Journal of Innovation & Knowledge 13 (2026) 100943

Contents lists available at ScienceDirect

Journal of Innovation & Knowledge

journal homepage: www.elsevier.com/locate/jik

Innovation Capabilities and Firm Performance: A Meta-analysis of the Schumpeter's Hypothesis

Filip Lestan *, Tommy H. Clausen

Nord University Business School, Universitetsalléen 11, 8026 Bodø, Norway

ARTICLE INFO

JEL codes:
O32
O47
O57
L25
D22

Keywords:
Capabilities
Firm performance
Innovation
Meta-analysis
Schumpeter

ABSTRACT

Prior empirical evidence on the relationship between innovation capabilities and firm performance remains inconsistent, leaving unresolved questions regarding the magnitude of this association and the conditions under which it varies. This study addresses this gap by conducting a cross-national meta-analysis of 54 independent samples from 19 countries ($N = 320{,}529$). Grounded in Schumpeter's hypothesis that innovation is a primary driver of economic growth, we distinguish between the Mark I. pattern (characterized by creative destruction) and the Mark II. pattern (characterized by creative accumulation). In support of Schumpeter's hypothesis, our findings indicate that, on average, innovation capabilities exhibit a positive, small-to-moderate, and statistically significant association with firm performance. When decomposing Schumpeter's hypothesis into its 'narrow' forms, the relationship is strongest for Mark I. and for studies combining both Mark I. and Mark II. patterns, whereas evidence for the Mark II. pattern alone suggests no meaningful performance effect. Additional analyses show that heterogeneity across studies is partly explained by contextual and methodological moderators, including the proximity of capability measures to performance outcomes, performance indicators, and study design characteristics. By synthesizing a broad base of empirical evidence and identifying the conditions under which innovation capabilities are associated with firm performance, this study provides a more precise and generalizable understanding of the innovation capabilities–firm performance relationship and strengthens the empirical foundations of the Schumpeterian framework.

Introduction

Since the early 1940s, researchers and practitioners have revisited the Schumpeterian claim that innovation capabilities enhance, rather than obstruct, firm performance (Cevik, 2025; Guerrero & Siegel, 2024; Schumpeter, 1934). This relationship remains central to contemporary debates on competitiveness, as firms increasingly rely on their ability to sense, seize, and transform innovation opportunities in dynamic markets (Moreira et al., 2024; Teece et al., 1997). Recent studies continue to highlight the strategic importance of innovation capabilities as a drivers of firm performance (López-Cabarcos et al., 2019; Piñeiro-Chousa et al., 2025), even as the literature continues to report conflicting evidence (Mendoza-Silva, 2021). Although innovation may entail substantial costs and uncertainty (Malik et al., 2022; Subramaniam & Youndt, 2005), Schumpeterian hypotheses suggest that firm-level innovation capabilities generate competitive advantage through processes of creative destruction (i.e., Mark I) and creative accumulation (i.e., Mark II).

Despite extensive empirical work, research findings remain inconsistent. For example, patent-based innovation capabilities have been reported to have significantly *negative* (DeCarolis & Deeds, 1999, pp. 963, model 3. and 4.), *positive* (Arora et al., 2014, oo. 332, model 2.), or *nonsignificant* effects (Kang et al., 2017, pp. 1364, model 1., 2., and 3.) on firm performance. Although several systematic reviews exist (Iddris, 2016; Mendoza-Silva, 2021; Moreira et al., 2024), no study has yet synthesized this fragmented evidence meta-analytically, as indicated by the absence of published meta-analyses, leaving the magnitude and variability of the innovation capability–firm performance relationship unresolved. This gap is particularly significant because inconsistent empirical findings call for systematic synthesis to clarify the true magnitude of the effect of innovation capabilities on firm performance (Piñeiro-Chousa et al., 2020).

The aim of this study is to quantitatively determine the overall magnitude of the relationship between innovation capabilities and firm performance, and to explain why and when (i.e., under what conditions) this relationship varies across studies. To achieve this aim, we employ meta-analysis as the most appropriate method. Specifically, we integrate

* Corresponding author at: Nord University Business School, Universitetsalléen 11, 8026 Bodø, Norway.
E-mail addresses: Filip.Lestan@Nord.No (F. Lestan), Tommy.H.Clausen@Nord.No (T.H. Clausen).

https://doi.org/10.1016/j.jik.2026.100943
Received 23 October 2025; Accepted 12 January 2026
Available online 21 January 2026

empirical findings across diverse dimensions of innovation capabilities, performance metrics, and contextual characteristics. Our study evaluates: (i) the overall effect of innovation capabilities on firm performance, including distinctions between the Mark I and Mark II patterns of Schumpeter's hypothesis; and (ii) the extent to which differences in capability proximity, performance measurement, cultural context, theoretical framing, and study design explain variability in prior findings.

By doing so, our research addresses the following questions: *What is the overall association between innovation capabilities and firm performance, and how various theoretical and methodological factors influence Schumpeter's hypothesis?* To answer this question precisely, we conducted a systematic search of studies published between 2001 and 2024, yielding 54 independent samples and 320,529 firm-level observations. We followed the latest 'Preferred Reporting Items for Systematic Reviews and Meta-Analyses' (PRISMA) guidelines and developed a four-step approach (Page et al., 2021). Effect sizes were extracted and aggregated using random-effects meta-analytic techniques (Hunter & Schmidt, 2000). We also performed a series of moderator analyses to examine differences across capability types, proximity levels, performance measures, and study-level attributes (Cooper et al., 2019). A summary of our results indicates that, on average, innovation capabilities are positively associated with firm performance. This relationship is particularly strong for Mark I patterns, proximal capabilities, and *ex-post* performance measures, while study design and measurement choices explain additional heterogeneity.

This research aims to make two distinct contributions. First, it advances theoretical understanding by clarifying both the magnitude (i.e., how much) and the conditions under which innovation capabilities are associated with firm performance, thereby refining the Schumpeterian hypotheses with large-scale empirical evidence. Second, it provides the first meta-analytic assessment of this relationship, offering a methodologically robust and generalizable foundation for future theorizing and practice. Practically, the findings guide scholars and practitioners on how to effectively leverage innovation capabilities to enhance firm performance, taking into account the type of Schumpeterian hypothesis, capability type, and performance objectives.

The paper proceeds as follows. First, we review the literature on Schumpeter's hypothesis and introduce the concepts of innovation capabilities, the proximity of innovation capabilities, and their implications for different dimensions of firm performance. We then develop arguments suggesting that the effect of innovation capabilities on firm performance is likely moderated by factors such as the sample's uncertainty avoidance, the theoretical frameworks employed, and study design. Next, we describe our search strategy, the samples selected, and the meta-analytic apparatus used in our research. Finally, we report our findings and discus their implications for both scholars and practitioners.

Literature Review and Hypotheses

A substantial body of research in innovation management, strategy and entrepreneurship highlights innovation as a central mechanism through which firms create and sustain competitive advantage (Guerrero & Siegel, 2024; Piñeiro-Chousa et al., 2020). This literature commonly argues that innovation enables firms to differentiate themselves, respond to market changes, exploit new technological opportunities, and ultimately enhance both financial and competitive outcomes (López-Cabarcos et al., 2019). Yet, despite widespread agreement on the importance of innovation, scholarly perspectives diverge regarding how and under what conditions innovation capabilities lead to superior performance (Wang et al., 2024; Yin et al., 2023). Competing theoretical lenses: such as Schumpeterian views of creative destruction and creative accumulation (Schumpeter, 1934), dynamic capabilities framework (Teece et al., 1997) and resource-based arguments (Barney, 1991), offer differing explanations concerning the origins, nature, and performance consequences of innovative activity. These perspectives suggest that the relationship between innovation capabilities and firm performance is heterogeneous rather than universal, shaped by firm characteristics, capability configurations, environmental conditions, and measurement approaches. Therefore, a systematic theoretical foundation is needed to clarify the specific mechanisms through which innovation capabilities influence firm performance and to motivate the Schumpeterian hypotheses that follow.

Schumpeter's Hypothesis

The Schumpeter's hypothesis suggests that innovation is the primary driver of economic growth (Schumpeter, 1934). We build on this logic and explain that innovation is the primary driver of competitive advantage at the firm-level. That is, firms that successfully develop and implement new products, processes, or business models can achieve superior performance by disrupting existing markets or improving efficiency (Minviel & Ben Bouheni, 2022). Innovation is therefore source of success *but* also a mechanism for structural change in the economy, creating a dynamic relationship between entrepreneurial activity, market competition, and economic development (Cevik, 2025; Yin et al., 2023). Therefore:

Hypothesis 1. Innovation capabilities are positively associated with firm performance.

The Schumpeter hypothesis is commonly articulated in two forms. Firm size is an extremely robust and important moderator that influences how innovation capabilities translate into firm performance (Hall et al., 2010). Schumpeter Mark I (i.e., creative destruction) emphasizes the role of small, entrepreneurial firms in driving radical innovations that disrupt established markets, highlighting competition through novelty rather than price (Guichardaz & Pénin, 2025). On the other hand, Schumpeter Mark II (i.e., creative accumulation) focuses on large, established firms, arguing that their resources, R&D capacity, and market power enable sustained innovation, although innovation may eventually diminish with excessive size or bureaucracy (King & Levine, 1993; Sevil et al., 2022). Together, these forms capture the dual view that both small startups and large incumbents can be engines of innovation, but through different mechanisms and under different conditions (Guerrero & Siegel, 2024).

Thus, effect of innovation capabilities on firm performance may depend on firm size (Hall et al., 2010). Smaller firms (Mark I) innovate through agility and disruption, while larger firms (Mark II) rely on resources and structured R&D (Sevil et al., 2022). This suggests the strength of the innovation–performance link varies by firm size. Beyond the impact of the innovation capabilities collectively in Hypothesis 1, we expect the magnitude to differ by firm size. Therefore:

Hypothesis 2. Innovation capabilities are positively associated with firm performance, with the strength of this relationship differing between Mark I and Mark II patterns.

Innovation Capabilities and Their Proximity

Given the existence of several systematic reviews on the innovation capabilities literature the following findings have emerged. Iddris (2016) found that studies from 2000 to 2015 on innovation capabilities are primarily investigated at the firm-level (90 % of the studies) followed by network or supply chain levels. Furthermore, Mendoza-Silva (2021) reports that majority of empirical studies are subject to two clear biases. First, the studies are influenced by selection bias (i.e., their primary focus is on firms sampled from developed countries). Second, in most studies, the methodological apparatus is influenced by common method bias (i.e., researchers used subjective data collection method to obtain data from questionnaires). This suggests that future research should investigate measures of innovation capabilities by considering both objective indicators (e.g., patents) that are verifiable, as well as subjective indicators (e.g., managerial ratings) that are self-reported. Next, Moreira et al. (2024), based on the studies published until the end of 2022, concluded that there is no one-size-fits-all conceptualization of innovation capabilities dimensions. They suggest that subsequent studies should investigate the ontological, such as the proximity of capabilities we argue here, and axiological dimensions surrounding the intricacies of the innovation capability domain.

Innovation capabilities (at the firm-level) are not simply the sum of individual or interpersonal capabilities (Salvato & Vassolo, 2018). They reflect the capacity to leverage resources, knowledge, and organizational processes to transform inputs (e.g., R&D investments) into outputs (e.g., patents) that enhance performance and competitive advantage (Piñeiro-Chousa et al., 2025). While individual actions influence innovation, firm-level capabilities emerge from dynamic interactions, coordination, and synergy within teams and management, rather than from any single contributor or metric (López-Cabarcos et al., 2019).

This ontological perspective suggests that innovation capabilities are positioned along three dimensions based on their proximity to firm performance. Proximal capabilities are *closely* linked to measurable innovation outcomes (e.g., patents) and directly reflect a firm's ability to generate value from innovation (Rubera et al., 2016; Wei & Lau, 2010). Distal capabilities (e.g., investment in knowledge acquisition), on the other hand, represent inputs or antecedent activities that support innovation from distant mechanism compared to proximal capabilities (Menor et al., 2007; Simonin & Özsomer, 2009). While distal capabilities are critical for building the foundation for innovation, their impact on performance is *indirectly* linked and may depend on how effectively they are translated into tangible innovation outputs. This suggests that there is a stochastic mechanism, where distal capabilities translate into proximal (Stam & Elfring, 2008; Tse et al., 2017; Wu et al., 2020). This translation process is captured by stochastic capabilities, which reflect the *combined* effect of distal and proximal mechanisms (Zhao & Chadwick, 2014; Zhou & Wu, 2010). Together, these dimensions of proximity capture both the processes and outcomes of a firm's innovation efforts, but their strength varies by alignment of the mechanism (Vandaie & Zaheer, 2014). Therefore:

Hypothesis 3. The positive association between innovation capabilities and firm performance varies depending on the proximity of innovation capabilities to firm performance.

Innovation Capabilities and Their Impact on Firm Performance

Innovation capabilities affect different types of firm performance. Firm performance is the extent to which a company achieves its strategic and operational objectives, including both *ex-post* (i.e., realized) and *ex-ante* (i.e., expected) outcomes (Souder et al., 2023). *Ex-post* financial performance metrics capture a firm's profitability, growth, and value creation (Pecko et al., 2025; Richard et al., 2009), while *ex-ante* measures reflect investors' expectations of future competitiveness and firm value (Ellis, 2006). Together, these metrics provide a comprehensive assessment of a firm's economic health and competitive success, serving as a key outcome for evaluating the effectiveness of capabilities such as innovation (Harris, 2001).

Distal capabilities contribute to *ex-post* (i.e., realized) firm performance, driving revenue growth and profitability (Lestan et al., 2025; Mihalache et al., 2012). On the other hand, proximal capabilities, such as patents and product launches, enhance *ex-ante* (i.e., expected) firm performance, increasing market share and customer engagement (Vandaie & Zaheer, 2014).

Souder et. al. (2023) categorized the determinants of firm performance as precisely defined, flexible, scaled or unscaled. This suggests that the effect of innovation capabilities on firm performance may depend on how performance is measured. Metrics that capture precisely defined outcomes (i.e., based on observation), such as profitability are likely to reflect the impact of innovation capabilities more directly than flexible (i.e., based on expectations) measures, such as market capitalization. Therefore:

Hypothesis 4. The positive association between innovation capabilities and firm performance varies depending on whether firm performance is measured using ex-post or ex-ante indicators.

Mixed Evidence on Innovation Capabilities and Firm Performance

Previous evidence on the innovation capabilities–firm performance is heterogeneous and studies report mixed and inconsistent results, including positive (e.g., Knight & Kim, 2009), non-significant (e.g., Fey, 2005) and negative associations (e.g., Gruber et al., 2008). Therefore, we articulate several study-level moderators to the main effect presented in Hypothesis 1 and collectively we consider them Hypothesis 5.

Studies reporting positive relationship between innovation capabilities and firm performance include Andrade-Rojas et al. (2024); Branzei and Vertinsky (2006); Lee et al. (2001). For example, from 2 independent samples, with a total sample size of 5691 and 3627 firms in France and Great Britain respectively, Ballot et al. (2015) reported a significant and positive relationship. Arunachalam et al. (2018) reported positive and moderate association based on the 190 manufacturing SMEs in India using survey data showing that both number of new products and R&D intensity (i.e., stochastic innovation capabilities) are positively associated with profitability of these firms. Similarly, Deligianni et al. (2017) reports that product diversification and R&D intensity (i.e. distal innovation capabilities), both are positively associated with the revenue growth rate based on longitudinal study of 129 firms in Greece.

Insignificant associations between innovation capabilities and firm performance were reported by studies other than those mentioned above. Díaz-Díaz et al. (2008), found that proximal innovation capabilities and firm performance are non-significant. Gómez et al. (2020), found that some distal dimensions of innovation capabilities have insignificant relationship with firm performance, based on sample of 8554 firms in Spain. Zhang et al. (2019) used China Innovation Survey (CIS) data of 1406 firms between 2005 and 2007 and reported that stochastic innovation capabilities have no impact on profitability of firms and follow nonmonotonic inverted U-shaped pattern.

Negative relationships between innovation capabilities and firm performance are also found in several studies (Hock-Doepgen et al., 2024; Kathuria et al., 2023; Penner-Hahn & Shaver, 2005). Based on 10-K annual reports from 9100 firms between 1994 and 2017, Schäper et al. (2023) found innovation capabilities have significant, strong and negative effect on firm performance. Next, Choi et al. (2011), using cross-sectional design and objective data from the Shanghai Stock Exchange Statistics and Fact Book of Shenzhen Stock Exchange, reports that both R&D intensity and number of patents are negatively associated with *ex-post* performance measure such as the revenue growth rate based on 548 listed firms in China. Similarly, using the same cross-sectional study design and objective data from S&P's Compustat database, Saldanha et al. (2017) reported that R&D intensity is negatively associated with revenues of 310 listed firms in the USA. The same negative association pattern, using the stochastic mechanism, was observed in Finland based on the sample 93 small and large firms for the R&D intensity and *ex-post* growth (Laamanen, 2005).

The inconsistent relationships should be attributed to three potential reasons. First, the diversity of samples also influences the magnitude of the effect size. Shane (1995) noted that uncertainty-accepting societies are particularly highly associated with innovation than uncertainty-avoiding societies because of the greater tolerance for risk. That said, in cultures with low uncertainty avoidance values (i.e., accepting uncertainty), firms could be more willing to take risks and adopt novel strategies, which fosters a more innovative environment (Craighead et al., 2009; Karhade & Dong, 2021; Knight & Cavusgil, 2004). These firms could be more flexible in their approach to problem-solving and less averse to experimentation, enabling them to capitalize on innovation capabilities more effectively. Oppositely, in cultures with high uncertainty avoidance values (i.e., avoiding uncertainty), firms may be more risk-averse and focused on maintaining stability, which could hinder the full utilization of innovation capabilities (Arrighetti et al., 2014; Boehe & Cruz, 2010; Frank et al., 2016).

Second, the inconsistent results may be attributed to theories and frameworks used in the previous studies. Some studies used dynamic capabilities as theoretical framework (Messersmith & Guthrie, 2010; Oh et al., 2012; Rodríguez-Duarte et al., 2007), whereas, other theoretical frames of reference used were appropriability (Kim et al., 2012), organizational design (Koufteros et al., 2002), inducement-opportunities framework (Li & Atuahene-Gima, 2002) or social capital (Maurer et al., 2011).

Third, the inconsistent results may be attributed to research design used in the previous studies. Some studies employed cross-sectional design (Gerasymenko et al., 2015; Hashai, 2011; McKelvie et al., 2018; Vorhies et al., 2011; Zhou et al., 2006, 2014; Zollo & Reuer, 2010), while other focused on the "time" dimensions through a longitudinal setup (Patel et al., 2015; Schubert & Tavassoli, 2020; Tatikonda et al., 2013). Given all these differences in previous studies, we expect that there will be moderation at the study-level. Therefore:

Hypothesis 5. At the study-level, the positive association between innovation capabilities and firm performance varies depending on the (a) uncertainty avoidance of the sample studied, (b) theoretical frameworks employed, and (c) study design.

Methodology

We systematically conducted a meta-analysis to address our research questions. This method offers the advantage of integrating results from multiple independent studies, many of which individually lack sufficient sample sizes or precise effect estimates (Cooper et al., 2019; Geyskens et al., 2009). By combining zero-order correlations coefficients and accounting for heterogeneity across studies, meta-analysis provides a more reliable estimate of the true relationship (Field & Gillett, 2010). All materials supporting findings of this study are available on the OSF repository (https://osf.io/z4bqx/).

Systematic Review

Search Strategy

We followed the latest 'Preferred Reporting Items for Systematic Reviews and Meta-Analyses' (PRISMA) guidelines and developed a four-step approach (Page et al., 2021). Adopting the latest search strategy proposed by Bergh et al. (2024), we focused exclusively on empirical studies published in the double-blind reviewed journals (in line with Geyskens et al. 2006 and Vanneste et al. 2014), which are known for their rigorous review process and high-quality publications. This approach ensured a reliable foundation for a robust and credible meta-analysis.

First, we performed topic search (i.e., Title, Keywords and Abstract) in the Web of Science and Scopus registers on September the 11th, 2024. The search string used were: ("innovation" AND "capabilit*" [to capture studies on capability or capabilities] AND "performance,"). This resulted in 1359 identified records from both registers. Then we removed 151 duplicates (identical or redundant[2] studies) leaving us with 1208 unique records. Next, we removed 16 records (i.e., 8 systematic reviews, 3 meta-analysis and 5 retracted[3] studies) not relevant for our study. This left us with 1192 records for full-text screening. We then screened full text of 1192 records. We initially could not retrieve two studies (Adbi et al., 2022; McGee & Dowling, 1994), but our scholarly network obtained and shared them with us upon request. We excluded 992 records due to several theoretical and methodological reasons, such as wrong study designs (i.e., not empirical), wrong publication types (i.e., professional business magazines), wrong populations (i.e., country- or industry-level studies), and wrong study outcomes (i.e., not firm-level performance). In the first pass with these criteria, we identified 200 studies relevant for our meta-analysis. Next, we excluded 148 studies to maintain quality (see 3.1.2. Inclusion Criteria) and non-independence (see 3.1.3. Non-independence Selection Criteria) because *"even one red sock (*i.e.*, bad study) amongst the white clothes (*i.e.*, good studies) can ruin the laundry* (Field & Gillett, 2010, p.667)". This left us with a final sample of 52 primary studies consisting of 54 independent samples, covering studies published in the period between 2001 and 2024, yielding 320,529 unique firms already investigated from 19 countries.

Second, we also searched for unpublished studies to avoid common method bias, using scholarly network of >10,000 scholars. We posted multiple calls for unpublished studies at various research societies and academies, investigating innovation capabilities and firm performance.

Third, since this was the first attempt, we argue here, to meta-analyse the innovation capabilities–firm performance relationship (using number of published meta-analyses as an indicator), we examined the references listed in the previous systematic reviews on innovation capabilities (Iddris, 2016; Mendoza-Silva, 2021; Moreira et al., 2024) and firm performance (Fainshmidt et al., 2016; Karna et al., 2016; Schilke et al., 2018) to find additional studies.

Finally, we used the 'snowballing' techniques, including backward (i.e., references) and forward (i.e., citations) tracking of each relevant article identified previously to find additional studies. Fig. 1 portrays the inclusion and study-selection procedure based on the PRISMA framework used in this study.

Inclusion Criteria

We included studies that met three criteria. First, studies had to examine both subjective and objective measures of innovation capabilities with firm performance metrics at the firm-level consistent with prior construct definitions (Ellis, 2006; Richard et al., 2009; Souder et al., 2023). Thus, we included studies with samples of firms (i.e., businesses and corporate entities) and excluded studies with samples of government agencies (Arora & Nandkumar 2012), universities (Slavova et al., 2016) or non-profit organizations (Mendoza-Abarca & Gras, 2019), for example. Additionally, we excluded studies with focal outcomes of the study beyond firm-level such as the alliance-level (Jiang et al., 2010), region-level (Mewes & Broekel, 2022) or industry-level (Mol, 2005). To reduce potential reverse causality, studies had to predict and test Schumpeter's hypotheses of innovation capabilities with firm performance at least simultaneously (i.e., one-way); studies that explored the effect of firm performance either *a priori* or *a posteriori* on innovation capabilities (e.g., Subramaniam & Youndt, 2005) were excluded from our sample.

Second, we included studies that reported the sample size (i.e., number of firms rather than firm-year observations in longitudinal setup) with Pearson rather than Spearman correlations (see Demirkan & Demirkan, 2012, for a practical application of both) because they align better with our meta-analysis, assuming linear one-way relationship between innovation capabilities and firm performance metrics. Sample sizes and correlation coefficients were needed because these values are required for calculating their effect size. Some studies were under-reported and lacked information about their sample size (i.e.,

[1] The same study published multiple times, either in different journals or under slightly altered titles.

[2] A study formally withdrawn from the scientific record due to errors, ethical issues, or misconduct.

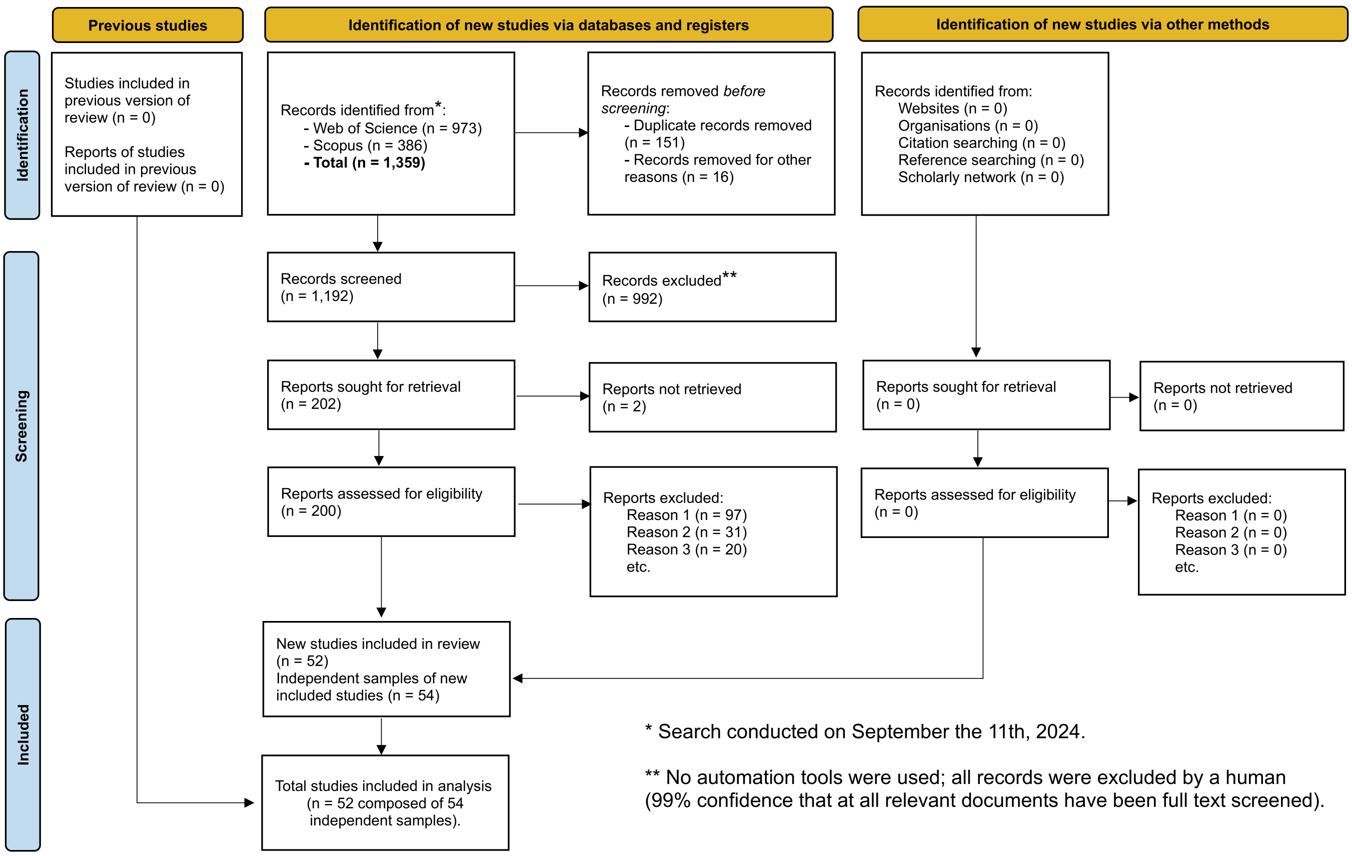

Fig. 1. PRISMA diagram for this meta-analysis which included searches of databases, registers and other sources.

number of unique firms) or did not report correlation matrices needed to calculate effect size. We contacted[4] authors of these studies and collected missing or under-reported data.

Third, we included studies with between firm-level research design (i.e., inter-firm differences between corporate parents or business units) rather than divisions or departments (i.e., intra-firm differences) within a single firm, as we do not report differences in findings within a single firm and its divisions or departments.

Non-independence Selection Criteria

To minimize confirmation bias, studies were coded by two experts independently. Coders agreed on 98 percent of initial codes, and discrepancies were resolved via discussion. We used three criteria to ensure that our meta-analysis offer an acceptable level of independence among correlation coefficients in our data set because many studies were based on overlapping datasets. First, for studies with multiple independent samples (Ballot et al., 2015; Zhou et al., 2014); correlation coefficients from each sample were included in our data set. Second, for studies with more than one correlation coefficient for a single relationship (because scholars either tested several performance metrics or involved multiple operationalizations of the same innovation capability constructs, for instance), we included all these correlations in our dataset and aggregated average effect size. Third, when studies relied on the same or overlapping data sources (e.g., Compustat, the Spanish Survey of Business Strategy), we included only one correlation coefficient in our meta-analysis. Specifically, we selected the correlation from the study with the largest sample size. If sample sizes were identical, we prioritized the correlation from the oldest study. However, if overlapping data sources were complemented by unique, self-conducted survey data that linked primary and secondary sources, we included both correlations in our analysis.

These procedures reduced 200 identified records assessed for our meta-analysis to final sample of 52 studies consisting of 54 independent samples. To make a qualitative assessment of the 54 independent samples to show the relevance of conducting a meta-analysis, and to derive suitable moderator variables for the meta-analysis, we present details of the included studies in supplementary Table A1. Collectively, these samples consist of 320,529 independent firms already investigated from 19 countries.

Measurements of Innovation Capabilities and Firm Performance

After reviewing the included studies, we grouped innovation capabilities into three categories: (i) distal, (ii) proximal and (iii) stochastic (i.e., distal and proximal linked in one-way). We focused on how constructs were measured, not labelled. For example, (Deligianni et al., 2017; Zhou & Wu, 2010) use ‘technological capabilities,’ while, (Chittoor et al., 2009) use ’innovation capability’ as their primary construct but these two different constructs were measured using the same indicator: R&D intensity. Therefore, we focus on the indicators of measurement rather than labels. Distal innovation capabilities indicate a measurement that include indicators of innovation inputs, while

[3] We remain thankful to the authors of three under-reported studies in our meta-analysis who provided data upon request. The initial contact was 28 October 2024; first reminders were sent on 31 October 2024; and the final (second) reminders were sent on 3 November 2024. We collected missing information for three out of three under-reported primary studies relevant for our meta-analysis leaving us with 100% response rate. First, Schäper et al. (2023) provided sample size (n=9,100) which has not been originally reported in their study. Second, Arrighetti et al. (2014) provided some correlations which have not been originally reported in their study, and Ballot et al. (2015) provided correlations for two independent samples of French and UK firms.

proximal innovation capabilities indicate a measurement that include dimensions of innovation outputs. A summary of mentioned variables is portrayed in Table 1.

We categorized firm performance into three groups: (i) *ex-post*, (ii) *ex-ante* (iii) combination of both. We focus on economic financial performance. When scholars focused on non-financial performance (Hulland et al., 2007), we omit these in the interests of being precise. *Ex-ante* performance indicates a metric that include dimensions of market-based measurement (i.e., Tobin's Q, Market-to-Book Value, Dynamic value). *Ex-post* performance indicates a metric that include dimensions of accounting-based measurement (i.e., based on realized observations). Nonetheless, we focus on studies that reflect measures of innovation capabilities and firm performance as simple, univariate single-order measurements or several, multivariate lower-order partials of the objective and subjective measures. We report difference in these measurements.

Table 1
Constructs operationalization of innovation capabilities and firm performance.

Construct	Measurement	Specific indicator
Innovation Capabilities	**Distal** (i.e., inputs or antecedent activities)	- R&D Expenditures (Li & Atuahene-Gima, 2002) - R&D Intensities (Deligianni et al., 2017) - R&D Manpower (Arrighetti et al., 2014) - Training Expenditures (Simonin & Özsomer, 2009) - # of conceptualization projects (Craighead et al., 2009) - Investment in machinery and external knowledge (Menor et al., 2007) - Expenditure on new products/ service development (Kim et al., 2012)
	Proximal (i.e., outputs or measurable outcomes)	- Patent applications (Rodríguez-Duarte et al., 2007) - Patent citations (Wu et al., 2020) - # of Patents (Fey, 2005) - Licenses Granted (Frank et al., 2016) - Labor Productivity (Patel et al., 2015) - Share of new products/services (Zhou & Wu, 2010) - # of new products/service (Arunachalam et al., 2018) - % of sales of new products/ services (McKelvie et al., 2018)
Firm Performance	***Ex-post*** (i.e., realized based on observed performance)	- Revenues or Sales (Penner-Hahn & Shaver, 2005) - Profit (Tatikonda et al., 2013) - Revenue Growth Rate (Hock-Doepgen et al., 2024) - Output Growth Rate (Mihalache et al., 2012) - Economic Value Added (Branzei & Vertinsky, 2006) - Return on Assets (Zhao & Chadwick, 2014) - Return on Equity (Deligianni et al., 2017) - Return on Sales (Schäper et al., 2023) - Total Shareholder Return (Menor et al., 2007)
	Ex-ante (i.e., based on expectations of future performance)	- Dynamic Value (Gerasymenko et al., 2015) - Tobin's Q (Schäper et al., 2023) - Market-to-Book Value (Zollo & Reuer, 2010)

Meta-Analytical Estimation

We conducted a meta-analysis of zero-order correlations using a random-effects model with Fisher's (z) transformation of these correlations (Hunter & Schmidt, 2000). First, we calculated the effect sizes by transforming observed zero-order correlation coefficients (r_i), that are biased in small samples, negatively skewed, and have a variance formula with inconvenient properties to Fisher's (z) as expressed in equation one:

$$\boldsymbol{Fisher's}(\boldsymbol{z}) = \frac{1}{2} \times \ln\left(\frac{1+r_i}{1-r_i}\right) \tag{1}$$

Using Fisher's (z) we obtain an effect size statistic that is less biased and affected by skewness (Borenstein et al., 2009). We then obtain the variance of Fisher's (z) as expressed in equation two:

$$\boldsymbol{Variance}_{\boldsymbol{Fisher's}\ (Z)} = \frac{1}{n-3} \tag{2}$$

We then have the variance of Fisher's (z), where (n) is the sample size used to compute the correlation. Results were back transformed to the correlation metric for interpretation as expressed in equation three:

$$\hat{\boldsymbol{r}}_{\boldsymbol{i}} = \frac{e^{2z_i} - 1}{e^{2z_i} + 1} \tag{3}$$

For our univariate meta-analysis, we combine the transformed Fisher's (z) correlations into a mean effect by taking their weighted average, where the weight of a study sample is inversely proportional to its variance as proposed by Hunter and Schmidt (2004). The estimated variance of the weighted mean is the reciprocal of the sum of the weights. We calculated the weighted mean effect using study sample sizes as weights as expressed in equation four:

$$\bar{\boldsymbol{z}} = \frac{\sum_{i=1}^{k} n_i z_i}{\sum_{i=1}^{k} n_i} \tag{4}$$

Next, we quantified the total variability of effect sizes across studies by calculating the observed variance, which reflects both sampling error and true differences between study populations. This observed variance was computed as the weighted sum of squared deviations of each study's effect from the weighted mean, divided by the total sum of weights as expressed in equation five:

$$\boldsymbol{S}^2_{\boldsymbol{obs}} = \frac{\sum_{i=1}^{k} n_i (z_i - \bar{z})^2}{\sum_{i=1}^{k} n_i} \tag{5}$$

Next, we estimated the portion of variance attributable to sampling error within studies. The mean sampling-error variance quantifies the variation expected purely from within-study error and was calculated as the weighted average of the individual study variances as expressed in equation six:

$$\overline{\boldsymbol{V}_{\boldsymbol{samp}}} = \frac{\sum_{i=1}^{k} n_i v_i}{\sum_{i=1}^{k} n_i} \tag{6}$$

where v_i is the variance of the Fisher's z-transformed correlation for study (i) and (n_i) is its sample size. Subtracting this mean sampling-error variance from the observed variance (S^2_{obs}) isolates the component of variability attributable to true heterogeneity among studies. Next, the between-study variance represents the variability in true effect sizes across studies, beyond what is expected from sampling error. It was calculated as expressed in equation seven:

$$\boldsymbol{\tau}^2 = \max\left(0, S^2_{obs} - \overline{V_{samp}}\right), \ \tau = \sqrt{\tau^2} \tag{7}$$

If the observed variance (S^2_{obs}) is smaller than the mean sampling-error variance $(\overline{V_{\text{samp}}})$, (τ^2) is set to zero. The square root, (τ), represents the standard deviation of the true correlations across studies. To quantify variability across studies, we computed Cochran's Q, which tests whether the observed dispersion of effect sizes exceeds what would be expected from sampling error alone as expressed in equation eight:

$$\boldsymbol{Q} = \sum_{i=1}^{k} w_i (z_i - \bar{z})^2, \; w_i = n_i \tag{8}$$

where (w_i) is the weight of study (i) (sample size for Hunter–Schmidt weighting), (z_i) is the Fisher's z-transformed effect size, and $(\bar{z})$ is the weighted mean effect. The degrees of freedom are $(df = k - 1)$, and (Q) follows a chi-square distribution. The proportion of total variance attributable to true heterogeneity was calculated using the (I^2) statistic as expressed in equation nine:

$$\boldsymbol{I}^2 = \frac{Q - df}{Q} \times \; 100\% \tag{9}$$

Where values near 0 % indicate low heterogeneity, while values closer to 100 % indicate that most of the variability reflects true differences among studies rather than sampling error. We used the function 'metacor' from the 'meta' package in RStudio for the calculation of the overall effect size (Harrer et al., 2021). It is a standardized measure of the magnitude of observed effects within collected studies in the developed dataset (Field & Gillett, 2010).

Prior studies used different measures, designs and samples; therefore, we used the same 'metacor' function while providing additional arguments in the subgroup analyses for the moderator analyses. They allowed us to collectively test hypotheses H2, H3, H4, and H5A to H5C, describing why studies focusing on proximal innovation metrics (e.g., patents) produces lower or higher effects than studies focusing on distal outcomes (e.g., R&D spendings), for example. The data structure included four main subgroups of moderators: (i) decomposed form of Schumpeter's hypothesis (three levels as Mark I, Mark II or combination of Mark I & II); (ii) capability proximity (three levels as distal; proximal; stochastic); (iii) performance metrics (three levels as ex-post; ex-ante; combination of both); and (iv) study-level moderators, such as uncertainty avoidance of the samples (two levels as high and low[5]); dynamic capabilities framework in the theoretical background of the study (two levels as yes or no); and study design (two levels as longitudinal and cross-sectional).

Common concern in meta-analyses is that effect sizes in the studies with smaller samples, cross-sectional designs or with subjective measures impact the magnitude of the overall effect size (IntHout et al., 2015; Rothstein et al., 2005). To address this, we conduct supplementary *post-hoc* tests to gain a deeper understanding of how various contextual considerations (e.g., study-level quality and measures) might influence the observed magnitude of the relationship between the innovation capabilities and firm performance.

Results

The Overall Schumpeter's Hypothesis

In Hypothesis 1, we predicted that innovation capabilities are positively associated with firm performance (the Schumpeter hypothesis taken as whole). In full support of Hypothesis 1, our meta-analysis results for each study's effect size, and the aggregate effect size for all studies, are presented graphically as a forest plot in Fig. 2. A total of 54 samples were included, providing 320,529 observations. The results show that while most effect sizes are positive, some studies report small or negligible effects. The aggregate effect size of the overall relationship is positive ($\hat{r} = 0.11$; $p < 0.001$, 95 % CI = [0.09, 0.13]), suggesting that, on average, innovation capabilities are positively associated with firm performance.

However, substantial heterogeneity was observed across studies ($Q = 762.34$, df = 53, $p < 0.001$; $I^2 = 93.0$ %, 95 % CI = [91.7 %, 94.2 %]), indicating that the strength of this relationship varies depending on study-specific factors such as the type of innovation capabilities assessed, and the measures of firm performance used. The random-effects model accounted for between-study variance ($\tau^2 = 0.0022$, 95 % CI = [0.0091, 0.0237]; $\tau = 0.047$, 95 % CI = [0.0955, 0.1540]), and all correlations were transformed using Fisher's z prior to analysis.

The 'Narrow' Version of the Schumpeter's Hypothesis

In Hypothesis 2, we predict that innovation capabilities are positively associated with firm performance, with the strength of this relationship differing between Mark I and Mark II hypotheses (i.e., the decomposed form of the Schumpeter hypothesis). Our results provide partial support for Hypothesis 2. We find that the positive effect of innovation capabilities on firm performance was strongest for Mark I hypothesis (i.e., creative destruction), where the aggregated effect size was positive and moderate ($\hat{r} = 0.15$; 95 % CI = [0.08, 0.23]; $k = 11$), with substantial heterogeneity ($Q = 86.95$, $I^2 = 88.5$ %). Studies examining both Mark I & II hypotheses also showed a positive, moderate relationship ($\hat{r} = 0.13$; 95 % CI = [0.11, 0.15]; $k = 30$), though heterogeneity remained high ($Q = 519.28$, $I^2 = 94.4$ %). In contrast, studies focusing exclusively on Mark II hypotheses (i.e., creative accumulation) hypothesis reported essentially no effect ($\hat{r} = -0.0002$; 95 % CI = [−0.03, 0.03]; $k = 13$) with lower heterogeneity ($Q = 21.17$, $I^2 = 43.3$ %). The results for the overall and 'narrow' forms of the Schumpeter hypothesis are illustrated in Fig. 3.

A test for subgroup differences indicated that the relationship between innovation capabilities and firm performance varies significantly across the subgroups of Schumpeterian hypotheses ($Q = 60.68$, df = 2, $p < 0.001$), suggesting that the type of hypothesis considered is an important moderator of the overall effect. All analyses were conducted using a random-effects model with inverse-variance weighting, Hunter-Schmidt estimation of τ^2, and Fisher's z-transformed correlations.

Potential publication or reporting bias in the relationship between innovation capabilities and firm performance was examined using funnel plots. As shown in Fig. 3, the distribution of effect sizes appears reasonably symmetrical across different forms of Schumpeterian hypothesis, providing an initial visual indication of low bias in the included studies.

Proximity of Innovation Capabilities and Firm Performance

In Hypothesis 3, we predicted that the positive association between innovation capabilities and firm performance varies depending on the proximity of innovation capabilities (i.e., stochastic, distal, and proximal) to firm performance. In full support of Hypothesis 3, our results and the test for subgroup differences indicated that the strength of the relationship between innovation capabilities and firm performance varies significantly by capability proximity ($Q = 7.84$, df = 2, $p = 0.020$), suggesting that proximal innovation capabilities are generally associated with the strongest performance effects ($\hat{r} = 0.21$; 95 % CI = [0.04, 0.36]; $k = 5$), though heterogeneity remained high ($Q = 79.57$, $I^2 = 95.0$ %). The results for each subgroup are presented in Table 2.

For stochastic proximity of innovation capabilities, the aggregate effect size was small but positive ($\hat{r} = 0.07$; 95 % CI = [0.05, 0.08]; $k = 28$), with substantial heterogeneity across studies ($Q = 187.86$, $I^2 = 85.6$ %). Distal proximity of innovation capabilities showed a stronger positive relationship ($\hat{r} = 0.14$; 95 % CI = [0.08, 0.20]; $k = 21$) and higher heterogeneity ($Q = 400.88$, $I^2 = 95.0$ %).

[4] Samples with low uncertainty avoidance culture values consists of: India, Great Britain, Canada, China, USA, Greece, Finland, Sweden, the Netherlands (Hofstede's Index below 60); on the other hand, countries with high uncertainty avoidance culture values consists of: Mexico, Italy, France, Brazil, Spain, Germany, Israel, South Korea, Turkey, Japan (Hofstede's Index greater than 60).

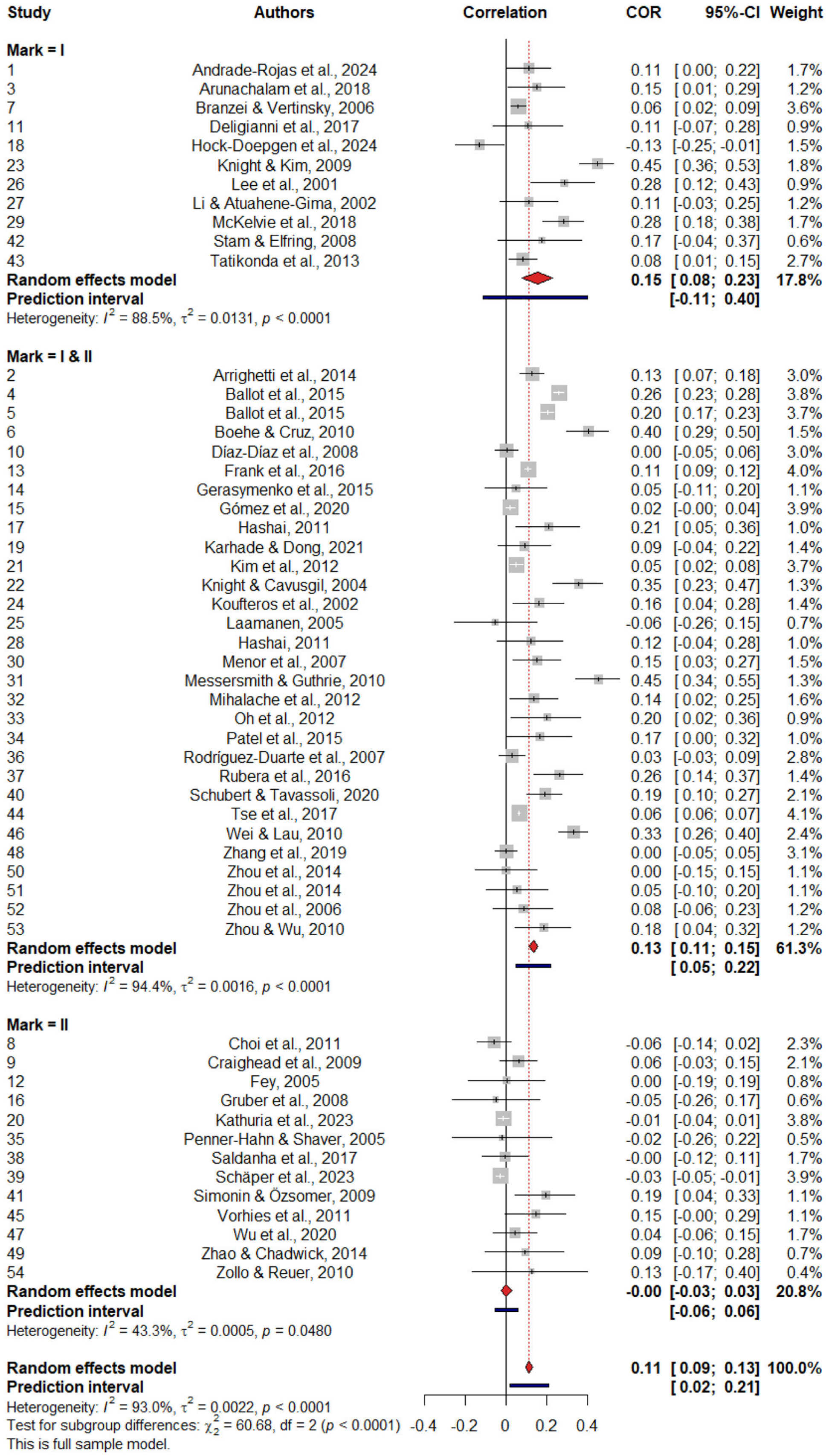

Fig. 2. Forest Plot of All Included Studies.Note: The figure presents the effect sizes (Fisher's z correlation) with 95 % confidence intervals for the relationship between innovation capabilities and firm performance divided into subgroups based on the Schumpeterian hypothesis.

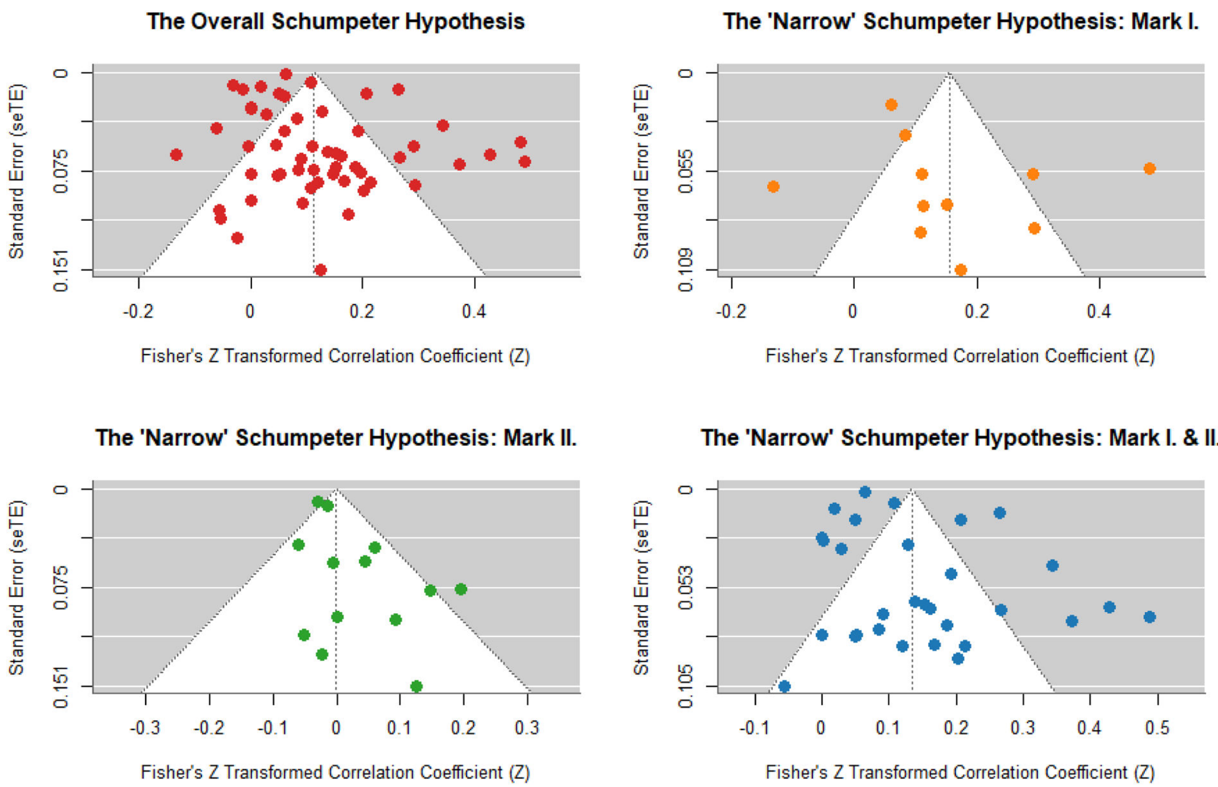

Fig. 3. Funnel plots for the association between innovation capabilities and firm performance.

Innovation Capabilities and Measurements of Firm Performance

In Hypothesis 4, we predicted that the positive association between innovation capabilities and firm performance varies depending on whether firm performance is measured using *ex-post* or *ex-ante* indicators. Our results are illustrated in Table 2. and provide full support for Hypothesis 4. Studies using *ex-post* measures showed a positive relationship ($\hat{r} = 0.12$; 95 % CI = [0.10, 0.14]; $k = 51$) with substantial heterogeneity ($Q = 671.81$, $I^2 = 92.6$ %). Albeit, one study used an *ex-ante* measure, reporting a small and non-significant effect ($\hat{r} = 0.05$; 95 % CI = [−0.11, 0.20]; $k = 1$). Two studies combining both measures showed a slightly negative effect ($\hat{r} = -0.03$; 95 % CI = [−0.05, −0.01]; $k = 2$) with low heterogeneity ($Q = 1.06$, $I^2 = 5.8$ %). A test for subgroup differences indicated that the type of performance measure significantly moderates the relationship between innovation capabilities and firm performance ($Q = 110.03$, df = 2, $p < 0.001$).

Study-level Moderator Analyses

In Hypothesis 5, we predicted, at the study-level, that the positive association between innovation capabilities and firm performance varies depending on the (a) uncertainty avoidance of the sample, (b) theoretical frameworks employed, and (c) study design. In partial support of the Hypothesis 5, our results are presented in Table 2. and indicate that only study design shows significant moderation, whereas uncertainty avoidance and theoretical framework not significant.

First, by comparing studies from low- and high-uncertainty avoidance cultures, we used uncertainty avoidance index (UAI). The mean effect size was positive and significant for both high-UAI ($\hat{r} = 0.116$, 95 % CI [.071, 0.160]) and low-UAI samples ($\hat{r} = 0.108$, 95 % CI [.087, 0.128]). However, the difference between groups was not statistically significant ($Q = 0.10$, $p = .75$), suggesting that the relationship between innovation capabilities and firm performance does not vary significantly across samples differing in their uncertainty avoidance.

Second, we examined whether the theoretical framework adopted in primary studies moderated the innovation capabilities–firm performance relationship. Studies using a dynamic capabilities framework ($\hat{r} = 0.113$, 95 % CI [.090, 0.137]) and those employing alternative frameworks ($\hat{r} = 0.113$, 95 % CI [.076, 0.149]) showed nearly identical effects. The difference between groups was not statistically significant ($Q = 0.00$, $p = .99$), indicating that the relationship between innovation capabilities and firm performance is consistent regardless of theoretical background.

Finally, we tested the moderating role of study design. Cross-sectional studies reported a significantly stronger relationship ($\hat{r} = 0.152$, 95 % CI [.095, 0.208]) than longitudinal studies ($\hat{r} = 0.083$, 95 % CI [.061, 0.104]), with the between-group difference statistically significant ($Q = 4.92$, $p = .03$). This suggests that the innovation capabilities–firm performance link tends to appear stronger in cross-sectional settings, potentially reflecting short-term associations, while longitudinal study designs yield more conservative estimates over time.

Post-hoc Tests and Robustness Checks

A post hoc analysis compared studies using unidimensional versus multidimensional measures of innovation capabilities as well as study quality. In the first stance, the results revealed a significant difference between the two groups of dimensionalities ($Q = 9.16$, $p = .003$). Studies using unidimensional indicators ($\hat{r} = 0.154$, 95 % CI [.098, 0.210]) reported substantially stronger relationships with firm performance than those employing multidimensional measures ($\hat{r} = 0.063$, 95 % CI [.047, 0.079]). This suggests that broader, multidimensional operationalizations of innovation capabilities may dilute the direct performance effect observed in narrowly defined, single-dimension indicators.

Next, we analysed whether study quality, based on AJG 2024 journal ranking, moderates the innovation capabilities–firm performance relationship. Studies in level four-star journals ($\hat{r} = 0.100$, 95 % CI [.081, 0.119]) reported lower effect sizes compared to lower-ranked journals (level 4: $\hat{r} = 0.182$; level 3: $\hat{r} = 0.281$), though the between-group difference was marginally non-significant ($Q = 5.87$, $p = .053$). This

Table 2
Meta-Analyses of the innovation capabilities and firm performance relationship.

	Overall Effect and Within-Subgroup Statistics										Between-subgroup statistics	
Meta-Analytical Variables	*K*	*N*	$\hat{r}$	SE	LLCI	ULCI	τ^2	I^2	(Q)	*p-value*	*p-value*	Q
Overall Schumpeter Hypothesis	**54**	**320,529**	**0.1135**	**0.0096**	**0.0947**	**0.1322**	**0.0022**	**93 %**	**762.3367**	**< 0.0001**	**< 0.0001**	**60.68**
Mark I.	11	5847	**0.1548**	0.0397	0.0769	0.2327	0.1143	88.50 %	86.9485	**< 0.0001**		
Mark I. & II.	30	297,628	**0.1340**	0.0111	0.1122	0.1558	0.0406	94.42 %	519.2755	**< 0.0001**		
Mark II.	13	17,054	**−0.0002**	0.0138	−0.0272	0.0268	0.0219	43.31 %	21.1663	**0.0480**		
Proximity of Capabilities											**0.0198**	**7.84**
Stochastic	28	296,357	**0.0653**	0.0081	0.0494	0.0813	0.0232	85.63 %	187.8645	**< 0.0001**		
Distal	21	21,913	**0.1418**	0.0327	0.0777	0.2058	0.1319	95.01 %	400.8804	**< 0.0001**		
Proximal	5	2259	**0.2097**	0.0848	0.0434	0.3759	0.1823	94.97 %	79.5749	**< 0.0001**		
Performance Measures											**< 0.0001**	**110.13**
Ex-post	51	311,219	**0.1193**	0.0095	0.1006	0.138	0.0447	92.56 %	671.8138	**< 0.0001**		
Ex-ante	1	163	**0.0490**	0.0791	−0.1059	0.204	*NA*	*NA*	*NA*	***NA***		
Both	2	9147	**−0.0293**	0.0105	−0.0498	−0.0088	0.0000	5.76 %	1.0611	**0.3030**		
Uncertainty Avoidance											**0.7528**	**0.10**
High	19	40,861	**0.1163**	0.0230	0.0711	0.1614	0.0823	93.9 %	295.3102	**< 0.0001**		
Low	35	279,668	**0.1083**	0.0106	0.0876	0.1290	0.0366	91.7 %	409.4932	**< 0.0001**		
Dynamic Capabilities Frame											**0.9856**	**0.00**
No	33	61,930	**0.1134**	0.0189	0.0764	0.1505	0.0917	94.22 %	553.2201	**< 0.0001**		
Yes	21	258,599	**0.1138**	0.0120	0.0903	0.1374	0.0262	89.91 %	198.2960	**< 0.0001**		
Study Design											**0.0265**	**4.92**
Longitudinal	22	312,310	**0.0830**	0.0110	0.0615	0.1046	0.0394	95.86 %	507.4288	**< 0.0001**		
Cross-sectional	32	8219	**0.1530**	0.0296	0.0950	0.2109	0.1491	85.42 %	212.6076	**< 0.0001**		
Post hoc tests												
Study focus											**0.0025**	**9.16**
Multidimensional	26	295,998	**0.0635**	0.0082	0.0474	0.0796	0.0232	86.51 %	185.2682	**< 0.0001**		
Unidimensional	28	24,531	**0.1555**	0.0293	0.0981	0.2129	0.1389	94.60 %	499.8393	**< 0.0001**		
Study Quality – AJG24											**0.0532**	**5.87**
Level 4*	46	312,520	**0.1002**	0.0098	0.0811	0.1194	0.0423	92.57 %	605.6513	**< 0.0001**		
Level 3	2	516	**0.2891**	0.0973	0.0983	0.4798	0.1226	89.65 %	9.6596	**0.0019**		
Level 4	6	7493	**0.1838**	0.0549	0.0761	0.2914	0.1228	95.79 %	118.7913	**< 0.0001**		

Notes. ***K*** = number of effect sizes; ***N*** = total number of observations; $\hat{r}$ = estimate of correlation; **LLCI** = lower bound of confidence interval for $\hat{r}$ at 95%*;* **ULCI** = upper bound of confidence interval for $\hat{r}$ at 95%*;* **SE** = indicates the precision (standard error) of the estimated average effect size; smaller values reflect more precise estimates; τ^2 = variance of the true effect size (tau-squared); (**Q**) = Within-subgroup effect based on Hunter and Schmidt's (2004); I^2 = Percentage (%) of variation across studies that s due to heterogeneity rather than chance; **Q** = Between-group effect based on Hunter and Schmidt's (2004) chi-square test for heterogeneity.

pattern suggests that higher-quality publications may yield more conservative estimates of the innovation capabilities–firm performance link, potentially reflecting more stringent methodological standards.

These post-hoc tests highlight the complexity of the association between innovation capabilities and firm performance and do not fully capture the heterogeneity. Several factors, beyond the study quality and measures, significantly influence both the strength and direction of this association. The findings highlight the importance of considering these additional moderators when interpreting meta-analytic results and suggest that studies incorporating unidimensional measurements of innovation capabilities and reported in lower ranked journals may report stronger associations between innovation and firm performance.

Discussion

This study set out to clarify how, and under what conditions, innovation capabilities are associated with firm performance. Building on Schumpeterian view, capability proximity logic, and the distinction between *ex-ante* and *ex-post* performance metrics, our meta-analytic results provide a robust and comprehensive synthesis of a fragmented body of evidence. Below, we discuss the theoretical meaning of our findings considering prior research and evaluate each of the five predicted hypotheses.

Schumpeter's Hypothesis and the Overall Effect

Consistent with the foundational Schumpeterian view that innovation serves as a key engine of firm success (Cevik, 2025; Guichardaz & Pénin, 2025; Schumpeter, 1934), our results show that innovation capabilities are positively associated with firm performance on average, supporting Hypothesis 1. This aligns with past research demonstrating that innovative activity enables firms to create differentiation, respond to environmental shifts, and generate economic value (Guerrero & Siegel, 2024; López-Cabarcos et al., 2019).

Similarly, our results also reflect the mixed and sometimes contradictory patterns reported in prior studies, including positive (e.g., Andrade-Rojas et al. 2024; Arunachalam et al. 2018), insignificant (e.g., Gómez et al. 2020; Zhang et al. 2019), and even negative associations (e.g., Hock-Doepgen et al. 2024; Schäper et al. 2023). The substantial heterogeneity found in our analyses echoes these divergent findings, reinforcing longstanding arguments that the innovation capabilities–firm performance relationship is not universal but contingent on conceptual, methodological, and contextual factors (Piñeiro-Chousa et al., 2020; Yin et al., 2023). Our moderator analyses therefore provide an important extension of this literature by identifying where these divergences originate.

Moderating Effects

Decomposed Schumpeter's Hypothesis: Mark I and mark II

Our results provide partial support for Hypothesis 2 by showing that the strength of the innovation capabilities–firm performance association differs across Schumpeter Mark I and Mark II contexts. Specifically, we find a moderate positive association for studies aligned with the Mark I logic of creative destruction, where smaller, *entrepreneurial* firms rely on agility and experimentation to generate disruptive innovations (Guichardaz & Pénin, 2025). This pattern echoes evidence from Branzei and Vertinsky (2006), and Knight and Kim (2009), which document strong performance effects for innovation indicators in smaller or more flexible firms.

Conversely, the absence of a positive association between innovation capabilities and firm performance in Mark II settings suggests that large, established firms do not consistently convert innovation capabilities into performance gains, despite their greater resource endowments (Hall et al., 2010). This implies that, we argue here, again, *entrepreneurial*, not big firms alone benefit from innovation in their performance. This aligns with research showing that large firms may experience bureaucratic inertia or diminishing marginal returns on innovation spending (Sevil et al., 2022), and supports the claim that creative accumulation does not guarantee performance improvements (Choi et al., 2011; Kathuria et al., 2023).

Together, our findings confirm that firm size and innovation regime meaningfully impact the innovation capabilities–firm performance link, offering the first meta-analytic substantiation of the dual Schumpeterian logic at the firm-level.

Proximity of Innovation Capabilities

We find strong support for Hypothesis 3: the closer innovation capabilities are to actual innovation outputs, the stronger their association with firm performance. This insight directly reflects the ontological argument that capabilities differ in how immediately they translate into value creation (Moreira et al., 2024). Our results show that **p**roximal capabilities (e.g., patents, new products or services) impose the strongest effects. This supports prior work arguing that these indicators are tightly linked to value appropriation and commercialization outcomes (Ceccagnoli, 2009; Rubera et al., 2016). Further, distal capabilities (e.g., knowledge acquisition, or R&D investments) show moderate effects, consistent with research suggesting that they function as foundations for future innovation but do not guarantee immediate performance benefits (Menor et al., 2007; Simonin & Özsomer, 2009).

Finally, stochastic capabilities, reflecting a mixture of distal and proximal indicators, yield the weakest effects, aligning with evidence that their performance impact is uncertain and dependent on conversion mechanisms (Stam & Elfring, 2008; Zhou & Wu, 2010). Our results confirm that innovation capabilities are not homogeneous, that proximity matters, and that ontological distinctions offer a meaningful explanation for inconsistencies reported across primary studies (Mendoza-Silva, 2021; Moreira et al., 2024).

Innovation Capabilities and Ex-post vs. Ex-ante Firm Performance Measures

Our findings fully support Hypothesis 4: the type of performance metric used influences the observed effect of innovation capabilities. Studies using *ex-post*, realized performance indicators (e.g., profitability or revenue growth) show stronger and more consistent effects. This aligns with research suggesting that realized outcomes more directly capture the economic consequences of innovative activity (Richard et al., 2009; Souder et al., 2023). By contrast, *ex-ante*, expectation-based measures (e.g., market capitalization or total shareholder returns) which are both *highly* relevant for investors, produce much weaker associations. This reinforces the argument that investor expectations and market capitalization incorporate a wider set of intangible or forward-looking signals (Ellis, 2006; Harris, 2001), which may dilute the observable contribution of innovation. Therefore, our results empirically demonstrate that measurement decisions–long acknowledged as a source of variance in the literature–influence the conclusions drawn about whether, at all, innovation capabilities pay off.

Study-Level Moderators: Cultural, Theoretical, and Design Differences

Hypothesis 5 is partially supported. Dynamic capabilities framework and cultural uncertainty avoidance do *not* significantly differentiate effect sizes, despite long-standing arguments that cultural preferences for risk-taking or stability shape innovative behaviour (Knight & Cavusgil, 2004; Shane, 1995). This suggests that while culture influences innovation inputs, the performance outcomes of innovation capabilities may be more universal than previously assumed.

By contrast, study design significantly moderates effects. Cross-sectional studies show stronger relationships than longitudinal studies, consistent with concerns raised by IntHout et al. (2015), Rothstein et al. (2005) and others that short-term or contemporaneous designs may overestimate, in our case the firm performance benefits of innovation capabilities. Longitudinal studies, which capture time lags and reverse causality concerns (Patel et al., 2015), produce more conservative estimates, indicating that innovation payoffs may materialize gradually. Our finding advances the methodological debate by empirically demonstrating how research design contributes to mixed evidence in the field.

Post-Hoc Tests: Dimensionality and Study Quality

Our post-hoc analyses further explain the heterogeneity in prior research. Studies using unidimensional measures of innovation capabilities (i.e., single indicator) report much stronger performance effects than those employing multidimensional constructs (i.e., multiple indicators), suggesting that narrow measures (e.g., R&D intensity alone) may overstate innovation's contribution, whereas broader measures distribute effects across several underlying dimensions (Piñeiro-Chousa et al., 2025; Salvato & Vassolo, 2018).

Additionally, studies published in higher-ranked journals tend to report smaller effect sizes. This pattern likely reflects stronger methodological rigor and suggests that earlier or lower-ranked studies may have inflated the innovation capabilities–firm performance relationship. This insight is consistent with concerns about common method bias and selection bias in the innovation capabilities literature (Mendoza-Silva, 2021; Moreira et al., 2024).

Theoretical Contributions and Practical Implications

From the theoretical standpoint, this meta-analysis makes several contributions to the scholarly understanding of the Schumpeterian hypotheses and the broader innovation capabilities–firm performance relationship. First, by synthesizing evidence across more than two decades of empirical work (2001–2024), we provide the most comprehensive test-to-date of the overall Schumpeterian proposition that innovation capabilities are associated with firm performance. Our findings confirm a positive association, thereby offering cumulative support for a foundational assumption in innovation theory. Importantly, the study also clarifies persistent inconsistencies in prior research by demonstrating that the magnitude of the innovation capabilities–firm performance link varies substantially depending on the form of the Schumpeterian hypothesis examined. Whereas previous studies often treated Schumpeter Mark I and Mark II arguments interchangeably, our results show that creative destruction mechanisms (Mark I) tend to yield stronger performance outcomes than creative accumulation mechanisms (Mark II) alone. This distinction advances Schumpeterian theory by empirically validating heterogeneity between its two core traditions.

Second, by integrating capability proximity, performance measurement, and study-level characteristics, our analysis extends theoretical work on how and under what conditions innovation capabilities relate to performance benefits. We show that proximal capabilities–those directly involved in innovation outputs–produce the strongest performance effects, supporting theories that emphasize the value of capabilities closest to commercialization. In contrast, more remote or stochastic capabilities exhibit weaker relationships, clarifying conceptual debates about which types of capabilities matter most for firm success. Similarly, our analysis highlights the importance of measurement choices by demonstrating that *ex-post* performance indicators more reliably capture innovation impacts than *ex-ante* indicators.

Finally, the moderating influence of study design and measurement dimensionality reveals that theoretical conclusions in this domain are shaped not only by substantive mechanisms but also by methodological decisions. By identifying these boundary conditions, our study contributes to more precise theorizing about innovation capabilities and offers a structured agenda for future research seeking to explain variance in observed outcomes.

From the practical standpoint, the findings of this study offer several actionable insights for practitioners. First, firms should recognize that *not* all innovation capabilities are equally impactful: proximal capabilities, which directly generate innovation outputs such as patents or new products, for example, are more strongly linked to performance, whereas distal or stochastic capabilities play a supportive but *indirect* role. This suggests that managers should prioritize investments and processes that convert innovation inputs into tangible outputs. Second, the results illustrate that the effectiveness of innovation capabilities depends on firm context, including size and strategic orientation. Smaller, entrepreneurial firms may benefit most from agile, disruptive innovation (Mark I), while larger incumbents may need to carefully structure R&D and innovation processes to avoid inefficiencies associated with creative accumulation (Mark II). Finally, performance measurement matters (a lot!): relying solely on expectations-based indicators may understate the benefits of innovation, so managers are encouraged to track both *ex-post* and *ex-ante* outcomes to obtain a comprehensive view of innovation effectiveness. These insights can guide firms in designing targeted innovation strategies and inform policymakers seeking to foster competitive, innovation-driven economies.

Overall, this meta-analysis clarifies several long-debated issues surrounding the innovation capabilities–firm performance relationship. Innovation capabilities matter, but their impact depends on proximity, measurement choices, firm size regimes, and research design. By situating these findings within Schumpeterian theory and capability ontology, with this study, we intended to provide a more nuanced and integrated explanation for decades of mixed empirical evidence.

Conclusion

This study aimed to quantitatively determine the overall magnitude of the relationship between innovation capabilities and firm performance, and to explain why and under what conditions this relationship varies across studies. By synthesizing evidence from >320,000 firms through a systematic review and meta-analysis, we examined the Schumpeterian hypothesis in both its broad and ‘narrow’ forms, distinguishing between Mark I (i.e., creative destruction, typically associated with entrepreneurial firms disrupting incumbents) and Mark II (i.e., creative accumulation, typically associated with large firms building on existing capabilities). We also assessed how different proximity of innovation capabilities–from distal processes, such as investment in new knowledge, to proximal outputs, such as patents and new products–relate to performance outcomes. Similarly, we evaluated how different metrics of firm performance measurements vary in the strength of their association with innovation capabilities.

Our findings illustrate that innovation is positively associated with firm performance overall, but the strength of this relationship varies substantially depending on the theoretical, contextual and methodological contingencies. Notably, proximal capabilities, which directly generate tangible innovation outputs, show the most significant performance effects, while Mark I innovation patterns are more strongly associated with performance gains than Mark II patterns alone. These results offer a more nuanced and integrated understanding of the mechanisms through which innovation influence firm performance. Importantly, this research provides a robust empirical foundation for scholars and practitioners seeking clarity on when, how, and why innovation capabilities matter, reinforcing the practical value of targeted innovation investments and advancing theoretical debates surrounding Schumpeter’s legacy in contemporary innovation research.

Despite our contributions, several limitations should be acknowledged. First, the heterogeneity of studies included in the meta-analysis points to a potential area for future research. The observed variability suggests that at least one significant unexamined moderator that we have not investigated but it is influencing the relationship between innovation capabilities and firm performance. Therefore, future research should explore additional contextual factor alongside innovation, such as industry characteristics or technological conditions, that may shape these dynamics.

Second, we acknowledge that all our data are correlational, leaving open the possibility of reverse causality. This implies that firm performance could, in some cases, influence the firm-level capabilities coded as innovation. Although, we controlled for the one-way relationship between innovation capabilities and firm performance, we cannot directly test this alternative explanation. The substantial variation observed in our results suggests that any situational effects of firm performance on innovation capabilities are likely limited. Relatedly, we note that our data are all cross-sectional, making causal conclusions of innovation capabilities on firm-level performance open to critique.

We also note that prior research, based on the number of effect sizes reported, has predominantly focused on distal and stochastic innovation capabilities, in contrast to proximal when testing Schumpeter’s hypotheses. We suggest that future research and analysis, in our view, are needed to fully understand the nuances and implications of these findings within the context of innovation capabilities and firm performance.

To conclude, we hope that our work inspires a generation of scholars to extend our findings in several ways. First, researchers should investigate distinctions in innovation capabilities, including process-level versus outcome-level measures, and investigate longitudinal effects (e.g., cross-lagged meta-analysis) to better understand *the* timing and persistence of the association between innovation capabilities and firm performance. Second, scholars should expand our cross-country comparisons using richer cultural indices (e.g., long-term orientation) or broader institutional contexts to clarify *why* some innovations translate more effectively into performance than others. Finally, future research should incorporate multidimensional, dynamic, and context-sensitive measures of innovation capabilities to enhance the explanatory power of the Schumpeterian hypothesis identified in this meta-analysis.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript. The authors have no relevant financial or non-financial interests to disclose.

Ethics approval

Not applicable, as this study did not involve human or animal subjects.

Consent

Not applicable, since the study did not involve collection of data from human participants.

Data, material and/or code availability

The data from this study comprise statistics extracted from publicly available academic work. The sample and R code for replication of this study is available from the Open Science Framework (https://osf.io/z4bqx/).

CRediT authorship contribution statement

Filip Lestan: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Tommy H. Clausen:** Conceptualization, Supervision, Writing – original draft.

Declaration of competing interest

The authors declare no competing interests.

Acknowledgements

We thank two anonymous reviewers and Editor M. Angeles López-Cabarcos for their constructive comments on earlier versions. We are thankful to authors of three under-reported studies who provided data. Finally, we thank participants of the 45th SMS Annual Conference in San Francisco, the 85th Annual Meeting of the Academy of Management in Copenhagen, as well as Professors Dermot Breslin, Michal Kozak, Ut Na and Johan Wiklund for their valuable comments on earlier versions of this research. All remaining errors are ours.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jik.2026.100943.

References

Adbi, A., Liu, X., & Mishra, A. (2022). Technology licensing and productivity growth: Evidence from manufacturing firms In developing economies. *M&Som-Manufacturing & Service Operations Management, 24*(1), 214–234. https://doi.org/10.1287/Msom.2020.0946

Andrade-Rojas, M., Saldanha, T., Kathuria, A., Khuntia, J., & Boh, W. (2024). How information technology overcomes deficiencies for innovation In small and medium-sized enterprises: Closed innovation vs. Innovation. *Information Systems Research*. https://doi.org/10.1287/Isre.2021.0096

Arora, A., Belenzon, S., & Rios, L. (2014). Make, buy, organize: The interplay between research, external knowledge, and firm structure. *Strategic Management Journal, 35*(3), 317–337. https://doi.org/10.1002/Smj.2098

Arora, A., & Nandkumar, A. (2012). Insecure advantage? Markets for technology and the value of resources for entrepreneurial ventures. *Strategic Management Journal, 33*(3), 231–251. https://doi.org/10.1002/Smj.953

Arrighetti, A., Landini, F., & Lasagni, A. (2014). Intangible assets and firm heterogeneity: Evidence from Italy. *Research Policy, 43*(1), 202–213. https://doi.org/10.1016/J.Respol.2013.07.015

Arunachalam, S., Ramaswami, S. N., Herrmann, P., & Walker, D. (2018). Innovation pathway to profitability: The role of entrepreneurial orientation and marketing capabilities. *Journal Of The Academy Of Marketing Science, 46*(4), 744–766. https://doi.org/10.1007/S11747-017-0574-1. Scopus.

Ballot, G., Fakhfakh, F., Galia, F., & Salter, A. (2015). The fateful triangle: Complementarities In performance between product, process and organizational innovation In France and The Uk. *Research Policy, 44*(1), 217–232. https://doi.org/10.1016/J.Respol.2014.07.003. Scopus.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Bergh, D. D., D'oria, L., Crook, T. R., & Roccapriore, A. (2024). Is knowledge really the most important strategic resource? A meta-analytic review. *Strategic Management Journal*. https://doi.org/10.1002/Smj.3645. *N/A*(N/A).

Boehe, D., & Cruz, L. (2010). Corporate Social responsibility, product differentiation strategy and export performance. *Journal Of Business Ethics, 91*, 325–346. https://doi.org/10.1007/S10551-010-0613-Z

Borenstein, M., Cooper, H., Hedges, L., & Valentine, J. (2009). Effect sizes for continuous data. *The Handbook Of Research Synthesis And Meta-Analysis, 2*, 221–235.

Branzei, O., & Vertinsky, I. (2006). Strategic pathways to product innovation capabilities In smes. *Journal of Business Venturing, 21*(1), 75–105. https://doi.org/10.1016/J.Jbusvent.2004.10.002

Ceccagnoli, M. (2009). Appropriability, preemption, and firm performance. *Strategic Management Journal, 30*(1), 81–98.

Cevik, S. (2025). Is Schumpeter right? Fintech and economic growth. *Economics Of Innovation And New Technology, 34*(7), 1095–1106.

Chittoor, R., Sarkar, M., Ray, S., & Aulakh, P. (2009). Third-world copycats to emerging multinationals: Institutional changes and organizational transformation In the Indian pharmaceutical industry. *Organization Science, 20*(1), 187–205. https://doi.org/10.1287/Orsc.1080.0377

Choi, S. B., Lee, S. H., & Williams, C. (2011). Ownership and firm innovation In A transition economy: Evidence from China. *Research Policy, 40*(3), 441–452. https://doi.org/10.1016/J.Respol.2011.01.004. Scopus.

Cooper, H., Hedges, L. V., & Valentine, J. C. (2019). *The handbook of research synthesis and meta-analysis*. Russell Sage Foundation.

Craighead, C., Hult, G., & Ketchen, D. (2009). The effects of innovation-cost strategy, knowledge, and action In The supply chain on firm performance. *Journal Of Operations Management, 27*(5), 405–421. https://doi.org/10.1016/J.Jom.2009.01.002

Decarolis, D., & Deeds, D. (1999). The impact of stocks and flows of organizational knowledge on firm performance: An empirical investigation of The biotechnology industry. *Strategic Management Journal, 20*(10), 953–968. https://doi.org/10.1002/(Sici)1097-0266(199910)20:10%253c953::Aid-Smj59%253e3.0.Co;2-3

Deligianni, I., Voudouris, I., & Lioukas, S. (2017). Do effectuation processes shape the relationship between product diversification and performance In new ventures? *Entrepreneurship Theory And Practice, 41*(3), 349–377. https://doi.org/10.1111/Etap.12210

Demirkan, I., & Demirkan, S. (2012). Network characteristics and patenting In biotechnology, 1990-2006. *Journal Of Management, 38*(6), 1892–1927. https://doi.org/10.1177/0149206311408319

Díaz-Díaz, N., Aguiar-Díaz, I., & De Saá-Pérez, P. (2008). The effect of technological knowledge assets on performance: The innovative choice In Spanish firms. *Research Policy, 37*(9), 1515–1529. https://doi.org/10.1016/J.Respol.2008.06.002

Ellis, P. D. (2006). Market orientation and performance: A meta-analysis and cross-national comparisons*. *Journal Of Management Studies, 43*(5), 1089–1107. https://doi.org/10.1111/J.1467-6486.2006.00630.X

Fainshmidt, S., Pezeshkan, A., Frazier, M., Nair, A., & Markowski, E. (2016). Dynamic capabilities and organizational performance: A meta-analytic evaluation and extension. *Journal Of Management Studies, 53*(8), 1348–1380. https://doi.org/10.1111/Joms.12213

Fey, C. (2005). External sources of knowledge, governance mode, and R&D performance. *Journal Of Management, 31*(4), 597–621. https://doi.org/10.1177/0149206304272346

Field, A. P., & Gillett, R. (2010). How to do A meta-analysis. *British Journal Of Mathematical And Statistical Psychology, 63*(3), 665–694. https://doi.org/10.1348/000711010x502733

Frank, A., Cortimiglia, M., Ribeiro, J., & De Oliveira, L. (2016). The effect of innovation activities on innovation outputs In The Brazilian industry: Market-orientation vs. Technology-acquisition strategies. *Research Policy, 45*(3), 577–592. https://doi.org/10.1016/J.Respol.2015.11.011

Gerasymenko, V., De Clercq, D., & Sapienza, H. (2015). Changing the business model: Effects of venture capital firms and outside ceos on portfolio company performance. *Strategic Entrepreneurship Journal, 9*(1), 79–98. https://doi.org/10.1002/Sej.1189

Geyskens, I., Krishnan, R., Steenkamp, J.-B. E. M., & Cunha, P. V. (2009). A review and evaluation of meta-analysis practices In management research. *Journal Of Management, 35*(2), 393–419. https://doi.org/10.1177/0149206308328501

Geyskens, I., Steenkamp, J.-B. E., & Kumar, N. (2006). Make, buy, or ally: A transaction cost theory meta-analysis. *Academy Of Management Journal, 49*(3), 519–543.

Gómez, J., Salazar, I., & Vargas, P. (2020). The role of extramural R&D and scientific knowledge In creating high novelty innovations: An examination of manufacturing and service firms In Spain. *Research Policy, 49*(8). https://doi.org/10.1016/J.Respol.2020.104030

Gruber, M., Macmillan, I., & Thompson, J. (2008). Look before you leap: Market opportunity identification In emerging technology firms. *Management Science, 54*(9), 1652–1665. https://doi.org/10.1287/Mnsc.1080.0877

Guerrero, M., & Siegel, D. S. (2024). Schumpeter meets Teece: Proposed metrics for assessing entrepreneurial innovation and dynamic capabilities In entrepreneurial ecosystems In an emerging economy. *Research Policy, 53*(5), Article 104984.

Guichardaz, R., & Pénin, J. (2025). Entrepreneurs "from within"? Schumpeter and the emergence of pure novelty. *Industrial And Corporate Change, 34*(4), 676–695.

Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the returns to R&D. In *Handbook of the economics of innovation, 2* pp. 1033–1082). Elsevier.

Harrer, M., Cuijpers, P., Furukawa, T., & Ebert, D. (2021). *Doing meta-analysis with R: A hands-on guide*. Chapman And Hall/Crc.

Harris, L. C. (2001). Market orientation and performance: Objective and subjective empirical evidence from Uk companies. *Journal Of Management Studies, 38*(1), 17–43.

Hashai, N. (2011). Sequencing the expansion of geographic scope and foreign operations by 'Born Global' Firms. *Journal Of International Business Studies, 42*(8), 995–1015. https://doi.org/10.1057/Jibs.2011.31

Hock-Doepgen, M., Heaton, S., Clauss, T., & Block, J. (2024). Identifying microfoundations of dynamic managerial capabilities for business model innovation. *Strategic Management Journal*. https://doi.org/10.1002/Smj.3663

Hulland, J., Wade, M. R., & Antia, K. D. (2007). The impact of capabilities and prior investments on online channel commitment and performance. *Journal Of Management Information Systems, 23*(4), 109–142. https://doi.org/10.2753/Mis0742-1222230406

Hunter, J. E., & Schmidt, F. L. (2000). Fixed effects vs. Random effects meta-analysis models: Implications for cumulative research knowledge. *International Journal Of Selection And Assessment, 8*(4), 275–292.

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*. Thousand Oaks, California: Sage.

Iddris, F. (2016). Innovation capability: A systematic review and research agenda. *Interdisciplinary Journal Of Information, Knowledge, And Management, 11*, 235–260.

Inthout, J., Ioannidis, J. P., Borm, G. F., & Goeman, J. J. (2015). Small studies are more heterogeneous than large ones: A meta-meta-analysis. *Journal Of Clinical Epidemiology, 68*(8), 860–869.

Jiang, R., Tao, Q., & Santoro, M. (2010). Alliance Portfolio diversity and firm performance. *Strategic Management Journal, 31*(10), 1136–1144. https://doi.org/10.1002/Smj.869

Kang, J., Kang, R., & Kim, S. (2017). An empirical examination of vacillation theory. *Strategic Management Journal, 38*(6), 1356–1370. https://doi.org/10.1002/Smj.2588

Karhade, P., & Dong, J. (2021). Innovation outcomes of digitally enabled collaborative problemistic search capability. *Mis Quarterly, 45*(2), 693–717. https://doi.org/10.25300/Misq/2021/12202

Karna, A., Richter, A., & Riesenkampff, E. (2016). Revisiting the role of the environment In the capabilities–Financial performance relationship: A meta-analysis. *Strategic Management Journal, 37*(6), 1154–1173.

Kathuria, N., Majumdar, S., & Peng, M. (2023). Institutional transitions, research and development, and exports from India. *Journal Of Management Studies, 60*(6), 1521–1548. https://doi.org/10.1111/Joms.12906

Kim, Y. K., Lee, K., Park, W. G., & Choo, K. (2012). Appropriate intellectual property protection and economic growth In countries At different levels of development. *Research Policy, 41*(2), 358–375. https://doi.org/10.1016/J.Respol.2011.09.003. Scopus.

King, R. G., & Levine, R. (1993). Finance and growth: Schumpeter might Be right. *The Quarterly Journal Of Economics, 108*(3), 717–737.

Knight, G., & Cavusgil, S. (2004). Innovation, organizational capabilities, and the born-global firm. *Journal Of International Business Studies, 35*(2), 124–141. https://doi.org/10.1057/Palgrave.Jibs.8400071

Knight, G., & Kim, D. (2009). International business competence and the contemporary firm. *Journal Of International Business Studies, 40*(2), 255–273. https://doi.org/10.1057/Palgrave.Jibs.8400397

Koufteros, X. A., Vonderembse, M. A., & Doll, W. J. (2002). Integrated product development practices and competitive capabilities: The effects of uncertainty, equivocality, and platform strategy. *Journal Of Operations Management, 20*(4), 331–355. https://doi.org/10.1016/S0272-6963(02)00018-9. Scopus.

Laamanen, T. (2005). Dependency, resource depth, and supplier performance during industry downturn. *Research Policy, 34*(2), 125–140. https://doi.org/10.1016/J.Respol.2004.11.004

Lee, C., Lee, K., & Pennings, J. M. (2001). Internal capabilities, external networks, and performance: A study on technology-based ventures. *Strategic Management Journal, 22*(6–7), 615–640. https://doi.org/10.1002/Smj.181. Scopus.

Lestan, F., Clausen, T. H., & Kabiraj, S. (2025). Why do R&D superstars differ? An empirical analysis of the world's top R&D investors. *International Journal Of Global Business And Competitiveness*. https://doi.org/10.1007/S42943-025-00135-8

Li, H., & Atuahene-Gima, K. (2002). The adoption of agency business activity, product innovation, and performance In Chinese technology ventures. *Strategic Management Journal, 23*(6), 469–490. https://doi.org/10.1002/Smj.233

López-Cabarcos, M.Á., Srinivasan, S., Göttling-Oliveira-Monteiro, S., & Vázquez-Rodríguez, P. (2019). Tacit knowledge and firm performance relationship. The role of product innovation and the firm level capabilities. *Journal Of Business Economics And Management, 20*(2), 330–350.

Malik, T. H., Kabiraj, S., & Lestan, F. (2022). Prestige of the decision ecology and risk-taking In R&D project In the biopharmaceutical sector. *Global Business Review*, 09721509221093484.

Maurer, I., Bartsch, V., & Ebers, M. (2011). The value of intra-organizational social capital: How it fosters knowledge transfer, innovation performance, and growth. *Organization Studies, 32*(2), 157–185. https://doi.org/10.1177/0170840610394301

Mcgee, J., & Dowling, M. (1994). Using research-and-development cooperative arrangements to leverage managerial experience - A study of technology-intensive new ventures. *Journal Of Business Venturing, 9*(1), 33–48. https://doi.org/10.1016/0883-9026(94)90025-6

Mckelvie, A., Wiklund, J., & Brattström, A. (2018). Externally acquired or internally generated? Knowledge development and perceived environmental dynamism In new venture innovation. *Entrepreneurship Theory And Practice, 42*(1), 24–46. https://doi.org/10.1177/1042258717747056

Mendoza-Abarca, K., & Gras, D. (2019). The performance effects of pursuing A diversification strategy by newly founded nonprofit organizations. *Journal Of Management, 45*(3), 984–1008. https://doi.org/10.1177/0149206316685854

Mendoza-Silva, A. (2021). Innovation capability: A systematic literature review. *European Journal Of Innovation Management, 24*(3), 707–734. https://doi.org/10.1108/Ejim-09-2019-0263

Menor, L. J., Kristal, M. M., & Rosenzweig, E. D. (2007). Examining the influence of operational intellectual capital on capabilities and performance. *Manufacturing And Service Operations Management, 9*(4), 559–578. https://doi.org/10.1287/Msom.1060.0131. Scopus.

Messersmith, J. G., & Guthrie, J. P. (2010). High performance work systems In emergent organizations: Implications for firm performance. *Human Resource Management, 49*(2), 241–264. https://doi.org/10.1002/Hrm.20342. Scopus.

Mewes, L., & Broekel, T. (2022). Technological complexity and economic growth of regions. *Research Policy, 51*(8). https://doi.org/10.1016/J.Respol.2020.104156

Mihalache, O., Jansen, J., Van Den Bosch, F., & Volberda, H. (2012). Offshoring and firm innovation: The moderating role of top management team attributes. *Strategic Management Journal, 33*(13), 1480–1498. https://doi.org/10.1002/Smj.1983

Minviel, J.-J., & Ben Bouheni, F. (2022). The impact of research and development (R&D) on economic growth: New evidence from kernel-based regularized least squares. *The Journal Of Risk Finance, 23*(5), 583–604.

Mol, M. (2005). Does being R&D intensive still discourage outsourcing? Evidence from Dutch manufacturing. *Research Policy, 34*(4), 571–582. https://doi.org/10.1016/J.Respol.2005.03.007

Moreira, A., Navaia, E., & Ribau, C. (2024). Innovation capabilities and their dimensions: A systematic literature review. *International Journal Of Innovation Studies*.

Oh, L., Teo, H., & Sambamurthy, V. (2012). The effects of retail channel integration through The use of information technologies on firm performance. *Journal Of Operations Management, 30*(5), 368–381. https://doi.org/10.1016/J.Jom.2012.03.001

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., Mcdonald, S., … Mckenzie, J. E. (2021). Prisma 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *BMJ (Clinical research ed.), 372*, N160. https://doi.org/10.1136/Bmj.N160

Patel, P., Kohtamäki, M., Parida, V., & Wincent, J. (2015). Entrepreneurial orientation-As-experimentation and firm performance: The enabling role of absorptive capacity. *Strategic Management Journal, 36*(11), 1739–1749. https://doi.org/10.1002/Smj.2310

Pecko, M., Lestan, F., & Kabiraj, S. (2025). Once in a blue moon': M&A case of prima bank slovakia. *Abhigyan*. https://doi.org/10.1177/09702385251367814

Penner-Hahn, J., & Shaver, J. M. (2005). Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms. *Strategic Management Journal, 26*(2), 121–140. https://doi.org/10.1002/Smj.436

Piñeiro-Chousa, J., López-Cabarcos, M.Á., Romero-Castro, N. M., & Pérez-Pico, A. M. (2020). Innovation, entrepreneurship and knowledge In the business scientific field: Mapping the research front. *Journal Of Business Research, 115*, 475–485.

Piñeiro-Chousa, J., López-Pérez, M. L., López-Cabarcos, M.Á., & Šević, A. (2025). R&D-driven companies' Profitability: Risk management from A corporate governance perspective. *The Journal Of Risk Finance, 26*(3), 451–468.

Richard, P. J., Devinney, T. M., Yip, G. S., & Johnson, G. (2009). Measuring organizational performance: Towards methodological Best practice. *Journal Of Management, 35*(3), 718–804.

Rodríguez-Duarte, A., Sandulli, F., Minguela-Rata, B., & López-Sánchez, J. (2007). The endogenous relationship between innovation and diversification, and The impact of technological resources on The form of diversification. *Research Policy, 36*(5), 652–664. https://doi.org/10.1016/J.Respol.2007.01.004

Rothstein, H. R., Sutton, A. J., & Borenstein, M. (2005). Publication bias In meta-analysis. *Publication Bias In Meta-Analysis: Prevention, Assessment And Adjustments*, 1–7.

Rubera, G., Chandrasekaran, D., & Ordanini, A. (2016). Open innovation, product portfolio innovativeness and firm performance: The dual role of new product development capabilities. *Journal Of The Academy Of Marketing Science, 44*(2), 166–184. https://doi.org/10.1007/S11747-014-0423-4. Scopus.

Saldanha, T., Mithas, S., & Krishnan, M. (2017). Leveraging customer involvement for fueling innovation: The role of relational and analytical information processing capabilities. *Mis Quarterly, 41*(1), 267. -+.

Salvato, C., & Vassolo, R. (2018). The sources of dynamism In dynamic capabilities. *Strategic Management Journal, 39*(6), 1728–1752. https://doi.org/10.1002/Smj.2703

Schäper, T., Jung, C., Foege, J., Bogers, M., Fainshmidt, S., & Nüesch, S. (2023). The S-shaped relationship between open innovation and financial performance: A longitudinal perspective using A novel text-based measure. *Research Policy, 52*(6). https://doi.org/10.1016/J.Respol.2023.104764

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo Vadis, dynamic capabilities? A content-analytic review of the current State of knowledge and recommendations for future research. *Academy Of Management Annals, 12*(1), 390–439.

Schubert, T., & Tavassoli, S. (2020). Product innovation and educational diversity In top and middle management teams. *Academy Of Management Journal, 63*(1), 272–294. https://doi.org/10.5465/Amj.2017.0741

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. Cambridge, Ma: Harvard University Press (Repr. New Bunswick: Transaction, 1983).

Sevil, A., Cruz, A., Reyes, T., & Vassolo, R. (2022). When being large is not an advantage: How innovation impacts the sustainability of firm performance In natural resource industries. *Sustainability, 14*(23), Article 16149.

Shane, S. (1995). Uncertainty avoidance and the preference for innovation championing roles. *Journal Of International Business Studies, 26*(1), 47–68. https://doi.org/10.1057/Palgrave.Jibs.8490165

Simonin, B., & Özsomer, A. (2009). Knowledge processes and learning outcomes In Mncs: An empirical investigation of the role of hrm practices In foreign subsidiaries. *Human Resource Management, 48*(4), 505–530. https://doi.org/10.1002/Hrm.20296

Slavova, K., Fosfuri, A., & De Castro, J. (2016). Learning by hiring: The effects of scientists' Inbound mobility on research performance In academia. *Organization Science, 27*(1), 72–89. https://doi.org/10.1287/Orsc.2015.1026

Souder, D., Shaver, J. M., Harris, J. D., & Alrashdan, A. (2023). Performance metrics In strategy research: A new metric and method for assessing dynamic value. *Strategic Management Journal*. https://doi.org/10.1002/Smj.3550. *N/A*(N/A).

Stam, W., & Elfring, T. (2008). Entrepreneurial orientation and new venture performance: The moderating role of intra- and extraindustry social capital. *Academy Of Management Journal, 51*(1), 97–111.

Subramaniam, M., & Youndt, M. (2005). The influence of intellectual capital on The types of innovative capabilities. *Academy Of Management Journal, 48*(3), 450–463. https://doi.org/10.5465/Amj.2005.17407911

Tatikonda, M., Terjesen, S., Patel, P., & Parida, V. (2013). The role of operational capabilities In enhancing new venture survival: A longitudinal study. *Production And Operations Management, 22*(6), 1401–1415. https://doi.org/10.1111/Poms.12038

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(Sici)1097-0266(199708)18:7%3c509::Aid-Smj882%3e3.0.Co;2-Z

Tse, C. H., Yu, L., & Zhu, J. (2017). A multimediation model of learning by exporting: Analysis of export-induced productivity gains. *Journal Of Management, 43*(7), 2118–2146. https://doi.org/10.1177/0149206315573998. Scopus.

Vandaie, R., & Zaheer, A. (2014). Surviving bear hugs: Firm capability, large partner alliances, and growth. *Strategic Management Journal, 35*(4), 566–577. https://doi.org/10.1002/Smj.2115

Vanneste, B. S., Puranam, P., & Kretschmer, T. (2014). Trust over time In exchange relationships: Meta-analysis and theory. *Strategic Management Journal, 35*(12), 1891–1902.

Vorhies, D., Orr, L., & Bush, V. (2011). Improving customer-focused marketing capabilities and firm financial performance via marketing exploration and exploitation. *Journal Of The Academy Of Marketing Science, 39*(5), 736–756. https://doi.org/10.1007/S11747-010-0228-Z

Wang, Y.-Z., Lo, F.-Y., & Huarng, K.-H. (2024). What shapes Innovative firms' Performance? A multi-level analysis. *Journal Of Innovation & Knowledge, 9*(4), Article 100599.

Wei, L., & Lau, C.-M. (2010). High performance work systems and performance: The role of adaptive capability. *Human Relations, 63*(10), 1487–1511. https://doi.org/10.1177/0018726709359720. Scopus.

Wu, L., Hitt, L., & Lou, B. (2020). Data analytics, innovation, and firm productivity. *Management Science, 66*(5), 2017–2039. https://doi.org/10.1287/Mnsc.2018.3281

Yin, X., Qi, L., Ji, J., & Zhou, J. (2023). How does innovation spirit affect R&D investment and innovation performance? The moderating role of business environment. *Journal Of Innovation & Knowledge, 8*(3), Article 100398.

Zhang, J., Jiang, H., Wu, R., & Li, J. (2019). Reconciling the dilemma of knowledge sharing: A network pluralism framework of firms' R&D alliance network and innovation performance. *Journal Of Management, 45*(7), 2635–2665. https://doi.org/10.1177/0149206318761575. Scopus.

Zhao, Z. J., & Chadwick, C. (2014). What we will do versus What we can do: The relative effects of unit-level npd motivation and capability. *Strategic Management Journal, 35*(12), 1867–1880. https://doi.org/10.1002/Smj.2184. Scopus.

Zhou, K., Li, J., Sheng, S., & Shao, A. (2014). The evolving role of managerial ties and firm capabilities In an emerging economy: Evidence from China. *Journal Of The Academy Of Marketing Science, 42*(6), 581–595. https://doi.org/10.1007/S11747-014-0371-Z

Zhou, K., Tse, D., & Li, J. (2006). Organizational changes In emerging economies: Drivers and consequences. *Journal Of International Business Studies, 37*(2), 248–263. https://doi.org/10.1057/Palgrave.Jibs.8400186

Zhou, K., & Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. *Strategic Management Journal, 31*(5), 547–561. https://doi.org/10.1002/Smj.830

Zollo, M., & Reuer, J. (2010). Experience spillovers across corporate development activities. *Organization Science, 21*(6), 1195–1212. https://doi.org/10.1287/Orsc.1090.0474