowledge generates innovation regardless of firm maturity. These results qualify those of Messeni et al. (2018), which show that age only moderates the phase of acquiring external knowledge for technological innovation, not the phases of internalization and exploitation.

Several limitations are acknowledged. First, the sample of 380 firms, while meeting statistical thresholds, represents a modest share of Ecuador's large-firm population, limiting generalizability. Second, the cross-sectional design precludes establishing the temporal precedence implicit in the mediation model; the external R&D purchases → internal R&D expenditure path reflects a theoretically hypothesized direction rather than an observed sequence, and self-reported data carry the risk of common method bias and subjective perception, lacking objective verification. This is particularly relevant compared with studies using administrative R&D data, such as Dimakopoulou et al. (2024), who drew on two waves of the Greek Community Innovation Survey; no equivalent administrative database exists for Ecuadorian firms, which is why this study relies on perceived occurrence rather than objective expenditure figures.

Third, firm age was measured using unequal ordinal categories and modeled as continuous, and the sample is skewed toward established firms (mostly >10 years), limiting conclusions about early-stage dynamics. Two firms had missing firm-age values and were excluded listwise from the moderation analyses (H6–H9, n = 378), while remaining in the sample for all other analyses. Moreover, given that four moderation hypotheses were tested simultaneously, the marginally significant H6 result (p = .045) should be interpreted with caution, as it would not survive a conservative correction for multiple comparisons.

Fourth, the model explains only 9.5% of the variance in internal R&D expenditure (R^2 = 0.095), suggesting that determinants beyond external R&D purchases (such as firm size, industry, prior innovation experience, and organizational slack) also shape firms' internal R&D expenditure. Fifth, although technological and non-technological innovation were estimated as reflective constructs, supported by loadings above 0.7 and AVE above 0.50, their indicators are conceptually heterogeneous (e.g., product innovation and patents for technological innovation; organizational practices and trademarks for non-technological innovation); a formative or second-order specification is a theoretically plausible alternative for future research employing a fresh model estimation.

Sixth, several respondent-level details could not be verified. The consulting firm delivered only the final, anonymized dataset: the exact breakdown of respondents by role (CEO versus other senior executives), confirmation that each of the 380 firms was represented by a single respondent, and the disposition of the 30 invitations (410 sent, 380 usable) that did not result in a usable response (e.g., refusals, incomplete questionnaires, or ineligible firms). These details would strengthen future replications of this design.

Seventh, although the sector-composition robustness check reported in Table 5 addresses the reviewer's minimum recommendation for a sensitivity analysis, geographic controls by city were not estimated in this study. Because firm location and industry sector are not independently distributed in this sample, a joint geographic-and-sector control model was not pursued at this stage and is left for future research.

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CONCLUSION

This study examined the relationship between external R&D purchases and internal R&D expenditure with technological innovation and non-technological innovation in large Ecuadorian companies, using internal R&D expenditure as a mediator and company age as a moderator. Based on PLS-SEM analysis, internal R&D expenditure emerges as the main structural determinant of innovation, exerting a strong effect on both technological and non-technological innovation, while external R&D purchases contribute directly and powerfully to non-technological innovation and channel their influence on technological innovation mainly through internal capabilities. This structural pattern (external R&D purchases → internal R&D expenditure → innovation) was confirmed through partial mediation, although the cross-sectional design does not allow this pattern to be interpreted as an observed temporal sequence.

Firm age negatively moderates only the external R&D purchases–technological innovation relationship, a pattern tentatively consistent with a compensatory interpretation in which firms with more limited internal capabilities rely more on external R&D. However, given that the sample is heavily skewed toward mature firms, that firm maturity can also confer advantages in acquiring external knowledge, and that this moderation loses significance once industry-sector controls are added, this finding should be read as a preliminary pattern rather than a definitive conclusion regarding younger versus mature firms. Once knowledge is internalized, the effect of internal R&D expenditure on innovation is independent of firm age, suggesting that the internal R&D channel operates consistently across firms regardless of maturity.

Future research should extend the model with additional internal drivers of internal R&D expenditure (firm-level resource endowments, organizational learning mechanisms, digital knowledge management systems). Moreover, it is interesting to broaden external R&D purchases to capture other external knowledge sources (customers, suppliers, competitors, consultants, universities, alliances, open innovation, informal search), and incorporate objective administrative R&D data, where available, to complement the perceptual measures used in this study.

AUTHOR CONTRIBUTIONS

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APPENDIX A. Distribution of the sample

Table A1. Distribution of participating firms by economic sector and business hub (ISIC classification)

ISIC	Sector	Guayaquil	Cuenca	Quito	Total	Relative Frequency
A	Agriculture, forestry and fishing	20	0	10	30	7.89%
B	Mining and quarrying	1	1	13	15	3.95%
C	Manufacturing	53	11	39	103	27.11%
D	Electricity and gas supply	0	2	3	5	1.32%
E	Water supply and waste management	1	0	0	1	0.26%
F	Construction	8	0	10	18	4.74%
G	Wholesale and retail trade	62	6	35	103	27.11%
H	Transportation and storage	5	0	5	10	2.63%
I	Accommodation and food services	5	0	7	12	3.16%
J	Information and communication	5	0	6	11	2.89%
K	Financial and insurance activities	8	5	17	30	7.89%
L	Real estate activities	8	0	8	16	4.21%
M	Professional and scientific activities	1	0	5	6	1.58%
N	Administrative and support services	0	0	7	7	1.84%
P	Education	1	0	0	1	0.26%
Q	Human health and social work	2	2	7	11	2.89%
S	Other service activities	1	0	0	1	0.26%
Total		181	27	172	380	100%

Note: ISIC = International Standard Industrial Classification of All Economic Activities. Sec. = ISIC Section.

Table A2. Distribution of participating firms by years of operation

Category	Years of operation	Frequency	Relative Frequency
1	Less than 1 year	1	0.26%
2	1–2 years	0	0.00%
3	2–5 years	4	1.05%
4	5–10 years	21	5.53%
5	10–15 years	110	28.95%
6	15–20 years	150	39.47%
7	More than 20 years	92	24.21%
–	Not reported	2	0.53%
Total		380	100%

APPENDIX B. QUESTIONNAIRE

Note: This questionnaire was originally distributed in Spanish; the following is its translated version for academic purposes.

INTRODUCTION

Dear Participant, we appreciate your time and willingness to participate in this survey. This questionnaire is part of a scientific research study aimed at exploring the impact of Knowledge Management (KM) investment on innovation results. The information you provide will be used solely for academic research, and all responses will be kept confidential. Your insights are invaluable in helping us understand key factors that contribute to the transformation of external and internal knowledge expenditures into innovation. Thank you for your contribution.

Table B1. Questionnaire

Variables	Item	Option
Expenditure on internal R&D activities in the last year (IRDE)	IRDE1. During the last year, the company made payments to researchers (including the payment of interns).	1 = Strongly disagree 2 = Disagree 3 = Neither agree nor disagree 4 = Agree 5 = Strongly agree
	IRDE2. During the last year, the company has made payments to technicians and assistants.	
	IRDE3. During the last year, it made current expenditures on R&D to improve the internal capabilities of employees.	

Table B1 (cont.). Questionnaire

Variables	Item	Option
Purchases of national and international R&D in the last year (ERDP)	ERDP1. During the last year, the company made research and development purchases in the country from universities, technology centers.	1 = Strongly disagree 2 = Disagree 3 = Neither agree nor disagree 4 = Agree 5 = Strongly agree
	ERDP2. During the last year, the company made research and development purchases in the country from private or non-profit institutions.	
	ERDP3. During the last year, the company made research and development purchases outside the country from technology centers, universities, and/or other private institutions with or without profit motives.	
Product and process innovation in the last year (TIO)	TIO1. During the last year, the company introduced innovations in goods (new or significantly improved goods; excluding resale of new goods acquired from other firms and modifications of a purely aesthetic nature) and/or services (new or significantly improved services).	1 = Strongly disagree 2 = Disagree 3 = Neither agree nor disagree 4 = Agree 5 = Strongly agree
	TIO2. During the last year, the company introduced significantly new or improved methods of manufacturing or producing goods or services.	
	TIO3. The company introduced support activities for its processes, such as maintenance systems or computer operations for purchasing or accounting, that were new or significantly improved.	
	TIO4. In the last year, how many patent applications has the company made to protect inventions or technological innovations?	1 = none 2 = at least one 3 = between two and three 4 = between four and five 5 = more than five
Non-technological innovations in the last year (N-TIO)	N-TIO1. During the last year, the company implemented new business practices and introduced new ways of organizing work or company procedures. (For example, supply chain management, knowledge management systems, business process reengineering, efficient production, quality management, education and training systems, etc.).	1 = Strongly disagree 2 = Disagree 3 = Neither agree nor disagree 4 = Agree 5 = Strongly agree
	N-TIO2. During the last year, your company made significant modifications to the product design or packaging of goods or services. Changes that affect product functionality or user characteristics are excluded. Such changes to product functionality would be product.	
	N-TIO3. During the last year, your company applied new marketing techniques for product positioning or promotion in the market (For example, the first-time use of a new advertising channel, introduction of customer loyalty cards, discount systems, the first-time use of franchising or distribution licenses, etc.).	
	N-TIO4. In the last year, how many trademark registrations, distinctive appearances, or copyrights on artistic compositions inherent to the company's activity have been carried out?	1 = none 2 = at least one 3 = between two and three 4 = between four and five 5 = more than five
Years since the company was established. Age (CA)	How many years has the company been established?	1. Less than one year 2. Between 1 and 2 years 3. Between 2 and 5 years 4. Between 5 and 10 years 5. Between 10 and 15 years 6. Between 15 and 20 years 7. More than 20 years

APPENDIX C. Common method bias assessment

Table C1. Results of Harman's single-factor test for common method bias

Total variance explained						
Component	Initial eigenvalues			Sums of squared loads of the extraction		
	Total	% of the variance	% cumulative	Total	% of the variance	% cumulative
1	6.435	42.900	42.900	6.435	42.900	42.900
2	1.804	12.027	54.927			
3	1.409	9.394	64.321			

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Table C1 (cont.). Results of Harman's single-factor test for common method bias

Total variance explained						
Component	Initial eigenvalues			Sums of squared loads of the extraction		
	Total	% of the variance	% cumulative	Total	% of the variance	% cumulative
4	1.050	6.998	71.319			
5	.714	4.757	76.076			
6	.582	3.882	79.958			
7	.509	3.393	83.351			
8	.440	2.933	86.284			
9	.406	2.705	88.989			
10	.384	2.563	91.552			
11	.321	2.140	93.692			
12	.293	1.951	95.643			
13	.273	1.817	97.460			
14	.201	1.343	98.803			
15	.180	1.197	100.000			
Extraction method: principal component analysis						

Table C2. Inner model collinearity statistics (Full collinearity VIF)

Construct	Full Collinearity VIF
CA (firm age)	1.008
ERDP	1.167
IRDE	1.580
TIO	1.499
N-TIO	1.456

Note: Each value represents the variance inflation factor obtained by regressing the corresponding construct against all other constructs in the model simultaneously, following Kock's (2015) full collinearity test procedure. All values fall well below the conventional threshold of 3.3, indicating that common method bias is unlikely to be a significant concern in this study. ERDP = external R&D purchases; IRDE = internal R&D expenditure; TIO = technological innovation; N-TIO = non-technological innovation.