Innovation
Organization & Management

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rimp20

How many to be different? The role of number and the partner type on innovation performance

Muhammad Ismail, Alejandro Bello-Pintado & Teresa García-Marco

To cite this article: Muhammad Ismail, Alejandro Bello-Pintado & Teresa García-Marco (2022): How many to be different? The role of number and the partner type on innovation performance, Innovation, DOI: 10.1080/14479338.2022.2084545

To link to this article: https://doi.org/10.1080/14479338.2022.2084545

Published online: 11 Jun 2022.

INNOVATION: ORGANIZATION & MANAGEMENT
https://doi.org/10.1080/14479338.2022.2084545

Routledge
Taylor & Francis Group

ARTICLE

OPEN ACCESS Check for updates

How many to be different? The role of number and the partner type on innovation performance

Muhammad Ismail, Alejandro Bello-Pintado and Teresa García-Marco

INARBE – Institute for Advanced Research in Business and Economics, Public University of Navarre, Pamplona, Spain

ABSTRACT

Collaboration with external partners for innovation is seen as a major driver of novel ideas. Previous studies have revealed the importance of collaboration with different partners on innovation performance; however, many questions regarding this association remain unresolved. This study aims to analyse the effects of collaboration with different types of partners on the innovation performance and how the cognitive distance affects this relationship. This study also distinguishes between incremental and radical innovations as outcomes of cooperation, and provides differing implications for the two innovations types. Based on empirical analyses performed on a sample of 12,000 Spanish firms, we found supportive evidence that both radical and incremental innovation require a distinct number of collaboration partners to optimise innovation performance. Further, relationship between the number of partners and innovation performance is moderated by the cognitive distance between the focal firm and the respective partner: positively for radical innovation and negatively for incremental innovation performance.

ARTICLE HISTORY
Received 03 April 2021
Accepted 27 May 2022

KEYWORDS
Open innovation; collaboration breadth; cognitive distance; radical and incremental innovation

Introduction

The concept of open innovation has become central to the field of innovation during the last decade. Open innovation is a means through which firms are able to gather the knowledge required to carry out innovation from external sources (Chesbrough, 2003), allowing them to maintain their competitive advantage (Laursen & Salter, 2006; Porter, 1990). Firms create novel ideas by using knowledge from a wide variety of sources, adopting formal and informal relationships (Laursen & Salter, 2014).

Researchers in the field have paid considerable attention to study how collaborating with different number of partner types (*collaboration breath*) can impact innovation (Laursen & Salter, 2014). The association between collaboration breadth and innovation performance has been demonstrated to be in the form of an inverted U-shape (e.g., Duysters & Lokshin, 2011; Hottenrott & Lopes-Bento, 2016; Oerlemans et al., 2013). However, this inverted U starts to take different shapes when the innovation is further distinguished between

CONTACT Alejandro Bello-Pintado alejandro.bello@unavarra.es

radical and incremental (Kobarg et al., 2019). The basic premise behind this relationship states that, when collaboration breadth becomes too large, the costs attached to managing a large number of partners start to cannibalise the gains.

Given the relevance of 'collaboration' as a means of deriving innovation performance, we find a portion of literature dedicated on analysing the reasons behind this U-shaped association, and factors that could possibly reform this relationship. For example, Carree et al. (2019) through their work re-enforce the existence of U-shape, and further demonstrate how this relationship is moderated by firm's absorptive capacity. Similarly, Hagedoorn et al. (2018) reveal how knowledge sharing mechanisms and characteristics of external knowledge environment can impact the effectiveness of collaboration breadth and modify the inverted U-shape. More recently, the work of Mathisen and Jørgensen (2021) shows how knowledge readiness can facilitate knowledge exchange and enhance innovation through collaboration. In this line, another important aspect that can affect the link between collaboration and innovation performance is cognitive difference amongst partners. Cognitive distance is broadly defined as the difference in resources and shared knowledge held by each firm. Because collaborating partners operate in different industries with different resources, these differences yield heterogeneous cognitive distances between a firm and its partners (Gavetti & Levinthal, 2000; Nooteboom et al., 2007), and these may affect the effectiveness of collaboration. Recent research in the field has called for further work on this issue (Mathisen & Jørgensen, 2021; Ovuakporie et al., 2021). In view of this discussion, this paper aims to answer the question of how difference or similarity in cognitive distance can alter the effectiveness of 'formal collaboration breadth' on radical and incremental innovation performance.

Formal collaboration is seen as an important element in the literature since it enables firms to derive improved innovation results (e.g., Belderbos et al., 2004; Bogers, 2011; Faems et al., 2005). Collaboration help firms to overcome the factors that can hamper the exchange of knowledge (Bogers, 2011) and also aids in development of absorptive capacity. Further, being formally connected helps in forming trustable relationships, which increases complementarities and reduces uncertainty with regard to partners' performance (Bogers, 2011; Powell et al., 1996). On the contrary, it adds complexity to the establishment and management of the communication and coordination with different partners, leading to a possible surge in transaction costs (Bogers, 2011; Duysters & Lokshin, 2011; Nieto & Santamaría, 2007). Further, it gives rise to the paradox of involuntary spillover or leakage of critical information, requiring the firm to put expensive appropriability strategies in place (Laursen & Salter, 2014).

Regarding the cognitive distance of partners, it is widely acknowledged that collaborating with distant partners benefit creativity and leads to higher innovation performance. For example, collaboration with a university is said to be associated with innovative originality and improved production; however, this distance can also be very challenging as distant firms share contrasting sets of logic, which are not what the firm is used to, and can unduly test a firm's absorptive capacity (Østergaard & Drejer, 2021). Collaboration with a distant partner can also hinder knowledge sharing, because it creates uncertainty and difficultly in coordination, as the internal structures of the firms might be very different (Boschma, 2005; Criscuolo et al., 2017; Østergaard & Drejer, 2021). As cognitive distance is responsible for both; gains in the form of novel ideas and costs of communication due to the gap in knowledge. We assert that it is highly significant for effecting the inverted U-shape, which is founded on amalgamation of the benefits from new knowledge and the costs attached to acquiring it (Hottenrott & Lopes-Bento, 2016).

Similar to collaboration breadth, firms that are seeking radical or incremental innovation should collaborate with firms that have contrasting cognitive distances. That is, firms that are looking for exploitative innovation (incremental innovation) rely more on partners that are cognitively closer, since their aim is to make improvements to existing technologies. However, firms that are aiming for exploratory innovation (radical innovation) are more concerned with introducing something very new and thus require partnership with firms that have a very different knowledge or resource base (Gilsing & Nooteboom, 2006; Nooteboom, 2000).

By analysing collaboration breadth and cognitive distance in concurrence, the study makes some important contributions. First, it advances the theoretical knowledge by responding to the existing gap regarding how cognitive differences amongst collaborating partners can modify the effectiveness of a collaboration outcome. This is important as factors influencing the effectiveness of knowledge sharing through collaboration are not fully understood (Bogers, 2014). Although the paradox of collaboration and knowledge heterogeneity has been examined and tested in several studies (Criscuolo et al., 2017; Haus-Reve et al., 2019; Noni De et al., 2018), the matter remains inconclusive and offers inconsistent empirical evidence. As this is central to the field of innovation, this issue has resurfaced in recent studies, but these remain limited and focused on testing the impact of cognitive distance on a single partner type (e.g., Lauvås & Steinmo, 2019; Mathisen & Jørgensen, 2021).

Secondly, this paper introduces the debate on how different collaborative strategies regarding collaborator type may enhance different types of innovation performance (radical vs. incremental). Finally, it provides relevant recommendations to managers regarding the collaborative innovation strategies that a firm may adopt to achieve radical or incremental innovation outcomes. Finally, it provides relevant recommendations to managers regarding the collaborative innovation strategies that a firm may adopt to achieve radical or incremental innovation outcomes.

Based on the findings through empirical analysis, this study confirms that cognitive distance exerts a significant moderation effect on the relationship between collaboration breadth and innovation performance since the moderation effect emerges as positive and quadratic for radical innovation performance and negative but linear for incremental innovation performance. This implies that firms that are seeking radical innovation can collaborate with partners that are cognitively distant since the gains associated with the new ideas that they bring in will be larger than the costs associated with them. However, at some point, as the number of partners increases, firms will be required to make investments in the form of the resources needed to capture new ideas from a large number of partners. Meanwhile, incremental innovation, which does not require so much novelty, would start to make losses instead of gains since the high cognitive distance starts to substitute the gains with losses as the increased knowledge gap amplifies the existing costs of collaboration.

The study is carried out using a large data panel that was built on information collected from more than 12,000 Spanish manufacturing and service firms from 2008 to 2016. The source is the Technological Innovation Panel (PITEC – Panel de Innovación Tecnológica), which is the Spanish contribution to the Community Innovation Survey (CIS; Martinez et al., 2017).

The paper is organised as follows: The next section outlines the conceptual framework and the hypothesis development. This is followed by a description of the data and the empirical model in section three. The fourth section consists of a discussion and the relevant implications.

Conceptual framework and hypothesis development

The underlying rationale of our study is built on the resource-based view (RBV) and the cognitive distance approach (Nooteboom, 2000), aiming to understand how the association between collaboration breadth (Hagedoorn et al., 2018; Laursen & Salter, 2014) and innovation performance can be affected by the difference in cognitive distances between a firm and its collaborating partners under the openness strategy.

RBV emphasises that a firm is able to sustain its competitive advantage as a result of the unique bundle of resources that it holds that others cannot perfectly replicate (Barney, 1991; Grant, 1996; Penrose, 1959). According to this view, firms differ in their resource position, and this heterogeneity produces differences in performance across firms. In a normal business setting, it is possible that a firm is faced with resource constraints and desires to expand its resources. It can do this either by acquiring resources through the expensive market mechanism (Grant, 1996) or by collaborating with external partners (Grant & Baden-Fuller, 2004). When a firms enters into a collaboration, it can access its partner's resources (i.e., assets, knowledge and capabilities for innovation) and also share risks and cost (Eisenhardt & Schoonhoven, 1996).

In line with Nooteboom et al. (2007), in this paper we propose to interpret resource heterogeneity in terms of cognitive distance between firms that hold these different resources. The term 'resources' is used in literature to define the amalgamation of assets, knowledge and capabilities that are built on human skills (Barney, 1991; Combs & Ketchen, 1999). Here, cognition denotes a broad range of mental activity based on the different levels of 'judgment, sense making and understanding of individuals'. Because each organisation has a different purpose, the shared focus, knowledge or shared interpretations amongst individuals within each organisation generate resource heterogeneity (Gavetti & Levinthal, 2000; Nooteboom et al., 2007).

In this paper, we postulate that collaboration breadth may interact with cognitive distance and have opposite implications for innovation performance depending on whether the firm's strategic objective is exploration or exploitation. This trade-off between different collaboration strategies (radical versus incremental) may limit the ambidextrous capacity of firms to achieve innovation performance.

Effects of collaboration breadth on radical and incremental innovation performance

Collaboration allows firms to partner up through alliances, cooperation or joint ventures for the joint development and commercialisation of an innovation (Enkel et al., 2009). Despite being an expensive form of engagement, collaboration has gained momentum as a channel of openness (Bogers, 2011). One of the possible explanations is that joint R&D increases the accessibility to and ease of carrying out innovative activities, leading to higher chances of engineering new products, because each partner brings in different resources (Miotti & Sachwald, 2003). The process might carry a high set-up cost (Laursen & Salter, 2014) but this is compensated for by the increased access to knowledge and the greater opportunity to engage in the creation of unique ideas (Powell et al., 1996). While a firm can acquire ideas from external sources without getting into formal contracts, the latter practice differs in terms of its benefits and limitations. For example, having no requirement to be formally linked can ease the process of linking; however, at the same time, a firm may indulge in over-search and this might start to divide the firm's attention, leading to reductions in knowledge gain (Ardito & Messeni Petruzzelli, 2017).

Once the firm begins to collaborate with heterogeneous partner types, these partners collectively form a unique portfolio (Hagedoorn et al., 2018; Laursen & Salter, 2014). The effective learnings from this portfolio are subject to stable interactive conditions; in the absence of these conditions, the learning outcomes are hampered (Boschma, 2005). Having the right number of partner types in a portfolio is critical because too many heterogeneous partners can adversely affect the course of innovative outcomes (Leeuw De et al., 2014). The diversity in the nature and goals of each collaborating partner also influences the innovation outcomes as each partner is a source of different experiences, information and further ties (Powell et al., 1996).

As the collaboration breadth (i.e., the number of different partners) widens, firms gain access to a variety of resources and opportunities to innovate, which are necessary to maintain their competitive advantage under the RBV. Firms benefit from the resources and expertise of their wide number of partners, especially in situations in which the resources are specialised or considerably expensive to acquire (Leeuw De et al., 2014) or when the assets needed to pursue an opportunity are an integral part of a partner's resources (Das & Teng, 2000). However, these gains do not last very long and soon reach an optimal point beyond which any increase in the number of partner types starts to affect innovative performance negatively (Deeds & Hill, 1996). This is because the firm faces the cost of coordination and organisation when managing R&D collaborations with a number of different partners. Additionally, increasing the collaboration breadth stimulates the risk of unintended knowledge exposure between the partners (Hottenrott & Lopes-Bento, 2016). As a result, these costs may eventually become larger than the gains achieved, reducing the overall innovation performance and leading to an inverted U-shaped relationship between collaboration breadth and innovation performance (Duysters & Lokshin, 2011; Hottenrott & Lopes-Bento, 2016; Oerlemans et al., 2013).

Although the overall relationship between collaboration breadth and innovation performance is curvilinear, all 'categories of innovation outcomes' cannot be generalised as having the same performance. Our hypothesis is that, to implement different collaboration strategies to achieve the desired innovation outcomes, for example, exploration for radical innovation or exploitation for incremental innovation, the number of partner types should be different. In this sense, firms that are looking for radical innovations engage in the production or introduction of products/services that can generate a new market or be completely novel for it, while enabling the firm to earn significant returns (Levinthal & March, 1993; Tiberius et al., 2021). Innovation that focuses on mere improvement, or is limited to the refinement or reinforcement of existing products or concepts is known as incremental innovation (Forés & Camisón, 2016; Ovuakporie et al., 2021). Additionally, the difference in outcome between radical and incremental innovation is affected by the resource diversity that a firm maintains by having different numbers of external partner types (Katila & Ahuja, 2002). Radical innovation, characterised by the development of ground-breaking ideas, is said to be complex, requiring a larger proportion of ideas that are entirely new to the existing knowledge base (Dewar & Dutton, 1986). Radical innovation requires the amalgamation of heterogeneous points of view that are widely spread outside the firm's boundaries across different organisations and the synthesis of these ideas to form something new and original (Rothaermel et al., 2006). Consequently, having a higher number of partner types increase the chances for a firm to innovate radically.

On the other hand, incremental innovation is aimed at bringing about minor changes (Chandy & Tellis, 1998), thus requiring knowledge that is mostly present inside the firm (Robertson et al., 2012) and limiting the requirement for a large number of partners. Incremental innovation, unlike radical innovation, is less risky and involves lower uncertainties, thus also reducing the need to involve large number of partners (Kobarg et al., 2019). Whilst sharing risk is one aspect of collaboration, it is also possible that, amongst a large number of collaborative partners, some may provide very similar or complementary (i.e., redundant) knowledge. Because radical innovation is exploratory and brings in higher returns, a firm can afford the costs associated with the risk of redundancy to some extent, whereas, a firm pursuing only incremental innovation might not be able to afford redundant alliances as they can turn out to be very expensive (Faems et al., 2005).

Entering into a collaboration is merely part of the open innovation process, but maintaining the relationship and coordinating with partners is equally important. The problems associated with coordination start to escalate as a firm increases its collaboration breadth, as it is required to filter out useful knowledge from a larger number of sources. To successfully achieve this, firms must invest a higher quantity of resources, without which it could fall victim to the problem of over-collaboration (Greco et al., 2016). Firms that are looking to achieve radical innovation can afford to make such investments and benefit from larger collaboration breadth (Ovuakporie et al., 2021).

The distinction in radical and incremental innovation do not end here, as sometimes firm is required to adopt different strategies or make different structural changes in order to support radical or incremental output (Ettlie et al., 1984). Firms that follow a radical innovation strategy are usually required to back their decision by enhancing their ability to support new business development, by opening new markets to sell the novel products (Henderson & Clark, 1990; Roberts & Berry, 1985). Collaborating with a larger number of different partner types allows firms to achieve 'market power, entry deterrence, and economies of scale and scope in such areas as R&D activities, production, and marketing' (Das & Teng, 2000, p. 49), which can help with and support the implementation and further selling of novel ideas or products in the market.

This leads us to hypothesise the following:

Hypothesis 1: Collaboration breadth has a curvilinear (inverted U-shaped) relationship with innovation performance. The optimal breadth is lower for incremental innovation than for radical innovation performance.

Moderating effect of cognitive distance on the relationship between collaboration breadth and innovation performance

Cognitive distance is based on resource heterogeneity and differences in firms' shared meanings, perceptions, interpretations and understandings (Nooteboom et al., 2007), making each one naturally distant from the others. The literature in the field has interpreted cognitive distance as knowledge heterogeneity among firms (Boschma, 2005; Criscuolo et al., 2017; Nooteboom, 2000).

According to March's (1991) study, a firm can alter its innovation performance outcome by engaging with various resources. Accordingly, a firm can adjust its innovation performance outcome by employing partners placed at different cognitive distances (Lavie & Rosenkopf, 2006). Because exploratory alliances are generally created to derive radical innovation (Jepsen et al., 2014), the effect of cognitive distance and collaboration breadth on radical innovation is in line with exploration. The literature has suggested that exploration is related to finding novel alternatives (Nooteboom et al., 2007). This requires firms to collaborate with a larger network of firms (Gilsing & Nooteboom, 2006), which are placed at a higher cognitive distance (Nooteboom, 2000), because radical innovation is characterised as a means of developing novelty, requiring new knowledge input (Dewar & Dutton, 1986). This necessary knowledge can be acquired from a broad number of interfaces existing outside the firm, allowing the firm to recombine and create ground-breaking ideas (Katila & Ahuja, 2002). Collaboration with partners that are cognitively too close would fail to deliver the novel input necessary to create any radical changes (Nooteboom, 2000).

The decision to collaborate with firms with dissimilar resources and capabilities leads to contrasting outcomes (March, 1991). For instance, alliances with cognitively proximate firms lead to the exploitation of existing knowledge, as opposed to cooperation with a cognitively distant firm, which can result in the exploration of novel opportunities (Lavie & Rosenkopf, 2006). This notion is based on the idea that collaboration with cognitively distant partners (like consultants, universities and research centres) brings in ideas and knowledge that are very different from those that the firm currently possesses or is developing. This allows the firm to combine the novel knowledge with its existing base and form something that is entirely new. However, collaboration with a firm that is cognitively closer (like firms within the same group, suppliers, customers and competitors) would not produce radical innovations but only lead to incremental improvements.

Distance in cognition exists due to the differences in industry-related contexts. For instance, most suppliers and direct competitors operate in similar industries and therefore have knowledge and expertise that is similar to what the focal firm already has (Lane & Lubatkin, 1998; Un & Asakawa, 2015), whereas partners like universities are said to be knowledge distant since the foundation of their basic operations is very different (Criscuolo et al., 2017; Muscio & Pozzali, 2013; Un & Asakawa, 2015). However, ideas from both cognitive streams (high and low) can only be profited from after they have been integrated with the existing knowledge base through 'coordination and communication' (Hoetker, 2005). This integration process carries costs, which are in the form of the tools necessary to transfer and absorb the knowledge from external sources. The cost of bridging or transferring knowledge from a cognitively distant partner can be relatively high compared with the investment required for bridging information from a cognitively proximate partner (Tzabbar et al., 2013).

In some cases, firms might even need specific investment to absorb information that is completely novel or is placed at a high cognitive distance. This specific investment, however, can also limit a firm's flexibility and could lead to increased dependence on a single source – resulting in a 'hold-up' problem (Nooteboom, 2000). Further, the prerequisite of a larger cognitive distance to achieve novel ideas leads to greater heterogeneity in the existing and accessed knowledge base, thus requiring higher absorptive capacity (Cohen & Levinthal, 1990) and increased effort to harmonise the distinction that prevails between the existing and the acquired knowledge (Lane & Lubatkin, 1998), amplifying the communication cost in return. Although collaborating with a partner at a lower cognitive distance increases the efficiency of communication, the ideas may lack the novelty that is needed for radical innovation.

Collaborating with a distant or proximate cognitive partner is also restricted by the fact that each firm holds a limited amount of information under the bounded rationality theory originally presented by Herbert Simon (1955). Firms respond to this restraint by reducing uncertainty and limiting their scope of decision-making within the boundaries of their awareness (Boschma, 2005) – that is, by collaborating with firms that are cognitively closer and are not entirely new to partnering. These situations are confined by a 'trade-off' between high and low cognitive distance partners because the former may be imperative to explore novelty and the latter to exploit efficiency (March, 1991). To collaborate with cognitively distant partners, firms carry out a 'distant search', which could be expensive and time consuming but is likely to be compensated for by the higher gains from radical innovation (Bauer & Leker, 2013; Meulman et al., 2018). Further, it is imperative to choose the right type of partner because both strategies could fail if the information is cognitively too distant and too different to be interpreted for incremental innovation or too close to make any difference to the existing knowledge base for radical innovation (Nooteboom, 2000). Additionally, collaboration carries the risk of outgoing knowledge spillover, which increases with the number of collaboration partners. Thus, firms employ various appropriability mechanisms to protect their knowledge, consequently affecting the governance cost (Cassiman & Veugelers, 2002; Nooteboom, 2000). In the background, the overall gain in terms of the difference in new ideas from low cognitive distance partners and the spillover cost associated with each partner is small (Nooteboom, 2000). Nevertheless, collaborating with cognitively distant partners brings in ideas that are very different and produces gains that are substantially larger than the spillover cost. This relative difference in gain and cost makes it feasible for firms to collaborate with more partner types that are cognitively distant for radical innovation performance. Although firms try to limit their knowledge sharing or spillage, some uncontrollable factors can still lead to leakage across organisations (Boschma, 2005). As a result, partnering with a less distant firm is only beneficial up to the point at which the gain in the form of the knowledge exchange is larger than the added cost of spillage and communication.

In sum, combining the arguments of collaboration breadth and cognitive distance, we propose the following hypothesis:

Hypothesis 2: The curvilinear (inverted U-shaped) relationship between collaboration breadth and radical innovation performance is positively moderated by cognitive distance.

Incremental innovation, on the other hand, is characterised by minor changes or incremental improvements in technology, which earn lower benefits (Chandy & Tellis, 1998). The main distinction between radical and incremental innovation concerns the degree of novelty of the innovation outcome and, hence, the degree of new knowledge and ideas required to carry out each respective strategy (Dewar & Dutton, 1986).

The effort required for incremental innovation as opposed to radical innovation is said to be far less, as are the accompanying returns and the risk of failure (Marsili & Salter, 2005). The amount of resources invested is also lower than in the radical innovation process because the required knowledge is mostly present within the firm (Robertson et al., 2012) or available from external partners that are cognitively close (Vermeulen et al., 2007). Incremental innovation is reported to draw information primarily from the internally available knowledge base (Kim & Kogut, 1996), subsequently expanding this scope to include the closely related external knowledge sources. Incremental innovation is more inclined towards enhancing the depth of knowledge, which is best supported by acquiring knowledge from a narrow range of closely related external information sources (Van den Bosch et al., 1999).

The knowledge involved in incremental innovation is also less complex (Dewar & Dutton, 1986), requiring firms to collaborate with partners that are cognitively closer (Zhang et al., 2007). Holding a diverse portfolio of partners can result in high coordination and integration costs (Combs & Ketchen, 1999). This increased cost can diminish or even result in negative returns from incremental innovation (Katila & Ahuja, 2002; Laursen & Salter, 2006). Thus, keeping in view the effect of cognitive distance and collaboration breadth, we hypothesise that collaborating with a lower number of partners placed at a low cognitive distance has a larger positive effect on incremental innovation performance.

Hypothesis 3: The curvilinear (inverted U-shaped) relationship between external collaboration breadth and incremental innovation performance is negatively moderated by cognitive distance.

Methodology

Data and sample

The study uses information from the Spanish Technological Innovation Panel (PITEC – Panel de Innovación Tecnológica).

The data set is a panel database that comprises more than 16,000 Spanish manufacturing and service firms; this study uses the data from 2009 to 2015. The data set includes detailed information regarding firms' R&D activities and collaborations with different actors. A panel data set provides an opportunity to study innovation behaviour from a dynamic perspective. Further, it provides direct variables representing radical and incremental innovation, which otherwise are represented by proxy variables (Laursen & Salter, 2006). The data set is built on innovation, newness to the market or an improvement to an existing product that was introduced in the period t-2 to t; this also ensures that there is sufficient time for the introduction of innovation and the evaluation of results (Langerak et al., 2008) and hence overcomes the limitation of simultaneity between innovation inputs and innovation outputs.

For the purposes of this study, the data incorporate both manufacturing and service firms that participated in radical and/or incremental innovation during the period 2009 to 2015.

Measures and variables

Dependent variables

The dependent variables represent the innovation performance of the firm, which is calculated as the percentage of the firm's total sales from innovation. A similar method has been used by other studies (e.g., Fernández-Olmos & Ramírez-Alesón, 2017; Laursen & Salter, 2006; Ovuakporie et al., 2021). Innovation is classified as radical or incremental, being new to the market or new to the company, respectively. Radical innovation is calculated as the percentage of total sales from innovation of a product or service that was new to the market in period t-2, whereas incremental innovation is the percentage of total sales from a product or service that was new to the firm in period t-2. The model uses logarithmic transformed variables to account for the left skewness of the dependent variables, that is, radical and incremental innovation performance (the significance of the Shapiro–Wilk test is 0.000 for both variables). The variables used for testing are calculated as radical/incremental performance = ln (1 + x), normalising the distribution.

Independent variables

Collaboration breadth is defined as the number of different partner types that the firm has collaborated with for innovation (Hagedoorn et al., 2018; Laursen & Salter, 2014). The survey asks whether the firms have carried out innovation projects with other agents and, in this case, who the partners were. The potential partners included in the questionnaire are firms within the group, suppliers, customers, competitors, consultants and commercial laboratories/R&D, universities and public research organisations. Collaboration breadth accounts for the number of different types of partners on which the firm relies for its innovative activities. The range of collaboration breadth is ranked from 1 to 7. A similar method to define a variable has previously been adopted by other works (Bayona-Saez et al., 2017; Laursen & Salter, 2006).

The cognitive distance/proximity of the external source depends on the similarity or differences in knowledge between the firm and its collaborating partners (Nooteboom et al., 2007). For instance, most of the suppliers and direct competitors operate in a similar industry and therefore carry knowledge and expertise that is similar to that of the focal firm (Criscuolo et al., 2017; Lane & Lubatkin, 1998; Un & Asakawa, 2015). Meanwhile, partners like universities are said to be knowledge distant since the foundation of their basic operations is very different (Muscio & Pozzali, 2013; Un & Asakawa, 2015). Using the scale of cognitive distance established by Criscuolo et al. (2017), we quantified the distances by assigning them a cognitive index on basis of this existing scale. The distance between the focal firm and the partner operating being in same group is least therefore the index assigned is 1. Similarly, being a little distant from the focal firm, supplier and customers are assigned an index 2, whereas index for competitors and consultants is 3 & 4 respectively. Being more distant from the firm, universities and R&D centres are given an index of 5. In the second step, we corrected for the difference in total number of partners in each cognitive category by taking weighted average and transformed these indexes using the following equation:

$$Cognitive\ distance = \frac{\sum (no\ of\ collaborating\ partners\ *\ cognitive\ index)^2}{(collaboration\ breadth + 1)}$$

By transforming these indexes, the value for cognitive distance is standardised on the basis of the firm's collaboration breadth to avoid problems with multi-collinearity and to more clearly analyse the effect of incremental change in the cognitive dimension on innovation performance. The weighted values were squared to enhance the dispersion between each cognitive category. Further, to ensure the completeness of analysis we added '1' to the collaboration breadth to prevent loss of data where a firm had no collaboration partner.

Control variables

Firm size can have a significant influence on innovative capabilities and innovation performance (Cassiman & Veugelers, 2006), we control its impact by taking the natural logarithm of the number of employees; this is to account for large firms' abilities to exploit economies of scale and possess heterogeneous groups of skilled workers (Fernández-Olmos & Ramírez-Alesón, 2017).

Internal R&D has a direct influence on the absorptive capacity of the firm, which, in return, can exert an impact on innovation performance (Cohen & Levinthal, 1990; Zahra & George, 2002) by increasing the speed of absorbing and implementing external knowledge. Thereby, R&D intensity and the percentage of employees holding higher qualifications are both controlled for because they can directly affect the innovation performance of the firm (Kobarg et al., 2019). R&D intensity is represented by a dummy variable that takes the value 1 when the firm invests in internal R&D on a continuous basis; otherwise, it takes the value 0.

We also control for the age of a firm because it can have a material impact on innovation performance (Coad et al., 2016). Further, firms' innovative behaviour is related to their industry affiliation (Martinez et al., 2017); hence, we control for industry effects following the OECD classification of industries in terms of technology intensity and knowledge intensity (OECD, 2005). We create three dummy variables representing manufacturing firms – 1) high-technology firms, 2) medium-technology firms and 3) low-technology firms – and two dummy variables for the different types of firm operating in the service industry: 1) knowledge-intensive firms and 2) low knowledge-intensive firms. As seen in Table 2, the data are distributed among manufacturing and servicing firms. There is consistency in firm distribution with the distribution of prevailing technology in Spain (OECD, 2005). Manufacturing firms make up around 58% of the data, whereas the service industry in total makes up around 42%, which is important for analysing the impact of the open innovation strategy on both the manufacturing and service sectors. More medium- and low-tech firms appear among the manufacturing firms, while the service sector is largely represented by highly knowledge-intensive firms. Firm size, as represented by number of employees, is consistent in being, on average, higher among service and lower among manufacturing firms.

Table 1. Variable descriptions.

Variable Name	Variable Description
Dependent Variables	
Radical Innovation Performance	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(1 + x)
Incremental Innovation Performance	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(1 + x)
Independent Variables	
Collaboration Breadth	The number of different types of partners that the firm has collaborated with for innovation, ranging from 1 to 7 types of partners. 1 represents only one type of partner used for collaboration and 7 represents seven types of partners used for collaboration.
Cognitive distance	The variable cognitive distance is defined by a continuous variable that takes value from 1 to 16.67.
Control Variables	
Firm Size	Number of employees (Ln)
R&D Intensity	Whether the R&D expenditure is continuous or occasional; the variables are in the form of a dummy which takes a value = 1 if expenditure is continuous and 0 otherwise.
High Skilled Labour	Percentage of highly skilled labour among total employees
Firm Age	Number of years since the creation of the firm (final year 2016)
Industry Indicator	The industry is divided into manufacturing and service, which are classified as high technology, medium technology, and low technology for manufacturing, and knowledge intensive and non-knowledge intensive for services. Each sector is represented by a dummy variable.
Year Indicator	The dataset consists of data from the year 2008 to 2016, and each year is represented as a variable to capture the economic influence on the firm's decision-making.

Table 2. Data distribution.

	Number of Firms	Percentage of Total	Average Number of Employees
High-technology firms	1,476	9%	201
Medium-technology firms	3,539	22%	199
Low-technology firms	4,250	26%	200
High Knowledge-intensive firms	5,286	33%	456
Low knowledge-intensive firms	1,494	9%	1,240
Total/Average	16,045	100%	459

*The number of firms differs from number of observation in the analysis as panel data were analysed.

Lastly, we take into account the year variable to control for the year-wise economic impact, which can influence innovation decision-making and hence innovation performance (Un & Asakawa, 2015). We achieve this by creating a dummy variable for each year to control for the unobserved factors.

An overview of the variables and their values are described in Table 1.

Descriptive analysis

The correlation matrix, along with the summary statistics representing the study variables, is presented in Table 3. The highest correlation among the variables is 0.79; this is between the R&D intensity and the percentage of highly skilled labour working in the organisation. This is because firms with highly skilled labour are more likely to undertake a large amount of R&D activities. The variables are further analysed by calculating the variance inflation factor (VIF); the highest VIF value is 2.64, which is well below the

Table 3. Correlation matrix.

Variables	M	S.D.	MIN	MAX	1.	2.	3.	4.	5.	6.	7.	8.
(1) Radical Innovation Performance	0.7	1.4	0	4.62	1							
(1) Incremental Innovation Performance	1.0	1.5	0	4.62	0.25*	1						
(1) Collaboration Breadth	1.1	1.7	0	7	0.21*	0.11*	1					
(1) Cognitive Distance	3.5	5.2	0	16.67	0.18*	0.06*	0.76*	1				
(1) Firm Size (ln)	4.1	1.8	0	10.63	0.01	0.05*	0.20*	0.07*	1			
(1) R&D Intensity (0 or 1)	0.4	0.5	0	1	0.38*	0.33*	0.31*	0.30*	0.07*	1		
(1) High Skilled Labour (%)	22.9	33.1	0	100	0.37*	0.35*	0.28*	0.27*	0.05*	0.79*	1	
(1) Firm Age (years)	32.8	19.9	1	347	−0.02*	0.03*	0.03*	−0.01	0.28*	0.03*	0.01	1
VIF					1.11	1.05	2.64	2.52	1.21	1.76	1.73	1.17

*p < 0.01, M = Mean, S.D. = Standard Deviation, MIN = minimum value, MAX = maximum value

prescribed cut-off of 10, indicating that there are no serious problems associated with multicollinearity in the model (Neter et al., 1996). Similarly, other correlations are within the low to medium range and therefore lie within the safe range (Tsui et al., 1995). Moreover, the mean value of radical and incremental innovation is quite low, but the standard deviation is larger than the mean value, which refers to the distribution of innovation results that is necessary to gauge differences in performance.

Estimation and results

Discussion

The estimations from the panel Tobit model are presented in Table 4 for radical and incremental innovation, respectively. The models are run in a hierarchical manner and expanded with the addition of different variables. Model I is the baseline model and contains the results of the effect of the control variables on the dependent variables. Model II and Model III add the direct effect of collaboration breadth and cognitive distance on innovative performance. Model IV provides the results of the full model, taking into account the direct and moderation effect of cognitive distance on the relationship between collaboration breadth and innovation performance.

Hypothesis 1 posits that both incremental and radical innovation performance have a curvilinear relationship with collaboration breadth; however, the optimal number of collaborating partners necessary to maximise innovation performance is not the same. The results are demonstrated through Model II (Table 4), which illustrates that the coefficients of collaboration breadth and its squared terms are significant, both for radical and for incremental innovation performance. The significance and negative sign associated with the beta-squared value indicates an inverted U-shape (Haans et al., 2016), which is also graphically presented in Figure 1, implying and reinforcing the importance of collaboration breadth as an explanatory variable that influences the innovation performance of a firm.

Further, to test the claim that the optimal number of collaboration partners is higher for radical innovation than for incremental innovation, we calculate the turning points of both curves (Haans et al., 2016), which are 9.43 and 7.97 for radical and incremental

Table 4. Results of the panel Tobit regression.

	Radical Innovation Performance				Incremental Innovation Performance			
	I	II	III	IV	I	II	III	IV
CollBrth		0.388***	0.323***	0.493***		0.199***	0.228***	0.321***
		(0.031)	(0.045)	(0.076)		(0.028)	0.039	(0.066)
$CollBrth^2$		−0.021***	−0.014**	−0.052**		−0.012**	−0.015***	−0.026
		(0.006)	(0.006)	(0.023)		(0.005)	(0.005)	(0.021)
CogDis			0.013**	0.045***			−0.006	0.022**
			(0.006)	(0.010)			(0.006)	(0.009)
CollBrth*CogDis				−0.036***				−0.027***
				(0.009)				(0.008)
$CollBrth^2$*CogDis				0.006**				0.003
				(0.002)				(0.002)
Firm Size	0.112***	−0.031	−0.029	−0.031	0.215***	0.095***	0.094***	0.093***
	(0.021)	(0.022)	(0.021)	(0.022)	(0.018)	(0.018)	(0.018)	(0.018)
R&D Intensity	1.631***	0.877***	0.873***	0.875***	1.194***	0.487***	0.489***	0.491***
	(0.056)	(0.051)	(0.051)	(0.051)	(0.048)	(0.043)	(0.043)	(0.043)
Firm Age	−0.005***	−0.007***	−0.006***	−0.007***	0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
High Skilled Labour	0.013***	0.005***	0.005***	0.005***	0.012***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry Indicator				included				
Year Indicator				included				
Constant	−2.706***	−1.069***	−1.079***	−1.091***	−1.608***	0.069	0.074	0.067
	(0.126)	(0.122)	(0.122)	(0.122)	(0.106)	(0.099)	(0.099)	(0.099)
No. of obs	59,621	40,882	40,882	40,882	59,621	40,882	40,882	40,882
Log likelihood	−51,306.3	−47,918.9	−47,916.9	−47,908.6	−65,286.1	−59,765.4	−59,764.8	−59,756.8
Prob > Chi^2	***	***	***	***	***	***	***	***
Wald chi^2	3827.42	2091.10	2095.11	2109.07	4244.19	1409.08	1410.31	1425.88
	(14)	(16)	(17)	(19)	(14)	(16)	(17)	(19)
AIC	102646.6	95,875.8	95,873.86	95,861.2	130,606.1	119,568.7	119,569.6	119,557.6
BIC	102799.5	96,039.6	96,046.23	96,050.8	130,759.1	119,732.5	119,742	119,747.2

CollBrth = Collaboration Breadth, CogDis = Cognitive Distance. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

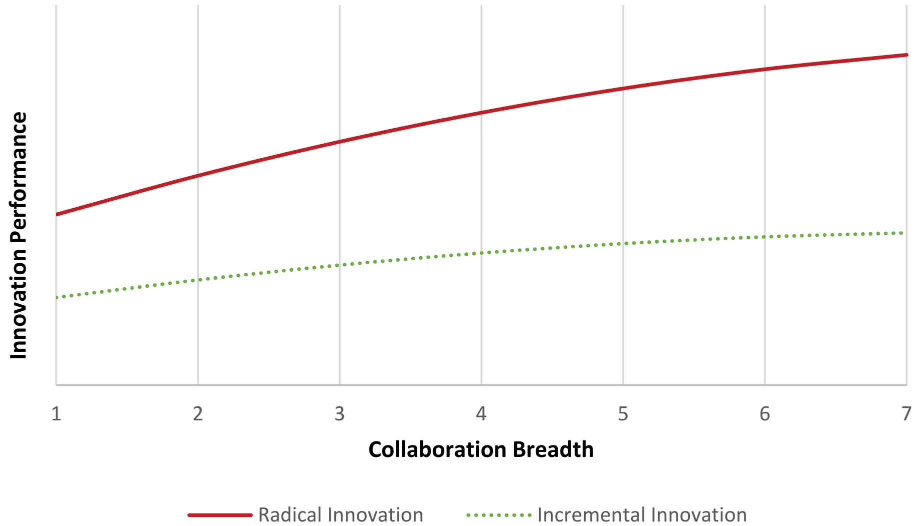

Figure 1. Collaboration breadth and innovation performance.

innovation performance, respectively. These turning points indicate that, beyond 10 partners for radical and beyond 8 partners for incremental innovation performance, businesses start to reap decreasing returns from collaboration with external sources. Thus, hypothesis 1 is verified.

Hypothesis 2 postulates that cognitive distance positively moderates the relationship between external collaboration breadth and radical innovation performance. The coefficients depicting the moderating effect of cognitive distance and its squared term are significant, with a beta value of −0.036 and 0.006, respectively. However, we can observe that the direction of these signs is the inverse when compared with the direct effect of collaboration breadth on innovation performance. This indicates a shape flip (Haans et al., 2016), which implies that the relationship between radical innovation and wide collaboration breadth is now benefitting from the high cognitive distance.

We further investigate the difference in effect based on high and low cognitive distance. However, since the model uses the average value of cognitive distance, we cannot directly observe the difference in the effects of high and low cognitive distance. Accordingly, we calculate the radical innovation performance output by replacing the average value of cognitive distance with the average ± standard deviation to represent the moderating effect of high and low cognitive distance, respectively (presented in Figure 2(a)). The difference in radical innovation performance due to the moderation of high and low cognitive distance is apparent, and this performance is greater when the cognitive distance is high. Thus, our assumption that cognitive distance positively moderates the relationship between collaboration breadth and radical innovation performance is supported.

The third hypothesis predicted that the relationship between external collaboration breadth and incremental innovation performance is negatively moderated by cognitive distance. The coefficient representing the moderation effect is significant and negative at −0.027; however, the squared term is statistically insignificant, implying the

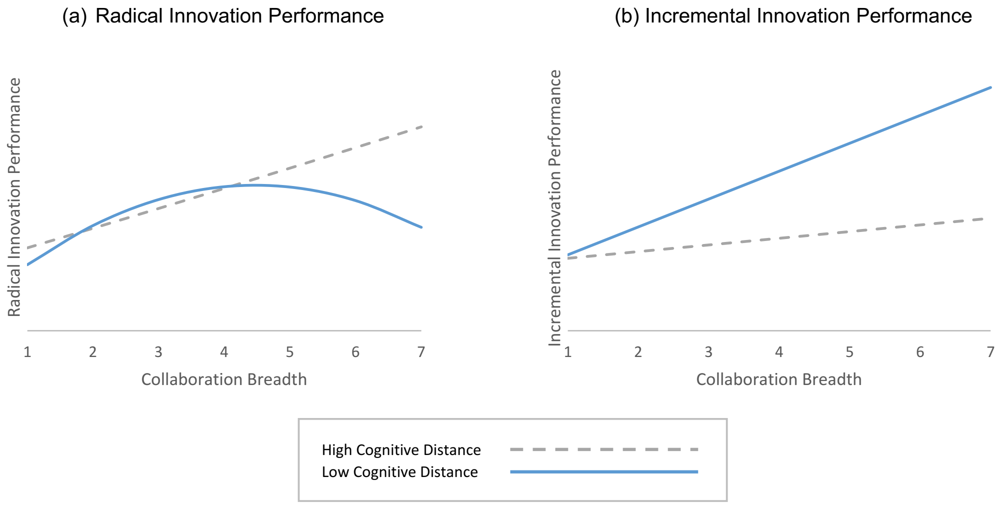

Figure 2. Moderation effect of cognitive distance on the relationship of collaboration breadth and innovation performance (a) Radical innovation performance (b) Incremental innovation performance.

'flattening' of the curve and the conversion of the relationship from quadratic to linear. This negative relationship indicates a substitution effect between the cognitive distance and the benefits received from collaboration, meaning that, as the collaboration breadth increases, the increase in cognitive distance works in the opposite direction. We further test the difference in the effect of high and low cognitive distance using the same technique, that is, replacing the average value of cognitive distance with the average ± standard deviation values. The result is graphically represented in Figure 2(b); the lines depict that the moderation effect of low cognitive distance on the relationship of collaboration breadth with innovation performance is greater than the moderation effect of high cognitive distance. This further strengthens our hypothesis that, for exploitation or incremental ideas, it is beneficial for a firm to collaborate with firms that are cognitively closer.

The shape flip for radical innovation and the flattening of the curve for incremental innovation are governed by the significance and sign of the beta associated with the variable representing the moderation effect on collaboration (Haans et al., 2016). The likely interpretation of the shape flip (conversion from an inverted U-shape to a U-shape) is based on the idea that, when a firm aims to collaborate with different cognitively distant partners, it must incur some internal investments to enhance its absorptive capacity (Gilsing & Nooteboom, 2006). Because this initial investment is fixed in nature, the benefits gained from a small number of external partners are not enough to cover it; however, once the firm begins expanding the collaboration breadth, the high costs start to be overtaken by the benefits attached to an increase in the number of partner types, leading to an overall enhanced radical innovation performance, creating a U-shape. Further, looking at the shape of the curve in Figure 2(a), we can observe that, after a certain number of partners, the radical innovation performance from collaboration with higher cognitive distance partners is significantly greater than the innovation performance achieved when the dominant strategy is to collaborate with lower cognitive distance partners. This implies that collaboration with partners that are cognitively too close fails to bring in ideas that are novel enough to produce disruptive changes (Nooteboom, 2000).

The moderation effect of cognitive distance on the relationship of collaboration breadth and incremental innovation is substituting; this is because the knowledge needed for incremental innovation mostly exists within or proximately close to the firm's boundary (Nooteboom, 2000). However, when a firm decides to collaborate with different partners that are cognitively far apart, they bring in ideas that are not needed or may not be utilised. However, the costs required to maintain a relationship with each of these partners are almost as big as the benefits earned, leading to a strong substitution effect and flattening the overall relationship. This implies that each extra partner with a high cognitive distance costs more than or almost equal to the benefit that it brings, making the relationship linear and almost horizontal. Additionally, if we observe the performance lines presented in Figure 2(b), we can see that incremental innovation performance from collaboration with partners with higher cognitive distance is significantly lower than that from collaboration with partners with low cognitive distance.

The findings reinforce the significance of choosing a collaboration partner based on cognitive distance for exploratory (radical) or exploitative (incremental) innovation (Nooteboom et al., 2007). While many previous studies have separately constructed the relationship of collaboration breadth and cognitive distance with innovation performance (e.g., Enkel & Heil, 2014; Leeuw De et al., 2014), we try to combine these variables and identify the optimal point of interaction that will maximise the innovation outcome.

From a theoretical standpoint, one can suggest that exploratory innovation requires new ideas that can be obtained from a distant or novel source. Our assumption that this effect can be inflated by simultaneously increasing the number of sources (collaboration partners) is as hypothesised. Similarly, too many external partners for exploitation may lead to high communication and transaction costs, which can be higher than the additional benefits earned from incremental innovation. Further, the assumption that cognitive distance has opposing effects on exploration and exploitation is clear and in line with our assumption that the exploitation of technology that already exists does not need as many novel ideas as inputs.

Robustness tests

As a robustness check, the values from the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are calculated and compared with each previous model. The decreasing values of the AIC and BIC and the chi-square suggest the relative goodness-of-fit for each model when compared with the previous one.

Conclusion, limitations and future research

The aim of this study is to advance the understanding of firms' innovation outcomes and how they can be influenced using strategies that are built on the interaction of different variables. As acknowledged by earlier studies that employing single type of strategy provides varied outcomes in terms of the innovation type. This study extends this idea by exploring collaboration strategy, considering two key variables in the literature on open innovation, collaboration breadth and cognitive distance. Collaboration is said to derive higher gains from joint innovation, and cognitive distance enables organisations to produce different innovation outcomes by altering their choice of external partner, making it interesting to study their combined effect on different innovation objectives.

The study is carried out by testing the direct effect of collaboration breadth on the innovation performance of a firm and the way in which this relationship is moderated by cognitive distance. Based on the empirical analysis, the study successfully establishes and reinforces the importance of these variables in explaining the innovation results of a firm.

Using knowledge from previous studies (Bogers, 2011; Kobarg et al., 2019; March, 1991; Steinmo & Rasmussen, 2018) and the empirical results, this work advances the literature by identifying optimal combinations of collaboration breadth and cognitive distance that can maximise radical and incremental innovation. This study highlights the significance of choosing a differentiated portfolio of collaboration partners based on cognitive distance aimed to achieve radical or incremental innovation. The results of this study allow greater confidence when choosing the number and type of partners to achieve different innovation outcomes.

In terms of the theoretical contribution, the study connects collaboration breadth and cognitive distance, as a way to understand effectiveness of collaboration for innovation performance. This work redirects the existing understanding by considering the ease or hindrance that cognitive distance could cause in collaboration process and demonstrate that collaboration breadth, as an explanatory variable of innovation performance, should consider different schemes. Since merely getting into collaboration with partner is not as straight forward and one must also consider other factors, such as cognitive heterogeneity in order to successfully acquire novel ideas and avert large communication costs. This finding is an extension of previous studies that exclusively discuss benefits of collaborating with different partner types on innovation performance. The empirical analyses complement the existing knowledge by demonstrating that not all categories of innovation outcomes (for e.g., radical and incremental) have equal associations with collaboration breadth and cognitive distance. Each type of innovation outcome must therefore be tested separately and future studies could focus on using specific innovation outcomes such as product or process innovation.

Advancing in the RBV stream of research, this study proposes cognitive heterogeneity as another factor that can play an important role in allowing firms to increase their resources base and improve innovation performance.

Further, the work holds important implications for practitioners as well. Innovation is seen as an important factor for maintaining the competitive advantage of firms. While open innovation may help firms to achieve innovation, it by no means is an off-the-shelf or self-deriving solution. Hence, to maximise results, firms must take care of multiple factors which otherwise can cause hinder the achievement of the desired innovation results through open innovation. This work deals with such important factors and suggests how managers can configure among a number of different partners and cognitive heterogeneity to lead to the achievement of innovation outcomes. Firms that aim to obtain incremental or radical innovation would be better off using these results to plan the combination of collaboration breadth and cognitive distance needed to achieve a particular goal. Otherwise, firms could find themselves undertaking expensive experimentation that may lead to large losses and failures. Although a manager must consider multiple factors to maximise the benefits from collaboration (e.g., social, geographical and organisational), this study can be a guide from the perspective of resource differences amongst firms.

Based on the results of this study, it may be said that firms that are seeking radical ideas can achieve these by collaborating with partners that are cognitively distant. However, the variation in the number of partner types can proportionally alter the extent of the innovation outcome. If a firm is an 'ambitious explorer', it will require a large number of partner types, most of which should be cognitively distant. On the other hand, firms aiming for incremental innovation, or the 'safe adoption' of already existing ideas, can achieve their goal by maintaining a collaboration breadth that is narrower than necessary for exploration. However, most of these partners must be cognitively close because a focus on exploitation only involves adopting changes that already exist outside the firm's boundaries. Additionally, policymakers and funding bodies across different countries that aim to design innovation incentives can use this study as a tool for guiding firms that seek their assistance, maximising the returns from their investments or accelerating innovation outcomes in their regions. This is particularly relevant in Spain, the source of our data, because Spain has a low R&D rate in comparison with other countries; this minimises the noise that may otherwise be created by the presence of other factors and maximises the confidence in the results.

However, it is important to acknowledge that large-scale databases have an inherent limitation: they lack in-depth and investigative questions. The questionnaire does not have a field that incorporates a direct measure of the depth of collaboration. Depth is a measure of the extent and intensity of the partnership between firms and has a different impact at each point (Kobarg et al., 2019). This variable allows the observation of the effect of collaboration strength, which may have some impact on the moderating effect of cognitive distance. Our inability to measure the depth leads us to assume that all collaborations carry similar strengths.

Secondly, the data set does not have the information necessary to measure objectively the similarities between the focal firm and its collaboration partner. This similarity in knowledge or technology can be used as a measure of cognitive distance (Nooteboom et al., 2007). Therefore, we try to overcome this by carefully using a cognitive distance scale that has been previously developed by Criscuolo et al. (2017) based on the differences and similarities of firm objectives. Because firms with similar objectives have similar resources and 'sense making' capabilities, they are more likely to be similar in cognitive dimensions (Nooteboom et al., 2007).

In addition to addressing the limitations presented above, future research could investigate the organisational structures that influence the innovation performance of firms. This investigation could be divided into surface- and deep-level differences in the human structure or the type of hierarchical or cultural structures that best suit open innovation performance. An important issue to research further is the limitations and dark side of open innovation; it is important to understand how collaboration with external sources affects the motivation of existing employees and the long-term sustainability of this model.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

His research was funded and conducted within the frameworks of the following projects: PID2020-115018RB-C31 and (AEI/FEDER, UE) research project financedby the ECO2017-86305-C4-4-R (AEI/FEDER, UE and the European Regional Development Funds; Spanish Ministry of Science and Innovation PID2019-105001GB-I00 and PID2020-115018RB-C31(Ministerio de Ciencia eInnovación-Spain; Spanish Ministry of Science, Innovation and Universities). PY20_01209 (PAIDI 2020)

ORCID

Muhammad Ismail http://orcid.org/0000-0003-3132-537X
Alejandro Bello-Pintado http://orcid.org/0000-0003-0186-716X
Teresa García-Marco http://orcid.org/0000-0002-1088-4706

References

Ardito, L., & Messeni Petruzzelli, A. (2017). Breadth of external knowledge sourcing and product innovation: The moderating role of strategic human resource practices. *European Management Journal Elsevier Ltd*, *35*(2), 261–272. https://doi.org/10.1016/j.emj.2017.01.005

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

Bauer, M., & Leker, J. (2013). Exploration and exploitation in product and process innovation in the chemical industry. *R&D Management*, *43*(3), 196–212. https://doi.org/10.1111/radm.12012

Bayona-Saez, C., Cruz-Cázares, C., García-Marco, T., & Sánchez García, M. (2017). Open innovation in the food and beverage industry. *Management Decision*, *55*(3), 526–546. https://doi.org/10.1108/MD-04-2016-0213

Belderbos, R., Martin, C., & Lokshin, B. (2004). Cooperative R & D and firm performance. *Research Policy*, *33*(10), 1477–1492. https://doi.org/10.1016/j.respol.2004.07.003

Bogers, M. (2011). The open innovation paradox: Knowledge sharing and protection in R&D collaborations. *European Journal of Innovation Management*, *14*(1), 93–117. https://doi.org/10.1108/14601061111104715

Bogers, M. (2014). Knowledge sharing in open innovation: An overview of theoretical perspectives on collaborative innovation. In Carmen de Pablos Heredero & David López, (Eds.), *Open innovation at firms and public administrations: technologies for value creation* (pp. 1–14). IGI Global, Hershey, PA. https://ssrn.com/abstract=1862536

Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*(1), 61–74. https://doi.org/10.1080/0034340052000320887

Carree, M., Lokshin, B., & Alvarez Alvarez, H. (2019). Technology partnership portfolios and firm innovation performance: Further evidence. *Journal of Engineering and Technology Management*, *54*, 1–11. https://doi.org/10.1016/j.jengtecman.2019.07.001

Cassiman, B., & Veugelers, R. (2002). R&D cooperation and spillovers: Some empirical evidence from Belgium. *American Economic Review*, *92*(4), 1169–1184. https://doi.org/10.1257/00028280260344704

Cassiman, B., & Veugelers, R. (2006). In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. *Management Science*, *52*(1), 68–82. https://doi.org/10.1287/mnsc.1050.0470

Chandy, R. K., & Tellis, G. J. (1998). Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *Journal of Marketing Research*, *35*(4), 474–487. https://doi.org/10.1177/002224379803500406

Chesbrough, H. (2003). The era of open innovation. *MIT Sloan Management Review*, *44*(3), 35–41. https://sloanreview.mit.edu/article/the-era-of-open-innovation/

Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: Does firm age play a role? *Research Policy*, *45*(2), 387–400. https://doi.org/10.1016/j.respol.2015.10.015

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553

Combs, J. G., & Ketchen, D. J. (1999). Explaining interfirm cooperation and performance. *Strategic Management Journal*, *20*(9), 867–888. https://doi.org/10.1002/(SICI)1097-0266(199909)20:9<867::AID-SMJ55>3.0.CO;2-6

Criscuolo, P., Laursen, K., Reichstein, T., & Salter, A. (2017). Winning combinations: Search strategies and innovativeness in the UK. *Industry and Innovation*, *25*(2), 115–143. https://doi.org/10.1080/13662716.2017.1286462

Das, T. K., & Teng, B. (2000). A resource-based theory of strategic alliances. *Journal of Management*, *26*(1), 31–61. https://doi.org/10.1177/014920630002600105

Deeds, D. L., & Hill, C. W. L. (1996). Strategic alliances and the rate of new product development: An empirical study of entrepreneurial biotechnology firms. *Journal of Business Venturing*, *11*(1), 41–55. https://doi.org/10.1016/0883-9026(95)00087-9

Dewar, R. D., & Dutton, J. E. (1986). The adoption of radical and incremental innovations: An empirical analysis. *Management Science*, *32*(11), 1422–1433. https://doi.org/10.1287/mnsc.32.11.1422

Duysters, G., & Lokshin, B. (2011). Determinants of alliance portfolio complexity and its effect on innovative performance of companies. *Journal of Product Innovation Management*, *28*(4), 570–585. https://doi.org/10.1111/j.1540-5885.2011.00824.x

Eisenhardt, K. M., & Schoonhoven, C. B. (1996). Resource-based view of strategic alliance formation: Strategic and social effects in entrepreneurial firms. *Organization Science*, *7*(2), 136–150. https://doi.org/10.1287/orsc.7.2.136

Enkel, E., Gassmann, O., & Chesbrough, H. (2009). Open R&D and open innovation: Exploring the phenomenon. *R&D Management*, *39*(4), 311–316. https://doi.org/10.1111/j.1467-9310.2009.00570.x

Enkel, E., & Heil, S. (2014). Preparing for distant collaboration: Antecedents to potential absorptive capacity in cross-industry innovation. *Technovation*, *34*(4), 242–260. https://doi.org/10.1016/j.technovation.2014.01.010

Ettlie, J. E., Bridges, W. P., & O'Keefe, R. D. (1984). Organization strategy and structural differences for radical versus incremental innovation. *Management Science*, *30*(6), 682–695. https://doi.org/10.1287/mnsc.30.6.682

Faems, D., Van Looy, B., & Debackere, K. (2005). Interorganizational collaboration and innovation: Toward a portfolio approach. *Journal of Product Innovation Management*, *22*(3), 238–250. https://doi.org/10.1111/j.0737-6782.2005.00120.x

Fernández-Olmos, M., & Ramírez-Alesón, M. (2017). How internal and external factors in fluence the dynamics of SME technology collaboration networks over time. *Technovation*, *64-65*, 16–27. https://doi.org/10.1016/j.technovation.2017.06.002

Forés, B., & Camisón, C. (2016). Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size? *Journal of Business Research*, *69*(2), 831–848. https://doi.org/10.1016/j.jbusres.2015.07.006

Gavetti, G., & Levinthal, D. (2000). Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterly*, *45*(1), 113. https://doi.org/10.2307/2666981

Gilsing, V., & Nooteboom, B. (2006). Exploration and exploitation in innovation systems: The case of pharmaceutical biotechnology. *Research Policy*, *35*(1), 1–23. https://doi.org/10.1016/j.respol.2005.06.007

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(S2), 109–122. https://doi.org/10.1002/smj.4250171110

Grant, R. M., & Baden-Fuller, C. (2004). A knowledge accessing theory of strategic alliances. *Journal of Management Studies*, *41*(1), 61–84. https://doi.org/10.1111/j.1467-6486.2004.00421.x

Greco, M., Grimaldi, M., & Cricelli, L. (2016). An analysis of the open innovation effect on fi rm performance. *European Management Journal Elsevier Ltd*, *34*(5), 501–516. https://doi.org/10.1016/j.emj.2016.02.008

Haans, R., Pieters, C., & He, Z. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, *37*(7), 1177–1195. https://doi.org/10.1002/smj.2399

Hagedoorn, J., Lokshin, B., & Zobel, A. (2018). Partner type diversity in alliance portfolios: Multiple dimensions, boundary conditions and firm innovation performance. *Journal of Management Studies*, *55*(5), 809–836. https://doi.org/10.1111/joms.12326

Haus-Reve, S., Dahl, R., & Rodríguez-Pose, A. (2019). Does combining different types of collaboration always benefit firms? Collaboration, complementarity and product innovation in Norway. *Research Policy*, *48*(6), 1476–1486. https://doi.org/10.1016/j.respol.2019.02.008

Henderson, R. M., & Clark, K. B. (1990). Architectural innovation. *Administrative Science Quarterly*, *35*(1), 9–30. https://doi.org/10.2307/2393549

Hoetker, G. (2005). How much you know versus how well I know you: Selecting a supplier for a technically innovative component. *Strategic Management Journal*, *26*(1), 75–96. https://doi.org/10.1002/smj.453

Hottenrott, H., & Lopes-Bento, C. (2016). R&D partnerships and innovation performance: Can there be too much of a good thing? *Journal of Product Innovation Management*, *33*(6), 773–794. https://doi.org/10.1111/jpim.12311

Jepsen, L. B., Dell'Era, C., & Verganti, R. (2014). The contributions of interpreters to the development of radical innovations of meanings: The role of 'pioneering projects' in the sustainable buildings industry. *R&D Management*, *44*(1), 1–17. https://doi.org/10.1111/radm.12035

Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *The Academy of Management Journal*, *45*(6), 1183–1194. https://doi.org/10.2307/3069433

Kim, D.-J., & Kogut, B. (1996). Technological platforms and diversification. *Organization Science*, *7*(3), 283–301. https://doi.org/10.1287/orsc.7.3.283

Kobarg, S., Stumpf-Wollersheim, J., & Welpe, I. M. (2019). More is not always better: Effects of collaboration breadth and depth on radical and incremental innovation performance at the project level. *Research Policy*, *48*(1), 1–10. https://doi.org/10.1016/j.respol.2018.07.014

Lane, P. J., & Lubatkin, M. (1998). Relative absorptive capacity and interorganizational learning. *Strategic Management Journal*, *19*(5), 461–477. https://doi.org/10.1002/(SICI)1097-0266(199805)19:5<461::AID-SMJ953>3.0.CO;2-L

Langerak, F., Hultink, E. J., & Griffin, A. (2008). Exploring mediating and moderating influences on the links among cycle time. *Journal of Product Innovation Management*, *25*(4), 370–385. https://doi.org/10.1111/j.1540-5885.2008.00307.x

Laursen, K., & Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal*, *27*(2), 131–150. https://doi.org/10.1002/smj.507

Laursen, K., & Salter, A. J. (2014). The paradox of openness: Appropriability, external search and collaboration. *Research Policy*, *43*(5), 867–878. https://doi.org/10.1016/j.respol.2013.10.004

Lauvås, T., & Steinmo, M. (2019). The role of proximity dimensions and mutual commitment in shaping the performance of university-industry research centres. *Innovation: Organization and Management*, 1–27. https://doi.org/10.1080/14479338.2019.1662725

Lavie, D., & Rosenkopf, L. (2006). Balancing exploration and exploitation in alliance formation. *Academy of Management Journal*, *49*(4), 797–818. https://doi.org/10.5465/amj.2006.22083085

Leeuw De, T., Lokshin, B., & Duysters, G. (2014). Returns to alliance portfolio diversity: The relative effects of partner diversity on firm's innovative performance and productivity. *Journal of Business Research*, *67*(9), 1839–1849. https://doi.org/10.1016/j.jbusres.2013.12.005

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic Management Journal*, *14* (S2), 95–112. https://doi.org/10.1002/smj.4250141009

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, *2*(1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Marsili, O., & Salter, A. (2005). 'Inequality' of innovation: Skewed distributions and the returns to innovation in Dutch manufacturing. *Economics of Innovation and New Technology*, *14*(1–2), 83–102. https://doi.org/10.1080/1043859042000228642

Martinez, M. G., Zouaghi, F., & Garcia, M. S. (2017). Capturing value from alliance portfolio diversity: The mediating role of R & D human capital in high and low tech industries. *Technovation*, *59*, 55–67. http://dx.doi.org/10.1111/radm.12244

Mathisen, L., & Jørgensen, E. J. B. (2021). The significance of knowledge readiness for co-creation in university industry collaborations. *Innovation: Organization and Management*, 1–18. https://doi.org/10.1080/14479338.2021.1882862

The Measurement of Scientific and Technological Activities Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data, 3rd ed.

Meulman, F., Reymen, I., Podoynitsyna, K., & Romme, L. (2018). Searching for partners in open innovation settings: How to overcome the constraints of local search. *California Management Review*, *60*(2), 71–97. https://doi.org/10.1177/0008125617745087

Miotti, L., & Sachwald, F. (2003). Co-operative R&D: Why and with whom? An integrated framework of analysis. *Research Policy*, *32*(8), 1481–1499. https://doi.org/10.1016/S0048-7333(02)00159-2

Muscio, A., & Pozzali, A. (2013). The effects of cognitive distance in university-industry collaborations: Some evidence from Italian universities. *The Journal of Technology Transfer*, *38*(4), 486–508. https://doi.org/10.1007/s10961-012-9262-y

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied linear statistical models* (4th ed.). Irwin/McGraw-Hill.

Nieto, M. J., & Santamaría, L. (2007). The importance of diverse collaborative networks for the novelty of product innovation. *Technovation*, *27*(6–7), 367–377. https://doi.org/10.1016/j.technovation.2006.10.001

Noni De, I., Orsi, L., & Belussi, F. (2018). The role of collaborative networks in supporting the innovation performances of lagging-behind European regions. *Research Policy*, *47*(1), 1–13. https://doi.org/10.1016/j.respol.2017.09.006

Nooteboom, B. (2000). Learning by interaction: Absorptive capacity, cognitive distance and governance. *Journal of Management and Governance*, *4*(1/2), 69–92. https://doi.org/10.1023/A:1009941416749

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., & van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. *Research Policy*, *36*(7), 1016–1034. https://doi.org/10.1016/j.respol.2007.04.003

Oerlemans, L. A. G., Knoben, J., & Pretorius, M. W. (2013). Alliance portfolio diversity, radical and incremental innovation: The moderating role of technology management. *Technovation*, *33*(6–7), 234–246. https://doi.org/10.1016/j.technovation.2013.02.004

Østergaard, C. R., & Drejer, I. (2021, August). Keeping together: Which factors characterise persistent university – Industry collaboration on innovation? *Technovation Elsevier Ltd*, 102389. https://doi.org/10.1016/j.technovation.2021.102389

Ovuakporie, O., Pillai, K., Wang, C., & Wei, Y. (2021). Differential moderating effects of strategic and operational reconfiguration on the relationship between open innovation practices and innovation performance. *Research Policy*, *50*(1), 1–17. https://doi.org/10.1016/j.respol.2020.104146

Penrose, E. T. (1959). *The theory of the growth of the firm*. John Wiley.

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, 1–39. https://hbr.org/1990/03/the-competitive-advantage-of-nations#:~:text=A%20nation's%20competitiveness%20depends%20on,suppliers%2C%20and%20demanding%20local%20customers

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, *41*(1), 116–145. https://doi.org/10.2307/2393988

Roberts, E., & Berry, C. (1985). Entering new businesses: Selecting strategies for success. *Sloan Management Review*, *26*(3), 3–17. efaidnbmnnnibpcajpcglclefindmkaj/https://dspace.mit.edu/bitstream/handle/1721.1/47449/enteringnewbusin00robe.pdf

Robertson, P. L., Casali, G. L., & Jacobson, D. (2012). Managing open incremental process innovation: Absorptive capacity and distributed learning. *Research Policy*, *41*(5), 822–832. https://doi.org/10.1016/j.respol.2012.02.008

Rothaermel, F. T., Hitt, M. A., & Jobe, L. A. (2006). Balancing vertical integration and strategic outsourcing: Effects on product portfolio, product success, and firm performance. *Strategic Management Journal*, *27*(11), 1033–1056. https://doi.org/10.1002/smj.559

Simon, H. A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics*, *69*(1), 99–118. https://doi.org/10.2307/1884852

Steinmo, M., & Rasmussen, E. (2018). The interplay of cognitive and relational social capital dimensions in university–industry collaboration: Overcoming the experience barrier. *Research Policy*, *47*(10), 1964–1974. https://doi.org/10.1016/j.respol.2018.07.004

Tiberius, V., Schwarzer, H., & Roig-Dobón, S. (2021). Radical innovations: Between established knowledge and future research opportunities. *Journal of Innovation & Knowledge& Knowledge*, *6*(3), 145–153. https://doi.org/10.1016/j.jik.2020.09.001

Tsui, A. S., Ashford, S. J., Clair, L. S. T., & Xin, K. R. (1995). Dealing with discrepant expectations: Response strategies and managerial effectiveness. *Academy of Management Journal*, *38*(6), 1515–1543. https://doi.org/10.2307/256842

Tzabbar, D., Aharonson, B. S., & Amburgey, T. L. (2013). When does tapping external sources of knowledge result in knowledge integration? *Research Policy*, *42*(2), 481–494. https://doi.org/10.1016/j.respol.2012.07.007

Un, C. A., & Asakawa, K. (2015). Types of R&D collaborations and process innovation: The benefit of collaborating upstream in the knowledge chain. *Journal of Product Innovation Management*, *32*(1), 138–153. https://doi.org/10.1111/jpim.12229

Van den Bosch, F. A. J., Volberda, H. W., & de Boer, M. (1999). Coevolution of firm absorptive capacity and knowledge environment: Organizational forms and combinative capabilities. *Organization Science*, *10*(5), 551–568. https://doi.org/10.1287/orsc.10.5.551

Vermeulen, P. A. M., Van den Bosch, F. A. J., & Volberda, H. W. (2007). Innovation in established service firms: A micro institutional perspective. *Organization Studies*, *28*(10), 1523–1546. https://doi.org/10.1177/0170840607068082

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *The Academy of Management Review*, *27*(2), 185–203. https://doi.org/10.2307/4134351

Zhang, J., Baden-Fuller, C., & Mangematin, V. (2007). Technological knowledge base, R&D organization structure and alliance formation: Evidence from the bio-pharmaceutical industry. *Research Policy*, *36*(4), 515–528. https://doi.org/10.1016/j.respol.2007.02.015