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RESEARCH ARTICLE

Geographical and cognitive proximity effects on innovation performance: Which types of proximity for which types of innovation?

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Abstract

The purpose of the paper is to explore the multi-dimensional and intersecting nature of proximity to drive innovation performance. Applying a multi-dimensional proximity framework, the study provides a deeper understanding of the importance of substitution and overlap mechanisms in the relation between geographical and cognitive proximity dimensions in innovation performance. The paper further analyses the moderation effect of organisational innovation in this relationship. Multivariate analysis proves the interaction effects between geographical and cognitive proximity, where cognitive proximity both substitutes and complements geographical proximity. However, external knowledge search for innovation along proximity dimensions differs depending on the type of innovation. Our findings corroborate the proximity paradox caused by lock-in effects with the optimal level of proximity influenced by the interdependencies between proximity dimensions. This inverse U-shaped relationship is flatter for firms that have adopted organisational innovation. External knowledge linkages should be tailored to the favourable characteristic of proximity to enhance firm innovation performance.

KEYWORDS
cognitive proximity, geographical proximity, innovation performance, organisational innovation, overlap, proximity paradox, substitution

INTRODUCTION

Collaboration is a key driver of innovation performance (Garcia Martinez, Zouaghi, & Sanchez Garcia, 2019; Nieto & Santamaría, 2007). The critical role of external knowledge linkages in facilitating new knowledge creation and improving firms' innovation performance has been established in innovation studies (Ehls, Polier, & Herstatt, 2020; Savino, Messeni Petruzzelli, & Albino, 2017; Zahra, Neubaum, & Hayton, 2020). In order to improve innovation performance or to adapt to a changing environment, firms search for external knowledge sources to increase the available knowledge base (March, 1991). Collaborating with suppliers, customers, universities and research centres and competitors can stimulate innovation by exposing firms to new knowledge (Faems, van Looy, & Debackere, 2005; Katila & Ahuja, 2002; Laursen & Salter, 2014).

An emerging body of literature indicates that proximity dimensions are important facilitators of inter-organisational collaboration (Knoben & Oerlemans, 2006). They increase the expected net benefits of the collaboration and augment the likelihood of its success (Bergé, 2016). Although proximity has been traditionally associated with geographical factors (Mattes, 2012), innovation studies increasingly apply multi-dimensional frameworks in the analysis of collaboration between actors (Balland, 2012; Hansen, 2015). In fact, proximity could be organisational, cognitive, social, institutional, cultural and technological (Boschma, 2005). Further, the proximity of different dimensions is not an independent relationship but can affect each other and to some extent substitute or complement each other (Broekel, 2015; Hansen, 2015). By studying how different proximity dimensions interact to drive innovation performance, one can find solutions to the challenges of coordination in knowledge transfer (Boschma, 2005).

The aim of this paper is therefore to understand the dynamics of inter-organisational collaboration by examining the role that geographical proximity plays in relation to cognitive proximity in innovation performance. Boschma (2005) defined geographical proximity as the geographical or spatial distance between actors and cognitive proximity as the similarities between actors in terms of their knowledge base. The intersecting relationship was analysed by using the substitution/complementarity approach (Hansen, 2015). Under the substitution-innovation mechanism, the absence of geographical proximity in the case of international cooperation can be substituted by cognitive proximity. The existence of similar capabilities and shared experiences between partners can foster collaboration for innovation over long distances (Capello & Caragliu, 2018; Garcia et al., 2018). According to the overlap-innovation mechanism, geographical proximity amplifies the effect of cognitive proximity on innovation performance (Zhao et al., 2022). A shorter geographic distance can reduce communication costs and promote the transfer and absorption of tacit knowledge (Petruzzelli, 2014).

Further, considering that radical and incremental innovation require distinct knowledge inputs (Garcia Martinez, Zouaghi, & Garcia Marco, 2017; Hsieh et al., 2018), we examine the distinct impact of multidimensional proximity on the two innovation types. Radical innovation represents a dramatic departure from existing technological trajectories and results from the harnessing of tacit knowledge whereas incremental innovations are minor improvements or simple adjustments in current technology, which are usually generated by explicit knowledge (Mascitelli, 2000; Zhou & Li, 2012). To that end, we proposed a typology of geographical-cognitive proximity configurations to examine if external knowledge search for innovation along proximity dimensions differs depending on innovation outcomes owing to their distinct knowledge characteristics.

Research also highlights how too much distance between actors may undermine interaction and learning (Nooteboom, 2000); therefore, adequate organisational responses and mechanisms are required to leverage external knowledge search for innovation (Molina-Morales, García-Villaverde, & Parra-Requena, 2014). Thus, in this paper, we analyse the moderating effect of organisational innovation in the relationship between proximity dimensions interactions and firm innovation performance. Organisational innovation involves the implementation of significant changes in business practices, workplace organisation and external relations (Enkel & Heil, 2014) aimed at improving employees' exploration and creativity (Ardito et al., 2018). Organisational innovation is a contingency that can alter the nature of the proximity interactions - innovation performance relationship.

Our research seeks to contribute to the literature on proximity and inter-organisational knowledge transfer in several ways. Applying a multi-dimensional proximity framework, the study provides a deeper understanding of the importance of substitution and overlap mechanisms in the relation between geographical and non-spatial proximity dimensions in fostering firm innovation performance (Hansen, 2015). Boschma (2005) suggested that proximity dimensions interact with each other to drive innovation; therefore, our paper provides empirical evidence to the research on the interaction effects of different proximity dimensions. Second, we extend research on the proximity paradox (Boschma & Frenken, 2010) and contrast the optimal level of proximity under different proximity configurations. Finally, we contribute to understanding the contingent role played by organisational innovation to enhance innovation performance in proximity contexts by demonstrating the flattening moderating effect of organisational innovation. By embracing new ways of working, levering technology and fostering inter-firm collaboration, firms can address the challenges of working in distant contexts (Arranz, Arroyabe, & Fernandez de Arroyabe, 2020).

The paper is structured as follows: The next section provides an overview of the literature associated with geographical and cognitive proximity and their interaction and the research hypotheses. The third section introduces the research method and the forth section presents the findings. Finally, section five discusses the results of the empirical study and in the sixth section, we present the main conclusions, underlining the contribution and further implications of this research.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

Dimensions of proximity and innovation performance

Among different dimensions of proximity, geographical proximity is one of the most widely discussed dimensions in the proximity literature (Knoben & Oerlemans, 2006). Boschma (2005) defines geographical proximity as the geographical or spatial distance between actors. Research shows that organisations are more likely to start collaborations if they share a geographical proximity (Balland, 2012). Geographical proximity facilitates face-to-face interaction, thus fostering innovation and knowledge sharing (Hervas-Oliver et al., 2018; Huber, 2012; Mattes, 2012; Torre & Rallet, 2005). In contrast, a large geographical distance hinders knowledge transfer, especially in the case of tacit knowledge (Gertler, 2003; Knoben & Oerlemans, 2006). In other words, creativity and innovativeness tend to cluster geographically

(Boschma, 2005). The literature however suggests that the effect of geography on knowledge transfer and innovation could be non-homogeneous and depend on the nature of the knowledge involved (i.e. tacit vs codified) (Mattes, 2012). This relationship varies in turn depending on the type of industry and the stage the project or collaborative activity is in (Ivarsson & Alvstam, 2009). Physical proximity is particularly relevant in the case of more applied cooperation with shorter time to market (Broström, 2010), in certain stages of knowledge transfer (Torre, 2008) and between different types of organisations (Ponds, van Oort, & Frenken, 2007). Bignami, Mattsson, & Hoekman (2020) concluded that collaboration in basic science and core knowledge areas is more negatively affected by geographical distance than collaboration within clinical science and exploration knowledge areas.

Whereas geographical distance negatively affects interactive learning and innovation, too much geographical proximity can also be harmful to these purposes (Boschma, 2005). Boschma & Frenken (2010) called this phenomenon the 'proximity paradox' and explained that it could happen due to the lack of openness and flexibility. They argue that proximity might negatively impact innovation due to the problem of spatial lock-in. Too much geographical proximity hinders the creation of interactive learning benefits that come from a mix of local and non-local actors (Boschma, 2005). Actors within a region could become a too 'inward-looking' community with weakened learning ability and lose their ability to generate new ideas or respond to new developments (Boschma, 2005; Gittelman, 2007). Hence, an optimal level of geographical proximity between actors needs to be reached and not surpassed to avoid negative effects on their innovation performance due to the lack of openness and flexibility (Boschma, 2005; Broekel & Meder, 2008).

Researchers increasingly recognise that the effect of geographical proximity on inter-organisational collaboration cannot be evaluated in isolation as other forms of proximity are significant in explaining collaboration and innovation performance (Hansen, 2015; Knoben & Oerlemans, 2006). Moreover, Boschma (2005) argued that geographical proximity per se is neither a necessary nor a sufficient condition for collaboration; it facilitates interactive learning by strengthening the other dimensions of proximity. As the other facets of proximity may provide alternative solutions to the problem of spatial lock-in in the region, geographical proximity is not a necessary condition. Besides, since knowledge transfer across large distances requires other forms of proximity to be effective, geographical proximity is not sufficient either. Hence, although traditional studies have emphasised the positive effect of geographical proximity, there are increasing calls to consider non-spatial forms of proximity besides geographical proximity to understand collaboration and innovation (Hansen, 2015; Paci, Marrocu, & Usai, 2014).

To address the above concerns, the present study includes cognitive proximity. Cognitive proximity refers to similarities in the way that partners perceive, interpret, understand and evaluate the external world (Knoben & Oerlemans, 2006; Nooteboom et al., 2007; Wuyts et al., 2005). Boschma (2005) states the importance of cognitive proximity to interact and share knowledge effectively since firms have an established tendency to search for partners close to their own knowledge base. Therefore, the cognitive boundaries of a firm determine the knowledge absorptive and innovative capabilities. However, he also highlights that too much cognitive proximity may result in 'cognitive lock-in' when actors are closed to new technologies and markets. When there is cognitive distance between actors, the tendency of their capacity to obtain new knowledge increases, but it could restrict learning due to communication problems. Therefore, a balance must be reached between cognitive distance, in the benefit of creativity and innovation and cognitive proximity, in behalf of absorptive capacity, to identify, interpret and exploit new knowledge. Nooteboom (2000) argues that information is useless if it is not new, but it is also useless if it is so new or so different that it cannot be understood. As a way to mitigate the potential risks from cognitive proximity, Maskell (2001) proposes that there must exist a geographical cluster with a common knowledge base composed of diverse, but complementary, knowledge sources. Hence, the optimal effect on inter-organisational collaboration for innovation is often a combination of proximities, based on different potential spillovers (Fitjar, Huber, & Rodríguez-Pose, 2016). This emphasises the multi-dimensional nature of proximity and at the same time the interdependence of all proximity dimensions (Boschma, 2005; D'Este, Guy, & Iammarino, 2013) with their mutual interaction (Ben Letaifa & Rabeau, 2013). In this paper, we examine the extent to which geographical proximity interacts with cognitive proximity to drive different innovation outcomes.

Interaction between geographic and cognitive proximity

Proximity studies have shown a complex set of relationships between dimensions of proximity characterised by substitution and overlap (Capaldo & Petruzzelli, 2014; Fitjar, Huber, & Rodríguez-Pose, 2016; Huber, 2012; Mattes, 2012). Hansen (2015) found that cognitive proximity can act as a substitute for geographical proximity as a tool for interaction. For high spatial distances, cognitive proximity is reported to be an important mechanism for scientific cooperation between researchers (Capello & Caragliu, 2018). However, research also shows that the relationship between geographical and cognitive proximities could be complementary in nature since interactions based on both geographical and cognitive proximities are more likely to occur than those characterised by only spatial proximity (Broekel & Boschma, 2012). This paper explores if external knowledge search for innovation along proximity dimensions differs depending on the type of innovation. Recognising that radical and incremental innovation require distinct types of knowledge, and, therefore, different forms of knowledge transfer mechanism (Szulanski, 1996), we establish a typology of geographical-cognitive proximity configurations (Figure 1) to examine the interaction effect between proximity dimensions on the two innovation types.

Cognitively close and geographically distant partners (Q1)

High cognitive proximity between collaborating partners tends to stimulate more geographically distant collaborations (Garcia et al., 2018). A shared knowledge base between partners facilitates long-distance collaborations, and cognitive proximity can be a substitute for geographical proximity in fostering interactive learning between actors (Hansen, 2015). The higher absorptive capacity of actors increases the cognitive proximity between partners, even if they are geographically distant (de Jong & Freel, 2010). High cognitive proximity facilitates communication, learning and knowledge sharing between partners and renders firms less dependent on co-location (Garcia et al., 2018; Phene, Fladmoe-Lindquist, & Marsh, 2006). Balland, Belso-Martínez, & Morrison (2016) report that cognitive proximity plays a key role in the transfer of tacit and complex knowledge, which is observed primarily in radical innovation as it facilitates effective communication and coordination. Because tacit knowledge in nature is deeply held by experienced individuals, high cognitive proximity enables knowledge transfer through interactive conversation and shared experience. Therefore, cognitive proximity matters more for explorative (radical) innovation activities than geographical proximity. Some cognitive proximity is also relevant for exploitative-focused innovation aimed to achieve incremental improvements taking place at the latest stages of the innovation process (Alpaydın & Fitjar, 2021). Incremental innovation is facilitated largely by explicit knowledge that can be easily exchanged, distributed and combined, and once codified it be applied by firms outside the geographical area of the emergence (Okuyama, 2017).

Despite the critical facilitative role of cognitive and geographical proximities in inter-organisational collaboration, too much shared common knowledge can be detrimental to knowledge creation and innovation (i.e. limits sources of novelty and creates a competence trap) (de Man & Duysters, 2005). Some cognitive distance is needed to ensure that interactive learning is effective (Boschma, 2005). Excessive cognitive proximity can lead to cognitive lock-in situations that undermine the effectiveness of collaboration and innovation. If cognitive proximity is too high, the potential for novelty in knowledge and learning becomes small. While partners need to share a similar knowledge base and expertise to understand each other, they need to be sufficiently different to learn from each other (Boschma, 2005; Nooteboom et al., 2007). When knowledge bases differ substantially, partners can potentially learn significantly from each other. However, too much cognitive proximity may yield diminishing and even negative returns since the learning

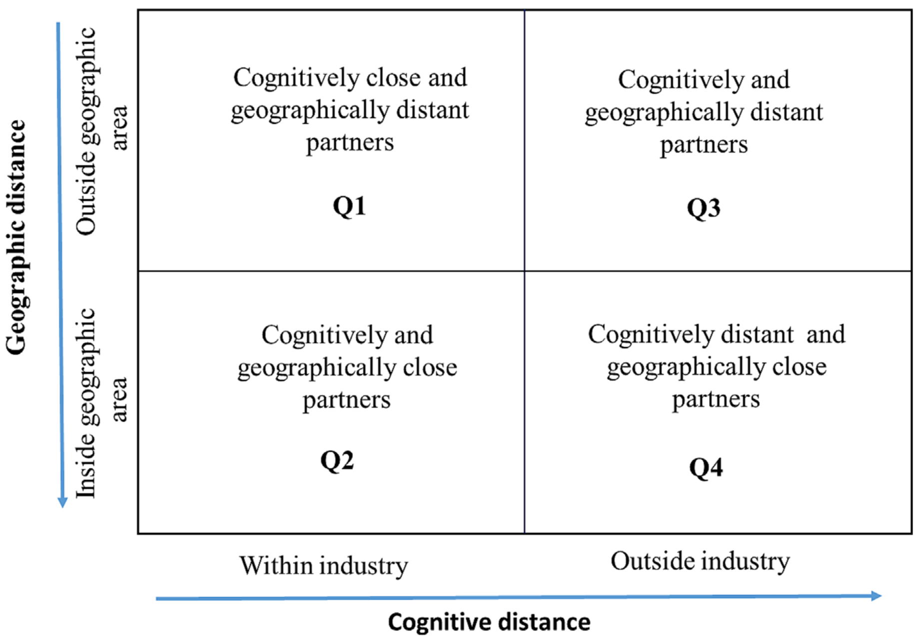

FIGURE 1 Collaboration distance matrix

process might not be very rich if actors exhibit a high level of cognitive overlaps. Hence, the degree of cognitive difference should be on the balance of being close enough to foster interactive learning and collaboration, but different enough to be able to exploit knowledge complementarities (Boschma, 2005). Therefore, we hypothesise the following:

Hypothesis 1a. Cognitively close knowledge of international origin is expected to have a curvilinear effect (inverted U-shape) on radical innovation.

Hypothesis 1b. Cognitively close knowledge of international origin is expected to have a curvilinear effect (inverted U-shape) on incremental innovation.

Cognitively and geographically close partners (Q2)

The interaction of geographical and cognitive proximity can foster interactive learning and knowledge dissemination among partners, often without a conscious decision among those involved (Paci, Marrocu, & Usai, 2014). Research suggests that physical and cognitive closeness is crucial for transferring tacit and complex knowledge beneficial for radical innovation (van Wijk, Jansen, & Lyles, 2008). A shorter geographic distance can reduce communication costs and promote the transfer and absorption of tacit and idiosyncratic knowledge (Petruzzelli, 2014), and cognitive proximity can lay the foundations for effective communication between actors. Cognitive proximity will be pronounced in an effective communication and coordination context. Mathisen & Jørgensen (2021) show how knowledge readiness can facilitate knowledge exchange and enhance innovation through collaboration. Firms with similar knowledge bases maybe more inclined to seek complementary knowledge within the geographical range of partners due to underlying shared norms and values (Boschma, 2005; Phene, Fladmoe-Lindquist, & Marsh, 2006), which can explain the general ease and success of knowledge exchanges in geographical clusters. Omobhude & Chen (2019) argue that the proximity of a science park increases the likelihood of cognitive proximity in terms of the interaction and cooperation among actors with similar capabilities and shared experiences. Further, the explicit and codified knowledge supporting incremental innovation can be easily transferred and shared under high spatial and non-spatial proximity contexts. In that sense, geographical proximity amplifies the effect of cognitive proximity on innovation performance (Zhao et al., 2022).

However, too much geographical and cognitive proximity can negatively impact innovation (Ben Letaifa & Rabeau, 2013). Excessive overlap in knowledge bases can obscure insights into a broader range of technology options and new market possibilities (Enkel & Heil, 2014). Further, firms can find themselves restricted to pre-existing knowledge, and over time lose their ability to assimilate new knowledge outside national boundaries and become unable to capitalise on new technological developments (Wu & Wu, 2014). Lin et al. (2012) argue that high levels of similarity between partners can be a significant impediment to the search process and hamper the development of novel innovation. Therefore, we propose the following hypotheses:

Hypothesis 2a. Cognitively close knowledge of national origin is expected to have a curvilinear effect (inverted U-shape) on radical innovation.

Hypothesis 2b. Cognitively close knowledge of national origin is expected to have a curvilinear effect (inverted U-shape) on incremental innovation.

Cognitively and geographically distant partners (Q3)

External knowledge from cognitively and geographically distant partners offers firms a greater opportunity for learning and exploration (Ehls, Polier, & Herstatt, 2020). This type of knowledge increases the probability of radical innovation by enabling firms the opportunity to access novel knowledge bases, pursue new scientific advances and trial new technologies (Wuyts, Dutta, & Stremersch, 2004). Duysters & Lokshin (2011) state that cognitive and geographical distance would benefit radical innovators searching for vast, unique and heterogeneous external knowledge to support their innovation endeavours. They should be going beyond the frontiers of their local linkage because firms that limit themselves to their well-known domains can lose the opportunity of finding new knowledge and capabilities. Thus, companies should explore new sources of knowledge outside their traditional networks and regions. Explicit knowledge for incremental innovation does not require a high level of coordination, trust or socialisation among partners for its transfer (Dhanaraj et al., 2004). Therefore, it can be transferred over a greater distance at a lower cost; hence, interactions between cognitively and geographically distant partners can facilitate incremental innovation.

However, a firm's ability to incorporate the knowledge that is both cognitively and geographically distant is challenging due to differences in national contexts and institutional environments from its own knowledge stock (Lavie & Miller, 2008). Further, geographically and cognitively distant partners generally present additional challenges, such as cognitive-normative distance and regulation policies in the different countries that can undermine the firm's ability to successfully manage inter-organisational collaboration and harm innovation performance (Lavie & Miller, 2008). Though cognitive and geographical distant knowledge is needed for innovations, too much distance would undermine a firm' ability to effectively use it for innovation (Phene, Fladmoe-Lindquist, & Marsh, 2006). Therefore, we propose the following hypotheses:

Hypothesis 3a. Cognitively distant knowledge of international origin is expected to have a curvilinear effect (inverted U-shape) on radical innovation.

Hypothesis 3b. Cognitively distant knowledge of international origin is expected to have a curvilinear effect (inverted U-shape) on incremental innovation.

Cognitively distant and geographically close partners (Q4)

Being geographically proximate facilitates face-to-face interactions between partners, and therefore fosters knowledge sharing and innovation through the exchange of high-quality information and tacit knowledge among partners (Boschma, 2005; Knoben & Oerlemans, 2006). Geographical proximity lowers coordination and transaction costs in collaboration which offers the opportunity to absorb knowledge from spillovers without maintaining cognitive proximity (Baptista & Swann, 1998). Firms in the same geographical cluster maybe inclined to enter into cognitively distant partnerships as it allows for the recombination of heterogeneous knowledge inputs (Liu & Ma, 2019) needed for breakthrough innovations (Hess & Rothaermel, 2011). In fact, geographical proximity can play a key role in the co-development and transfer of tacit and sticky knowledge by facilitating interactions, social embeddedness and trust between cognitively distant partners (Asheim, Coenen, & Vang, 2007).

However, developing excessive geographical proximity may hinder the process of knowledge production because it can create spatial lock-in situations that have a negative influence on learning and innovation (Molina-Morales, García-Villaverde, & Parra-Requena, 2014). Boschma (2005) affirms that geographical proximity by excess limits learning because it generates confinement and promotes high specialisation, losing the ability to adapt to new developments in more distant areas. Hence, geographical proximity between actors should be 'optimal' as too much or too little spatial closeness may negatively impact firm's innovation performance (Balland, Boschma, & Frenken, 2015). Therefore, we put forward the following hypotheses:

Hypothesis 4a. Cognitively distant knowledge of national origin is expected to have a curvilinear effect (inverted U-shape) on radical innovation.

Hypothesis 4b. Cognitively distant knowledge of national origin is expected to have a curvilinear effect (inverted U-shape) on incremental innovation.

The moderating effect of organisational innovation

Too much geographic or cognitive distance between partners can create difficulties in the acquisition and absorption of novel and distant knowledge and requires firms to provide organisational responses to address these challenges (Wu & Wu, 2014). Inter-organisational collaboration studies have demonstrated the importance of absorptive capacity in enabling firms to take advantage of external knowledge sources (Cohen & Levinthal, 1990; Zahra & George, 2002). Absorptive capacity enables the exploration, assessment, integration and use of new knowledge in the organisation. In addition to prior knowledge, firms need to develop organisational capabilities to integrate and apply existing and new external knowledge (Eisenhardt & Martin, 2000; Kogut & Zander, 1992). Empirical studies have emphasised the complementarity nature of organisational and technological innovations in their effect on innovation performance (Anzola-Román, Bayona-Sáez, & García-Marco, 2018; Camisón & Villar-López, 2014; Damanpour, Walker, & Avellaneda, 2009; Mothe & Thi, 2010) and the facilitative role of organisational innovation in inter-organisational collaboration (Arranz, Arroyabe, & Fernandez de Arroyabe, 2020; Grant & Baden-Fuller, 2004).

Organisational innovation involves the introduction of all changes directed at improving existing processes at the core of an organisation's structure (OECD, 2005). These new organisational methods can relate to innovations in work processes, workplace practices or new organisational methods in external relations. This view of organisational innovation is similar to Cohen & Levinthal's (1990) concept of innovation capability referring to the organisational capabilities to successfully adapt and implement new ideas, products and processes. These capabilities are regarded as crucial to achieve higher adaptability and flexibility within the organisation (Mothe & Thi, 2010) and mitigate the drawbacks and task conflicts in distant contexts (Garcia Martinez, Zouaghi, & Sanchez Garcia, 2019).

Having an adequate organisational culture and climate open to accept risk, leadership and autonomy can foster team creativity and increase tolerance of failure and unsuccessful ideas in conducting complex innovation processes (Chang et al., 2012). The literature highlights the importance of developing organisational culture routines with ethics geared towards interdepartmental connectedness and decision-making, which increase trust and foster collaboration among employees (Popa, Soto-Acosta, & Martinez-Conesa, 2017) as a means to help firms integrate widely dispersed knowledge.

Firms may effectively use external search through the implementation of a set of organisational routines that support employees' efforts to share and combine external knowledge by reinforcing their social ties (Martini, Neirotti, & Appio, 2017). The role of workplace climate (e.g. closer connections and interpersonal attraction among group members) has largely been overlooked in the field of innovation as a dynamic capability that can stimulate innovation performance (Strese et al., 2016) and shape a individual's potential absorptive capacity to recognise and understand external knowledge assets (Garcia Martinez, Zouaghi, & Sanchez Garcia, 2019).

In this context, our study explores the contingent role played by organisational innovation to enhance innovation performance in proximity contexts. We hypothesise that organisational innovation can weaken the positive effects of proximity interactions while at the same time reducing the potential impacts (the so-called down-side effects) from high cognitive and geographic distance. This implies a change in the shape of the inversed U-shape relationship of H1 to H4 – the curve becomes flatter when firms adopt organisational innovation. Accordingly, we propose the following hypothesis:

> **Hypothesis 5.** Organisational innovation moderates the relationship between geographic-cognitive proximity interaction and innovation performance. The inverted U-shaped relationship will be flatter when firms implement organisational innovations.

METHOD

Sample and data

The data for the empirical study has been drawn from the Spanish Technological Innovation Panel (PITEC) database, which is a statistical instrument for studying the innovation activities of Spanish companies overtime. The data is compiled by the Spanish National Statistics Institute (INE). This database provides information on firms' innovation activities for manufacturing, services and agricultural sectors. In this study, the focus is on manufacturing firms that have cooperated at least one time with external partners over the period 2008–2016. Our final sample contained 34,637 observations.

Variables

Dependent variables

Innovative performance is the dependent variable of the model measured as the percentage of the firm's total sales from innovation (Beck, Lopes-Bento, & Schenker-Wicki, 2016; Laursen & Salter, 2006; Ovuakporie et al., 2021). We distinguish between incremental and radical innovation, depending on their degree of novelty to the company or the market place, respectively. Radical innovation performance is measured as the firm's sales share in year *t* from innovations new to the market during the period between *t-2* and *t*. Incremental innovation performance is defined as the firm's sales share in year *t* from innovations new to the firm during the period between *t-2* and *t*.

Independent variables

Following prior research (Dooley, Kenny, & Cronin, 2016; Phene, Fladmoe-Lindquist, & Marsh, 2006), we establish a typology of four proximity configurations representing combinations of geographical and cognitive proximity. The collaborative distance matrix (Figure 1) indicates low and high levels of geographical and cognitive proximity so the interaction effects between proximity dimensions on firm innovation performance can be explored. To operationalise the proximity variables, we used PITEC questions where firms indicate if they have cooperated with different partner types during the period between *t-2* and *t*. For geographical proximity, the spectrum ranges from close proximity representing collaboration with other Spanish-based organisations to distant cooperation with partners located in Europe, the USA and the rest of the world. In the case of cognitive proximity, the spectrum varies from collaboration with cognitively close partners within sister organisations, suppliers and customers to more cognitively distant partners, such as consultants, public research labs, universities or competitors. We mapped responses to the collaborative distance matrix to generate the following quadrants: (Q1) Cognitively close and geographically distant partner represents the partner category of sister organisations, suppliers and customers located outside of the geographic area (i.e. EU, USA and all other countries); (Q2) Cognitively and geographically close partner represents the partner category of sister organisations, suppliers and customers located inside the geographic area (i.e. Spain); (Q3) Cognitively and geographically distant partner represents a collaboration with consultant organisations, public research labs, universities or competitors located outside of the geographic area (i.e. EU, USA and the rest of the world); and (Q4) Cognitively distant and geographically close partner represents consultant organisations, public research labs and universities or competitors located inside the geographic area (i.e. Spain). For each quadrant, the resulting dummy variables representing the number of partners were summed up; for instance, for Q1, the number of partner types is 6 depicting all possible combinations between the cognitive space and geographical location.

Moderator variable

Organisational innovation (OI) was operationalised using PITEC questions where firms indicate if they have introduced new organisational practices, such as: (1) the introduction of new business practices for organising procedures, (2) the introduction of new methods of organising work responsibilities and decision making and (3) the introduction of new methods of organising external relations with other firms or public institution. Each category is measured by a dummy variable defined as 0 if no activities in the particular category have taken place and 1 if they are. Following previous PITEC empirical studies (Anzola-Román, Bayona-Sáez, & García-Marco, 2018; Arranz et al., 2019; García-Marco, Zouaghi, & Sánchez, 2020), we created a dummy variable (OI) that is coded as 1 if the organisation had implemented at least one new organisational practice in the period of study, and 0 otherwise.

Control variables

Firm size is measured by the natural logarithm of the number of employees; further, we controlled for the nonlinear effects of firm size by calculating firm size squared (Garcia Martinez, Zouaghi, & Sanchez Garcia, 2019). R&D intensity is determined by a firm's R&D spending as a proportion of its total sales (Laursen & Salter, 2004). Export intensity is calculated by the logarithm of the ratio of export sales to total sales (Antolín et al., 2013). Finally, we controlled for industry effects with dummy variables and included time-dummies to control for period effects that might influence inter-organisation collaboration and firm innovation performance (Lin, 2014). Table A1 in Appendix A describes the variables used in this study.

Model specification

The dependent variables (share of turnover generated by radical and incremental innovation) are double-censored and conditioned on values between 0 and 100; hence, ordinary least squares (OLS) regression is not applicable as its estimates are not consistent when the residuals are not normally distributed. Therefore, we use a Tobit model for the analysis (Greene, 2012). Since the data for both measures of innovation outcomes are highly skewed to the left, the assumption of a normal distribution of the residuals made in a Tobit analysis is violated (significance of Shapiro–Wilk test of 0.000 for both dependent variables). Thus, we followed Laursen & Salter (2006) and used the logarithmic transformation of the dependent variables to satisfy the assumption of normality of residuals for the Tobit model. The model introduces a latent variable, Y*, as a logarithmic transformation of an observed measure of innovative performance, Y: that is, Y* = ln (1 + ratio of new product sales to total sales × 100). It is then assumed that the latent variable of the innovative performance of a firm is a function of a number of explicative variables. In addition, we established a lag structure in our data by measuring the explanatory and control variables (except for industry dummies which do not vary across panel waves) in year *t-1*, consistent with the survey implementation rhythm, to avoid simultaneity and reverse causality problems (Mairesse & Mohnen, 2010). This reduced our sample to an unbalanced panel of eight years and 34,637 observations.

The random-effects Tobit specification of our models is as follows:

$$Y_{it}^{*} = a_0 + \alpha_1 \mathrm{CCGD}_{it-1} + \alpha_2 \mathrm{CCGDsq}_{it-1} + \sum\nolimits_i^j \Upsilon \mathrm{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

$$Y_{it}^{*} = \beta_0 + \beta_1 \mathrm{CCGC}_{it-1} + \beta_2 \mathrm{CCGCsq}_{it-1} + \sum\nolimits_i^j \Upsilon \mathrm{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

$$Y_{it}^{*} = \varphi_0 + \varphi_1 \mathrm{CDGD}_{it} + \varphi_2 \mathrm{CDGDsq}_{it-1} + \sum\nolimits_i^j \Upsilon \mathrm{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

$$Y_{it}^{*} = \nu_0 + \nu_1 \mathrm{CDGC}_{it-1} + \nu_2 \mathrm{CDGCsq}_{it-1} + \sum\nolimits_i^j \Upsilon \mathrm{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

The observed dependent variable (y) is expressed as:

$$\begin{cases} y_{it} = y^{*}_{it} & \text{if } y^{*}_{it} > 0 \\ y_{it} = 0 & \text{if } y^{*}_{it} \le 0 \end{cases}$$

where y_{it}^{*} refers to the latent (unobserved) variable and α; β; φ and υ are regression coefficients, $\sum_i^j \Upsilon \mathrm{Controls}_{it}$ refers to the set of other control variables that are not displayed in the equation. The random effects ρ_i and the error term ε_{it} are assumed to be identically distributed $N(0,\sigma_\alpha^2)$, and $N(0,\sigma_\varepsilon^2)$ and independent of $x_{i1},\dots,x_{it}$, with zero means and variances, σ_α^2 and σ_ε^2 respectively (Al-Malkawi, Bhatti, & Magableh, 2014; Nishitani, 2010).

We follow the procedure suggested by Haans, Pieters, & He (2016) to test the inverted U-shaped relationship between proximity dimensions interactions and innovation performance: first, the first term coefficients of the independent variables (α_1; β_1; φ_1 and υ_1) are significant and the coefficients of their quadratic term (α_2; β_2; φ_2 and υ_2) should be significantly negative. Second, within the range of sample data, the slope of both ends of the inverted U-shaped curve must be steep enough. In other words, when each independent variables take the minimum values, $\alpha_1 + 2\alpha_2\text{CCGD}_{min}; \beta_1 + 2\beta_2\text{CCGC}_{min}; \varphi_1 + 2\varphi_2\text{CDGD}_{min}$ *and* $\nu_1 + 2\nu_2\text{CDGC}_{min}$ are significantly positive, while when the independent variables take the maximum values, $\alpha_1 + 2\alpha_2\text{CCGD}_{max}; \beta_1 + 2\beta_2\text{CCGC}_{max}; \varphi_1 + 2\varphi_2\text{CDGD}_{max}$ *and* $\nu_1 + 2\nu_2\text{CDGC}_{max}$ are significantly negative. Third, the turning point needs to be located within the range of the data.

To test the moderated curvilinear relationship, we add the interaction terms as depicted below:

$$Y^*_{it} = a_0 + \alpha_1\text{CCGD}_{it-1} + \alpha_2\text{CCGDsq}_{it-1} + \alpha_3\text{CCGD}_{it-1} * \text{OI}_{it-1} + \alpha_4\text{CCGDsq}_{it-1} * \text{OI}_{it-1} + \sum\nolimits_i^j \Upsilon\text{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

$$Y^*_{it} = \beta_0 + \beta_1\text{CCGC}_{it-1} + \beta_2\text{CCGCsq}_{it-1} + \beta_3\text{CCGC}_{it-1} * \text{OI}_{it-1} + \beta_4\text{CGCsq}_{it-1} * \text{OI}_{it-1} + \sum\nolimits_i^j \Upsilon\text{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

$$Y^*_{it} = \varphi_0 + \varphi_1\text{CDGD}_{it} + \varphi_2\text{CDGDsq}_{it-1} + \varphi_3\text{CDGD}_{it-1} * \text{OI}_{it-1} + \varphi_4\text{CDGDsq}_{it-1} * \text{OI}_{it-1} + \sum\nolimits_i^j \Upsilon\text{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

$$Y^*_{it} = \nu_0 + \nu_1\text{CDGC}_{it-1} + \nu_2\text{CDGCsq}_{it-1} + \nu_3\text{CDGC}_{it-1} * \text{OI}_{it-1} + \nu_4\text{CDGCsq}_{it-1} * \text{OI}_{it-1} + \sum\nolimits_i^j \Upsilon\text{Controls}_{it-1} + \rho_i + \varepsilon_{it}$$

RESULTS

The random-effects Tobit models were estimated with STATA 16 econometrics software. Table 1 summarises the descriptive statistics, pairwise correlations and collinearity diagnostic for the variables used in the empirical study, except for the year and sectoral dummies. Correlation values among all variables are generally low to moderate, suggesting there is a low risk of facing collinearity issues or redundancies with this set of variables. This is confirmed by the analysis of the variance inflation factor (Vif) values. The maximum Vif value is 1.34, which is far below the threshold value of 10, suggesting the absence of multicollinearity problems in the models (Neter et al., 1996).

Tables 2 and 3 present the random-effects Tobit models for radical and incremental innovations, respectively, after correcting for sample selection bias through a two-stage Heckman procedure (Heckman, 1976). In the first step, called the selection equation, the probability of whether or not the firm engages in external collaboration for innovation is examined, with a random-probit model. The main purpose of this step is to calculate the correction factor, named the inverse Mills ratio (IRM). In the second step, IMR is added to the second-stage regressions. The results remain substantively unchanged, indicating that our results are robust and that selection bias may not be a big concern (Table 4).

Hypothesis 1 predicts an inverted U-shaped relationship between cognitively close knowledge of international origin (CCGD) partners and firm innovation performance. Models 1.1 and 2.1 (Tables 2 and 3) show that the linear coefficients of CCGD are significantly positive for radical ($\alpha = 0.932$, $p < 0.01$) and incremental innovation performance ($\alpha = 0.543$, $p < 0.01$) and the quadratic term coefficients are negative and significant for radical

TABLE 1 Descriptive statistics and correlation coefficients.

			Correlation coefficients									
Variables	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1.Radical innovation	8.179	20.657	1									
2.Incremental innovation	13.131	27.132	0.011*	1								
3. CCGD	0.138	0.539	0.096*	0.053*	1							
4. CCGC	0.201	0.504	0.090*	0.056*	0.499*	1						
5. CDGD	0.105	0.567	0.071*	0.027*	0.511*	0.321*	1					
6. CDGC	0.411	0.953	0.107*	0.066*	0.466*	0.582*	0.473*	1				
7.OI	0.411	0.492	0.127*	0.102*	0.179*	0.233*	0.137*	0.238*	1			
8.R&D intensity	0.043	0.341	0.066*	0.017*	0.027*	0.031*	0.028*	0.068*	0.021*	1		
9.Export intensity	1.438	1.479	0.061*	0.066*	0.132*	0.089*	0.107*	0.132*	0.097*	0.006	1	
10. Firm size (Ln)	4.066	1.394	0.043*	0.065*	0.219*	0.203*	0.188*	0.240*	0.237*	−0.068*	0.165*	1
Vif			1.34	1.34	1.23	1.21	1.24	1.20	1.32	1.34	1.33	1.32

Note: $N = 34{,}637$; SD = standard deviation; Vif = Variance Inflation Factor.
*$p < 0.01$.

TABLE 2 Random-effects Tobit models for radical innovation performance.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5	Model 1.6	Model 1.7	Model 1.8
Main effects								
CCGD	0.932*** (0.088)				1.751*** (0.180)			
CCGDsq	−0.124*** (0.024)				−0.334*** (0.064)			
CCGC		1.148*** (0.139)				1.072*** (0.141)		
CCGCsq		−0.317*** (0.077)				−0.274*** (0.080)		
CDGD			0.466*** (0.028)				0.613*** (0.092)	
CDGDsq			−0.028*** (0.011)				−0.071*** (0.020)	
CDGC				0.900*** (0.065)				0.885*** (0.066)
CDGCsq				−0.136*** (0.016)				−0.138*** (0.017)
Moderator								
OI					0.873*** (0.055)	0.947*** (0.058)	0.881*** (0.054)	0.974*** (0.059)
Control variables								
Firm Size	0.498*** (0.057)	0.504*** (0.056)	0.529*** (0.059)	0.479*** (0.055)	0.430*** (0.055)	0.426*** (0.055)	0.450*** (0.055)	0.403*** (0.054)
Firm Sizesq	0.01 (0.00)	0.01 (0.00)	0.001 (0.001)	0.001 (0.001)	0.001(0.001)	0.001(0.001)	0.001 (0.001)	0.001 (0.001)
R&D intensity	0.483*** (0.076)	0.481*** (0.076)	0.491*** (0.076)	0.455*** (0.075)	0.464*** (0.074)	0.464*** (0.075)	0.475*** (0.075)	0.441*** (0.074)
Export intensity	0.092*** (0.023)	0.101*** (0.023)	0.098*** (0.023)	0.092*** (0.022)	0.093*** (0.023)	0.097*** (0.023)	0.096*** (0.023)	0.088*** (0.027)
Moderation Effects								
OI* CCGD					−1.114*** (0.194)			
OI* CCGDsq					0.263*** (0.067)			
OI* CCGC						−0.786*** (0.274)		
OI* CCGCsq						0.170 (0.159)		
OI* CDGD							−0.589*** (0.190)	
OI* CDGDsq							0.125*** (0.044)	
OI* CDGC								−0.732*** (0.122)
OI* CDGCsq								0.147*** (0.034)
IMR	0.002***-(0.000)	0.019*** (0.004)	0.001*** (0.002)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Log-likelihood	−33856.51	−33853.99	−33913.72	−33795.49	−33730.68	−33718.48	−33778.31	−33661.03

Note: Standard error in parentheses. Industrial effects and year effects are included in all models.
*Significant at 5%.
**Significant at 1%.
***Significant at 0.1%.

TABLE 3 Random-effects Tobit models for incremental innovation performance.

	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5	Model 2.6	Model 2.7	Model 2.8
Main effects								
CCGD	0.543*** (0.086)				0.763*** (0.178)			
CCGDsq	−0.063*** (0.024)				−0.041 (0.065)			
CCGC		0.744*** (0.131)				0.707*** (0.133)		
CCGCsq		−0.109 (0.073)				−0.118 (0.076)		
CDGD			0.302*** (0.067)				0.300*** (0.082)	
CDGDsq			−0.019* (0.011)				−0.019 (0.016)	
CDGC				0.747*** (0.061)				0.729*** (0.062)
CDGCsq				−0.121*** (0.016)				−0.124*** (0.016)
Moderator								
OI					0.814** (0.049)	0.823*** (0.051)	0.778*** (0.048)	0.903*** (0.053)
Control variables								
Firm Size	0.824*** (0.024)	0.811*** (0.049)	0.836*** (0.050)	0.798*** (0.049)	0.755*** (0.049)	0.748*** (0.049)	0.771*** (0.049)	0.732*** (0.049)
Firm Sizesq	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)	−0.006*** (0.001)
R&D intensity	0.178*** (0.067)	0.173** (0.067)	0.180*** (0.067)	0.142** (0.067)	0.167*** (0.066)	0.161** (0.066)	0.169** (0.066)	0.127*** (0.067)
Export intensity	0.147*** (0.021)	0.149*** (0.020)	0.150*** (0.021)	0.141*** (0.021)	0.143*** (0.021)	0.145*** (0.021)	0.146*** (0.021)	0.137*** (0.020)
Moderation Effects								
OI* CCGD					−0.428** (0.192)			
OI* CCGDsq					0.004(0.68)			
OI* CCGC						−0.911*** (0.260)		
OI* CCGCsq						0.385** (0.152)		
OI* CDGD							−0.223*** (0.168)	
OI* CDGDsq							0.018 (0.035)	
OI* CDGC								−0.823*** (0.115)
OI* CDGCsq								0.178*** (0.033)
IMR	0.001(0.000)***	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.001)	0.001*** (0.000)
Log-likelihood	−1573.48	−44190.38	−44256.79	−44162.03	−44096.26	−44059.06	−44118.59	−44013.38

Note: Standard error in parentheses. Industrial effects and year effects are included in all models.
*Significant at 5%.
**Significant at 1%.
***Significant at 0.1%.

($\alpha = -0.124$, $p < 0.01$) and incremental innovation performance ($\alpha = -0.063$, $p < 0.01$). These findings provide preliminary evidence for the inverse U-shaped CCGD-innovation performance relationship. Subsequently, we estimate the slopes at various levels of CCGD and the turning points of the curves by using the utest command in Stata (Lind & Mehlum, 2019). As shown in Tables 5 and 6 column 1, the curves take the hypothesised inverse U-shape as the slope is significantly positive at the lower bound and significantly negative at the upper bound of CCGD. Sasabuchi (1980) test provides support for the composite hypothesis that the increasing relationship at the left hand and decreasing relationship at the right hand are established contemporarily. Moreover, the turning points and their confident intervals estimated by the Fieller method (Haans, Pieters, & He, 2016) indicate that the turning points are definitely within the data range. Thus, Hypotheses H1 is supported. Figure 2 depicts that the CCGD-radical innovation performance relationship and the CCGD-incremental innovation performance relationship are captured by an inverse U-shape.

Hypothesis 2 predicts an inverted U-shaped relationship between cognitively and geographically close (CCGC) partners and firm innovation performance. Models 1.2 and 2.2 (Tables 2 and 3) provide support only to our hypothesising that CCGC displays diminishing returns for radical innovation performance. The relationship between CCGC and incremental innovation performance is linear. As shown in Table 5 column 2, the curve does not take the hypothesised U-shape as the slope is significantly positive at the lower bound but insignificant at the upper bound of CCGD. Sasabuchi (1980) test also rejects the curvilinear relationship for radical innovation. Moreover, the turning point and their confident intervals estimated by the Fieller method (Haans, Pieters, & He, 2016) indicate that the turning point is definitely outside the data range. Thus, Hypothesis H2 is not supported.

Hypothesis 3 suggests an inverted U-shape relationship between cognitively and geographically distant (CDGD) partners and innovation performance. Models 1.3 and 2.3 (Tables 2 and 3) show that the linear coefficients of CDGD partners are positive and significant ($p < 0.01$) for both radical and incremental innovation performance, whereas the squared terms are negative and statistically significant. As shown in Tables 5 and 6 column 3, the curves take the hypothesised inverted U-shape as the slopes are significantly positive at the lower bound and significantly negative at the upper bound of CDGD. Sasabuchi (1980) test also provides support for the inverted U-shape hypothesis. Moreover, the turning points and their confident intervals estimated by the Fieller method (Haans, Pieters, & He, 2016) indicate that the turning points are definitely within the data range Thus, Hypotheses H3 is supported. Figure 3 depicts that the CDGD-radical innovation performance relationship and the CDGD-incremental innovation performance relationship are captured by an inverse U-shape.

Finally, Hypothesis 4 suggests a curvilinear relationship between cognitively distant and geographically close (CDGC) partner firm innovation performance. Models 1.4 and 2.4 (Tables 2 and 3) show a positive and significant linear term and a negative and significant squared term for CDGC partners for both radical and incremental innovation. As shown in Tables 5 and 6 column 4, the curves take the hypothesised inversed U-shape as the

TABLE 4 Random-Probit models for firm's decision to engage in external collaboration for innovation.

Variables	Coefficients
Firm Size	0.359 (0.021)***
Export intensity	0.079 (0.013)***
R&D intensity	0.174 (0.042)***
Group	0.318 (0.047)***
External R&D	0.919 (0.032)***
Industry dummies	Yes
Year dummies	Yes
Log-likelihood	−12082.89

Note: Standard errors in parentheses. Standard errors are reported in parenthesis.
*Significant at 5%.
**Significant at 1%.
***Significant at 0.1%.

TABLE 5 Test of inverse U-shaped relationships - radical innovation.

	H1: CCGD	H2: CCGC	H3: CDGD	H4: CDGC
Slope of lower bound	0.931***	1.147***	0.466***	0.900***
Slope of upper bound	−0.557**	−0.118	−0.377*	−0.462***
Estimated turning point	3.756***	1.813***	8.282***	3.304***
95% CI turning point:				
Fieller method	(3.793; 5.722)	(−.256; −.137)	(5.797; 9.118)	(3.257; 3.964)
Data range	(0; 6)	(0; 2)	(0; 15)	(0; 5)
Sasabuchi test (t-value)	2.26**	Reject H2	2.76***	3.92***

*Significant at 5%.
**Significant at 1%.
***Significant at 0.1%.

TABLE 6 Test of inverse U-shaped relationships - incremental innovation.

	H1: CCGD	H2: CCGC	H3: CDGD	H4: CDGC
Slope of lower bound	0.219*	0.744***	0.302***	0.746***
Slope of upper bound	−0.544***	0.305	−0.273*	−0.463***
Estimated turning point	4.280***	n/a	7.882***	3.085***
95% CI turning point:				
Fieller method	(3.608; 5.643)	(−.221; −.022)	(5.007; 8.773)	(3.166; 4.131)
Data range	(0, 6)	(0; 2)	(0; 15)	(0; 5)
Sasabuchi test (t-value)	2.30**	Reject H2	2.30***	3.73***

*Significant at 5%.
**Significant at 1%.
***Significant at 0.1%.

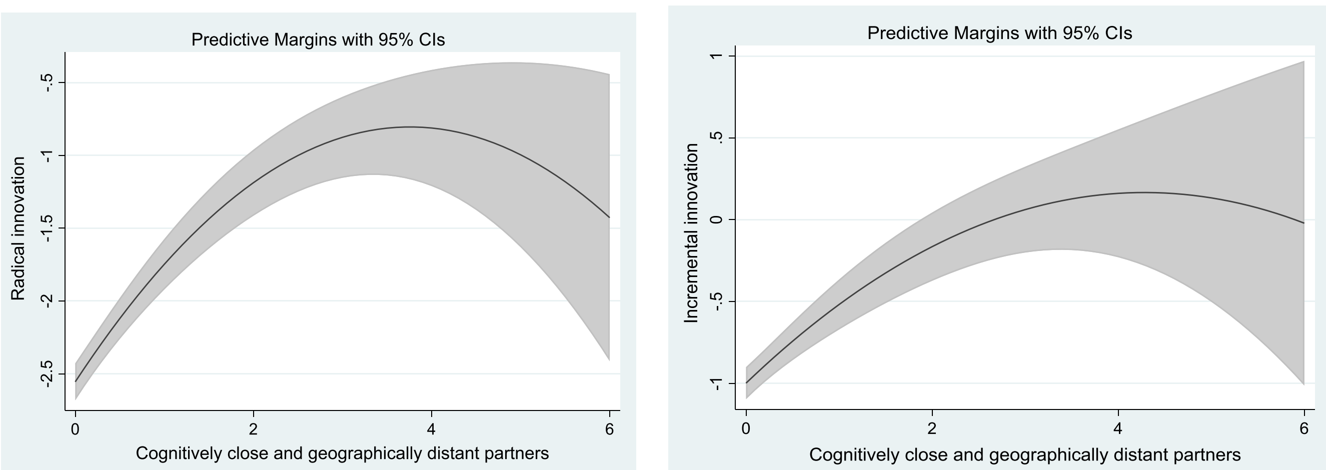

FIGURE 2 The relationship between cognitively close and geographically distant partners and innovation performance

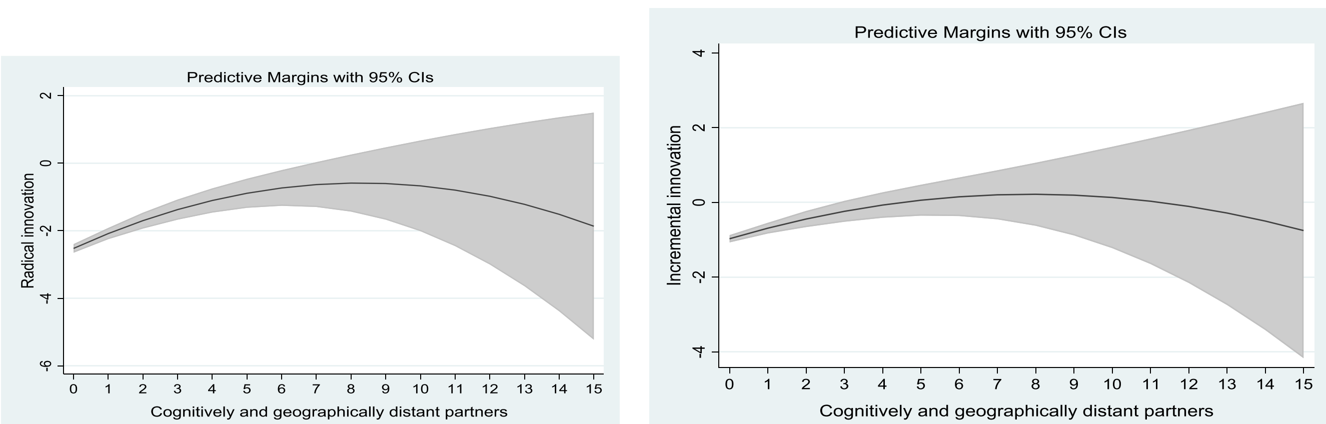

FIGURE 3 The relationship between cognitively and geographically distant partners and innovation performance

slopes are significantly positive at the lower bound and significantly negative at the upper bound of CDGC. This is also confirmed by the Sasabuchi (1980) test. Moreover, the turning points and their confident intervals estimated by the Fieller method (Haans, Pieters, & He, 2016) indicate that the turning points are definitely within the data range Thus, Hypotheses H4 is supported. Figure 4 depicts that the CDGC-radical innovation performance relationship and the CDGC-incremental innovation performance relationship are captured by an inverse U-shape.

Moderating effects

After introducing the interaction terms of the independent variables and their quadratic terms with OI into the equation, the inflexion points of the three curves are as follows:

$$CCGD^* = \frac{-\alpha_1 - \alpha_{3*OI}}{2\alpha_2 + \alpha_4 * OI}$$

$$CDGD^* = \frac{-\varphi_1 - \varphi_{3*OI}}{2\varphi_2 + \varphi_4 * OI}$$

$$CDGC^* = \frac{-\nu_1 - \nu_{3*OI}}{2\nu_2 + \nu_4 * OI}$$

$$CCGDP^* = \frac{-\alpha_1 - \alpha_3 * OIP}{2\alpha_2 + \alpha_4 * OIP} \quad CGCP^* = \frac{-\beta_1 - \beta_3 * OIP}{2\beta_2 + 2\beta_4 * OIP}$$

Thus, the partial derivation can be obtained as follows:

$$\frac{\partial CCGD^*}{\partial OI} = \frac{\alpha_1\alpha_4 - \alpha_2\alpha_3}{2(\alpha_2 + \alpha_4 OI)^2}$$

$$\frac{\partial CDGD^*}{\partial OI} = \frac{\varphi_1\varphi_4 - \varphi_2\varphi_3}{2(\varphi_2 + \varphi_4 OI)^2}$$

$$\frac{\partial CDGC^*}{\partial OI} = \frac{\nu_1\nu_4 - \nu_2\nu_3}{2(\nu_2 + \nu_4 OI)^2}$$

With the change of OI, the inflection point varies. Since the denominators: $2(\alpha_2 + \alpha_4 OI)^2$, $2(\varphi_2 + \varphi_4 OI)^2$ and $2(\nu_2 + \nu_4 OI)^2$ are strongly greater than 0, the inflexion points depend on the signs of the numerators, in order words, if $\alpha_1\alpha_4 - \alpha_2\alpha_3$, $\varphi_1\varphi_4 - \varphi_2\varphi_3$ and $\nu_1\nu_4 - \nu_2\nu_3$ are positive, then the inflexion point will move to the right as OI increases. If $\alpha_1\alpha_4 - \alpha_2\alpha_3$, $\varphi_1\varphi_4 - \varphi_2\varphi_3$ and $\nu_1\nu_4 - \nu_2\nu_3$ are negative, the turning point will move to the left with the increase of OI.

Hypothesis 5 postulates that the inverse U-shaped curve between geographic-cognitive proximity interactions and innovation performance is flatter when firms implement organisational innovations. Models 1.5 and 2.5 (Tables 2 and 3) show the linear and quadratic interaction coefficients between the moderating variable OI and CCGD. According to $\alpha_1\alpha_4 - \alpha_2\alpha_3 = 0.061 > 0$ for radical innovation and $\alpha_1\alpha_4 - \alpha_2\alpha_3 = 0.017 > 0$ for incremental innovation, the value of $\frac{\partial CCGD^*}{\partial OI}$ is greater than 0, which reflects that the inflection point shifts to the right from 2.887 to 4.751 for radical innovation and from 3.537 to 7.758 for incremental innovation as firms engage in organisational innovation. To better interpret these moderation effects, Figure 5 illustrates the inverse U-shaped curve between CCGD and innovation performance at different levels of OI. The evidence provides support for Hypothesis 5a that the curve for CCGD has a less pronounced inverted U-shape for firms that engage in organisational innovation compared to those that do not introduce organisational innovations.

Figure 6 shows changes in the relationship curve between CDGD and innovation performance at low and high levels of OI. The position of the inflection points moves to the upper right from 3.375 at a low level of OI to 17.387 at a high level of OIP for radical innovation. Similarly, for incremental innovation, according to $\varphi_1\varphi_4$-$\varphi_2\varphi_3 = 0.001 > 0$, the inflection point shifts to the right from 7.230 to 9.244, indicating that the inverted U-curve flattens for firms that engage in organisational innovation, which supports Hypothesis 5c.

Finally, Figure 7 shows that the effect of CDGC on innovation performance presents the following change: the values of $\upsilon_1\upsilon_4$-$\upsilon_2\upsilon_3 = 0.029$ for radical innovation and

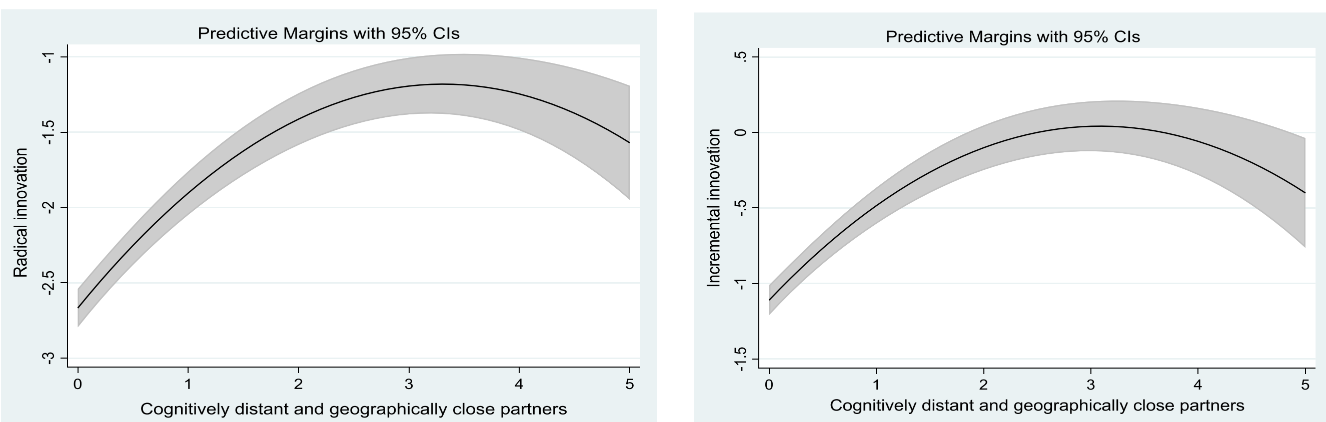

FIGURE 4 The relationship between cognitively distant and geographically close partners and innovation performance

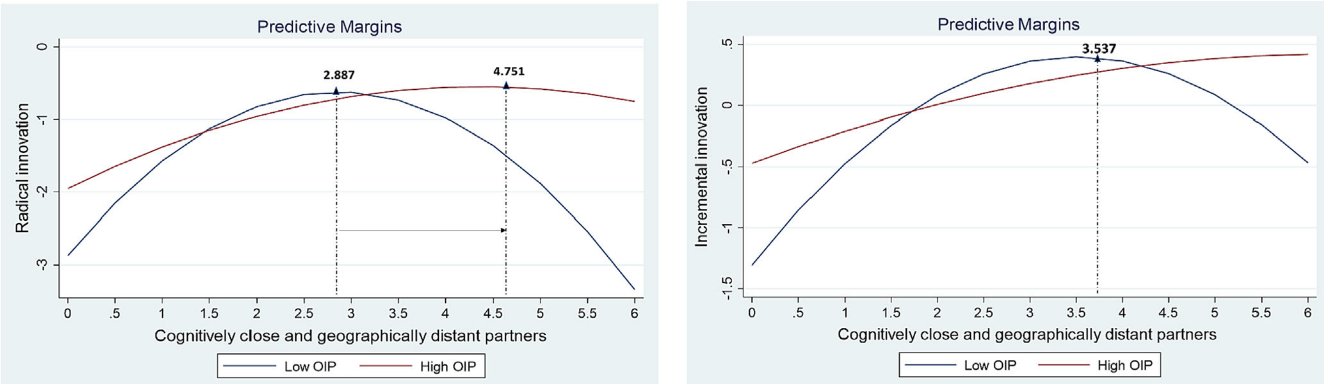

FIGURE 5 The moderating effect of organisational innovation in the relationship cognitively close and geographically distant partners and innovation performance

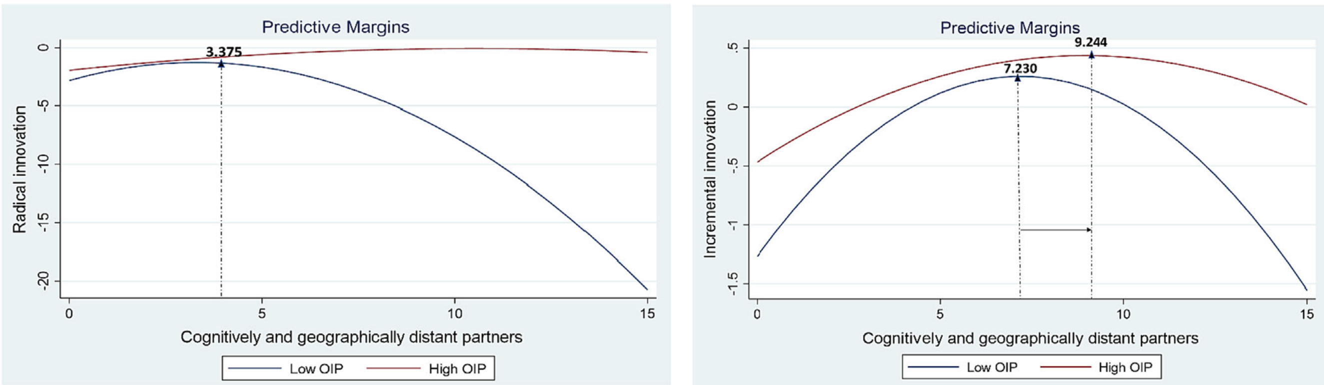

FIGURE 6 The moderating effect of organisational innovation in the relationship cognitively and geographically distant partners and innovation performance

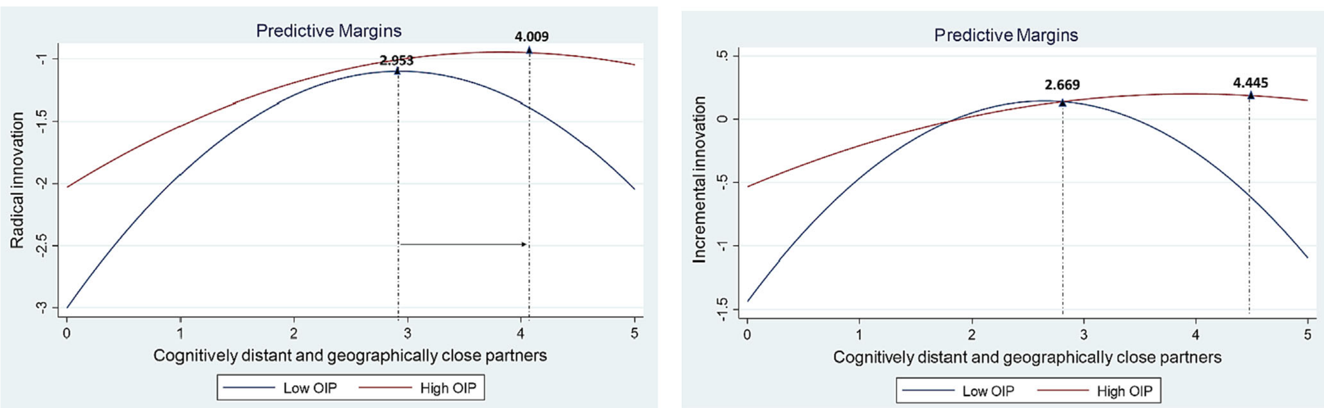

FIGURE 7 The moderating effect of organisational innovation on the relationship cognitively distant and geographically close partners and innovation performance

$\upsilon_1\upsilon_4$-$\upsilon_2\upsilon_3 = 0.027$ for incremental innovation are both greater than 0, and the curve's inflexion point moves to the right from 2.953 to 4.009 for radical innovation and from 2.669 to 4.445. Hence. Hypothesis 5d is supported.

Taking all together, the evidence provides support for Hypothesis 5 that the inverse U-shaped relationship between geographic-cognitive proximity interaction and innovation performance has a flatter curvature in firms that have adopted organisational innovation practices. Table 7 reports a summary of our tested hypotheses.

Robustness checks

To further validate the results and test their consistency, we applied an Ordered Probit model similar to Tsinopoulos, Yan, & Sousa (2019) where the dependent variables were decomposed into 7 levels namely, “0”, when a firm has no new product sales, 1 to 5 when the mean value of product sales is lower than 10%, 25%, 50%, 75%, 90%, respectively, and 6 when the mean value of product sales is in the upper 10%.

The results are shown in Tables A2 and A3 in Appendix A and are consistent with the main models of Tables 2 and 3. The random-ordered probit model is defined on the basis of a latent continuous variable Y_i as follows:

$$Y_1^* = X_i\beta_i + \varepsilon_i$$

where X_i is a vector of the explanatory variables, including the control variables mentioned above; β_i is a vector of the coefficients to be estimated; and ε_i is the randomly distributed error term, which is assumed to be normally distributed with zero mean and unit variance (Jalayer et al., 2018).

TABLE 7 Hypothesis testing.

	Radical innovation performance	Incremental innovation performance
Direct Effects		
H1: Cognitively close and geographically distant (Q1)	Supported	Supported
H2: Cognitively and geographically close (Q2)	Not supported	Not supported
H3: Cognitively and geographically distant (Q3)	Supported	Supported
H4: Cognitively distant and geographically close (Q4)	Supported	Supported
Moderating effect		
H5a: Cognitively close and geographically distant (Q1) * OIP	Supported	Supported
H5b: Cognitively and geographically close (Q2) * OIP	n/a	n/a
H5c: Cognitively and geographically distant (Q3) * OIP* OIP	Supported	Supported
H5d: Cognitively distant and geographically close (Q4) * OIP	Supported	Supported

Although Y_i* is unobserved, the ordered probit model translates the latent variable into the observed innovation performance outcome Y_i as follows:

$$y_i = 0 \ if \ y_1^* < 0$$

$$y_i = 1 \ if \ y_1^* < \mu_1$$

$$y_i = 2 \ if \ \mu_1 < y_1^* < \mu_2$$

$$y_i = j \ if \ y_1^* < \mu_{j-2}$$

where μ_i refers to the threshold levels, which are empirically estimated. The results were highly robust to these changes in specification.

DISCUSSION

This paper adopted a multi-dimensional perspective on proximity to explore how geographical and cognitive proximities and their interaction impact firm innovation performance. Moreover, we investigated the moderating effect of organisational innovation in the proximity interaction-innovation performance relationship. The relationship was analysed by using the substitution/complementarity approach (Hansen, 2015). To that end, we established a four-proximity typology representing combinations of geographical and cognitive proximity and empirically tested the synergetic effects between proximity dimensions on radical and incremental innovation performance.

The results of this study show that there is a considerable degree of interaction between geographical and cognitive proximity. We found that while proximity facilitates innovation performance overall, there is an interplay between geographical and cognitive proximity. Cognitive proximity both substitutes and complements geographical proximity. We found that inter-organisational innovation for innovation may be both (geographically and cognitively) closer and more distant. These findings support Boschma’s (2005) premise that geographical proximity per se is neither a necessary nor a sufficient condition for learning and interaction.

Our empirical work provides support for the so-called substitution-innovation mechanism [H1 & H4], whereby distance in one proximity dimension can be compensated by proximity in the other dimension (Hansen, 2015; Menzel, 2015).

Hypothesis 1 posits a curvilinear relationship between cognitively close knowledge of international origin and innovation performance. Results show that the combination of low levels of geographical proximity and high levels of cognitive proximity positively impact innovation performance (Model 1.1 and Model 1.2). Firms seem to bridge low geographical proximity to their partners with higher cognitive proximity. A shared knowledge base between partners facilitates long-distance collaborations, and cognitive proximity can be a substitute for geographical proximity in fostering interactive learning between actors (Hansen, 2015). However, high cognitive proximity can be detrimental to knowledge creation and innovation, as some cognitive distance is needed to ensure that interactive learning is effective (Boschma, 2005). The significance and negative sign associated with the quadratic term coefficients CCGDsq for both radical and incremental innovation performance indicates an inverted U-shape (Haans, Pieters, & He, 2016), providing support for H1.

Hypothesis 4 postulates that cognitively distant knowledge of national origin has a curvilinear relationship with innovation performance. Findings indicate that the combination of low geographical and high cognitive proximity is also significant for both radical and incremental innovation performance (Model 1.4 and Model 1.4), suggesting that geographical proximity offers firms the opportunity to absorb knowledge from spillovers without maintaining cognitive proximity (Baptista & Swann, 1998). However, developing excessive geographical proximity between actors could cause spatial lock-in situations that have a negative influence on learning and innovation (Molina-Morales, García-Villaverde, & Parra-Requena, 2014). The significance and negative sign associated with the quadratic term coefficients CDGCsq for both radical and incremental innovation performance indicates an inverted U-shape (Haans, Pieters, & He, 2016), providing support for H4.

Taken together, these results provide empirical support to the substitution-innovation mechanism, where the disadvantages of high geographical distance can be overcome by cognitive proximity (Huber, 2012). Geographically distant partnerships combined with high levels of cognitive proximity are positively associated with innovation performance. Low cognitive proximity combined with high geographical proximity also displays a positive relationship with innovation, as suggested by the main linear effect coefficients. Although these effects on firm's innovation performance are non-linear supporting the proximity paradox. Interestingly, with regard to 'distant' partners, collaboration with cognitively close and geographically distant partners is more likely to enhance radical innovation performance whereas cognitively distant and geographically close partners are more likely to drive incremental innovation performance. These results are in contrast to prior understanding highlighting the importance of cognitive distance for breakthrough innovation (Hess & Rothaermel, 2011) suggesting a trade-off where high cognitive proximity facilitates communication and knowledge sharing between partners and renders firm less dependent on co-location (Garcia et al., 2018; Phene, Fladmoe-Lindquist, & Marsh, 2006). The relative importance of cognitive distance for incremental innovation also indicates a substitution-innovation mechanism where firms in the same geographical cluster maybe inclined to enter in cognitively distant partnerships to overcome spatial lock-in situations as it allows for the recombination of heterogeneous knowledge inputs (Liu & Ma, 2019).

Our results also provide some support for the hypothesis of an overlap-innovation mechanism that geographical proximity may play a complementary role in building and strengthening other proximity dimensions (Boschma, 2005). Hypothesis 3 suggests that the relationship between cognitively distant knowledge of international origin has a curvilinear relationship with radical and incremental innovation performance. While cognitive and geographical distance exposes partners to knowledge of boarder scope, enhancing firm innovation, it also poses greater demands on the cognitive abilities of the actors and their ability to leverage the innovation potential of inter-organisational collaboration. Therefore, innovation performance will diminish as cognitive and geographical distance increases. Findings indicate that the combination of high geographical proximity and high cognitive proximity is significant for both radical and incremental innovation performance (Model 1.3 and Model 2.3). However, too much geographical and cognitive distance maybe harmful to innovation despite offering the greatest potential for learning and opportunity exploitation (Dooley, Kenny, & Cronin, 2016). The significance and negative sign associated with the quadratic term coefficient CDGDsq for both radical and incremental innovation performance indicates an inverted U-shape (Haans, Pieters, & He, 2016), providing support for H3. In contrast, we did not find support for Hypothesis 2 predicting a curvilinear relationship between cognitively close knowledge of national origin and innovation performance.

In addition, our results corroborate the proximity paradox (Boschma & Frenken, 2010) finding significant non-linearities for the different proximity configurations. Proximity facilitates interactive learning but too much proximity may make learning new knowledge difficult, while access to heterogeneous resources and diverse knowledge benefits creativity and innovation (Nooteboom, 2000). In contrast, being too far apart may undermine interaction and learning. There is therefore an optimal level of proximity somewhere between full and zero values (Boschma & Frenken, 2010; Broekel & Boschma, 2012). Further, the optimal level for each proximity configuration is influenced by the interdependencies between proximity dimensions (Boschma, 2005).

Further, our results reveal the contingent role of organisational innovation in the relationship between proximity interactions and innovation performance. Findings indicate that organisational innovation can overcome the drawbacks of searching broadly in cognitive and geographic contexts and enhance innovation performance. We found that organisational innovation weakens (i.e. flattens) the inverted U-shaped relationship between proximity interactions and innovation performance (Figures 5 to 7). Specifically, we show that the curve has a less pronounced inverted U-shape for firms that engage in organisational innovation compared to those that do not introduce organisational innovations.

CONCLUSIONS

Despite generally accepting the importance of inter-organisational collaboration on firm innovation performance, the facilitating role of proximity in such a context remains a topic of debate. Aiming to contribute to this discussion, this paper has examined the multi-dimensional and intersecting nature of proximity to drive innovation performance and the differential impact of different configurations of proximity dimensions on radical and incremental innovation performance owing to their distinct knowledge characteristics.

The main conclusion of this study is that the proximity of different dimensions is not an independent relationship but can affect each other, and to some extent substitute or complement each other. We found that cognitive proximity can be a substitute for geographical proximity in fostering interactive learning between actors (Hansen, 2015). It can also be a complementary relationship. In same cases, geographical proximity amplified the effect of cognitive proximity on innovation performance (Zhao et al., 2022). Therefore, our findings provided support for the substitution and overlap mechanisms for innovation.

The results of this study corroborated the proximity paradox emphasised by Boschma & Frenken (2010) caused by lock-in effects, that is, close enough distance is conducive to innovation while too much proximity can undermine innovation. We found that organisational innovation weakens the inverted U-shaped relationship between proximity interactions-innovation performance, highlighting its critical role in supporting inter-organisational knowledge transfer.

Our study has important implications for research. First, this study contributes to understanding the influence of various forms of proximity on firm innovation performance. Although the effect of proximity dimensions on innovation and collaboration has been studied before, the paper has examined the intersecting nature of proximity to drive innovation performance. In doing so, it addressed increasing calls for more multi-dimensional proximity research considering non-spatial forms of proximity besides geographical proximity and their interplay to understand collaboration and innovation (Balland, Boschma, & Frenken, 2015). Our study showed the importance of substitution and overlap mechanisms in the relation between geographical and cognitive proximity dimensions in fostering firm innovation performance (Hansen, 2015). These results further our understanding of the phenomenon of proximity in the dynamics of inter-organisational collaboration for innovation and inspire us to expand the analysis to the interactions between the various proximity dimensions in different business settings.

Second, the results of the paper contribute to the recent debate suggesting that external knowledge search for innovation along proximity dimensions varies depending on the type of innovation (Balland, Belso-Martínez, & Morrison, 2016; Quatraro & Usai, 2017). While proximity facilitates innovation performance overall, different configurations of proximity dimensions impact innovation outcomes differently. Our study extended existing research by clarifying the typology of proximity dimensions that facilitate radical and incremental innovations owing to the distinctive knowledge characteristics of these two innovation types.

The third and most important contribution of the study is to extend the understanding of the contingent role of organisational innovation to enhance innovation performance in proximity contexts. Our findings illustrate that organisational innovation can overcome the drawbacks of high cognitive and geographic distance between partners and enhance innovation performance. By embracing new ways of working, levering technology and fostering inter-firm collaboration, firms can address the challenges of working in distant contexts (Arranz, Arroyabe, & Fernandez de Arroyabe, 2020). Distant cognitive and geographic searches may result in information overload, making it challenging to identify relevant and valuable external knowledge (Ovuakporie et al., 2021). Advanced IT solutions, such as innovative search algorithms, knowledge management systems (KMS) and data analytics tools can enhance the efficiency of information search and retrieval (Adams & Lamont, 2003; du Plessis, 2007). KMS typically offer advanced search and retrieval functionalities, enabling a more targeted and focused approach to identifying and accessing relevant knowledge from cognitively and geographically distant partners. Managers can narrow down searchers to find the information they need without being overwhelmed by a vast amount of data. The wider application of AI technology in inter-organisational collaboration would offer efficiency gains in knowledge identification and retrieval (He et al., 2020).

Virtual collaboration tools such as video conferencing, project management platforms and cross-functional collaboration platforms can enhance innovation collaboration beyond space and cognitive boundaries (Marion & Fixson, 2021). These digital tools facilitate real-time communication, fostering a more connected and inclusive work environment and collaborative strategies. The increasing prevalence of digitalisation opens up new opportunities for inter-organisational innovation, but firms must be proactive in transforming their internal processes, culture and capabilities to leverage the benefits of digital transformation (Chirumalla, 2021).

Our findings have important implications for practice, in terms of the design of innovation policies aimed at facilitating knowledge exchange through inter-organisational collaboration for innovation. The finding that there is an interplay between geographical and cognitive proximity suggests that external knowledge linkages should be tailored to the favourable characteristic of proximity to enhance firm innovation performance. Companies should create enabling conditions for proximity to unfold depending on the innovation outcome. Our results indicated that for radical innovation, cognitive proximity can be a substitute for geographical proximity for knowledge transmission because similar capabilities and common channels of communication can foster inter-organisational collaboration at long distances (Hansen, 2015). The higher absorptive capacity of actors increases the cognitive proximity between partners, even if they are geographically distant (de Jong & Freel, 2010). Developing collaboration with cognitively close and geographically distant partners is a relatively faster strategy and renders firms less dependent on colocation (Garcia et al., 2018; Phene, Fladmoe-Lindquist, & Marsh, 2006). Radical knowledge is often written down and can therefore travel across distances (Halkier et al., 2012). However, the effective leverage of this advantage requires firms to overcome challenges in long-distance collaboration, such as differences in time zones, inter-cultural communication barriers and potential misunderstandings due to cultural differences (Ambos & Ambos, 2009; Ho, Ghauri, & Kafouros, 2019). Overcoming these challenges often requires robust communication strategies, the use of collaboration tools and digital technologies and a commitment to building strong relationships (Deschênes, 2024).

Additionally, findings also reported the relative importance of cognitive distance for incremental innovation to overcome spatial lock-in situations. To allow for the recombination of heterogeneous knowledge inputs, firms need to develop their absorptive capacity. The more the inputs obtained differ (the more cognitively distant), the more urgent the need for firm's capacity to directly assimilate and acquire the specific knowledge of interacting partners become (Bertrand & Mol, 2013). Hence, internal capabilities play a more important role in incremental innovation than the specific location. Firms with high absorptive capacity make better use of externally generated knowledge, leading to improved innovation performance (Cohen & Levinthal, 1990). Therefore, companies are encouraged to implement mechanisms to support their absorptive capacity (Enkel & Heil, 2014). For instance, firms should cultivate a learning culture that fosters knowledge acquisition and values continuous learning (Darwish et al., 2020). Therefore, they should focus on retaining and recruiting employees with prior knowledge related to the firm's domain to reduce the learning curve and accelerate the acquisition and assimilation of new knowledge (Sancho-Zamora et al., 2021). Firms need to learn to exchange knowledge across the entire organisation and business ecosystem (Müller, Buliga, & Voigt, 2021), creating open communication channels and information flows to encourage all actors to share their insights, experiences and ideas. Firms should encourage cross-functional thinking within the organisation by creating multidisciplinary R&D teams that bring together individuals with diverse skills and expertise to facilitate knowledge exchange and perspectives (Zouaghi, Garcia-Marco, & Martinez, 2020), contributing to organisational absorptive capacity (Yildiz, Murtic, & Zander, 2024).

This study has some limitations. First, the study solely focuses on the impact of proximity dimensions on innovation outcomes. Future analysis should concentrate on proximity effects at different stages of the innovation funnel from idea generation and development to commercialisation. The relative role of spatial and non-spatial proximity at each stage would provide a more complete vision of proximity dynamics by incorporating aspects such as protection mechanisms (Anzola-Román et al., 2019). Second, future studies should further develop the conceptualisation of proximity dimensions and their interaction (Steinmo & Rasmussen, 2016). Cognitive proximity seems to be linked to the individual level of analysis – it is defined by the similarity of knowledge of actors, whereas geographical proximity is more closely related to the organisational level – it refers to the spatial separation of agents (Boschma, 2005). Hence, understanding these differences and levels of analysis would enable firms to develop support mechanisms to foster collaborations at individual and/or organisational levels depending on the innovation outcome. Third, the PITEC database measures organisational innovation at a high level of aggregation and does not allow for further differentiating specific organisational mechanisms (i.e. teamwork, supply chain management) (Armbruster et al., 2008). However, the unavailability of more disaggregated data led to the procedure followed by previous studies being adopted. Finally, the study uses data from Spain. The model should be applied to other countries to test if the results obtained can be generalised, what differences emerge and whether specifying contextual variables (e.g. societal trust and legal system) may affect the relationship proximity dimensions and innovation performance.

AUTHOR CONTRIBUTIONS

All authors contributed equally.

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CONFLICT OF INTEREST STATEMENT

The authors have no financial or nonfinancial interests to disclose.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

The research uses secondary data and the sources of this data set are cited in the reference list. According to the research ethical rules of Spain, no ethical approval is required.

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APPENDIX

TABLE A1 Description of variables.

Variables	Type	Definitions
Dependent Variables		
Radical Innovation	Continuous	Percentage of the firm's total sales in year *t* from innovations new to the market during the period between *t-2* and *t* (Ln)
Incremental Innovation	Continuous	Percentage of the firm's total sales in year *t* from innovations new to the firm during the period between *t-2* and *t* (Ln)
Independent Variables		
Cognitively close and geographically distant partners (**CCGD**)	Continuous	Sister organisations, suppliers and customers located outside of the geographic area (i.e. EU, USA and all other countries)
Cognitively and geographically close partners (**CCGC**)	Continuous	Sister organisations, suppliers and customers located inside the geographic area (i.e. Spain)
Cognitively and geographically distant partners (**CDGD**)	Continuous	consultant organisations, public research labs, universities or competitors located outside of the geographic area (i.e. EU, USA and the rest of the world);
Cognitively distant and geographically close partners (**CDGC**)	Continuous	consultant organisations, public research labs and universities or competitors located inside the geographic area (i.e. Spain)
Moderating variable		
Organisational innovation **(OI)**	Dichotomous	Dummy variable indicating whether or not a firm introduced at least one organisational innovation practice
Control variables		
Firm Size	Continuous	Number of employees (Ln)
R&D intensity	Continuous	R&D expenditure as a proportion of total sales
Export intensity	Continuous	Ratio of export sales to total sales
Industry	Dichotomous	Dummy variables indicating the sector where the firm operates
Year	Dichotomous	Dummy variables indicating the year to which observations belong (2008–2013)

TABLE A2 Ordered probit results for radical innovation performance.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5	Model 1.6	Model 1.7	Model 1.8
Main effects								
CCGD	0.368*** (0.036)				0.416*** (0.041)			
CCGDsq	−0.041*** (0.010)				−0.064*** (0.064)			
CCGC		0.469*** (0.139)				0.435*** (0.058)		
CCGCsq		−0.132*** (0.032)				−0.114*** (0.033)		
CDGD			0.191*** (0.028)				0.241*** (0.037)	
CDGDsq			−0.011*** (0.004)				−0.026*** (0.008)	
CDGC				0.354*** (0.026)				0.349*** (0.027)
CDGCsq				−0.053*** (0.006)				−0.054*** (0.007)
Moderator								
OI					0.367*** (0.023)	0.375*** (0.023)	0.351*** (0.022)	0.389*** (0.024)
Control variables								
Firm Size	0.189*** (0.022)	0.188*** (0.027)	0.198*** (0.022)	0.178*** (0.055)	0.158*** (0.022)	0.157*** (0.023)	0.166*** (0.022)	0.148*** (0.022)
Firm Sizesq	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.006(0.004)	0.007(0.004)	0.006 (0.004)	0.006 (0.004)
R&D intensity	0.199*** (0.031)	0.198*** (0.030)	0.201*** (0.030)	0.187*** (0.031)	0.192*** (0.030)	0.191*** (0.009)	0.195*** (0.030)	0.181*** (0.030)
Export intensity	0.038*** (0.009)	0.042*** (0.009)	0.040*** (0.009)	0.037*** (0.009)	0.037*** (0.009)	0.040*** (0.009)	0.039*** (0.009)	0.036*** (0.009)
Moderation Effects								
OI* CCGD					−0.366*** (0.079)			
OI* CCGDsq					0.083*** (0.026)			
OI* CCGC						−0.278*** (0.114)		
OI* CCGCsq						0.052 (0.066)		
OI* CDGD							−0.207*** (0.078)	
OI* CDGDsq							0.045*** (0.018)	
OI* CDGC								−0.296*** (0.051)
OI* CDGCsq								0.061*** (0.014)
IMR	0.001***-(0.000)	0.001*** (0.00)	0.001*** (0.002)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Log-likelihood	−30393.40	−330388.21	−30442.41	−30337.78	−30262.86	−30263.07	−30316.25	−30211.53

*Significant at 5%.
**Significant at 1%.
***Significant at 0.1%.

TABLE A3 Ordered probit results for incremental innovation performance.

	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5	Model 1.6	Model 1.7	Model 1.8
Main effects								
CCGD	0.201*** (0.034)				0.215*** (0.039)			
CCGDsq	−0.125*** (0.009)				−0.024* (0.012)			
CCGC		0.292*** (0.053)				0.277*** (0.053)		
CCGCsq		−0.048 (0.029)				−0.050 (0.080)		
CDGD			0.115*** (0.026)				0.116*** (0.033)	
CDGDsq			−0.007* (0.004)				−0.007 (0.020)	
CDGC				0.283*** (0.024)				0.277*** (0.024)
CDGCsq				−0.045*** (0.006)				−0.047*** (0.006)
Moderator								
OI					0.323*** (0.019)	0.315*** (0.020)	0.308*** (0.019)	0.346*** (0.021)
Control variables								
Firm Size	0.309*** (0.019)	0.304*** (0.019)	0.313*** (0.019)	0.299*** (0.019)	0.283*** (0.019)	0.4281*** (0.019)	0.4289*** (0.019)	0.275*** (0.019)
Firm Sizesq	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)
R&D intensity	0.070*** (0.026)	0.068*** (0.026)	0.071*** (0.026)	0.056** (0.026)	0.066** (0.026)	0.064** (0.026)	0.067** (0.026)	0.051* (0.026)
Export intensity	0.057*** (0.008)	0.057*** (0.008)	0.058*** (0.008)	0.055*** (0.008)	0.055*** (0.008)	0.056*** (0.008)	0.056*** (0.008)	0.053*** (0.008)
Moderation Effects								
OI* CCGD					−0.267*** (0.075)			
OI* CCGDsq					0.043* (0.025)			
OI* CCGC						−0.335*** (0.104)		
OI* CCGCsq						0.141** (0.061)		
OI* CDGD							−0.091*** (0.067)	
OI* CDGDsq							0.008 (0.014)	
OI* CDGC								−0.323*** (0.046)
OI* CDGCsq								0.072*** (0.013)
IMR	0.004***- (0.000)	0.004*** (0.001)	0.004*** (0.001)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Log-likelihood	−39904.52	−39864.74	−39924.24	−39836.56	−39769.97	−39744.16	−39796.37	−39699.69

*Significant at 5%.
**Significant at 1%.
***Significant at 0.1%.