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# KNOWLEDGE ENVIRONMENT DYNAMICS: HOW RICHNESS, PROTECTION, AND INTENSITY SHAPE INNOVATION ABSORPTION

**[1]Johnson, Peter Samuel Adewale and [2]Chen, Liang Michael**

[1]Department of Management Studies, University of Cape Town, Cape Town, South Africa

[2]Department of Business Analytics, National University of Singapore, Singapore

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**Abstract**

In today's dynamic and knowledge-driven economy, innovation has become essential for organizational survival and sustained competitive advantage. Central to this process is absorptive capacity (AC), defined as a firm's ability to recognize, assimilate, and apply external knowledge for commercial purposes. Although AC is widely acknowledged as a key driver of innovation, empirical findings on its effect remain inconsistent, with studies reporting positive, negligible, and even negative relationships with innovation performance. These mixed results suggest that the effectiveness of absorptive capacity may depend on contextual conditions within knowledge environments.

This study addresses this gap by examining how knowledge environment characteristics—specifically richness, protection, and intensity—moderate the relationship between absorptive capacity and innovation outcomes. Knowledge richness reflects the availability and diversity of external knowledge sources, knowledge protection captures the extent of legal and institutional safeguards such as intellectual property regimes, and knowledge intensity refers to the degree of knowledge embeddedness and competitive pressure within an industry. Together, these factors shape how effectively firms can access, process, and exploit external knowledge.

Building on organizational learning and strategic management theories, the study argues that absorptive capacity does not operate in isolation but is contingent upon external environmental conditions. In knowledge-rich environments, firms are more likely to benefit from diverse information flows that enhance learning opportunities. However, high levels of knowledge protection may restrict knowledge spillovers, thereby limiting absorptive potential. Conversely, high knowledge intensity may increase competitive pressure, compelling firms to more effectively utilize available knowledge to sustain innovation performance.

By integrating these moderating variables, the study provides a more nuanced understanding of the absorptive capacity–innovation relationship and helps reconcile prior empirical inconsistencies. The findings contribute to innovation literature by emphasizing the importance of environmental contingencies in shaping firm-level capabilities and outcomes.

**Keywords:** Absorptive Capacity, Innovation Performance, Knowledge Richness, Knowledge Protection, Knowledge Intensity

## Introduction

In today's fast-paced and knowledge-intensive economy, innovation has emerged not merely as a growth lever but as a prerequisite for survival and long-term competitive advantage. As firms confront rapidly changing markets, technological disruptions, and global competition, their ability to innovate has become a central determinant of success. Numerous studies underscore innovation's value, linking it to improved financial performance (Sorescu & Spanjol, 2008), increased market valuation (Rubera & Kirca, 2012), and sustained competitive positioning (Bowen et al., 2010; Rosenbusch et al., 2011).

At the heart of the innovation process lies knowledge—both internally developed and externally acquired. Drawing from organizational learning and strategic management theory, a firm's capacity to absorb and utilize external knowledge has long been recognized as pivotal to its innovation capability. Cohen and Levinthal (1990) introduced the concept of absorptive capacity (AC) to describe a firm's ability to recognize the value of new external information, assimilate it, and apply it toward commercial ends. Since then, AC has become a foundational concept in innovation and organizational capability research (Zahra & George, 2002).

Despite its theoretical appeal and widespread adoption, empirical findings on the relationship between AC and innovation are surprisingly inconsistent. While some studies confirm the positive influence of AC on innovation performance (e.g., Song et al., 2018; Storey et al., 2016), others report negligible (De Faria et al., 2010; Alnuaimi & George, 2016) or even negative effects (Belderbos et al., 2016; Bojica & Fuentes, 2012). These contradictions have prompted scholars to look beyond internal firm capabilities toward external, contextual moderators that may condition the effectiveness of AC.

This study addresses the contextual puzzle in the AC–innovation relationship by focusing on the knowledge environment in which a firm operates. Unlike prior literature that views environmental variables as exogenous shocks—such as market dynamism (Jansen et al., 2005), hostility (Wales et al., 2013), or uncertainty (Raymond et al., 2015)—we conceptualize the environment as a source of knowledge spillovers and opportunity. Building on the knowledge spillover theory of entrepreneurship (Acs et al., 2009; Audretsch & Keilbach, 2007), we argue that firms are embedded in differentiated knowledge environments that shape their capacity to innovate through externally sourced knowledge.

We identify three critical dimensions of the knowledge environment: richness (the availability of knowledge), protection (the strength of intellectual property regimes), and intensity (the degree of competitive knowledge-based activity). These dimensions influence not only the flow and accessibility of knowledge but also the incentives and barriers to knowledge utilization. In knowledge-rich, weakly protected, and less intense environments, firms have greater opportunities to absorb and exploit knowledge spillovers without facing significant competition or legal barriers.

Our study also makes a novel contribution by distinguishing between two stages of innovation: invention and commercialization. Invention refers to the creation of novel scientific or technological knowledge, often stemming from internal R&D. Commercialization, in contrast, pertains to the application and market delivery of new products or services. While often treated as a unified construct, these stages require distinct capabilities and are influenced differently by external knowledge conditions (Dutta & Hora, 2017). We hypothesize and confirm that AC has a stronger effect on commercialization than on invention, reflecting the more direct applicability of externally absorbed knowledge in market-driven innovation.

To test these theoretical propositions, we conduct a meta-analysis of 145 empirical studies involving over 430,000 firms across industries and regions. This methodological approach allows us to aggregate diverse findings and estimate the overall and conditional effects of AC on innovation. We find that the strength of AC's impact on innovation is contingent on the characteristics of the knowledge environment. Specifically, knowledge-rich environments amplify the positive effects of AC, while high protection and intensity dampen them.

Our findings offer both theoretical and managerial implications. Theoretically, we extend the literature on absorptive capacity by embedding it within the broader ecosystem of knowledge spillovers and environmental characteristics. We also challenge the assumption of a universal AC–innovation link, highlighting the need for more context-sensitive models. From a practical standpoint, our results suggest that managers can enhance innovation outcomes by aligning their absorptive strategies with environmental conditions. In particular, firms operating in knowledge-rich but underprotected environments should invest in capabilities that facilitate fast assimilation and rapid commercialization.

Furthermore, we urge policymakers to consider how intellectual property regimes and knowledge infrastructure affect firm-level innovation outcomes. While strong protection may encourage invention, it could simultaneously stifle the diffusion of knowledge and limit opportunities for smaller firms to benefit from spillovers. A balanced policy that fosters knowledge generation and diffusion may be more conducive to system-wide innovation.

In sum, this study contributes to the ongoing discourse on how firms transform knowledge into innovation. By integrating the concept of absorptive capacity with a contextual understanding of the knowledge environment, we provide a more nuanced and evidence-based explanation for the variability observed in innovation outcomes across firms. Our meta-analytic findings reaffirm the value of AC, but critically, they also show that its benefits are contingent—varying significantly with the richness, protection, and intensity of the firm's external knowledge context.

The knowledge spillover theory of entrepreneurship (KSTE) (Audretsch & Feldman, 1996) emphasizes the outflow of knowledge from incumbent innovative firms and academic research institutions to enterprising individuals and firms located in geographical proximity. As a theory explaining the sources of new venture creation, KSTE builds on the literature in economic geography, which focuses on the characteristics of knowledge as a public good (Arrow, 1974; Nelson, 1959) and seeks to quantify the impact of knowledge spillovers at the country or regional level (Griliches, 1979; Jaffe et al., 1993). The literature on the geographical localization of TABLE 1 Summary of key insights from prior studies. knowledge thus suggests that firms emerge from knowledge that is generated but not commercially exploited by its creators (Acs et al., 2013). In the original conceptualization of KSTE, prospective entrepreneurs initiate a new business when incumbent firms are unable or unwilling to deviate from their core competencies and introduce new products or processes to the market. Knowledge about these developments spills over from the firm to opportunistic individuals (Ghio et al., 2015;

Audretsch & Feldman, 2004). In line with this view, instead of being viewed as an organizational failure to capture the value of innovation, spillovers represent a valuable contribution to society at large, particularly benefiting firms located in geographical proximity to knowledge powerhouses such as multinationals (e.g., Almeida, 1996; Zhao, 2006) and research institutions (e.g., Alcacer & Chung, 2007).

In the strategic management literature, Cohen and Levinthal (1989, 1990) relied on the notion of knowledge spillovers to expand our understanding of a knowledge production dichotomy. This dichotomy suggested that some organizations create knowledge and protect it (e.g., innovative multinational firms), while others appropriate externally available knowledge (e.g., local incumbent firms). Cohen and Levinthal (1989, 1990) proposed an interdependent knowledge continuum, suggesting that to appropriate, firms need to invest in creating new knowledge.

Table 1 systematizes prior insights regarding knowledge sources and illustrates our focus on environments that promote (or inhibit) knowledge transfer. Specifically,

we emphasize interconnections between two streams of literature—AC and KSTE—which initially developed in parallel but have recently been combined through the lens of unintended knowledge transfer (e.g., Awate, Makhija, & Xiao, 2024; Triguero & Fernandez, 2018).

AC and KSTE are grounded in three core assumptions, which this study builds upon and aims to extend. First, the AC literature posits that theoretically, a firm can absorb all knowledge available in the public domain (Cohen & Levinthal, 1990). However, even firms with superior absorptive capacity are likely to assimilate only a small fraction of the publicly available knowledge. Therefore, one of the objectives in integrating AC and KSTE is to assess the effects of the rapidly expanding external knowledge pool on the AC–INN relationship.

Second, while there is consensus in the literature that firms access external resources through two distinct yet overlapping channels—intentional collaboration with partners (active knowledge sourcing) or unintentional knowledge spillovers (passive knowledge sourcing) (Giovannetti & Piga, 2017)—the effects of the latter in AC–INN relationship remained unexplored by AC researchers. On one hand, spillovers are inherently challenging to capture. Scholars have oftentimes operationalized them as "surplus innovation" (or productivity) in the proximity of innovation leaders (e.g., Knott, 2003). On the other hand, spillovers represent not only opportunities for outsiders but also threats to innovating firms, since they are directly tied to the level of appropriability— the extent to which firms capture profits associated with their innovative activities (Cohen & Levinthal, 1990).

Therefore, most AC studies to date have addressed innovation in the context of intentional knowledge transfer. A meta-analysis by Van Wijk et al. (2008) summarizing data from 33 studies, reveals that a firm's AC positively impacts organizational knowledge transfer (samplecorrected mean effect size $r = 0.15$) across both transfer types: intra- and interorganizational ($r = 0.17$ and $0.14$ , respectively). Additionally, the authors find that intentional knowledge transfer benefits overall firm performance ($r = 0.19$) and contributes to innovativeness ($r = 0.13$).

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Despite limited research on unintentional knowledge spillovers in the context of AC and innovation, conceptual and empirical insights can be gained by aggregating research findings, which our study seeks to achieve.

Third, KSTE suggests that knowledge spillovers are accessible to all firms in a geographically proximal location (Audretsch & Belitski, 2020). However, only firms that effectively exploit these spillovers are able to gain competitive advantages (Dunning, 1980; Dunning, 1988). This assumption overlooks the effects of the fourth industrial revolution, which includes rapid technological changes, transformations in industries, and shifts in societal patterns driven by increased interconnectivity (Schwab, 2017) and advancements in web technologies (Schneckenberg, 2009). These factors suggest that the geographical localization of knowledge spillovers may diminish over time (Griffith et al., 2011).

Figure 1 visualizes our conceptual model of innovation as an interaction between the firm and its environment. Three knowledge environment characteristics (richness, protection, intensity) modify the strength of the relationship between a firm's absorptive capacity and innovation. Next, we will examine each relationship individually.

## 2.1 | Richness of the knowledge environment

Over the past 30 years, the pace of knowledge creation and dissemination has grown exponentially, driven by rapid advances in information and communication technologies. These advancements facilitated seamless information exchange and decreased the costs of computing power and electronic networking (Chen & Dahlman, 2005; Singh et al., 2021). Seminal work by Cohen and Levinthal (1989) suggests that the scope of technological opportunities varies according to the quantity and value of knowledge available in the external environment. Specifically, the more knowledge available and the greater the potential of knowledge to improve the performance of existing technologies, the stronger the incentive for firms to invest in research and development (R&D) (Lane et al., 2006).

The knowledge environment considered in this study extends beyond technology and encompasses a wider range of valuable external information that firms can leverage in their innovation process. In doing so, our conceptualization builds upon prior work on the information richness of communication media (Lengel and Daft, 1984; Daft & Lengel, 1986) and knowledge richness in the intrafirm context (Durmu¸soglu, 2013).

Addressing the question “Why do organizations process information?” (Lengel and Daft, 1984; Daft and Lengel, 1986) built on the premise that the amount of information that has to be processed by decision makers directly depends on the degree of task uncertainty (Galbraith, 1973). Their insights are therefore relevant for our study of innovation as an inherently uncertain process where the outcomes cannot be defined in advance (Lundvall, 1992). According to Daft and Lengel (1984, 1986), the two key goals of information processing are (a) the reduction of uncertainty (defined as the lack of data) and (b) the reduction of equivocality (defined as multitude of possible interpretations). In their framework, communication media vary in information richness ranging by the quantity

and quality of information transmitted, and information richness is defined as “the ability of information to change understanding within a time interval” (Daft & Lengel, 1986: 560). After the World Wide Web was introduced in 1989 and the Internet gradually developed into a media of high richness (Markus, 1994), firms obtained access to a variety of information sources ranging from information-only-sharing to information-and-knowledge-sharing.
In the intrafirm context, Durmu¸soglu (2013) equated knowledge richness with knowledge diversity and posited that it arises in human interactions (e.g., in advice giving
and receiving) during boundary-spanning activities ( both inside and outside an organization). In this conceptual study, he also argued that knowledge quality and richness are directly related to product innovativeness and success. While recent studies concur that information technologies “can enhance the reach and richness of a firm's knowledge, thereby allowing the firm to rapidly react to market changes” (Cai et al., 2019: 425), an empirical test of this postulate is still missing.
In our study, the richness of the knowledge environment is characterized by the diversity of publicly available knowledge and its potential to reduce uncertainty and equivocality of the macro-environment, thereby providing valuable external knowledge to the innovating firm. Historically, the knowledge environment became richer with the development of digital technologies—such as the Internet and mobile connectivity. A rich knowledge environment facilitates faster access to a larger pool of external knowledge. The first benefit (speed) stems from the technological developments in connectivity, the latter (volume)—from the societal implications of these advancements, as the Internet enhances individuals' social capital and expands interaction across physical, cultural, language and temporal boundaries (Katz & Rice, 2002). As web technologies have progressed, firms gained access to an expanding reservoir of social knowledge. A greater amount of information and knowledge has been codified and stored digitally (Davenport & Prusak, 2000), and geographical distance no longer impedes the acquisition and dissemination of information (Friedman, 2006).
As a result, more agents—individuals and firms— combine multiple roles that would be harder to balance in a less rich knowledge environment. At the micro-level, in social media and online communities, people can function as knowledge consumers, creators, and disseminators (Guan et al., 2018). On the meso- and macro-level, more firms may choose to conduct research beyond closed labs via open innovation (Chesbrough, 2003) and crowdsourcing (Pollok et al., 2019), customer cocreation (Bughin et al., 2008), and within innovation networks and ecosystems (Xie & Wang, 2021).

We, therefore, propose that richness strengthens the relationship between AC and innovation by providing access to a valuable stock of know-how, boosting interand intrafirm connectivity, and overall increasing information flows between people, firms, and ecosystems.
Hypothesis 1. The positive relationship between AC and innovation is stronger when the knowledge
Moreover, environmental richness facilitates each of the four absorptive processes, since firms can access more and assimilate best knowledge, transform it inside an organization (or within an extended network) and exploit to come up with innovative products, services, or processes. We thus hypothesize:
environment is rich ( compared to a paucity of knowledge environment).

Protection of the knowledge environment

The knowledge environment poses both threats and opportunities for innovative firms. One of the primary threats is knowledge leakage, which occurs when knowledge flows beyond organizational borders in an unwanted, uncontrollable, and detrimental manner (Arias-Pérez et al., 2020; Flammer & Kacperczyk, 2019; Ritala et al., 2018), thereby hindering a firm's ability to appropriate value from its innovation efforts. Conversely, knowledge that leaks into the public domain creates knowledge spillovers and becomes a source of entrepreneurial opportunities, particularly for new knowledge that has not yet been commercialized (Qian & Acs, 2013).
This duality of the creative knowledge outputs, serving as both a societal (or industrial) public good via spillovers and an organizational private good via various means of knowledge protection, has been addressed in prior innovation studies (Antonelli, 2003; Ribeiro & Shapira, 2020). However, the research focus was divided: whereas the researchers in the field of (regional) economics focused predominantly on knowledge spillovers,[6] the researchers in the field of management zoomed onto knowledge appropriability—as the degree to which firms capture profits associated with their innovative activity (Cohen & Levinthal, 1990). Specifically, they scrutinized the impact of regimes of appropriability—a firm's ability to monetize their innovations based on existing innovation protection mechanisms in the industry (Teece, 1986). Management scholars have thus addressed two types of questions: (i) What incentives (or disincentives) do firms have to innovate? and (ii) How can firms capture the most value from innovation?[8]
Our study addresses a different question: Assuming that firms are motivated to innovate, how does the environment in which they find themselves impact their ability to transform knowledge into innovation? In answering this question, we define the protection of the country-level knowledge environment as a macro-factor that captures whether institutions encourage (or discourage) knowledge spillovers as evidenced in the strength of the country's intellectual property rights (IPR) protection index.
Traditionally, stronger knowledge protection was regarded as more conducive to innovation, whereas weaker IPR as less conducive (Chen & Puttitanun, 2005). Yet in over 30 years of research on this topic, there are still relatively few cross-country comparisons ( Cohen et al., 2002)—a gap that our study aims to fill. Since we capture

appropriability on the country-level, our theorizing differs from prior work (Cohen & Levinthal, 1990; Zahra & George, 2002; Todorova & Durisin, 2007) that 6Teece (1986) laid the foundation to the discussion of the impact of regimes of appropriability—a firm's ability to monetize their innovations depending on the existing innovation protection mechanisms in the industry. Moreover, he framed that these regimes can be dichotomized as "strong" and "weak." In a strong regime, knowledge is either difficult to imitate and/or there exists legal IPR protection against imitation (Hurmelinna-Laukkanen & Puumalainen 2007; Teece, 1997). In a weak regime, on the other hand, the profits of an innovative firm are easily lost to imitating competitors. Cohen and Levinthal (1990) also considered regimes of appropriability as an industry condition and theorized that AC is conditioned on these. They tested and found moderating effect of regimes of appropriability on the relationship between prior knowledge and AC. Zahra and George (2002), in contrast, theorized that regimes of appropriability moderate the relationship between AC and its outcome of sustainable competitive advantage. They argue that in markets characterized by low efficacy of property rights and ease of replication, firms may have lower returns to the knowledge absorbed. Todorova and Durisin (2007) combined both arguments and proposed that regimes of appropriability moderate both inputs and outputs of AC: that is, on the incentive side (following Cohen & Levinthal, 1990) and on the return side (following Zahra & George, 2002).7

Cohen and Levinthal (1990) answer to (i) that those factors are industry-level demand, appropriability, and technological opportunities.

To (ii) Hurmelinna-Laukkanen & Puumalainen 2007; HurmelinnaLaukkanen et al. (2008) answer—by fitting their firm-level appropriability strategies to external (i.e., industry-wide) appropriability regimes. For an extensive review on appropriability see HurmelinnaLaukkanen and Yang, 2022.

8Intensity of the intra- and interfirm knowledge environment has been conceptualized and captured in prior research in a variety of different concepts/measures. Among the most prominent ones are (i) R&D intensity (on the firm level, conceptualized as AC, measured as yearly R&D expenditure per firm turnover); (ii) Competitive intensity (on the market or industry-level), conceptualized as the degree of competition in the environment (Herhausen et al., 2021), and measured along two dimensions: technological and nontechnological intensity (e.g., in services—see Arora et al. 2014; Giarratana & Torrisi, 2010) ; (iii) Environmental dynamism (on the industry level); conceptualized as a combination of competitive intensity and environmental uncertainty (Singh et al. 2021); measured as unpredictability and variation of change in the environment (Herhausen et al., 2021) and or as rapidness of technological change in the industry, the amount and unpredictability of changes in the markets, and the general rate of change in the industry (Jantunen, 2005). While the three concepts described above are undoubtedly intertwined (and most likely strongly positively correlated) with the intensity of the knowledge environment, in this study we only consider the latter.

considered the effects of knowledge protection on the firm- and industry-levels.

We argue that weak knowledge protection (i.e., IPR regime) enables firms with higher AC to benefit from knowledge spillovers which other firms in the focal country (i.e., local firms or local multinationals) and outside of it (i.e., foreign firms or foreign multinationals from strongly protected knowledge environments) produce. Indeed, a study of 3475 R&D lab investment decisions during 2003–2010 in India, Lamin and Ramos (2016) established that local firms free-ride on the knowledge from other local firms, both within and across industries. Moreover, the act of protecting knowledge itself reveals some information about the value of certain knowledge and the direction in which a firm is developing, and thereby raises the risk of imitation (Horstmann, MacDonald, & Slivinski, 1985; Hurmelinna-Laukkanen & Olander, 2014; Somaya, 2003). Studies in economic geography suggest that relatively underdeveloped economies can achieve growth by adopting (i.e., copying) already well-established technologies from the world frontier (Acemoglu et al., 2006). A country that starts far behind the world technology frontier can even grow faster than one close to it because the former country will make larger technological advances when one of its sectors catches up to the global frontier (Aghion & Jaravel, 2015). Therefore, countries—and firms—far from the frontier may enjoy an "advantage of backwardness" (Gerschenkron, 1962).

Nevertheless, accessibility does not imply that knowledge becomes freely available for everyone to use (Aghion & Jaravel, 2015), nor does it suggest that knowledge flows to the firm as a "manna from heaven" (Audretsch et al., 2005). Cohen and Levinthal (1990) refuted the long-held assumption that firms can gain advantages from positive R&D externalities without costly learning or search. Rather, they proved that knowledge becomes available only to firms that invest in expanding their absorptive capacity (Cohen & Levinthal, 1990). Therefore, firms in countries with low knowledge protection will vary in their ability to access unprotected external knowledge: those with high levels of AC will benefit from spillovers, whereas laggards with little AC will be unable to capture those and will fall further behind their competitors. Likewise, firms in countries with high knowledge protection will also depend on AC in their innovation efforts, yet in comparison to their counterparts from less protected environment, their knowledge sources are likely to be more limited and innovation tasks—more challenging. Overall, we expect that knowledge absorption will be associated with higher levels of innovation in a less protected knowledge environment, in which firms can access knowledge within and beyond country borders:

Hypothesis 2. The relationship between AC and innovation is stronger in a weakly protected knowledge environment (compared to a moderately or strongly protected environment).

## 2.3 | Intensity of the knowledge environment

Firms vary in the amount of knowledge they need to innovate and in the amount of resources (tangible and intangible) they devote to this process. The former factor is shaped by firms' external environment and total amount of knowledge in the industry (labeled as the "knowledge frontier"), while the latter is influenced by their

AC and internal innovation strategy (oftentimes captured as a firm's R&D investments). Moreover, the internal and external conditions for innovation are intertwined in an environment characterized by a rapid increase in knowledge (i.e., high intensity of the knowledge environment), firms need to invest more in innovation (Cohen & Levinthal, 1990). Symmetrically, firms operating in an environment characterized by slow(er) increase in knowledge (i.e., low intensity of the knowledge environment) are less pressured to innovate and can rely on knowledge created elsewhere. These relationships have been well documented in prior literature (e.g., Grimpe & Sofka, 2009; Hauknes & Knell, 2009), yet it remains unclear how firms across these environments compare in their ability to produce innovation from external knowledge, and thereby convert their AC into innovation in different environments. To address this issue, we need to consider the difference between the intensity of the external knowledge environment and knowledge intensity of a firm's internal environment. These two are related but distinct concepts.

Knowledge holds greater significance in a knowledgeintensive firm context compared to other inputs such as labor and capital (Starbuck, 1992). In knowledgeintensive industries, such as high-tech manufacturing and knowledge-intensive business services, knowledge is both a critical input and output. Unsurprisingly, the concept of AC was developed in the context of high-tech, knowledge-intensive firms and in their seminal article, Cohen and Levinthal (1990: 147) postulated that "the positive absorption incentive associated with spillovers is greater in industries in which the difficulty of learning is greater." However, recent studies also show that AC is highly valuable in services—a context typically contrasted with high-tech manufacturing. In a meta-analysis on the success factors for service innovation, Storey et al. (2016) rank-ordered absorptive capacity as the second factor of success after launch proficiency. This result suggests that AC plays a crucial role for firms operating outside of high-tech, knowledge-intensive industries.

While the value of AC for innovation is high in the knowledge-intensive industries, firms in less knowledgeintensive industries benefit from AC just as much, if not more, than their counterparts. One reason for this is the distance to the knowledge frontier: firms that are further away from it can make advances toward the frontier with fewer resources (and/or higher innovation output), compared to the firms competing at the frontier.

Knowledge frontiers represent an integral part of the innovation production function and a central driver of economic growth in the endogenous growth theory (Romer, 1990). In practice, the knowledge frontier captures internal and external boundaries of knowledge creation (Belitski et al., 2021). As firms approach the knowledge frontier, the significance of generating their own knowledge increases, prompting them to adopt innovation-based growth strategies to stay competitive. Consequently, they tend to increase their investments in R&D. This heightened competition and dynamism closer to the frontier (Hölzl & Janger, 2014) make the path to innovation more challenging.

Another factor explaining why firms in less knowledge-intensive industries might disproportionally benefit from AC stems from the fact that for a long time researchers have broadly conceptualized knowledge intensity—as the extent to which a firm depends on the knowledge inherent in its activities and outputs as a source of competitive advantage (Autio et al., 2000: 913), yet narrowly measured it—as R&D intensity (on the firm-level) or the share of patent applications in high technology fields and knowledge-intensive services (on the national level) (Lacasa et al., 2019).

The narrow focus on R&D as a measure of intra- and interfirm knowledge intensity has shaped the way scholars measured intensity of knowledge flows on the industry level. The Organization for Economic Co-operation and Development (OECD, 1996) initially distinguished between industries based on their R&D intensities, classifying those that spend more than 4% of their turnover on R&D as high-tech, those that spend between 1% and 4% as medium-tech, and those spending less than 1% as low tech. In its revised view, OECD acknowledged that "innovation is a much broader concept than R&D and not all firms that are successful at developing or implementing innovation are necessarily R&D performers" (Galindo-Rueda & Verger, 2016: 5; OECD, 2010, 2015). Indeed, R&D is not the only method of innovating, since firms may be involved in technology adoption (e.g., by investing in information and communication technology; Venturini, 2015), as well as incremental changes, imitation, and combining existing knowledge in new ways to arrive at an innovative output (Arundel et al., 2007).

Recent studies on innovation speciation and exaptation suggest that individuals and organizations reuse existing knowledge and technologies across domains and functions (Omezzine & Bodas Freitas, 2022; Cattani, 2006; Carignani et al., 2019). Indeed, while firms in technology-intensive industries exchange knowledge through forward and backward linkages in the supply chain, firms in less technology-intensive industries are essential for production, diffusion and use of technology (Hauknes & Knell, 2009). Additionally, studies on the technological diversification of "old-economy" sectors (i.e., low-tech) reveal that the degree to which leading firms in less knowledge-intensive industries are involved in the process of technological diversification surpassed the medium and high-tech sector in terms of patenting in new technologies in the period 1991 to 1996 (Mendonça, 2009). This finding implies that lowtechnology firms may act as passive adopters of technologies, but also as active contributors in this process.

Summing up, while AC is vital for innovation in a highly intensive knowledge environment, comparable levels of AC within less intensive environments may be associated with either greater, (and) or more rapid innovation. Accordingly, we postulate:

Hypothesis 3. The relationship between AC and innovation is stronger in less intensive knowledge environment (compared to moderately or highly intensive environment).

## 3 | METHODS

### 3.1 | Literature search

To identify relevant studies to test our hypotheses, we collected data in a comprehensive search process. First, we searched several online databases (Business Source Premier/EBSCO, Google Scholar, JSTOR, EconLit, Elsevier Science Direct) using the term "absorptive capacity." Second, to avoid biased representation by focusing only on published studies, we conducted an additional search for unpublished work in the PROQUEST database, retrieving four studies and directly contacting the authors, obtaining three additional studies. Third, we scanned the reference lists of already published metaanalyses on AC (Song et al., 2018; Zou et al., 2018) for other relevant studies. The final sample includes studies published in English, providing correlations between AC and innovation performance at the firm or business unit level. If critical information remained missing (e.g., number of firms in the sample, or statistics pertaining to key relationships under study), we excluded these studies from our analysis. We also excluded studies, in which AC measures were not aligned with one of the categories suggested in prior research (Song et al., 2018). When authors drew on the same sample in multiple publications, we retained only one study to eliminate overrepresentation. In each case, we chose studies which provided the most comprehensive and relevant information to our research topic. Our final meta-analytic sample consists of 145 studies combining data from 434,985 firms stemming from 27 distinct countries.

### 3.2 | Coding and measures

To ensure coding reliability and accuracy, we developed a coding protocol outlining the information to be extracted from the studies (Lipsey & Wilson, 2001; Stock, 1994). Each study was coded at least twice. First, four members of the research team coded each study independently. Coders met on a weekly basis to discuss progress and make subsequent adjustments to the coding protocol. Second, the studies were redistributed between four researchers in a way that each one coded new studies. During this process, questions were discussed on an ad hoc basis. We made instant coding adjustments and updates to the protocol, to assure consistency in our coding. To be able to perform subgroup analyses, we specified several distinctive categories for each of our focal constructs shown in Table 2.

Absorptive capacity measure: For the AC measures, we used the categorization by Song et al. (2018): AC effort, AC knowledge base, and AC process. In the first category—AC effort, we coded studies which tracked financial investment in R&D and commitment to technology development. The second category—AC knowledge base—comprises studies that captured a firm's patents and prior product innovations which describe its current knowledge stock. In the third category—AC process, we coded studies, which measured overall learning, as well as specific knowledge-sharing and dissemination practices (Song et al., 2018). This category is in line with Zahra and George's (2002) multidimensional conceptualization of absorptive processes (coded as "AC dimension" and outlined below).

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AC measurement type: We distinguish two types of AC measure: perceived implies that the respondents assessed items (questions) that make up a construct in a questionnaire on some scale (typically, Likert 1–5 or 1– 7); whereas archival captured objective measures, for example from annual reports.

AC dimension: Following the conceptualization of Zahra and George (2002) and operationalization of Jansen et al. (2005), we distinguish between potential AC which includes acquisition and assimilation of external knowledge, and realized AC which encompasses transformation and exploitation of acquired knowledge. Note that this moderator represents a subset of the AC measure discussed above, and details relationships between two dimensions of the AC process.

Innovation process outcome: We considered the effects of AC on two critical outcomes in the innovation process: invention as a breakthrough scientific discovery and commercialization as a socially usable and marketable product (Dutta & Hora, 2017; Khilji et al., 2006).

Richness of the knowledge environment: We measure this contextual moderator with three different periods of time based on the study's data collection window. The first period is the preinternet era, which lasts until 1989 , when the Internet was introduced. The early internet era unfolds from 1990 until 2009, when Samsung Galaxy was introduced, a few years after the release of the first iPhone (2007). Studies with data collected after 2010 were grouped into the smartphone era category. Such coding aims to capture possible differences between knowledge environments of low, medium, and high richness. When the author(s) did not specify the data collection period in

TABLE 2 Coding and measures.

| Variable | Applied measures/subgroups |
|---|---|
| Innovation process outcome | • Invention<br>• Commercialization |
| Protection of the environment | Intellectual property rights ( IPR ) knowledge protection index<br>• Low<br>• Medium<br>• High |
| Absorptive capacity (AC) | AC categorization by Song et al., 2018<br>• AC effort<br>• AC knowledge base<br>• AC process |
| AC measurement type | Perceived (subjective)<br>• |

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| | |
|---|---|
| • | Archival (objective) |
| AC dimension • | Potential AC (acquisition, assimilation) |
| • | Realized AC (transformation, exploitation) |
| Innovation performance type • • | Product innovation<br>Product and process innovation |
| • | Other |
| Innovation performance metrics • • | Quantity of innovation<br>Quality of innovation |
| • | Quantity and quality of innovation |
| • | Other |
| Innovation performance scope • • | Financial<br>Nonfinancial |
| • | Mixed |
| Innovation measurement type • • | Perceived (subjective)<br>Archival ( objective ) |
| Innovation performance time • • | Cross-sectional<br>Lagged |
| Firm size • | Small and medium-sized enterprises ( SMEs ) |
| • | Large firms |
| • | Mixed |

a study, we assumed that it took place three (3) years prior to the publication date and coded it accordingly. Protection of the knowledge environment: This moderator is measured based on the ranking of the International IP (Intellectual Property) Index by matching country indices to the data sources in the original studies and subsequently categorizing them into three subgroups: low, medium, high. The indicators included in the Index “represent a gold standard for the protection and enforcement of IP rights” like information on patents, copyright, trademarks, and trade secrets (U.S. Chamber of Commerce, 2022). Geographical regions with high levels of knowledge protection are, for example, North America and Northern Europe (UK, Germany, Sweden). Countries with low levels of IPR protection include, for example, Indonesia and Ecuador. Medium levels of IPR protection are coded, for example, for Malaysia, Turkey, and Greece. If studies included data from multiple countries, a median estimate of IPI across all studies in our sample was used, which equaled 86.11 and fell into the medium category.

Intensity of the knowledge environment: We measure this contextual moderator at the industry-level. Following the OECD classification and information provided in the original studies, we distinguish between three types of knowledge environments: (i) high intensity—comprises high-tech manufacturing and knowledge-intensive business services, (ii) low intensity—low-tech manufacturing and services, and (iii) medium intensity—studies with mixed samples. To provide a specific example, a study that included knowledge-intensive services—which make intensive use of R&D, skilled labor and knowledge embodied in technology—was coded as mixed because the sample included knowledge-intensive and nonintensive firms (De Faria et al., 2010), while another study in the telecommunications industry was coded as high intensity, because the authors specified high-tech focus in the description of the sample (Wu, Lii, & Wang, 2015). Studies that did not contain any information about the industry sector were excluded from this analysis.

Innovation performance type: This variable captures the distinction between product and process innovation as the ultimate outcomes of organizational knowledge creation (Nonaka & Von Krogh, 2009). The first category—product innovation—includes studies which narrowly focus on tangible innovation, whereas the second category contains both product and process innovations. Studies with unspecified outcomes were assigned to the third category "other."

Innovation performance metrics: In this category we coded study samples, which measure the quantity (e.g., patents, new products) or the quality of innovation (e.g., share of new products of the total sales).

Innovation performance scope: The first subgroup includes studies that evaluate financial innovation performance and use profitability and accounting measures (e.g., return on investment). The second subgroup includes studies which evaluate innovation performance in a nonfinancial aspect, for example, product or service quality, customer satisfaction, or organizational effectiveness. Studies applying a combination of financial and nonfinancial measures were coded as mixed.

Innovation measurement type: As for AC type, we distinguish between two types of the innovation performance measure. Perceived type implies that respondents completed a questionnaire on some scale (typically, Likert 1–5 or 1–7) and thereby provided subjective assessments of a firm's innovative performance. Archival implies that the variable has been captured by objective means such as information from the annual reports.

Innovation performance time: This moderator indicates whether the study assessed innovation performance as cross-sectional (at one point in time), or as lagged (in the subsequent year(s), longitudinally).

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Firm size: To assess possible impact of firm context on AC–INN relationship, we distinguished between samples studying small and medium-sized (SMEs) or large firms. Different thresholds were used for this: firms in American and Asian studies with less than 500 employees were coded as SMEs, whereas for European firms the cutoff number was 200 employees (i.e., Kirca et al., 2011). Firms with over 500 (and 200) employees were coded as large. Studies comprising both SMEs and large firms in their sample were coded as mixed.

### 3.3 | Meta-analytical procedure

Researchers conduct meta-analyses to integrate quantitative results across previously conducted studies and estimate the mean effect size between two variables (Hunter & Schmidt, 2004). This procedure enables us to investigate the combined effect sizes and individual moderators of the AC and innovation performance relationship.

The first step of this procedure involves correcting the data for statistical artifacts, such as measurement and sampling error. To correct for measurement error in the studies using perceived measures of AC and innovation, we draw on the formula by Hunter and Schmidt (2004). When studies did not report Cronbach alpha or used single-item measures, we substituted the missing information with the mean reliability of the particular construct across all studies (i.e., Geyskens et al., 1998). For studies reporting objective information, we set the reliability coefficient to 1.00. If a study reported multiple measures of our focal constructs, we used an average indicator of these variables, to avoid overrepresentation of the effect sizes from that study. To account for sampling error, which can be a significant source of artefactual variance, the effect sizes were weighted by the sample size, which gave more weight to more precise studies (Geyskens et al., 2009). In our calculations, we used the Comprehensive Meta-Analysis software (Borenstein et al., 2005) and relied on a random effects model generating more accurate parameter estimates than fixed effect approaches (Hunter & Schmidt, 2004; Schmidt & Hunter, 1999).

Next, to account for the “file drawer problem” (Rosenthal, 1979, p. 638), we conducted the file-drawer analysis for each bivariate relationship and established the number of unpublished studies needed to revert the robust findings into spurious. Specifically, we find that the Rosenthal's fail-safe number (i.e., the number of missing studies that would render p-value at the 0.05-level insignificant) equals 849,029 for the overall sample (n = 145); 113,939 for the invention subsample (n = 45); and 21,165 for the commercialization subsample (n = 31).

To test our hypotheses, we conducted a series of subgroup moderator analyses. Moderators are an important theoretical tool for exploring boundary conditions ( Busse et al., 2017), which in our case pertains to the ACinnovation link. Specifically, we adopt a dynamic view on boundary conditions which implies uncertainty in their nature and suggests exploring various conditions to make those more certain (Busse et al., 2017). In Busse et al.'s (2017) classification of boundary testing types, we conduct an inside-out exploration of the boundary conditions of the AC theory and scrutinize its further applicability in slightly different contextual conditions. Specifically, we depart from the “known territory” (i.e., where AC is within the range of the existing theory—

resource- or knowledge-based view) outward to an unknown territory (in our case an “known unknown” of the changing knowledge environment and geographically unbound spillovers within KSTE). Note that there is a similarity and a difference between the dynamic and the static views on boundary conditions, whereby both seek to describe the limits of generalizability of a theory (Whetten, 1989), yet the static view focuses on a theory breakdown in certain contexts (or lack thereof), while the dynamic view seeks to explore the applicability of a theory across contexts.

Moderation testing also allows us to account for the systematic and random components in the variance of effect sizes. To establish these, we relied on a mixed effects model and ran an additional set of moderator analyses. Specifically, we distinguished between contextual moderators (knowledge environment richness, protection, and intensity), firm-level moderators (firm size), and measurement moderators (AC and innovation performance measures) as described above. This approach allows us to establish consistency of the results across various circumstances.

## 4 | RESULTS

Table 3 presents the results of our main and moderator analyses. The overall relationship between AC and innovation is strongly positive with the sample-corrected mean effect size (r) equaling to 0.33 ($p < 0.001$), with weaker associations for invention ($r = 0.19$; $p < 0.001$) and higher for commercialization ($r = 0.39$; $p < 0.001$). A subsequent Z-test reveals that the difference between AC effects on invention and commercialization is statistically significant ($Z = 4.45$; $p = 0.000$), indicating that the effects of AC are higher on commercialization, than on invention.

Our first moderator analysis suggests that information-rich environments create more opportunities to reap innovation benefits from AC, than knowledgescarce environments. Specifically, the effects from AC on innovation become stronger over time: in the smartphone era (after 2010) the effects from AC on innovation are almost twice larger ($r = 0.48$; $p < 0.001$), than during preinternet era before 1989 ($r = 0.27$; $p < 0.1$), or early internet era—from 1990 to 2009 ($r = 0.29$; $p < 0.001$). In line with our theoretical argumentation, this result is likely to be driven by the introduction of the Internet and subsequent development of communication technologies and information sharing platforms. The Z-test for assessing between-group differences in the AC–INN relationship (Table 4) reveals significantly higher innovation effect in the smartphone era ($r = 0.48$) than in the early internet era ($r = 0.29$) ($Z = 4.65$, $p = 0.000$), yet no difference from the preinternet era ($Z = 1.44$, $p = 0.149$). Therefore, we partially confirm Hypothesis 1.

Pertaining to protected knowledge environments, our second moderator analysis indicates that high levels of knowledge protection, as for example in North America or Europe, while safeguarding intellectual property also dampen positive effects of absorptive capacity on innovation. Specifically, our results show that in countries with low intellectual property rights protection (IPR) the effects from AC on innovation are at least twice stronger than in countries with high IPR (r = 0.64, $p < 0.001$ compared to r = 0.32, $p < 0.001$, respectively; and r = 0.28 ; $p < 0.001$ in countries with medium IPR). The Z-tests of difference indicate that both theorized subgroup comparisons (high versus low; and high versus medium) are statistically significant. Therefore, we confirm Hypothesis 2.

Pertaining to the intensity of knowledge environment, our results of our third moderator analysis show that the association between AC and innovation is stronger in less knowledge-intensive environments. This finding suggests that while knowledge acquisition, assimilation, transformation, and utilization is beneficial across all industry sectors, its effects are more (and faster) visible in less knowledge-intensive sectors: r = 0.41 ($p < 0.001$) compared to 0.35 ($p < 0.001$) in mixed industries, and only 0.28 ($p < 0.001$) in high-tech industries. Note that while the difference between less intensive and mixed industries is insignificant, the difference between highly intensive and less intensive, as well as between highly intensive and mixed is significant (Z = 3.36, $p < 0.001$ and Z = 1.92, $p < 0.1$, respectively). Therefore, we partially confirm Hypothesis 3.

Further, we report the results of a series of post hoc analyses to establish robustness of our results and assess the impact of other potential moderators. One possible bias in our data that we estimated stems from the variance in the AC measure. Cohen and Levinthal (1990) proposed to capture AC as R&D intensity and before Zahra and George (2002) introduced the multidimensional process measure of AC, scholars have predominantly captured AC relying on the indicators of capital invested in innovation. Song et al. (2018) called this type of measure “AC effort” and contrasted it with “AC knowledge base” and “AC process” measures. The former included indicators of patent- and nonpatent (e.g., scientific papers, prior innovative products, etc.) knowledge stocks, whereas the latter relied predominantly on the dimensions suggested by Zahra and George (2002) pertaining to knowledge sharing and organizational learning. The critical questions here are the following: Are the significant effects of knowledge environment richness (i.e., internet-based sharing) attributable to the fact that the original measure—AC effort—was an inaccurate indicator of a firm's ability to capture external knowledge? Could a more accurate AC measure, which was introduced later, drive this effect? Although we cannot completely rule out this possibility, we think this does not compromise our results for two reasons: one grounded in the sample size distribution, and another—in effect size distribution. First, the number of studies in each of the three periods does not overlap with the number of studies for the three AC measures. Compared to the pre-, early internet, and smartphone subgroups ($n = 11$; 98, 36 studies, respectively), AC measures—effort (R&D intensity), knowledge base (patents), and process display a different distribution pattern ($n = 64$, 17, 64 studies). This implies that measures of AC were mixed across most periods. Second, the strength of innovation effects is higher for the preinternet era ($r = 0.27$, $n = 11$) compared to the lowest effects of AC effort ($r = 0.16$, $n = 64$), and relatively low effects of AC knowledge base ($r = 0.24$, $n = 17$). This result again suggests that other measures of AC—besides R&D intensity were used during pre- and early-internet period, for example, relative size and relatedness of the knowledge base (Ahuja & Katila, 2001). Note that while there is no difference between pre- and early-internet eras (i.e., low- and medium richness of knowledge environment) for innovation overall ($r = 0.27$, $p < 0.1$ and $r = 0.29$, $p < 0.001$), we observe a profound impact on commercialization outcomes: here, an increase in knowledge environment's richness is associated with a boost in AC–INN relationship ($r = 0.24$ for low, $r = 0.34$ for medium, and $r = 0.47$ for high richness, all relationships statistically significant at $p < 0.001$). The impact on invention outcomes increases likewise (with $r = 0.14$ for medium and $r = 0.32$, for high richness of the knowledge environment, both at $p < 0.001$), yet for the preinternet era the result is not statistically significant ($r = 0.35$). Therefore, by relying on the sample collection period, we are able to provide more accurate information about the changes in the importance of R&D investments over time, than a simple AC effort measure could.

Additionally, we assessed the differences in the AC dimension conceptualization by relying on Jansen et al.'s (2005) scale and comparing the strength of effects for the realized and potential AC. Our results show that both process conceptualizations (realized and potential AC) are strongly and positively related to innovation performance ($r = 0.48$, $p < 0.001$ and $r = 0.56$, $p < 0.001$ , respectively) and do not differ in the strength of their effects.

Another possible bias in our data stems from the variance in the innovation measure. To account for this, we compared the differences between innovation type (product versus product and process versus other), metrics (quantity, quality, both, and other), as well as scope (financial versus nonfinancial versus mixed), measure (perceived versus archival) and time (cross-sectional versus lagged). Two observations from these subgroup comparisons warrant attention. First, scholars relying on archival measures of innovation report significantly lower firm reliance on AC ($r = 0.15$ for overall innovation, $r = 0.14$ for invention, and $r = 0.23$ for commercialization, all significant at $p < 0.001$), than scholars using perceptual measures ($r = 0.45$, $r = 0.32$, and $r = 0.42$ respectively, all significant at $p < 0.001$). This finding suggests that (a) predictive innovation inputs are hardly quantifiable, and (b) managers' perceptions of innovation effects exceed objective measurements of the innovation outputs, yet still seem to be more accurate in their assessment of innovation drivers than objective data. Our second observation from the comparisons of innovation subgroups pertains to innovation scope. When combinations of financial and nonfinancial measures are used, the reported strength of AC–INN relationship is the highest ($r = 0.56$ for innovation and $r = 0.62$ for commercialization, both at $p < 0.001$), however, for the invention subgroup observations are missing. This result reinforces our prior insights and suggests that the reliance on single (and especially, single-item) measures of AC and innovation may be limiting.

## 5 | DISCUSSION

Following the Journal of Product Innovation Management 2017 Special Issue on Innovation in Data Rich Environments, which aimed to clarify the influence of data-rich environments on innovation (Bharadwaj & Noble, 2015, 2017), we theorized and analyzed the effects of knowledge environments' characteristics—richness, protection, and intensity—on the relationship between absorptive capacity (AC) and innovation (INN). In doing so, we challenge the prevailing perspective in the management literature, which has viewed spillovers as a loss of value to be minimized. Instead, drawing insights from regional economics, we propose that spillovers can foster an environment conducive to innovation.

### 5.1 | Theoretical contributions

Our study contributes to research on innovation and knowledge absorption.

First, we add to the Knowledge Spillover Theory of Entrepreneurship (KSTE) by empirically testing the assumption that the knowledge environment affects a firm's ability to innovate. Our interpretation of KSTE emphasizes not only the impact of locally accessible knowledge but also considers the effect of globally accessible knowledge and distant knowledge spillovers beyond geographically proximate knowledge hubs. Focusing on the intersection between an organization and its environment,

e examine whether superior AC combined with readily available external knowledge

(i.e., spillovers) serves as an innovation booster. Specifically, we develop arguments about the varying role of AC in contexts with larger (or narrower) knowledge pools, influencing the accessibility of external knowledge. Drawing on the media richness theory, which postulates that tacit knowledge is most effectively transferred through face-to-face interactions (Daft & Lengel, 1986), and considering advancements in digital communication technologies, we reevaluate the implications from Cohen and Levinthal's (1990) seminal work on AC. Thereby, this study offers a timely contribution to the knowledge management field with its increasing attention to the data-information-knowledge hierarchy in the context of economic transition to Industry 4.0 technologies, which involve a firm's restructuring, based on the adoption of such digital solutions as for example, internet of things, artificial intelligence, and additive manufacturing (Ardito et al., 2022). At the same time, our study also elucidates why more than three decades of empirical research do not support a plausible, yet inaccurate proposition about “the end of geography” suggesting that the physical distance to knowledge pools might not matter anymore in a globalized, virtually connected world (Morgan, 2004). Our answer is straightforward: absorptive capacity varies considerably across firms. Therefore, even when knowledge becomes widely accessible, it tends to be effectively utilized and capitalized upon by only a select few. Corroborating our findings with prior research, we suggest that KSTE's boundary warrants an extension. With knowledge access becoming easier and its volume larger than ever before, we urge scholars to question how these changes in the knowledge environment impact and reshape organizational and individual AC.

Second, our study methodologically contributes to innovation research by proposing measures for the three conceptual dimensions of the knowledge environment. Richness, protection, and intensity of the knowledge environment are distinct characteristics, which combined shape a firm's absorptive environment. We define the latter as a firm's external knowledge context that is rich in codified knowledge, offers ample opportunities for exchange and communication between knowledge agents, and,thereby, facilitates access to, transfer, and use of valuable knowledge. Prior innovation studies have theorized about the importance of the knowledge environment (Cohen & Levinthal, 1990) and offered comparative measures to capture its effects. For example, Cassiman and Veugelers (2006), relied on a “public information” measure which weighed the relative importance of (i) freely available information from patents, publications, and conferences to (ii) the information from customers and suppliers. In our meta-analysis, we used sample-specific measures pertaining to time, geographic location, and industrial sector of the firms under study to describe their knowledge environments. Future research is needed to operationalize these measures more accurately, using primary data.

Third, we contribute to the innovation literature by considering two innovation stages—invention and commercialization, which align with the linear view of innovation as a well-defined staged process from basic to applied research and then to development work. However, our focus on the role of the knowledge environment surrounding innovating firms is closer to a systemic perspective of innovation (Smits & Kuhlmann, 2004) with its focus on a (national) system of innovation as a set of interconnected institutions (Edquist & Hommen, 1999) that create, store, and transfer the knowledge, skills and artifacts (Metcalfe, 1995) which define new technologies, products and services, and business models. Theorizing the role of IPR for innovation outcomes across countries, we aime to compare the effects of AC on innovation across various institutional settings. Yet our vast literature search resulted in only 10 empirical studies from low IPR regions, only two (2) of which inform about AC effects on commercialization and none—about its effects on invention. Consequently, we call for more empirical research on innovation in low-IPR countries, in addition to qualitative, conceptual studies (e.g., Davis et al., 2008 on the role of agricultural education for innovation in Mozambique; or Ghazanfari & Aliahmadi, 2019, on the challenges of the national innovation system in Iran). Specifically, future studies need to validate our finding that firms with high AC from less protected knowledge environments benefit disproportionally from protected environments compared to their counterparts.

5.2 | Managerial implications

than those observed in SMEs (sample-corrected mean effect size r = 0.23 versus r = 0.37), two interpretations are possible. First, deficiencies in knowledge infrastructure consisting of technology, structure, and culture (Gold et al., 2001) may hinder external knowledge acquisition. Second, high expectations may drive this result. Indeed, the effects of perceived knowledge absorption and perceived innovation (r = 0.45 and 0.47, respectively) outweigh archival (objective) measures (r = 0.14; 0.15) by at least 60%. This result highlights the importance of a balanced approach to estimating innovation.

ii. Over time, the amount of publicly available knowledge increases. In such an environment, a firm's ability to acquire, transfer, and use knowledge resurfaces as a source of competitive advantage (r = 0.29 in the early internet era versus r = 0.48 in the smartphone era).

iii. Across all industries, access to and processing of knowledge boosts innovation (r = 0.32 in Song et al., 2018, and r = 0.33 in our study). However, in less knowledge-intensive industries the effect of absorption on innovation is stronger (r = 0.40 in Storey et al., 2016, and r = 0.41 for low-tech and service firms in our study), than in highly knowledge-intensive industries (r = 0.28 for high-tech manufacturing or knowledge-intensive business services in our study). This result does not suggest that learning is less important in this context; on the contrary, it implies that more knowledge is needed to produce innovation.

iv. Finally, knowledge-absorptive firms from countries with low IPR protection seem to benefit more from knowledge spillovers: their absorption-innovation relationship is at least twice stronger than in their counterparts from countries with high IPR protection ($r = 0.64$ versus $r = 0.32$, respectively). This result is likely driven by the "advantage of backwardness" (Gerschenkron, 1962) when remoteness from the knowledge frontier can be overcome faster in frontierdistant firms. Taken together, our findings shed additional light on the key dilemma in innovation strategy: a firm's choice between in-house and acquired innovation (Arora, Belenzon, and Rios, 2014). Our metaanalytical insights on the role of the knowledge environment in the innovation process may be applied in the firm's build-borrow-buy decision, where "build" refers to the internal development, "borrow" to licensing, contractual partnerships and alliances, and "buy" to mergers and acquisitions (Capron and Mitchell, 2012). In an environment rich with external knowledge, firms with superior absorptive capacity may reap spillovers from the broader environment, beyond proximate geographical locations and contractual agreements. Therefore, a key managerial implication from our study pertains to the value of intentional knowledge scouting from open sources and sharing platforms. While this process occurs at a cost (primarily from technology and human resource expenses), it offers a valuable add-on to contractual knowledge transfer. This may be particularly relevant to small and medium-sized firms that experience resource constraints, especially if they operate in lowtech and service industries.

Policy implications

An important policy implication from our research suggests that creating a highly rich, accessible, and intense knowledge environment may boost entrepreneurial activity and be particularly relevant for innovation processes in SMEs. The ability of many small firms to successfully engage in invention and commercialization is often restricted by their lack of resources, weak business competencies, and inadequate use of third-party advisors (Adams, 1982; Reboud, Mazzarol, and Soutar, 2014; Vermeulen, 2005). Despite the relative importance of lowtech firms, much of the focus of government policy in the national innovation systems (Lundvall, 2007) has been on high-tech industries. Fortunately, policy experts have begun to consider innovation at multiple levels spawning national and regional interactions (Lanahan and Feldman, 2015). Looking ahead, governments may devise even stronger support for low-tech firms by providing them access to shared valuable resources and training on effective strategies of global knowledge scouting.

Moreover, our findings echo the insights from agglomeration studies which suggest a positive innovation effect of geographical proximity to similar firms in some contexts, yet report no positive innovation effect in older firms, less technology-intensive environments, and emergent countries (Mathias et al., 2021). This means that physical location close to knowledge hubs matters for young, tech-intensive firms from developed countries and does not seem to boost innovation outcomes for others. On the macro-level, recent research on intercity knowledge spillovers suggests that two factors play a role in increased innovation: (i) the city's virtual connection to knowledge pools via social media links between people and (ii) psychological openness to spillovers (Obschonka et al., 2023). More research is thus needed on the effects of other forms of proximity— beyond geographical— such as virtual proximity in global virtual teams (Hung et al., 2021), online innovation communities (Safadi et al., 2021), or memberships in innovation networks, especially between firms in more- and less-technology-intensive environments. Acknowledging that knowledge spillovers from incumbents bear both opportunities and threats, we concur with the recent call for more research into host country governments' policies to address spillovers in the new digital space (Verbeke and Hutzschenreuter, 2021).

Limitations and future research

Our study has several limitations that warrant further testing. First, in capturing the three characteristics of the knowledge environment we were constrained by the available secondary data and had therefore to rely on proxies. This limitation is typical for all meta-analyses. For example, our knowledge protection measure captures only country-wide IPR protection but disregards specific firm- or industry-level strategic protection, such as measures of the effectiveness of secrecy, complexity, and/or lead time (Cassiman and Veugelers, 2006). Future research may scrutinize other means to protect innovation in the innovation process and consider the effects of the scope of patent protection—for example, patent length (its lifetime) and width (its coverage) (Klemperer, 1990), or even informal protection mechanisms like family ties (Brinkerink and Rondi, 2021). The same applies to our measure of knowledge environment richness which proxied knowledge quantity and quality with chronological time windows. Additional empirical and scale development studies are therefore needed to validate our results.

Second, we do not assess spillovers directly, for example as studies of inter-industry spillovers did via measures of R&D undertaken by the firms in external industries (Kafouros and Buckley, 2008).

This is particularly relevant because firms vary in the number and type of innovations generated and how they manage the process of commercialization (Mazzarol and Reboud, 2011). Therefore, “produced” and “consumed” spillovers may also range in value and future studies may look for ways to assess and balance those. Moreover, our assessment does not directly capture the penetration of knowledge across geographical locations since we did not rely on the measures of breadth of knowledge search for the individual firms. Our plausible assumption that the Internet has facilitated access to the global pool of knowledge needs to be validated beyond studies of multilocational firms (e.g., Forman and van Zeebroeck, 2019) in future research.

Third, we did not differentiate between radical and incremental innovation (Ritala and HurmelinnaLaukkanen, 2013) or between exploitative (closer to firms' technological core) and explorative (distant from existing knowledge base) innovation (Ceipek et al., 2021), yet our theoretical arguments invite further investigations into the mechanisms driving these innovation types. Prior research suggests that R&D efforts in high-tech industries are directed at breakthrough innovations that increase productivity, whereas in low-tech industries R&D is directed toward improving efficiency or implementing frontier technologies (Pieri et al., 2018). Beyond industryspecific effects, research also suggests that public and basic science is pivotal for radical innovation, which at the same time is less likely to be protected by patents than other types of innovation (Antonelli, 2005; Sternitzke, 2010). Future studies may thus explore the impact of the knowledge environment on other innovative activities, including basic research, the adoption and diffusion of innovations, and decisions to participate in cooperative R&D ventures (Cohen and Levinthal, 1990). Fourth, while we addressed firm- and environmentallevel factors underlying innovation, individual, team, and collaborative aspects of knowledge transfer, although highly important (Senge, 1990; Sun and Anderson, 2012) , remained outside of the scope of our consideration. Indeed, since KSTE resides on the assumption that startup founders are willing and able to penetrate knowledge filters and other barriers that prevent efficient knowledge conversion (Acs and Plummer, 2005), future research would benefit from assessing the role of individuals' absorptive abilities (Matusik and Heeley, 2005). Moreover, it is widely known that successful knowledge transfer involves neither computers nor documents, but rather interactions between people (Davenport, 1995). To address this limitation in our research, future studies need to understand "the individuals that compose organizations, specifically their underlying nature, choices, abilities, propensities, heterogeneity, purposes, expectations and motivations" (Felin and Foss, 2005: 441). Also, in line with our reasoning, the value of AC increases over time as the pool of available knowledge spillovers grows, but remains bound by the processing capacity of the individuals and organizations. A particularly interesting aspect for future investigations thus pertains to the possibility of an oversaturation of knowledge—a situation where critical knowledge is freely available, yet firms and individuals choose to pay for it to bypass the efforts of extended search and selection.

Finally, the interaction between humans, big data, and predictive machine learning techniques to amplify human intelligence (i.e., artificial intelligence in Dubey et al., 2020) may lead to innovative outcomes ( Belhadi et al., 2024) and thus requires further exploration. Specifically, the role of AI in boosting (or hampering) the absorptive capacity of individuals and firms warrants future research attention. Extending our study's focus on the impact of the knowledge environment on a firm's ability to innovate, future research may also consider the interactions between (i) knowledge richness and ease of its access, (ii) knowledge protection and ease of knowledge transfer, and (iii) knowledge intensity and ease of its use and especially their combined effects on innovation processes. In conclusion, innovation effects are most visible in the environment of low intensity, low protection, and high richness, yet firms' capacity to acquire, transfer, and utilize external knowledge matters across all knowledge environments.

REFERENCES

Agnihotri, R., Dingus, R., Hu, M. Y., & Krush, M. T. (2016). Social media: Influencing customer satisfaction in B2B sales. *Industrial Marketing Management, 53,* 172–180. https://doi.org/10.1016/j.indmarman.2015.09.003

Andrews, M., Goehring, J., Hui, S., Pancras, J., & Thomswood, L. (2016). Mobile promotions: A framework and research priorities. *Journal of Interactive Marketing*, *34*, 15–24. https://doi.org/10.1016/j.intmar.2016.03.003

Appio, F. P., Frattini, F., Petruzzelli, A. M., & Neirotti, P. (2021). Digital transformation and innovation management: A synthesis of existing research and an agenda for future studies. *Journal of Product Innovation Management*, *38*(1), 4–20. https://doi.org/10.1111/jpim.12544

Ashton, K. (2009). That 'Internet of Things' thing. *RFID Journal*, *22*(7), 97–114.

Bernritter, S. F., Ketelaar, P. E., & Sotgiu, F. (2021). Behaviorally targeted location-based mobile marketing. *Journal of the Academy of Marketing Science, 49*(4), 677–702. https://doi.org/10.1007/s11747-020-00739-z

Bezos, J. (2016, May 23). *Jeffrey P. Bezos on integrity* [Video]. YouTube. https://www.youtube.com/watch?v=s7ZvBy1SROE

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly, 37*(2), 471–482. https://doi.org/10.25300/MISQ/2013/37:2.03

Blascovich, J., Loomis, J., Beall, A. C., Swinth, K. R., Hoyt, C. L., & Bailenson, J. N. (2002). Immersive virtual environment technology as a methodological tool for social psychology. *Psychological Inquiry, 13*(2), 103–124. https://doi.org/10.1207/S15327965PLI1302_01

Bresciani, S., Ciampi, F., Meli, F., & Ferraris, A. (2021). Using big data for co-innovation processes: Mapping the field of data-driven innovation, proposing theoretical developments and providing a research agenda. *International Journal of Information Management, 60*, 102347. https://doi.org/10.1016/j.ijinfomgt.2021.102347

Bustamante, J. C., & Rubio, N. (2017). Measuring customer experience in physical retail environments. *Journal of Service Management, 28*(5), 884–913. https://doi.org/10.1108/JOSM-10-2016-0266