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Knowledge Sharing Infrastructure and Dynamic Capability Formation: Panel Evidence from Innovation-Driven Firms

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Abstract. The requirements for structured knowledge-sharing investments within organizations to yield actual innovation capability are poorly understood. Further, organizations are increasingly adopting these investments. Based on dynamic capability theory, knowledge-based view, and absorptive capacity theory, Research and Development (R&D) intensity, as an institutionalized proxy for Structured Knowledge-Sharing (SKS) intensity, is conceptualized. This study finds a lagged impact of R&D intensity on the manifestation of innovation capability. Using a six-year unbalanced panel (2020 to 2025) of 129 firms listed in the United States that formally disclose their R&D expenditure, estimated with entity and time fixed-effect models and clustered standard errors, the study indicates a consistent investment-realization pattern: contemporaneous R&D intensity is negatively associated with revenue growth (indicating cost of investment phase), while lagged R&D intensity is positively and significantly linked to revenue growth. This result holds when controlling for firm age and market competition, excluding Coronavirus Disease 2019 (COVID-19)-period observations, restricting the sample to non-outlier R&D firms, and subsampling by the technological environment. A mediation analysis gives partial support for absorptive capacity as a transmission mechanism. The core association retains validity across industries, as technological intensity does not moderate the relationship. The framework developed in this study is a temporally explicit, firm-level framework for assessing investments in Knowledge Management (KM).

Keywords: Knowledge sharing, innovation capability, dynamic capabilities, R&D intensity, innovation-driven organizations.

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1. Introduction

Knowledge-sharing has gained growing recognition as a means through which organizations sustain their competitiveness. Nonetheless, not enough research exists on the determinants of knowledge-sharing that would result in the development of capabilities through time. Although past research has predominantly focused on the behavioral precursors (trust, leadership, and social capital) of knowledge-sharing at the micro-level, there still lacks a systematic investigation on how firm-level investments in structured knowledge infrastructure accumulate into innovation capability over time (Cheikh-Ammar et al., 2024). This is important because innovation capability may be formed through cumulative knowledge integration processes, meaning that its occurrence should take into account the timing and continuity of investments in knowledge, for which longitudinal evidence remains sparse. The current research attempts to fill this void by testing the ability of Structured Knowledge-Sharing (SKS) capabilities, measured using R&D intensity, to predict innovation capability with a time lag in terms of revenues and profit generation.

From a project and production management standpoint, R&D programs function as multi-year investment projects whose payoffs emerge through staged knowledge integration milestones rather than immediate deliverables. Grasping the temporal lag between knowledge-sharing expenditure and capability formation carries direct consequences for R&D portfolio evaluation, production system architecture, and engineering management decision-making.

This research is driven by three key questions. The first is to determine whether R&D intensity at the firm level is a good proxy for the intensity of structured knowledge-sharing activities and whether it can therefore be used to predict how a firm's ability to innovate will develop over time. The second question is to consider whether the relationship between firm-level investments in knowledge-sharing activities and future innovations is in fact a temporally based one, i.e., investments that a company makes today in knowledge sharing influence the types of innovations it is able to create in the future, rather than having an immediate impact on its ability to innovate. Finally, the third question considers whether or not the technological context of the industry or sector in which a firm operates has a moderating effect on the investment-to-capability pathway of the firm.

This gap carries practical consequences. Firms that evaluate knowledge management investments using same-period financial metrics will systematically undervalue long-cycle capability building (Kumar et al., 2024), a knowledge integration process that takes 12-24 months to generate measurable revenue impact will appear as a cost rather than an investment in annual reporting cycles (Li et al., 2025). This misalignment between capability-development timelines and performance-evaluation cycles may explain the tendency of organizations to consistently underinvest in formalized knowledge infrastructure, particularly during periods of revenue pressure (Saharti, 2025) .

The results provide consistent support for the hypothesis that structured knowledge-sharing infrastructure exerts a lagged positive association with innovation capability. According to the model, lagged R&D intensity is a positive and significant predictor of revenue growth ($b = 0.381$, $p < 0.001$). Furthermore, this finding is robust when firm age and market competition intensity are included as additional control variables ($b = 0.378$, $p < 0.001$). The positive, but statistically insignificant, relationship with profitability aligns with the expectation that profitability is a later, more distal manifestation of capability development than revenue growth. The moderating role of industry technological intensity is not significant, which indicates the investment-realization mechanism operates across technological environments rather than being restricted to high-technology industries.

This paper is structured as follows. Section two focuses on the development of theory. Section three states three testable hypotheses. Section four presents the data, variable definitions, and estimation technique. Section five presents the main regression results, robustness checks, moderation analysis, and mediation test. Section six discusses the theoretical and managerial implications. Section seven presents limitations and suggestions for future research. Section eight concludes.

Fig. 1 presents the conceptual framework linking the key constructs of this study. The framework positions SKS intensity as the primary independent variable, with internal knowledge integration and absorptive capacity as the mediating mechanism, and enterprise innovation capability as the latent dependent construct reflected through revenue growth and profitability.

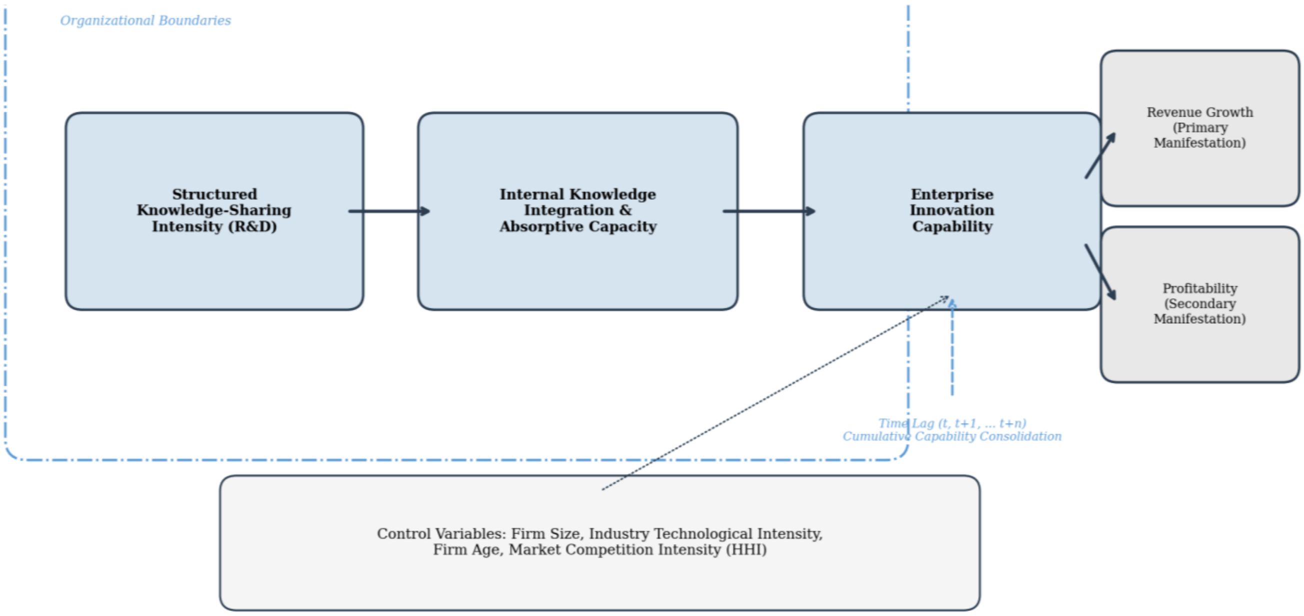

Fig. 1. Conceptual framework linking structured knowledge sharing to innovation capability manifestation

2. Theoretical Foundation

2.1. Knowledge Sharing Structures as Institutionally Supported Infrastructure

Knowledge sharing is the fundamental construct of Knowledge Management (KM) research. Much early research has studied behavioral antecedents of knowledge sharing: trust, leadership, organizational culture, and social networks. These contributions develop an understanding of how individuals share knowledge and how collaborative climates influence the flow of knowledge. They are, however, mostly micro-focused and do not explain the routinization of knowledge sharing at the level of the enterprise. At the enterprise level, especially in firms with an innovation focus, knowledge sharing becomes an institutionalized infrastructure. Structured knowledge-sharing infrastructure includes formal, resource-supported systems for supporting knowledge creation, integration, and recombination in a structured way. Examples are organizationally dedicated R&D functions, project teams that are cross-functional in composition, experimentation and learning routines, documentation systems, and boundary spanning roles (Cheikh-Ammar et al., 2024; Sayegh et al., 2024).

Structured knowledge-sharing infrastructure should be distinguished from informal knowledge sharing. Behavioral knowledge sharing relates to the willingness of an individual to share knowledge and how often they engage in exchanges of this kind. Structured knowledge-sharing infrastructure refers to how much a firm invests in developing knowledge integration routines that can be carried out repeatedly over time. The structured approach to knowledge sharing is particularly appropriate to enterprise-level capability development where robust integration systems are needed.

R&D intensity is a macro-level operationalization of structured knowledge-sharing infrastructure. R&D expenditure supports systems of cross-functional integration, experimentation, and codification of technical insights, and recombining knowledge from different fields. In agreement with the knowledge-based view of the firm, competitive advantage emerges through the integration of knowledge, rather than its isolated possession (Grant, 1996). R&D functions in a firm provide the institutionalized, infrastructural support for integration in structured settings for learning. Absorptive capacity theory also links R&D intensity to the ability of the firm to recognize and learn from valuable new knowledge (Cohen and Levinthal, 1990). It allows us to understand R&D intensity as an indicator of systematic, resource-based processes for both creating and integrating new knowledge.

2.2. Innovation Capability and Its Manifestations

Innovation capability is defined as a firm's ability to sustainably mobilize, integrate and commercialize knowledge. While measuring outputs of innovation at certain points in time, innovation capability is a long-lasting accumulation of routines and infrastructure at the firm level, where their activities coordinate (Abou-Moghli, 2025).

In structural equation modeling, latent constructs are unobservable variables that manifest in observable indicators (MacKenzie et al., 2005). When indicators are reflective, in that they are caused by the latent construct and do not define it, a change in the latent construct results in co-movement across all indicators. Innovation capability (the firm’s ability to integrate, recombine and commercialize knowledge), as described by Teece et al. (1997), is not directly observable from archival financial data. Innovation capability is, therefore, a competency that develops over time through the accumulation of routines, processes, and human capital. Over time, a firm with greater innovation capability would demonstrate successful recombination of knowledge and achieve greater market success and revenue growth as a result. Once an organization has successfully commercialized its innovations and thus grown revenues, subsequent operational efficiencies from matured and scaled innovation processes will be reflected in profitability.

Revenue growth is selected as the primary reflective indicator of innovation capability because it provides real demand-side validation of the market's acceptance of a product or service by the buyer, without the confounds introduced by pricing strategy, cost structure, or short-term reinvestment decisions that complicate profitability as an early-stage indicator (Penrose, 1959). Profitability is retained as a secondary reflective indicator to test whether the capability signal ultimately extends to margin improvement, as outlined in Davis et al. (2024).

2.3. Dynamic Investment-Realization Pattern

Dynamic capability theory draws on knowledge accumulation and capability development over time. Knowledge integration processes require time to align and commercialize. R&D investment spurs the initial experimentation, codification, and integration in the knowledge development of such capabilities. This will typically incur initial alignment costs and resource spillovers. Performance implications may thus be neutral to negative in the initial period. Over the subsequent periods, however, the knowledge gained increases absorptive capacity and adaptive learning, and market growth can follow based on the innovation introduced (Teece, 2007).

The temporal mechanism can therefore be expressed as: SKS Intensity (t) leads to Knowledge Integration and Absorptive Capacity Increase, which leads to Capability Consolidation, which leads to Innovation Capability Realization (t+1, t+n). This investment pattern cost-benefit analysis across periods underlies the theoretical reasoning for contemporaneous and lagged empirical impacts. Fig. 2 illustrates this dynamic mechanism.

3. Hypotheses

3.1. Structured Knowledge-Sharing Intensity and Innovation Capability Manifestation

In light of the earlier discussion, structured knowledge-sharing intensity represents an organization-wide commitment to maintaining a formal knowledge-sharing system for integrating and creating new knowledge. According to the knowledge-based view of the firm, organizations are viewed as repositories of heterogeneous knowledge within an industry. However, there are no direct relationships between knowledge stocks and competitive advantage. Competitive advantage comes from organizations that are able to effectively mobilize, integrate and recombine dispersed knowledge into valuable outcomes (Grant, 1996). For the purposes of this research, R&D intensity will be measured as a formal knowledge-sharing system or forum. Organizations have embedded knowledge-recombination routines through the use of organized R&D functions or systems that provide a means for aligning market and technology, while improving the understanding of both through iterative processes of experimentation, learning and developing knowledge codification procedures necessary for retaining and institutionalizing newly created knowledge (Statsenko et al., 2023).

H1: Structured knowledge-sharing intensity is positively associated with innovation capability manifestation.

3.2. Investment-Phase Costs and Temporal Realization of Knowledge Investments

While H1 provides a sense of the directional overall relationship, dynamic capability theory admits a time-varying, potentially non-linear relationship. Capability expression is path-dependent and history-dependent. Three interrelated mechanisms explain the lagged effect. First, there is a build-up of absorptive capacity, meaning the knowledge must be acknowledged, assimilated, transformed, and operationalized before it can translate into productive gains (Cohen and Levinthal, 1990). Second, there is a product and service development process through stages of design, prototyping, testing, and rollout. Third, there is a developmental process for market diffusion and adoption. These mechanisms suggest a twofold temporal pattern, allowing short-term contemporaneous effects to correlate with poor performance outcomes due to the cost of being in the investment phase. Once knowledge has been assimilated and commercialized, it may support innovation-driven market growth.

H2: Prior-period structured knowledge-sharing intensity is positively associated with subsequent innovation capability manifestation.

3.3. Industry Technological Intensity as a Contextual Boundary Condition

The structured knowledge-sharing intensity is theorized to enhance the capability-building of all firms; however, its impact is expected to be moderated by the industry's technological intensity. In high-technology industries, knowledge quickly becomes outdated, product life cycles are short-lived, and competition is fierce. The theory of dynamic capabilities shows the importance of knowledge integration across all areas of the industry. It is expected that conditioning will be better than elimination.

H3: The effect of structured knowledge-sharing intensity on the manifestation of innovation capability is moderated by industry technological intensity.

4. Method

4.1. Research Design

A longitudinal quantitative design is employed to analyze the temporal relationship between knowledge-sharing intensity and the realization of innovation capability. A panel data structure is employed to model intra-firm dynamics across time while controlling unobserved heterogeneity at the firm level. The longitudinal design is justified theoretically by dynamic capability theory (Abou-Moghli, 2025; Teece, 2007). By studying the firms over six fiscal years, the present design permits an examination of the temporal ordering of knowledge- sharing investment and performance realization. The empirical strategy combines fixed effects estimation of panel data with dynamic panel data modeling. Firm fixed effects account for time-invariant firm-level characteristics, while year fixed effects capture macroeconomic shocks, regulatory changes, and industry-wide technological shifts.

4.2. Data Source and Sample Selection

The empirical analysis is based on archival financial data sourced from firms listed in the U.S. Securities and Exchange Commission (SEC) EDGAR database. The observation period covers the fiscal years 2020 to 2025. Firms are included if they reported R&D expenditure in at least one fiscal year, provided complete financial information to construct dependent and control variables, and belong to innovative sectors with continuous R&D activity. The final data set consists of 129 unique publicly listed firms and 560 firm-year observations after screening and validation. Table 1 summarizes the panel structure.

4.3. Variable Measurement

4.3.1. Independent variable: Structured knowledge-sharing intensity

The measure of SKS intensity is defined as the ratio of R&D expenditure to total revenue: R&D_Intensity = R&D_Expenditure/Total_Revenue. The degree to which the organization invests resources into the development of a formal knowledge-sharing infrastructure is ascertained through this measure (Gonenc and Poleska, 2022; Li, 2025).

This operationalization meets three criteria for construct validity. First, it is objective because R&D expenditure is an audited financial disclosure that does not suffer from perceptual bias or retrospective rationalization. Second, it is consistent with theory because the knowledge-based view attributes sustained competitive advantage to resource-backed, not possession-based knowledge integration routines. Third, it has an unambiguous boundary because R&D intensity measures institutionalized resource-backed knowledge integration rather than informal interpersonal exchange. In keeping with the work of Cohen and Levinthal (1990), R&D expenditure also develops the systematic capacity of recognition, assimilation, and exploitation of new knowledge, making it a theoretically grounded indicator of sustained investment in knowledge-integration. The ratio form (R&D/Revenue) normalizes for firm size, enabling meaningful cross-firm comparison.

4.3.2. Dependent variable: Innovation capability manifestation

The primary dependent variable is revenue growth, operationalized as the year-on-year change in total revenue: Revenue_Growth = [Revenue(t) - Revenue(t-1)] / Revenue(t-1). Profitability, operationalized as net profit divided by total assets, is used as a secondary dependent variable.

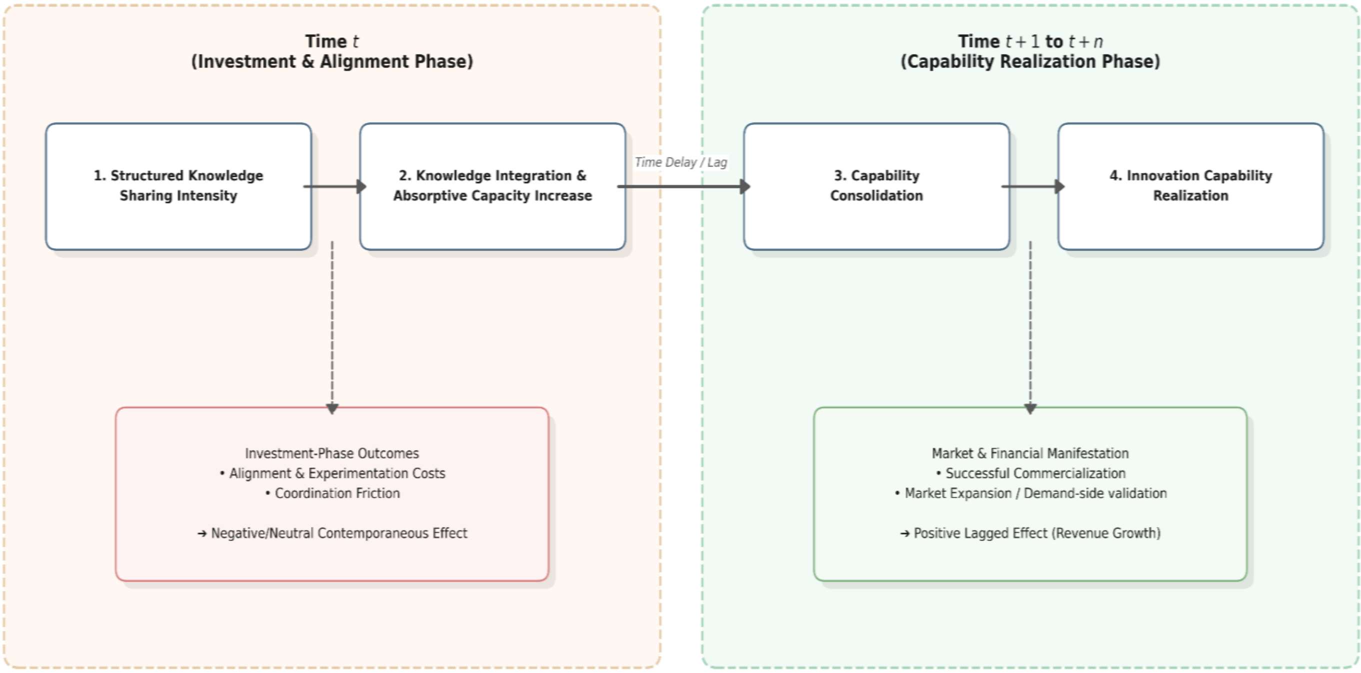

Fig. 2. Dynamic mechanism of structured knowledge sharing and innovation capability realization

Table 1. Panel structure summary

Metric	Value
Unique firms	129
Unique years	6 (2020-2025)
Total observations	560
Panel type	Unbalanced

4.3.3. Control variables

The model incorporates four control variables. Firm size is measured as the natural logarithm of total assets, reflecting the potential advantages of scale economies and more diversified knowledge bases. Industry technological intensity (Is_High_Tech) is operationalized as a binary indicator distinguishing high-technology sectors. Firm age is measured as the natural log of years since the firm first registered with the SEC (taken from EDGAR filing records), which represents organizational inertia and cumulative learning, both of which may influence the R&D-to-performance relationship independently (Sorensen and Stuart, 2000). Market competition intensity is operationalized as the Herfindahl-Hirschman Index (HHI) computed from revenue shares in each SIC-year cell; lower HHI values indicate higher competitive intensity (Rhoades, 1993). HHI is calculated based on revenue shares within the sample and should be interpreted as a within-sample measure of revenue concentration among innovation-active firms.

4.4. Addressing Endogeneity

A primary methodological concern is reverse causality. Firms anticipating future revenue growth may increase R&D investment in advance. Revenue growth persistence is controlled by including lagged revenue growth as an explanatory variable in dynamic specifications. To further address potential endogeneity and simultaneity, System Generalized Method of Moments (System GMM) estimation is employed. System GMM controls unobserved heterogeneity, uses internal instruments derived from lagged values, addresses reverse causality, and accounts for dynamic adjustment.

System Generalized Method of Moments (GMM) alleviates three identification problems that are prevalent in panel data on firm performance. First, reverse causality is dealt with by instrumenting contemporaneous R&D intensity with its own lagged values, as past investments predict current investment but should be exogenous to current revenue shocks. Second, dynamic panel bias is addressed by including lagged revenue growth as a regressor to account for persistence in the outcome variable. Third, time-invariant unobserved heterogeneity is dealt with through entity fixed effects that absorb stable firm characteristics, including managerial quality, organizational culture, and strategic positioning. However, System GMM does not eliminate all sources of endogeneity. It is not possible to deal with unobserved confounders correlated with both

R&D investment and revenue growth through internal instrumentation alone (Blundell and Bond, 1998). Therefore, all findings in this study are interpreted as longitudinal associations consistent with dynamic capability theory and not as causal estimates.

5. Results

5.1. Descriptive Statistics

Table 2 presents descriptive statistics for all study variables. Pearson correlation coefficients were computed for all study variables (N = 413). No pairwise correlations exceed conventional multicollinearity thresholds. The highest correlation is between profitability and firm size ($r = 0.469$, $p < 0.001$). R&D intensity shows no significant contemporaneous correlation with revenue growth ($r = -0.009$, $p = 0.850$), affirming the temporal hypothesis that performance effects emerge only through lagged specifications. Firm age is uncorrelated with R&D intensity ($r = -0.001$, $p = 0.980$).

Table 2. Descriptive statistics

Variable	Mean	Median	Std. Dev.	Min	Max
R&D Intensity	1.777	0.084	9.581	0.000	79.934
Revenue Growth	0.635	0.051	3.944	-0.710	34.620
Profitability	-0.419	0.032	2.651	-22.152	0.498
Log Assets	20.348	20.853	3.288	7.831	26.623
Firm Age (ln)	2.731	3.178	0.862	0.000	3.434
HHI	0.740	1.000	0.300	0.230	1.000

Note: HHI = Herfindahl-Hirschman-Index. Firm Age measured as the natural log of years since first SEC registration. R&D = Research and Development. ln = natural logarithm.

5.2. Contemporaneous Effects

Contemporaneous fixed-effects regression results show that contemporaneous R&D intensity is negatively associated with revenue growth ($b = -0.260$, $p = 0.012$), consistent with the investment-phase costs argument. Contemporaneous R&D intensity has no significant effect on profitability.

5.3. Lagged Effects and Temporal Dynamics

Table 3 presents the lagged fixed-effects regression results. In Table 3, Model A and Model B report results for revenue growth (RevGrowth) as the dependent variable, with Model B adding firm age and the Herfindahl-Hirschman Index (HHI) as additional controls. Model C and Model D report results for profitability as the dependent variable. Lag R&D Intensity is the one-period lagged ratio of R&D expenditure to total revenue. Log Assets is the natural logarithm of total assets. High-Tech is a binary indicator for high-technology industry sectors. Firm Age is the natural log of years since first SEC registration. N is the number of observations, Firms is the number of unique firms, and Within R2 is the within-entity explanatory power.

Table 3. Lagged fixed-effects models with extended controls

Variable	Model A RevGrowth	Model B RevGrowth (+Controls)	Model C Profit	Model D Profit (+Controls)
Lag R&D Intensity	0.381*** (0.025)	0.378*** (0.027)	0.026 (0.027)	0.027 (0.028)
Log Assets	2.964* (1.321)	2.952* (1.324)	1.091* (0.526)	1.074* (0.518)
Is High-Tech	-0.615** (0.213)	0.650 (1.175)	0.220 (0.263)	-0.003 (0.631)
Firm Age	---	-0.821 (0.908)	---	-0.291 (0.416)
HHI	---	2.308 (2.373)	---	-0.634 (1.080)
N	413	413	431	431
Firms	121	121	129	129
Within R2	0.617	0.619	0.266	0.270

Note: Entity and time fixed effects included. Clustered standard errors (entity level) in parentheses. RevGrowth = Revenue Growth. Profit = Profitability. Lag R&D Intensity = one-period lagged ratio of R&D expenditure to revenue; Is High-Tech = binary indicator for high-technology sector. HHI = Herfindahl-Hirschman-Index. N = number of observations. R2 = within R-squared. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The direction and significance of the lagged R&D intensity coefficient are robust to the inclusion of firm age and HHI as additional controls (Model B: b = 0.378, $p < 0.001$ vs. Model A: b = 0.381, $p < 0.001$), consistent with the argument that the investment-realization pattern reflects a generalizable dynamic capability mechanism rather than firm-lifecycle or market-structure artifacts.

5.4. Dynamic Panel Estimation

To deal with endogeneity and revenue persistence, the difference GMM model was estimated using two-stage least squares (2SLS) with lagged level instruments (Lag2 and Lag3 of revenue growth and R&D intensity as instruments for first-differenced endogenous regressors). After differencing and instrument availability, 56 firm-year observations are used across 56 firms in the final GMM sample. The GMM specification shows that the lagged R&D intensity coefficient is also positive and statistically significant: b = 0.307 (SE = 0.080; $p < 0.001$). This means that the key finding remains robust to reverse causality instrumentation. The lagged revenue growth coefficient is positive (b = 0.740), but not significantly so ($p = 0.311$), suggesting limited dynamic persistence once endogeneity is accounted for. The AR(2) test shows no second-order autocorrelation in the differenced residuals (autocorrelation = -0.046), and the Hansen J-test does not reject the null of valid overidentifying restrictions (J = 0.101, $p = 0.750$). The number of instruments (6) is much smaller than the number of firms (56), preventing instrument proliferation from finite-sample bias. These results indicate a longitudinal association consistent with dynamic capability theory.

5.5. Robustness Checks

Supplementary robustness checks, including misjudgment at the 1st and 99th percentiles, alternative R&D scaling measures, and a squared-term non-linearity test, confirm that the primary lagged finding is stable.

5.5.1. COVID-period robustness and R&D heterogeneity

To evaluate whether the lagged positive relationship between SKS intensity and revenue growth has been affected by pandemic-related disruptions, Model B was re-estimated on a restricted panel excluding fiscal years 2020 and 2021 (n = 327 observations, 110 firms). The coefficient for lagged R&D intensity is positive and significant (b = 0.413, $p < 0.001$), suggesting that the investment-realization pattern is not an artifact of COVID-period revenue volatility. Model B was also re-estimated on a restricted subsample of firms whose R&D intensity is between the 10th and 90th sample percentiles (n = 335 observations; 100 firms). The coefficient of the lagged R&D intensity is positive and significantly different from zero (b = 0.546, $p < 0.001$). This implies that the investment-realization pattern is not driven by a handful of hyper-R&D-intensive firms (Petersen, 2009). Cluster-robust standard errors are reported for all specifications. Table 4 and Fig. 3 summarize the robustness results across all specifications.

Table 4. Robustness: lag R&D intensity coefficient across specifications

Specification	b (beta)	SE	p	N	R2
Full Sample (Original)	0.381	0.025	<0.001	413	0.617
Full Sample (+Firm Age +HHI)	0.378	0.027	<0.001	413	0.619
COVID Robust (2022-2025)	0.413	0.052	<0.001	327	0.723
R&D P10-P90 Subsample	0.546	0.115	<0.001	335	0.864
High-Tech Only	0.387	0.024	<0.001	248	0.591
Non-High-Tech Only	0.383	0.063	<0.001	165	0.828

Note. All models include entity and time fixed effects with clustered standard errors (entity level). b = standardized coefficient. SE = standard error. N = number of observations. R2 = within R-square. HHI = Herfindahl-Hirschman-Index. P10-P90 = firms between the 10th and 90th percentiles of R&D intensity.

5.6. Industry Moderation

The interaction term (Lag_RD_Intensity x Is_High_Tech) does not have a significant impact (b = 0.059, $p = 0.303$). For a closer look at the null-moderation result, the lagged fixed-effects model was estimated separately for the high-technology (n = 69 firms, 248 observations) and non-high-technology (n = 54 firms, 165 observations) subsamples. The coefficient for the lagged R&D intensity is positive and significant in both sub-samples: high-technology, b = 0.387, SE = 0.024, $p < 0.001$, non-high-technology, b = 0.383, SE = 0.063, $p < 0.001$. The near-equivalent point estimates indicate a universal investment-realization pattern that operates with essentially the same magnitude in all technology environments.

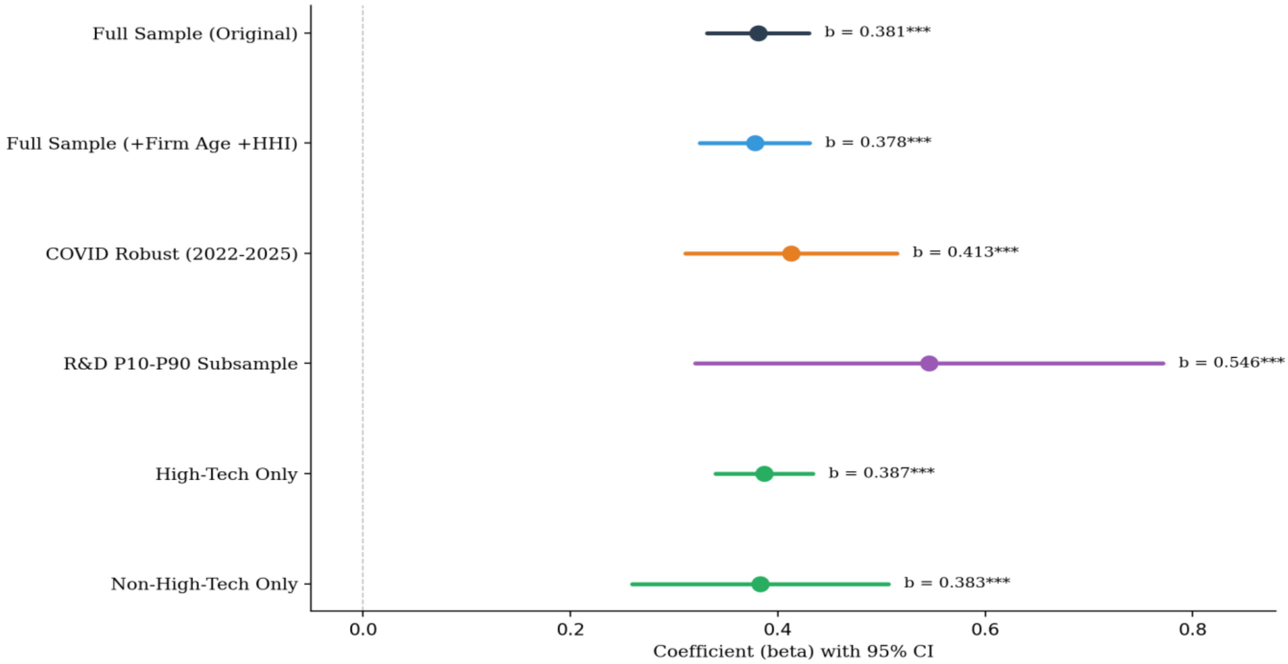

Fig. 3. Robustness of lagged R&D intensity coefficient across model specifications

Note: All coefficients are statistically significant at $p < 0.001$. b = standardized coefficient. CI = 95% confidence interval. HHI = Herfindahl-Hirschman-Index.

5.7. Mediation Analysis

To assess the mediating role of knowledge integration and absorptive capacity, a causal mediation analysis was conducted using a bootstrapping indirect-effects approach (Preacher and Hayes, 2008) with 1,000 replications. The proxy for absorptive capacity was prepared as a two-year rolling average of R&D intensity lagged one period, aligning with Cohen and Levinthal's (1990) view of R&D investment as a mechanism for developing organizational capacity (N = 413, 121 firms). Table 5 presents the mediation results, and Fig. 4 illustrates the path diagram.

Table 5. Mediation analysis results

Step	Path	b	p-value	Interpretation
Total (c)	Lag_RD to RevGrowth	0.378	<0.001	Total effect confirmed
a-path	Lag_RD to Absorptive Cap	0.581	<0.001	R&D builds absorptive capacity
b-path	Absorptive Cap to RevGrowth	0.250	0.235	Positive but not significant
Direct (c')	Lag_RD to RevGrowth	0.229	0.130	Attenuated from 0.378
Indirect	Bootstrap N=1,000	0.136	CI: [-0.133, 0.604]	CI includes zero partial support

Note: Lag_RD = lagged R&D intensity. RevGrowth = Revenue Growth. Absorptive Cap = Absorptive Capacity proxy (two-year rolling average of lagged R&D intensity). b = coefficient. CI = 95% bootstrapped confidence interval.

6. Discussion

6.1. Structured Knowledge Sharing as a Dynamic Capability Mechanism

According to the findings, systematic knowledge sharing contributes to a firm's growth, which is distinct from an increase in productivity. The data show a bimodal temporal structure: current R&D intensity is associated with lower revenue growth, while past R&D intensity is positively related to market growth (Kumar et al., 2024). Thanks to the temporal asymmetry, static interpretations are not permitted in the knowledge-sharing-performance relationship. Therefore, the findings are consistent with the notion that structured knowledge sharing is aimed not at enhancing short-term performance but at strengthening the firm's adaptive capability over the longer term (Saharti, 2025).

The mediating analysis provides details on absorptive capacity as a transmission mechanism of knowledge-sharing infrastructure to innovation outcomes in a theoretical context. The robust a-path finding that the accumulation of R&D investments predicts absorptive capacity is in line with Cohen and Levinthal's (1990) foundational argument. The b-path is not significant, which does not refute full mediation but shows the need for measurement independence in future study designs.

6.2. Capability Manifestation: Growth Before Profit

Previous research shows a link between R&D intensity and revenue growth. External market validation of innovation through the successful commercialization of reconfigured knowledge drives revenue growth. Profitability measures the ratio of what goes into an organization to what comes out, such as capital intensity, pricing, and processes (Davis et al., 2024). The findings support a staged approach to innovation capability development, noting that knowledge sharing first leads to wide proliferation impact before causing efficient diffusion.

6.3. Implications for Engineering and Knowledge Management Evaluation

Organizations should track KM performance at three time horizons simultaneously to avoid the misjudgment documented in this study. Using current-year R&D intensity relative to current-year revenue growth as the sizing metric identifies the investment-phase cost signal or the expected short-term disruption associated with building new knowledge-integration infrastructure. Managers use of one-year lagged metrics means that if R&D investment in year T leads to accelerated revenue growth in year T+1, then the investment-realization mechanism is operating as expected. Utilizing a three-year rolling average provides insight into the compounding effect of the capability formation process, allowing managers to see whether this knowledge infrastructure is creating sustained competitive advantage. A chief knowledge officer who merely presents same-period R&D and revenue data to senior leadership will consistently understate the value of a KM investment and create structural pressure for early disinvestment.

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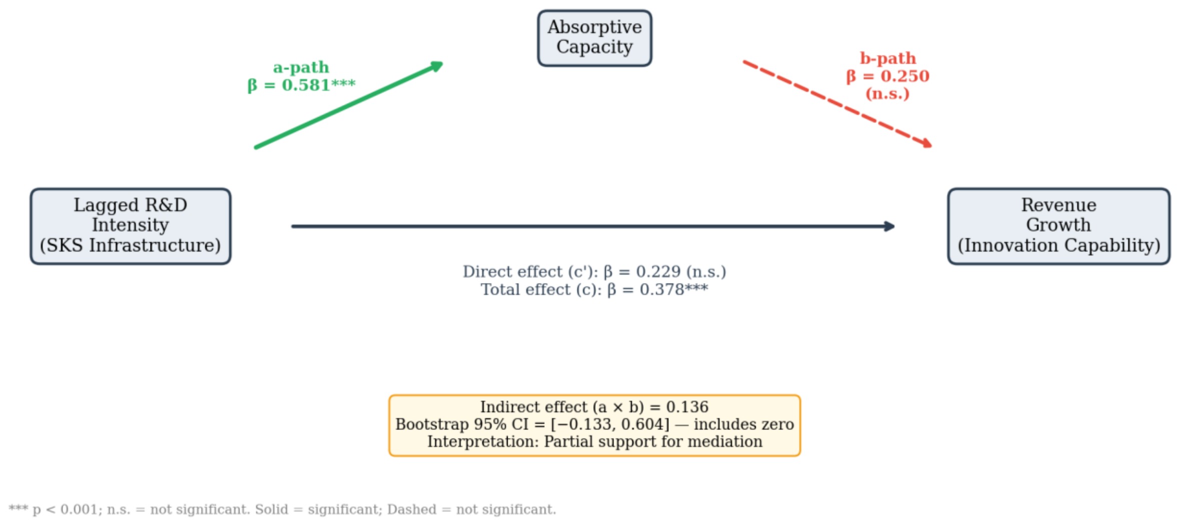

Fig. 4. Mediation path analysis: absorptive capacity as mediator between SKS infrastructure and revenue growth

Note: SKS = Structured Knowledge-Sharing, *** $p < 0.001$, n.s. = not significant, solid line = significant path, dashed line = not significant path.

When R&D intensity is high and same-period revenue growth is flat or negative, managers should apply a disciplined diagnostic to separate capability-building cost signals from operational inefficiency signals. If a company continues to spend on R&D and pipeline indicators remain active, such as patents filed, products in development, and customer pilots initiated, then flat or negative top-line growth in the same period signals an investment-phase disruption, not a strategy failure. On the contrary, when R&D intensity is high but pipeline activity remains stagnant, a structural review of knowledge processes should be initiated.

For engineering and production managers who oversee R&D project portfolios, the one-period investment-realization lag reported here implies that project evaluation criteria should incorporate capability-formation milestones alongside conventional cost-schedule-scope indicators. Production systems built on continuous knowledge integration, such as lean engineering, concurrent product development, and agile R&D management, benefit from protected investment windows that match evaluation timescales with the empirically observed capability-development cycle.

6.4. Cross-Industry Applicability

The lack of moderation for industry technological intensity (H3) needs theoretical interpretation. Three explanations complement each other. First, dynamic capability theory asserts that firms in competitive markets must reconfigure their resources to maintain a competitive position in their industry (Teece, 2007). The ability to integrate and reconfigure knowledge does not belong solely to high-technology environments. Rather, it is an essential adaptive necessity in any industry characterized by demand uncertainty and technological change.

Second, the sample design may lead to lower variance in the technological moderator. The U.S. listed firms that comprise the panel are only those that voluntarily disclose their R&D expenditures, meaning all firms have adopted at least a moderate technological orientation. Third, the close coefficients from the nearly-identical sub-samples (0.387 vs. 0.383) reframe the null result as a strengthening of the core finding. Organizations across the full sample and sub-samples benefit from continued structured investment in knowledge-sharing, with similarly-sized lagged impacts on revenue generation.

The near-identical effect sizes seen among the high technology and low technology sub-samples ($b = 0.387$ vs $b = 0.383$) show that this finding cannot be limited simply to those companies identified as technologically innovative (Innovation Driven). In addition, companies located in “lower technology” industries that invest in some form of structured knowledge-sharing system can also realize benefits on par with those of their counterparts in high-technology industries in terms of revenue by investing in R&D during prior periods. The limitation of our sample to include only companies that are publicly traded in the United States and provide R&D spending data excludes any companies with zero formal R&D expenditures. Future studies should investigate whether informal investments in structured knowledge-sharing systems are able to create similar temporal benefits for firms that do not report formal R&D expenditures.

7. Limitations and Future Research

7.1. Study Limitations

The sample is limited to firms listed in the U.S. and subject to SEC mandatory disclosure rules. U.S. institutional conditions, strong intellectual property protection, liquid capital markets, and investor expectations of R&D transparency create a specific incentive structure for R&D investment that may not generalize to firms in other national contexts.

All firms in the sample are publicly listed companies with sufficient scale to formally disclose R&D expenditures, and are therefore systematically larger, more resource-endowed, and more innovation-oriented than the typical small or medium-sized enterprise (SME). The current findings must not be applied to SMEs without dedicated replication studies.

The observation period of six years (2020 to 2025) contains the COVID-19 pandemic and macroeconomic disruption. While entity and time fixed effects absorb common time shocks, idiosyncratic firm-level responses during the pandemic period may confound the analysis. The COVID-exclusion robustness check (Section 5.5.1) demonstrates that the core finding holds in the post-pandemic subsample.

This research provides insight regarding managerial decision-making and provides guidance for R&D project portfolio management and the processes used to evaluate performance within those portfolios. Managers of R&D portfolios should modify the time frame over which their organization evaluates performance to include lagged performance metrics at multiple time horizons for each project. Specifically, the data support a three-tier refinement to the evaluation framework. (1) Compare R&D investment costs and revenue growth within the same period to allow for the identification of financial investment (cost) signals in the investment phase of the project. (2) Compare R&D investment from the prior year against current revenue growth to assess whether capability is beginning to emerge. (3) Utilize rolling three-year averages for the evaluation of compounded capability development. If managers do not adjust the evaluation process to account for time lags, they will systematically undervalue their knowledge-sharing investments and create institutional pressures to divest too soon.

7.2. Future Research Directions

The current study’s major limitation is its reliance on firm-level financial disclosures as the sole proxy for knowledge-sharing intensity. Future studies must use multi-level and multi-method measurement strategies. At the micro level, the use of questionnaire survey instruments measuring cross-functional collaboration quality, self-reported frequency of knowledge-sharing, and organizational climate for learning would help complement the firm-level archival proxy used here (Cheikh-Ammar et al., 2024). The use of social network analysis on co-authorship networks, internal communication data, or inter-departmental project participation could enable measuring knowledge flows topology on the network level (Hoang et al., 2023).

The mediation analysis presented in Section 5.7 provides preliminary evidence, but the measurement origins of the absorptive capacity proxy and the independent variable overlap with R&D intensity. Future work should independently measure absorptive capacity using the ACAP survey instrument (Jansen et al., 2005) or patent citation-based measures to test the full mediation chain with measurement independence (Zahra and George, 2002).

The sample pertains only to U.S. firms. Subsequent research should be conducted in Germany, China, and other developing-market contexts where formal R&D investment might be replaced by informal knowledge transfer. Government innovation policy is an essential institutional moderator in such contexts.

8. Conclusion

Structured knowledge-sharing intensity in relation to enterprise innovation capability manifestation has been explored using a longitudinal panel of 129 public companies analyzed over 6 years. A two-part relationship is identified as follows. While contemporaneous R&D intensity is negatively associated with revenue growth, lagged R&D intensity is positively associated with subsequent revenue growth ($b = 0.378$, $p < 0.001$). This finding is robust across all specifications, including corrected firm age controls, COVID-exclusion, R&D outlier trimming, and industry subsamples. The structured knowledge-sharing mechanism operates with uniform magnitude across technological environments, and preliminary evidence supports absorptive capacity as a transmission mechanism. Organizations that invest in building a system of institutionalized knowledge integration will be better positioned to develop sustainable innovation capabilities over time. By focusing on the temporal nature of knowledge sharing, this paper encourages researchers in KM to move from static performance models toward longitudinal capability-based approaches.

In terms of answering the research questions set out in Section 1, RQ1 indicates that the SKS intensity, operationalized via R&D intensity, and the manifestation of innovation capability show a positive and significant association. With regards to RQ2, it is clear that the relationship is time-bound, in that the R&D intensity of the prior period predicts future periods' revenue growth, whereas R&D intensity in the current period is negatively correlated with the current period's revenue growth, showing an investment-realization lag of one fiscal year. Finally, concerning RQ3, industry technological intensity fails to act as a moderator, thereby implying generalizability across technological contexts.

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The author used Claude AI solely for formatting and organizational assistance. No AI tools were used to generate scientific content, analysis, conclusions, or references. All content was reviewed and validated by the author.

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