How Does Outside-In Open Innovation Influence Innovation Performance? Analyzing the Mediating Roles of Knowledge Sharing and Innovation Strategy

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How does outside-in open innovation influence innovation performance?

Analyzing the mediating roles of knowledge sharing and innovation strategy

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ABSTRACT

Embracing outside-in open innovation (OI) can result in a plethora of organizational advantages, including improved innovation performance. Although some studies have found that outside-in OI improves innovation performance, others have shown that it has no effect, or even a negative effect. This mixed empirical evidence leads to a need to unpack the relationship between outside-in OI and innovation performance, and to examine how certain key mediating variables related to the outside-in OI process can ensure that outside-in OI turns into improved innovation performance. Thus, this article aims to examine the influence of outside-in OI on innovation performance considering the mediating roles of knowledge sharing and innovation strategy. The article draws on a cross-industrial sample of 112 firms. Data are analyzed using a set of ordinary-least-squares regression models and the bootstrap procedure. Results show that knowledge sharing and innovation strategy fully mediate the relationship between outside-in OI and innovation performance.

INTRODUCTION

In an increasingly competitive business environment, firms can gain competitive advantage when they create relevant product and/or service innovations [1, 2]. In accordance with the open innovation (OI) model [3, 4], firms can improve their innovation potential by purposefully going beyond their boundaries using inflows of knowledge in their innovation processes (i.e., outside-in OI). The literature has identified several outside-in OI mechanisms, including alliances [5], OI intermediaries, crowdsourcing [6], and in-licensing agreements [7], and argued that embracing outside-in OI can result in a multitude of advantages, such as greater access to external knowledge, shared risk with partners, better understanding of customer needs, and improved innovation performance [3, 8-10].

Although some empirical studies have shown that outside-in OI boosts innovation performance [5, 8, 9, 11], others have found that it has no effect on innovation performance, or even a negative effect [12-16]. Moreover, scholars have found cases of failed outside-in OI projects, where firms did not achieve their predefined innovation performance objectives [17, 18].

This mixed empirical evidence leads to confusion about how firms can attain a better innovation performance by embracing outside-in OI. One reason why previous research has obtained mixed findings may be differences between firms' internal practices for managing innovation processes, because tapping into external knowledge creates a set of managerial challenges [19-22]. One of these managerial challenges is to ensure that employees have an accurate understanding of the firm's knowledge needs to be able to identify and value relevant external knowledge [19]. Another managerial challenge is to make sure that the relevant external knowledge is in a form that can be used internally, and is transferred to the appropriate business units and departments [21]. These challenges highlight that firms may need to introduce a set of internal practices when engaging in outside-in OI to increase the probability of innovation performance improvement. This implies that internal practices may mediate the relationship between outside-in OI and innovation performance [19, 23]. Surprisingly, however, most previous studies have only directly related outside-in OI to innovation performance [8, 9, 11, 24], and to the best of our knowledge, only Foss, et al. [19] have considered internal practices as a mediator of such relationship. However, while Foss, et al. [19] have provided empirical evidence for a positive indirect effect of outside-in OI on innovation performance through internal practices, they have only included one type of external partners (i.e., customers) in the analysis. Thus, this article aims at unpacking the relationship between outside-in OI and innovation performance to analyze how firms can turn outside-in OI into improved innovation performance through internal practices, considering a wider range of external partners.

In the field of OI, there is some evidence showing that knowledge sharing and a clear innovation strategy, which are two types of internal practices, are essential when firms want to transfer outside-in OI into improved innovation performance [17, 19, 20, 25]. On one hand, knowledge sharing between firms and external partners is likely to increase a firm's capability to identify and value different areas of knowledge that are relevant to the innovation process, and to assimilate and exploit the absorbed knowledge effectively, thereby boosting innovation performance [17, 26]. For example, Faems, et al. [5] found that, in the case of strategic alliances, a lack of knowledge sharing between the partnering firms slows innovation activity, leading to an unsuccessful performance outcome. In addition, several scholars have argued that sharing knowledge inside firms - among internal business units and employees - helps the assimilation and exploitation of external knowledge during innovation processes, which in turn leads to increased innovation performance [19, 27]. On the other hand, a clear innovation strategy, as a formal statement indicating innovation areas, roadmaps and required resources, determines the scope and direction of external search, which in turn enables firms to identify the required knowledge that is relevant to their innovation activity [22]. Likewise, the innovation strategy helps firms to assess the fit between external knowledge and internal innovation needs, thereby ensuring enhanced innovation performance [22, 28, 29]. Moreover, having an innovation strategy with a formal planning process, a budget cycle, and a review procedure, can improve the internal coordination and synchronization of external knowledge [27]. This can facilitate the assimilation and exploitation of absorbed knowledge from external sources, and thereby boost innovation performance [27].

As knowledge sharing, inside firms and between firms and external partners, and innovation strategy are internal practices that are closely related to the outside-in OI process [17, 19, 20, 25] and that can boost innovation performance [19, 30], this paper studies them as potential mediators of the relationship between outside-in OI and innovation performance, to overcome the above-discussed differences in understanding of how firms can take advantage of outside-in OI. The paper draws on a cross-industrial sample of 112 firms that are active in OI. Data were collected via a survey of senior executives, and analyzed using a set of ordinary-least-squares (OLS) regression models and the bootstrap procedure. Results show that outside-in OI is not directly related to innovation performance. Instead, this relationship is fully mediated by knowledge sharing and innovation strategy. On one hand, this means that to translate outside-in OI into improved innovation performance, firms need to constantly and systematically share knowledge within and beyond their boundaries. On the other hand, this implies that firms need to develop an innovation strategy that makes innovation areas and required resources clear, and that establishes a formal planning process to obtain the same result.

Consequently, this study makes a twofold contribution to the field of OI. First, it shows that engaging in outside-in OI activities is not sufficient to guarantee an improvement in innovation performance. Second, it shows that outside-in OI can turn into improved innovation performance through the internal practices of knowledge sharing and innovation strategy, which helps explain why some outside-in OI activities are successful and others are not.

The following sections of the paper present the theoretical background and hypotheses development, the methodology, the data analysis, the results, and the discussion and conclusion.

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

The hypothesized relationships between outside-in OI, knowledge sharing, innovation strategy and innovation performance are represented by the six arrows in Figure 1. In this section, we discuss: (1) the impact of outside-in OI, knowledge sharing and innovation strategy on innovation performance (i.e., H1, H4 and H5 – see Table 4, Models III, IV, and V); (2) the effect of outside-in OI on knowledge sharing and innovation strategy (i.e., H2 and H3 – see Table 4, Models I and II); and (3) the impact of knowledge sharing on innovation strategy (i.e., H6 - see Table 4, Model II).

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The direct link between outside-in OI and innovation performance

Outside-in OI consists of purposefully using the ideas, skills and knowledge of a wide range of external partners (e.g., customers, suppliers, universities, competitors) to accelerate internal innovation processes [3]. To access the ideas, skills and knowledge of their external partners, firms can use various mechanisms, including alliances, OI intermediaries, crowdsourcing, and in-licensing agreements [5-7, 31].

Collaborating with external partners can give firms easier access to valuable external ideas, skills, and knowledge [32]. In accordance with the resource-based view, extended to the collaboration of firms with external partners [33, 34], this access to valuable external ideas, skills and knowledge allows firms to improve internal innovation activities by including previously inaccessible resources. In that sense, outside-in OI improves the quantity, quality and diversity of ideas, skills and knowledge, and thereby complements existing internal resources and capabilities [33, 35]. This provides firms with the opportunity to improve their innovation capabilities, which can result in improved innovation performance [11, 24, 27].

Collaborating with external partners can also help firms to obtain required resources quickly, which is particularly important with regard to tacit resources (i.e., non-observable knowledge and skills), as these are slow to develop internally [33]. This quick access to required tacit resources may facilitate and foster the innovation process, which can result in enhanced innovation performance. In addition, outside-in OI can improve innovation processes by providing resources from external partners, which can reduce innovation-related costs and risks [33]. This is especially important for firms operating in highly-competitive markets based on cost-driven strategies [33]. Moreover, collaborating with external partners to capture their knowledge may enhance the firm's technological capabilities (i.e., set of tasks and procedures that bring together external and internal knowledge), enabling it to better incorporate the external resources into its innovation processes. By turning external and internal resources more easily into novel configurations, firms can increase the probability of innovation success [36].

Accordingly, a recent case study on the Lilly Open Innovation Drug Discovery (OIDD) platform describes Lilly as tapping into external knowledge to develop successful innovations. Through the OIDD platform, Lilly has met a great number of scientists who can help its internal research teams develop new and/or improved drugs and biopharmaceuticals; and this has boosted innovation performance [37]. In this line, in a cross-industrial study on Dutch firms, Belderbos, et al. [38] found that by engaging in outside-in OI with external partners (i.e., competitors, suppliers, customers, and universities or research institutions) on R&D projects, firms are likely to boost their innovation performance in terms of percentage of total sales resulting from new products or services. Similarly, Faems, et al. [24] showed that when manufacturing firms conduct outside-in OI with external partners, their innovation performance improves, measured by the total turnover derived from new product development. Likewise, Knudsen [12] found that when European manufacturing and service firms engage in outside-in OI alongside private research institutions, universities and suppliers, this increases the percentage of total sales resulting from innovation. Similarly, in an empirical study on Korean firms in the Information and Communications Technology (ICT) sector, Hwang and Lee [39] showed that by sourcing knowledge externally, firms can improve their innovation performance, measured by the percentage of total sales from new products in the market. Finally, based on a large sample of Spanish manufacturing firms, Santamaría, et al. [40] provided empirical evidence of the positive effect of outside-in OI mechanisms, such as alliances, on new product development. Thus, we hypothesize that:

H1: Outside-in OI is positively related to innovation performance.

The indirect links between outside-in OI and innovation performance: Knowledge sharing and innovation strategy

Outside-in OI and knowledge sharing

Several scholars have defined knowledge sharing as making knowledge accessible to stakeholders, both internal (e.g., employees) and external (e.g., customers, suppliers) [41, 42]. When embracing outside-in OI, firms gain access to potentially valuable resources, such as ideas and knowledge of external partners. A firm's recognition capacity (a component of absorptive capacity), conceptualized as the ability to identify these resources and value them, is critical in any innovation process [43, 44]. Knowledge sharing with external partners provides firms with more information about the external partner's resources, and so enables them to better understand and synthesize external resources [5]. By better understanding and synthesizing external resources, firms can better assess the fit between the external knowledge and that which they require for innovation [27]. Accordingly, Faems, et al. [5] found that, in a research and development collaboration project, partner firms organized technical meetings to foster knowledge sharing, and so to gain better understanding of each other's technical knowledge. Because of these meetings, both partner firms could better assess and use suitable external knowledge for their innovation activity. In fact, in a study of the partnership between DreamWorks and Hewlett-Packard, Narsalay, et al. [45] showed that the firms even encouraged the exchange of sensitive technical and business information which helped them assess each other's knowledge and innovation needs since, as a former Director of Open Innovation at HP Labs stated, "without sharing knowledge and open communication between partners, I do not think we could have got a really [valuable knowledge] from collaboration" (p. 3).

Despite the importance of knowledge sharing with external partners, several scholars have acknowledged that sharing knowledge inside firms (i.e., among internal stakeholders) is also crucial to identifying relevant knowledge for innovation [19, 27]. Sharing knowledge internally gives employees a better understanding of the firm's knowledge and innovation needs. In fact, this better understanding of the firm's knowledge and innovation needs shapes the scope and the direction of the firm's external search, which in turn eases the process of identifying and evaluating external knowledge [27]. For example, in a study on the alliance between Esthetique and L'Oréal, Ness [46] found that both firms did not only share knowledge with each other, but also internally, by promoting joint product-related meetings and activities after starting the collaboration. Thus, when embracing outside-in OI, knowledge sharing is an internal practice that firms must implement to improve their recognition capacity, which is critical to innovation purposes. In line with this reasoning, we postulate that:

H2: Outside-in OI is positively related to knowledge sharing.

Outside-in OI and innovation strategy

Various authors have argued that innovation strategy involves a set of management and coordination activities adopted by firms to organize their innovation processes [47, 48]. These activities include the development of innovation roadmaps, a clear perspective on areas that require innovation, a formal planning process, budget allocation, and a review procedure [47-49]. An innovation strategy communicates a clear direction for innovation by specifying focal innovation areas that the firm needs to address [47, 50]. By determining focal innovation areas, firms can identify the knowledge that they require to complete their innovation processes.

In addition, implementing a formal planning process and review procedure may help firms obtain more information about their innovation activities and performance levels, which is likely to result in a better understanding of their knowledge needs to achieve innovation success [48, 51]. Understanding knowledge needs shapes the scope and direction of the firm's external knowledge search, helping it identify valuable knowledge for its focal innovation areas [44]. The innovation strategy also helps internal processes to identify external knowledge and to assess how well external knowledge fits the firm's knowledge needs [22, 28, 29]. Accordingly, Brunswicker and Vanhaverbeke [20] found that small and medium-sized enterprises engaging in external knowledge sourcing have an innovation strategy, a formal planning process, and formal innovation project control. Similarly, in a multiple case study of Italian firms, Chiaroni, et al. [28] showed that firms embracing outside-in OI activities develop a formal planning process and a review procedure to evaluate the progress of their innovation projects. Accordingly, we posit that:

H3: Outside-in OI is positively related to innovation strategy.

Knowledge sharing and innovation performance

In addition to improving the ability to identify and access external knowledge (i.e., recognition capacity) during outside-in OI activities, Cohen and Levinthal [43] suggested that assimilation and exploitation capacities (i.e., the other two components of absorptive capacity) are also important to the firm's innovation capability and performance. After identifying the relevant external knowledge, firms need to analyze, process and diffuse it internally (i.e., assimilation capacity) [52]. Assimilation capacity enables firms to transform external knowledge into forms that they can use internally [52]. External knowledge is usually absorbed in a form that employees are unable to interpret and understand [27]. In that sense, knowledge sharing between firms and external partners can help firms to obtain more information about the characteristics of the external knowledge, and thereby make it more understandable for employees [52]. Moreover, sharing knowledge between firms and external partners fosters social integration between external partners and the firm's employees [5, 53]. As a result, employees are likely to improve their attitudes, which is crucial for better interpreting and understanding external knowledge [52]. Apart from exchanging knowledge with external partners, firms should also share knowledge in-house, to ensure that the absorbed external knowledge is available to the different business units and departments [19].

After assimilating the external knowledge, firms need to determine how to apply it and combine it with internal knowledge (i.e., exploitation capacity) [43, 52]. Knowledge sharing between firms and external partners can facilitate the alignment process between external and internal knowledge, as the involved actors understand better the knowledge required for innovation processes [5]. As a result of this alignment, firms can improve the various combinations of internal and external knowledge [27]. Moreover, retrieving already assimilated external knowledge is crucial for such combinations. Internal knowledge sharing can foster this retrieving process, leading to a more efficient combination of internal and external knowledge. By improving combinations of internal and external knowledge, firms can use it more effectively, and so leverage external knowledge into new contexts and methods of application [27, 52].

Accordingly, in a cross-industrial study, Lin [54] found that internal knowledge sharing is positively related to innovation performance. Likewise, based on a dataset of 169 Danish large firms from 29 industries, Foss, et al. [19] showed that information exchange between employees across different departments of a firm improves innovation performance, measured by innovation capacity and profitability, relative to competitors. In a similar vein, in a survey-based empirical study involving high-technology firms from China, Wang and Wang [55] showed that knowledge sharing inside firms has a positive impact on innovation performance. Similarly, in a research and development collaboration project, Faems, et al. [5] found that when the partners share technological information, they improve their innovation performance. Overall, knowledge sharing inside firms and with external partners can pave the way for the assimilation and the exploitation of external knowledge, and thereby foster innovation performance. Thus, we hypothesize that:

H4: Knowledge sharing is positively related to innovation performance.

Innovation strategy and innovation performance

An innovation strategy can support the assimilation of external knowledge, because it makes clear the characteristics of the knowledge required for innovation, and thereby helps firms to understand and interpret external knowledge [52]. Innovation consists of identifying applications for the assimilated external knowledge and combining external knowledge with internal knowledge (i.e., exploitation capacity) [27, 52]. In that sense, an innovation strategy can lead to improved exploitation of external knowledge, because a formal planning and a review process that are part of the innovation strategy help to identify applications for such external knowledge, and also to combine the assimilated external knowledge with internal knowledge [22]. In this line, Kogut and Zander [56] argued that the firm's capability to generate new applications using external knowledge leads to improved innovation performance. Thus, firms can take advantage of external knowledge by developing an innovation strategy that supports combinative capabilities.

Accordingly, in the context of SMEs, Brunswicker and Vanhaverbeke [20] showed that innovation strategy and innovation project control are positively associated with innovation performance, measured by income derived from innovation. Similarly, in the area of highly innovative projects, Salomo, et al. [57] found that having a formal process for managing and controlling innovation projects leads to improved innovation performance, from the product, market, and finance perspectives. Therefore, we postulate that:

H5: Innovation strategy is positively related to innovation performance.

Knowledge sharing and innovation strategy

As discussed above, knowledge sharing supports the assimilation of knowledge, making external knowledge available to employees in a form that is understandable to them. Active observation and monitoring of the internal innovation process to identify potential applications for the assimilated knowledge, is crucial for the exploitation of such knowledge [27]. To observe and monitor the internal innovation process effectively, firms need to introduce certain formal processes, such as a formal planning and a review procedure [48, 58]. Also, having sufficient information about the focal innovation areas is important for effectively monitoring the internal innovation process [50]. These formalities and focal innovation areas need to be specified and implemented through an innovation strategy [47, 48].

Knowledge sharing can facilitate the assimilation of external knowledge [19]. Once the assimilated external knowledge is available across the whole organization, firms need to explore potential applications of it, and determine how to combine it with internal knoweldge [43, 52]. An innovation strategy determines the scope of the observation and monitoring of the innovation process, thereby supporting the identification of potential applications of the assimilated external knowledge [28, 44]. Moreover, an innovation strategy helps employees to effectively match the internal and the assimilated external knowledge [27], and provides firms with sufficient information about knowledge needs, helping them to filter out unfeasible assimilated external knowledge [29]. Thus, developing an innovation strategy is crucial once firms have assimilated the external knowledge captured through knowledge sharing [22, 27]. In line with these arguments, we posit that:

H6: Knowledge sharing is positively related to innovation strategy.

METHODOLOGY

Data collection and sample

The data for this study comes from a survey completed mainly by senior executives working in the fields of R&D and innovation (i.e., Chief Innovation Officers, Chief Technology Officers, R&D Directors, and OI Directors) belonging to Exnovate, the European Network of Excellence on Open and Collaborative Innovation (www.exnovate.org), a non-profit organization through which OI practitioners can learn about OI and exchange best practices. The Exnovate network contains approximately 7000 OI practitioners, mostly located in Europe and the United States, almost one third of whom work in large companies that actively engage in OI. This makes the sample relevant to this study and minimizes key-informant bias [59].

A first email invitation was sent to a subset of 2234 OI practitioners. To increase the response rate, the potential participants were divided into several waves, and reminder emails were sent to nonrespondents. In the end, 160 responses were received. Some of these contained missing values on the key variables of this study, which reduced the final sample to 112 companies. To assess late-response bias, various statistical tests (ANOVA test, two-sample t-test, and Chi-square test) were conducted, comparing early and late respondents based on the key variables in this paper and on the variables related to firm characteristics. The results showed that there are no significant differences between early and late respondents in terms of outside-in OI, knowledge sharing, innovation strategy, innovation performance, firm size, OI duration, innovation intensity, and industry groups. These results confirm the absence of late-response bias. 53.6% of the respondents work in manufacturing companies. The others work in various service industries, including professional services, wholesale, transportation, public utilities, finance, insurance, real estate, and retail. Agriculture and mining represent 4.5% of the respondents. Finally, most respondents (88.4%) are innovation experts who work in R&D departments; in other departments that engage in OI (i.e., sales, marketing, purchasing, operations, and logistics); or have senior management positions in their company. This indicates that the respondents are suitable for this study. Table 1 depicts the sample distribution across industry groups and job roles.

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Measures

To operationalize the constructs of knowledge sharing, innovation strategy, and innovation performance, a set of perceptual measures were adopted from the survey developed by Atos Consulting to study the implementation of the OI activities of their company clients [60]. This was to our knowledge the most detailed survey that has examined how firms organized OI activities internally, which is the focus of our study. Moreover, this survey included relevant scale items to measure the constructs in our study, and was designed to collect data from C-level managers (i.e., senior executives working in the fields of R&D and innovation, including Chief Innovation Officers, Chief Technology Officers, R&D Directors, and OI Directors), which made it suitable for our study. To refine the adopted measures, we conducted a first pretest with 30 MBA students, which enabled to improve the wording and usability of such measures. To further refine the measures, we conducted a pilot study with three OI practitioners.

The knowledge sharing construct captures the extent to which a firm shares knowledge inside the firm itself, and with external partners. Respondents ranked the following three items on a five-point Likert scale, between 1 "Strongly Disagree" and 5 "Strongly Agree": (1) Both internal and external knowledge sharing takes place continuously and is well-supported by knowledge management process; (2) there is systematic knowledge sharing within my company; and (3) in our company there are regular discussions as to whether people are working effectively together.

The innovation strategy construct captures the extent to which a firm manages and coordinates its innovation processes based on an innovation strategy. Respondents ranked the following three items on a five-point Likert scale, between 1 "Strongly Disagree" and 5 "Strongly Agree": (1) My company has a strong innovation strategy relative to competitors; (2) innovation is managed throughout the company (i.e., there is a formal planning process, C-level approval, budget cycle, review procedure, substantial number of people have innovation targets); and (3) my company has a clear view on how it wants to develop its product portfolio (i.e., complete product roadmaps, identified areas to innovate, and necessary resources assigned).

The innovation performance construct measures a firm's innovation success. Respondents ranked the following three items on a five-point Likert scale, between 1 "Strongly Disagree" and 5 "Strongly Agree": (1) In regards to innovation, my company is more successful than three years ago; (2) in regards to innovation, my company is more successful when compared to competitors; (3) I am satisfied with the current performance, in regards to innovation, within my company. Measuring innovation performance is particularly challenging, because the literature includes different types of innovation performance measures [e.g., 61, 62]. A number of studies have used patent data (e.g., patent counts) as an objective measure of innovation performance [e.g., 63, 64]. However, "given firm-specific variations in the propensity to patent, and given the very real possibility that patents are an input into the product development process and not an output," using patents as a measure of innovation performance has major limitations [65, p. 51]. Moreover, “most patents are not commercialized and they are widely acknowledged to be a partial indicator of the innovation process only, since many innovations are only partly covered by patent protection, or not patented at all” [9, p. 134]. The propensity for patenting also differs considerably between industries, and therefore using this measure for innovation performance is problematic with a cross-industrial dataset [66], which is the case in our paper. Thus, most recent studies of OI, particularly those using survey data, have measured innovation performance using self-reporting subjective measures, asking firms to rate their innovation success (on Likert scales) by comparing current innovation performance with past innovation performance, or with competitors’ innovation performance [e.g., 11, 19, 27, 61, 67]. In line with this recent research in OI, we measured the firm’s innovation performance by asking respondents to compare their current innovation performance with both their past innovation performance and the innovation performance of their competitors (i.e., three subjective measures of innovation performance). These self-reporting subjective measures of innovation performance are widely used in the literature, because they are relatively straightforward and unambiguous in capturing the conceptual domain of the construct, and they have also proved to be sufficiently reliable [e.g., 11, 19, 27, 61, 67]. In addition, asking for a direct comparison with past innovation performance and competitors’ innovation performance makes it possible to measure the superiority of innovation performance explicitly [68]. To check the validity of the subjective measure of innovation performance, we triangulated this measure with a self-reporting objective item of innovation performance based on the percentage of revenue generated by products or services introduced to the market. The objective data were available for a subset of 103 firms. The correlation between these objective data and the average of the three subjective measures of innovation performance was positive and significant ($r=0.316$, p-value$=0.001$), indicating the validity of our subjective measure of innovation performance.

Finally, the outside-in OI construct captures the extent to which a firm engages in outside-in OI activities for its internal innovation purposes. Respondents were asked how often each of the following five activities occurred [69]: (1) My company uses crowdsourcing (the act of taking a job that is traditionally performed by an employee and outsource it to an undefined, generally large group of people in the form of an open call); (2) we use information intermediaries to find and use external ideas (companies that help innovating companies to use external ideas more rapidly); (3) my company uses alliances to acquire additional knowledge; (4) we use brainstorms and invite our entire network to join; and (5) my company licenses Intellectual Property (IP) from other companies. These items were ranked on a five-point Likert scale: 1 "Never," 2 "Rarely," 3 "Sometimes," 4 "Often," and 5 "Always." The survey included a clear explanation of two relatively new OI activities (i.e., crowdsourcing and information intermediaries) to ensure that all respondents interpreted them properly. As the focus of this research is to capture the firm's overall outside-in OI activities, we did not discriminate between different types of outside-in OI activities, and thus created a composite average measure (an arithmetic mean) for all five outside-in OI activities.

To avoid potential confounding effects, and in line with the previous literature, we controlled for a set of firm-level characteristics that can influence innovation performance [9, 20, 24]. we controlled for firm size by using the number of employees as a proxy. Larger firms have more resources to invest in outside-in OI, which may affect innovation performance. Thus, respondents indicated the number of internal employees in their company, based on five categories (see Table 2), and four dummy variables were included, being the benchmark dummy the last category (i.e., >15000 employees). We also added four dummy variables to control for the duration of OI, and created a benchmark for the last category (i.e., >10 years). Respondents answered the question "how long has open innovation been implemented in your organization?" based on five categories, of which the last was defined as the benchmark dummy (see Table 2). We also controlled for the intensity of outside-in OI activities over the last three years, measured by "the percentage of new products or services in the last 3 years including externally obtained knowledge." Four dummy variables were added to the model, as respondents were provided with five categories, where the benchmark dummy was the last one (i.e., 81-100%), to indicate outside-in OI intensity (see Table 2). Finally, we included 7 dummy variables for 8 different industries in the model, based on Standard Industrial Classification (SIC) codes (i.e., agriculture, forestry, and fishing; mining; manufacturing; transportation and public utilities; wholesale trade; retail trade; finance, insurance, and real estate; and professional services) to control for potential cross-industry differences related to outside-in OI activities and innovation processes.

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DATA ANALYSIS

Construct analysis

To test the factor structure and convergent and discriminant validities of the constructs, we conducted a confirmatory factor analysis (CFA) using the maximum likelihood method in AMOS 22.0. To evaluate goodness of fit, we used chi-square ($\chi 2$), goodness of fit index (GFI), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The results showed an acceptable fit for the hypothesized four-factor model (χ^2= 78.865 with df = 71 (χ^2/ df = 1.11) and p-value = 0.244; GFI = 0.908; CFI = 0.979; RMSEA = 0.032; 90 % CI for RMSEA = (0-0.065); SRMR = 0.059). All the fit indices were acceptable in light of the recommended cut-off values [70].

In addition, the four-factor model was significantly better in chi-square than the other more parsimonious models. For example, we tested a three-factor solution in which the items of the following constructs were set to load on a single factor: innovation strategy and innovation performance ($\Delta\chi^2$ = 9.714, Δdf = 3, p-value = 0.02); knowledge sharing and innovation performance ($\Delta\chi^2$ = 47.027, Δdf = 3, p-value < 0.001); outside-in OI and innovation performance ($\Delta\chi^2$ = 54.456, Δdf = 3, p-value < 0.001); knowledge sharing and innovation strategy ($\Delta\chi^2$ = 22.396, Δdf = 3, p-value < 0.001); knowledge sharing and outside-in OI ($\Delta\chi^2$ = 11.825, Δdf = 3, p-value = 0.008); and innovation strategy and outside-in OI ($\Delta\chi^2$ = 43.372, Δdf = 3, p-value < 0.001). All these results supported the hypothesized four-factor structure.

Thereafter, we analyzed in detail the factor loadings of the items. All standardized factor loadings were significant and greater than the suggested cut-off value of 0.45 [71] except for the outside-in OI construct (item 1: 0.43 and item 5: 0.36, but both significant and very close to the threshold). To check for discriminant validity, we compared the square root of the average variance extracted (AVE) of each construct with the correlation of that construct with all other constructs. The square root of the AVE of each construct was higher than its correlation with all the other constructs, except for innovation performance, where it was the same as the correlation with innovation strategy. These results supported the discriminant validity of the constructs [72].

Finally, we calculated the corrected item-total correlation, composite reliability (CR) values, Cronbach alphas coefficients, and Omega coefficients to assess the reliability of the constructs. All items had the corrected item-total correlation above the cut-off value of 0.25 (between 0.33 and 0.6) [73]. The Cronbach alpha coefficients ranged from 0.64 to 0.72, the CR values from 0.63 to 0.73, and the Omega coefficients from 0.64 to 0.73. All reliability coefficients were very close to the recommended cut-off value of 0.7 [72-74]. Moreover, the Cronbach alpha coefficients of all four constructs did not improve if any of their items was removed. Overall, these results indicate adequate reliability for all four constructs in this study. Table 3 shows the CR values, Cronbach alpha coefficients, and Omega coefficients.

----- INSERT TABLE 3 ABOUT HERE -----

Common method variance

This study is vulnerable to common method variance (CMV), as data were collected from a single informant in each firm [75]. However, the fact that the dependent and independent variables were proximally separated in the questionnaire reduced the potential CMV issue [76]. Thus, the respondents were not primed to connect the independent and dependent variables, which limited the chance that their responses to one set of questions would affect their answers to the other questions. Moreover, as most of the measures related to outside-in OI activities and the two mediating variables were quite objective, the probability of overemphasizing the use of outside-in OI activities, innovation strategy, and knowledge sharing was reduced. Therefore, even if the dependent variable is inflated to some extent while the independent variable and the mediators are accurately measured, the results of this study are more likely to have an underestimation bias than an overestimation bias.

Nevertheless, to test the possibility of the results being biased by CMV, we first conducted the Harman's single-factor test [75, 76], based on CFA, using the maximum likelihood method, and setting all the items related to the dependent and independent variables to load on a single factor. The results showed that the single-factor model did not provide an acceptable fit with the hypothesized model (χ^2= 146.281 with *df* = 77 and p-value < 0.001; GFI = 0.816; CFI = 0.813; RMSEA = 0.09; SRMR = 0.09). The hypothesized four-factor model provided a significant chi-square improvement over the single-factor model ($\Delta\chi^2$ = 67.416, Δdf = 6, p-value < 0.001). The hypothesized four-factor model also improved other fit indices compared to the single-factor model (ΔGFI = 0.09; ΔCFI = 0.17; ΔRMSEA = 0.06; ΔSRMR = 0.03). Moreover, the subjective measure of innovation performance was positively correlated with a self-report objective item of innovation performance, which gives validity to the subjective measure of innovation performance used in this study. Based on all this evidence, we concluded that the CMV's effect was not large enough to bias the results of the study.

Statistical methods

Table 3 shows the minimum and maximum values, means, standard deviations, and correlations of the constructs. An examination of the correlation between independent variables showed that multicollinearity was not a concern in this study. We also calculated the variance inflation factor (VIF) for the four constructs in all regression models. The VIF ranged between 1.33 and 2.44, indicating that multicollinearity was not a significant issue in the regression models. We calculated the skewness and kurtosis of all items to check their distribution. The results showed that all items were normally distributed (i.e., skewness ranged from -0.834 to 0.531, and kurtosis from -1.048 to 0.866) [77]. In addition, the results showed that outside-in OI was positively associated with innovation performance ($r=0.22$ and $p<0.05$), and with both mediators - knowledge sharing ($r=0.49$ and $p<0.001$) and innovation strategy ($r=0.43$ and $p<0.001$).

To test the hypothesized model and to understand how outside-in OI affects innovation performance through knowledge sharing and innovation strategy (i.e., mediation analysis), we adopted the procedure suggested by Edwards and Lambert [78], Hayes [79], which has been largely used by scholars to test mediated relationships. Given that the dependent and mediating variables are continuous, we conducted a set of ordinary-least-squares (OLS) regression models [80] to estimate (see Table 4): (1) the effect of outside-in OI on the two mediators of knowledge sharing and innovation strategy (Model I and II); (2) the impact of knowledge sharing on innovation strategy (Model II); (3) the total effect of outside-in OI on innovation performance (Model IV); (4) the direct influence of outside-in OI on innovation performance (Model V); and (5) the impacts of both mediators on innovation performance (Model V). Thereafter, we estimated the indirect effect of outside-in OI on innovation performance through the mediators of knowledge sharing and innovation strategy. To estimate the indirect effect, we used the product of regression coefficients from the above-mentioned estimations (1), (2) and (5). To test the significance of the indirect effects, we used the bootstrapping procedure [81], which is free of the normally-distributed errors assumption. Specifically, we used 5000 bootstrapping samples to calculate bias-corrected confidence intervals for the significance test [78, 79, 82]. Before conducting all these analyses, we calculated an arithmetic mean of the items of each construct to create single indicators for each construct. All analyses were conducted in SPSS 23.0, and the indirect effects were tested using the PROCESS macro 2.16.1 [79]. The assumption of the normally-distributed errors in the OLS regression model was fulfilled, indicating that the OLS estimation is consistent. we checked the homoscedasticity assumption of the OLS regression by plotting the residuals against the predicted values of innovation performance (i.e., dependent variable), outside-in OI (i.e., independent variable), innovation strategy and knowledge sharing (i.e., mediating variables). No pattern in the plots was found, indicating that the homoscedasticity assumption was fulfilled.

RESULTS

Table 4 shows that outside-in OI is positively related to both knowledge sharing (Model I: $\beta = 0.498$, $p<0.001$) and innovation strategy (Model II: $\beta = 0.211$, $p=0.021$), supporting hypotheses 2 and 3, respectively. There is also a positive relationship between knowledge sharing and innovation strategy (Model II: $\beta = 0.442$, $p<0.001$), supporting hypothesis 6.

Table 4 also shows the total (Model IV) and direct (Model V) effects of outside-in OI on innovation performance. Some of the control variables and industry dummies have a significant effect on innovation performance (Model III). Including outside-in OI (Model IV) added a significant explained variance (3.4% - $\Delta F=4.562$, $p=0.035$). Results indicated that the total effect of outside-in OI on innovation performance is positive and significant ($\beta=0.245$, $p=0.035$). Including the two mediators (i.e., knowledge sharing and innovation strategy) to the model (Model V) added a significant explained variance (30.4% - $\Delta F=35.369$, $p<0.001$). The direct effect of outside-in OI on innovation performance is no longer significant (Model V: $\beta = -0.073$, $p = 0.449$), and thus the first hypothesis is not empirically supported. However, knowledge sharing is significantly and positively related to innovation performance (Model V: $\beta = 0.226$, $p=0.019$), which supports the fourth hypothesis. The relationship between innovation strategy and innovation performance is also significant and positive (Model V: $\beta = 0.615$, $p < 0.001$), which supports hypothesis 5.

----- INSERT TABLE 4 ABOUT HERE -----

The three possible indirect effects of outside-in OI on innovation performance were also estimated. As shown in Table 5, all three possible indirect effects are significant. Namely, outside-in OI significantly influences innovation performance via knowledge sharing (Indirect effect #I: $\beta = 0.113$; 95% CI = [0.025; 0.247]), via innovation strategy (Indirect effect #III: $\beta = 0.13$; 95% CI = [0.033; 0.274]), and following the path through both knowledge sharing and innovation strategy (Indirect effect #II: $\beta = 0.135$; 95% CI = [0.069; 0.291]).

----- INSERT TABLE 5 ABOUT HERE -----

Overall, the results show that the relationship between outside-in OI and innovation performance is indirect. Knowledge sharing and innovation strategy fully mediate the impact of outside-in OI on innovation performance. This indicates that firms can only turn outside-in OI into improved innovation performance through innovation strategy and knowledge sharing.

ROBUSTNESS ANALYSES

As the homoscedasticity assumption of the OLS was fulfilled, we also checked the robustness of the significance tests by using heteroscedasticity-consistent standard error (HC3 estimator) [83]. The results did not differ from those found without using the HC3 estimator.

As this paper focuses on the linear relationship between outside-in OI and innovation performance, we needed to ensure that there is no curvilinear association between these variables. To do so, we added the square values of outside-in OI to the model. The model fit remained the same (ΔR^2=0.014, F change=1.843, p=0.178) and a non-significant coefficient for the squared term was found, supporting the linearity of the association between outside-in OI and innovation performance. we also found support for the linearity of relationships between outside-in OI and the two mediators, and between the two mediators and innovation performance.

As this article also studies the mediating effects of knowledge sharing and innovation strategy in the relationship between outside-in OI and innovation performance, we tested their potential moderating effects by adding two interaction terms to the model. To avoid a multicollinearity issue that could emerge from adding the squared and interaction terms, we centred the values of outside-in OI, knowledge sharing, and innovation strategy on their means before multiplying [84]. The model fit remained unchanged for the knowledge sharing interaction term (ΔR^2=0, F change=0.011, p=0.915) and for the innovation strategy interaction term (ΔR^2=0.001, F change=0.044, p=0.835). No significant moderating effects were found, supporting the mediating effects of knowledge sharing and innovation strategy.

Another concern in this study is the potential endogeneity of outside-in OI and innovation intensity, which can inflate the relationship between outside-in OI and innovation performance. Innovation intensity can influence the level of engagement in outside-in OI activities, and simultaneously affect innovation performance. To control for this potential endogeneity issue, we included a proxy for innovation intensity in the model using the percentage of revenue spent on innovation. To control for the fixed effects of innovation intensity, we included four dummy variables. Respondents indicated "what percentage of your revenue is spend on innovation in the last year?" based on five categories (1: 0-5%, 2: 6-10%, 3: 11-15%, 4: 16-20%, and 5: more than 20%), the last of which was considered as the benchmark category. After adding this variable, the sample size decreased to 99 firms due to missing values. We found the same results for all hypotheses and no significant changes regarding the direct (β=0.001, p=0.993) and indirect effects (#I: β=0.107, significant at 90%; #II: β=0.153 and #III: β=0.157, significant at 95% confidence level), supporting the robustness of the results.

As previous studies argue, firms that use patents in their innovation processes are likely to boost their innovation performance, regardless of whether or not they engage in outside-in OI [65, 85]. Moreover, case-based evidence suggests that firms only use a fraction of their patents in innovation processes, and that this fraction differs between firms [4]. Therefore, we controlled for the effect of patent usage heterogeneity on innovation performance to ensure that our results are not confounded by this effect. To do so, we included four dummy variables in the model. Respondents indicated "what percentage of your patents are you actually using to create new products or services during the last 3 years?" based on five categories (1: 0-5%, 2: 6-10%, 3: 11-15%, 4: 16-20%, and 5: more than 20%), the last of which was considered as the benchmark category. This measure captures the percentage of the firm's patents used in the innovation process. However, this measure does not capture the number of patents developed by the firm during the innovation process. Due to some missing values for this variable, the sample for this analysis was 92 firms. All hypotheses were supported except H1 (β=0.037, p=0.772), which is consistent with the findings we present in the Results section, and supports the robustness of our results. We found no substantial changes in the indirect effects (#I: β=0.094, significant at 90%; #II: β=0.136 and #III: β=0.162, significant at 95% confidence level) of outside-in OI on innovation performance, which shows that our results are not confounded by the use of patents in the innovation process.

DISCUSSION AND CONCLUSION

Theoretical Implications

OI is increasingly popular in innovating firms, which assume that simultaneously tapping into internal and external knowledge sources leads to stronger innovation performance. Despite this assumption, empirical studies have shown that engaging in outside-in OI leads to mixed results. Some studies provided empirical evidence confirming that outside-in OI boosts innovation performance [5, 8, 9, 11], and others have found that outside-in OI has no effect or even damages innovation performance [12-15, 86]. This mixed empirical evidence may be explained in different ways. One reason could be the adoption of different firms' internal practices for managing innovation processes. In line with previous studies, we assume that companies require a particular type of internal organization to tap successfully into external knowledge (e.g., Foss, et al. [19]). Outside-in OI requires a set of appropriate internal practices to reach out and collaborate effectively with external partners, and thus to assimilate and integrate their knowledge into internal innovation processes [19-22].

To unpack the link between outside-in OI and innovation performance, we set up a model to test whether internal practices help OI-adopting firms improve their innovation performance. As presented in Figure 1, we tested whether outside-in OI has a direct effect on innovation performance, or if the relationship is mediated by certain internal practices for managing innovation processes. More precisely, we focused on the management of innovation processes through knowledge sharing and innovation strategy as critical practices for leveraging the knowledge of external partners. These practices were introduced as mediators of the relationship between outside-in OI and innovation performance. The empirical analysis shows that if the internal practices of knowledge sharing and innovation strategy are introduced as mediators of the relationship between outside-in OI and innovation performance, outside-in OI impacts innovation performance indirectly rather than directly, as the relationship is fully mediated by both knowledge sharing and innovation strategy.

The empirical findings of this research highlight the importance of the internal practices of knowledge sharing and innovation strategy for successful outside-in OI activities, and have a set of academic implications. In the past, OI scholars have focused on the benefits of working with external partners [e.g., 9, 24]. A lot of attention has concentrated on how and why firms should connect to partners [e.g., 11, 24]. This focus has developed historically, although Chesbrough's seminal work on OI [3, 87] pays considerable attention to the internal management of outside-in OI activities. The results of this study indicate that an exclusive focus on the relationship with external partners is unsuitable to estimate correctly the impact of outside-in OI on innovation performance. Internal practices that help firms perform outside-in OI activities have to be taken into account, explaining how they can have a positive impact on innovation performance. Since both knowledge sharing and innovation strategy fully mediate the impact of outside-in OI on innovation performance, it can be concluded that if studies ignore the internal organization of OI when measuring the impact of outside-in OI on innovation performance, their results may be considerably biased. This finding addresses the call by West and Bogers [88] to conduct further research on the relationship between outside-in OI and performance. It suggests that it is essential to incorporate internal practices when analyzing the impact of OI activities on firms' innovation success, and thereby clarifies why some outside-in OI activities are successful and others are not.

So far, only a few papers from the field of OI have studied the role of internal practices in outside-in OI activities [19, 20, 30]. By unpacking the relationship between outside-in OI and innovation performance, this study adds to the literature by introducing two internal practices as critical factors for making outside-in OI activities successful. In addition, the results of this research further build on the indirect effect of embracing outside-in OI with customers on innovation performance found by Foss, et al. [19], by considering a wider range of external partners in the analysis. Finally, the results of this study complement the research conducted by Lakemond, et al. [30] who considered outside-in OI and internal practices as independent variables to predict innovation performance, but did not analyze how outside-in OI and internal practices may be related in determining innovation performance.

Managerial Implications

The findings of this research also have interesting managerial implications. If the internal practices of knowledge sharing and innovation strategy are important to guarantee successful outside-in OI, managers cannot just start working with OI overnight. Success is only guaranteed when a firm is internally prepared and organized for OI. Thus, this study has two major takeaways for managers: (1) An exclusive focus on establishing innovation-oriented relationships with external partners (i.e., embracing outside-in OI) is not sufficient to boost innovation performance; and (2) managers that intend to use outside-in OI should prepare the company internally by developing an innovation strategy and internal and external knowledge sharing processes, if they want to boost innovation performance. In fact, capabilities related to the internal organization of OI (e.g., knowledge sharing and innovation strategy) can be considered as dynamic capabilities [89]. These capabilities have to be developed over time, leading to the idea of OI maturity. Enkel, et al. [90] developed a 5-level OI maturity framework to measure the effectiveness of OI in firms. It is based on three major internal capabilities: climate for innovation, partnership capability, and internal process.

The empirical results of this paper show that the internal organization of OI is the forgotten dimension in the field of OI. Despite Chesbrough's seminal work [3, 87], case-based evidence [21, 22, 28] and the development of practical management tools, such as the OI maturity framework, both scholars and managers have almost exclusively focused on how to reach out to partners without considering the need to adapt internally to the new OI requirements. The new imperative is to take a balanced approach to OI development, focusing simultaneously on how to reach out to partners and how to change the firm internally.

Limitations and Future Research

This study has some limitations. First, further research should validate the findings. It is difficult to find a large sample of OI-adopting companies. External validation of the findings is crucial and it will require large sample surveys. Second, we limited their attention to two internal practices and did not include other practices, such as those related to corporate culture. It is only possible to understand the full impact of internal organization on OI effectiveness if all practices are considered. Third, we did not differentiate between outside-in OI activities in our model. In any type of outside-in OI (e.g., R&D alliance, crowdsourcing, OI intermediaries, in-licensing), it is crucial to have a clear innovation strategy if firms want to improve innovation performance [e.g., 22]. However, some types of outside-in OI (e.g., R&D alliances) require more extensive knowledge sharing between the focal firm and external partners than others (e.g., OI intermediaries and in-licensing agreements), where knowledge exchange with external partners is very limited or even inexistent [e.g., 10, 40, 91]. Therefore, it is reasonable to expect that each specific outside-in OI activity will affect the level of knowledge sharing with external partners differently. Thus, future research should provide a detailed analysis of the interaction between external knowledge sharing (i.e., knowledge sharing between the focal firm and external partners) and each specific outside-in OI activity to refine our study. For this detailed analysis, future research could use project-level datasets to investigate the specific outside-in OI mechanism applied, and the extent of knowledge sharing with external partners, in each specific innovation project.

Fourth, although our measures of innovation performance are widely used in the literature and they have also proved to be sufficiently reliable, future studies could further validate our measure of innovation performance by using objective secondary data on new product or service market introduction announcements (i.e., number of new products or services introduced to the market) [e.g., 27, 92, 93]. These data can be collected from secondary sources, such as editorially controlled new product announcements, technical and trade magazines, and product catalogues or press releases related to new products or services. [e.g., 92, 93].

Fifth, as this study is based on cross-sectional data, causal relationships between outside-in OI, knowledge sharing, innovation strategy and innovation performance are difficult to establish [e.g., 94]. Therefore, future research should develop longitudinal and/or experimental designs to confirm the causality between these constructs. Nevertheless, it can be difficult to obtain longitudinal data from senior managers or involve them in experiments, due to their busy schedules. Moreover, company policy can prevent senior managers from taking part in research, particularly experimental studies, due to confidentiality concerns. As developing longitudinal or experimental studies with managers can be problematic, future research could conduct computational experiments or simulations [95] to test the causality between the constructs in this study and to check the reciprocal relationships between them over time. Finally, the concept of OI maturity (and dynamic capabilities) indicates that OI management is a long-term process requiring continuous improvement to internal practices. The analysis conducted in this paper is static, but a dynamic analysis would be highly welcome, to explain how the development of different internal practices leads to more effective OI over time, and how different strategies to develop internal practices lead to more effective OI activities.

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FIGURES AND TABLES

Figure 1. Hypothesized model.

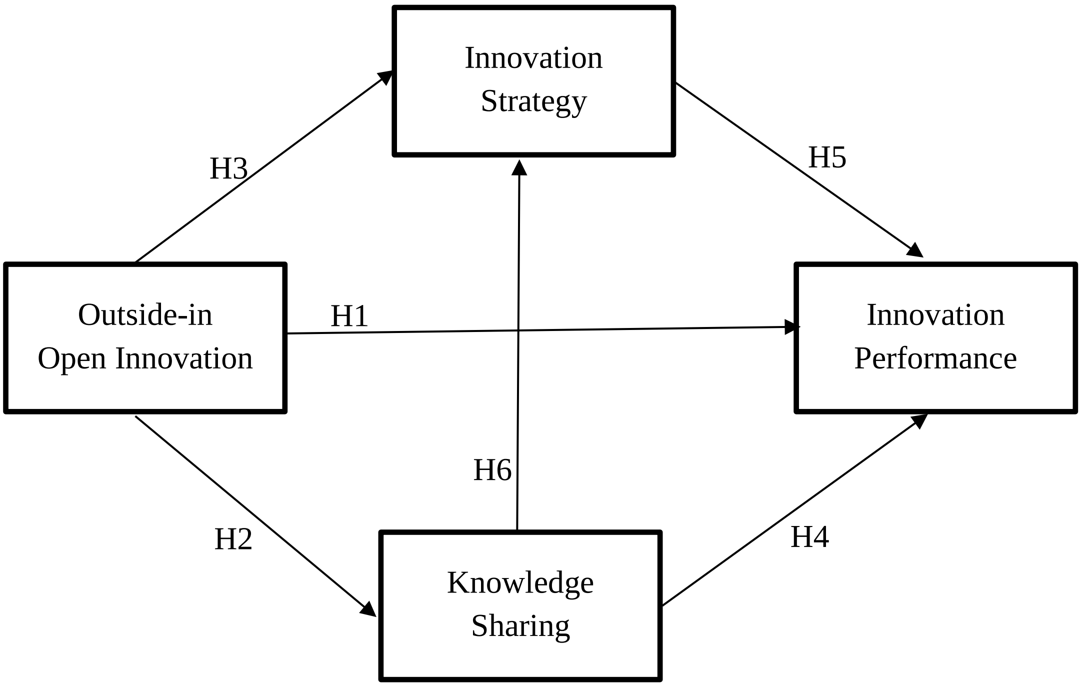

Table 1. Sample distribution across industry groups (based on SIC codes) and respondent job roles

Industry groups	***%***
Agriculture, Forestry, and Fishing	1.8
Mining	2.7
Manufacturing	53.6
Transportation and Public Utilities	2.7
Wholesale Trade	8.9
Retail Trade	4.5
Finance, Insurance, and Real Estate	3.6
Professional Services	22.2
Respondent job roles	***%***
Innovation, R&D, and technology experts	55.3
Management (senior level)	25
Sales, marketing, and purchasing	6.3
Operations and logistics	1.8
Other	11.6

Table 2. Sample characteristics by control variables

Number of employees in 2013	***%***
1-500	20.5
500-1000	3.6
1000-5000	12.5
5000-15000	17.9
>15000	45.5
OI duration as of 2013	***%***
< 1 year	18.8
1 - 3 years	19.6
3- 5 years	19.6
5 - 10 years	20.5
> 10 years	21.5
Outside-in OI intensity over the last 3 years as of 2013	
0-20%	53.6
21-40%	17
41-60%	17
61-80%	5.3
81-100%	7.1

Table 3. Range, means, standard deviations, correlations, squared root of AVE, CR, Cronbach alpha, and omega coefficients

	Min	Max	Mean	SD	1	2	3	4	CR	Cronbach alpha	Omega coefficients
1- Innovation performance	1	5	3.18	0.77	0.64				0.67	0.67	0.69
2- Outside-in OI	1.2	4.4	2.89	0.70	0.22^{*}	0.52			0.63	0.64	0.64
3- Knowledge sharing	1.3	5	3.41	0.83	0.49^{**}	0.49^{**}	0.69		0.73	0.72	0.73
4- Innovation strategy	1.3	5	3.65	0.83	0.65^{**}	0.43^{**}	0.54^{**}	0.66	0.69	0.68	0.69

Note: Omega coefficients are calculated based on Heise and Bohrnstedt's omega.
Two-tailed test: * p<0.05, ** p<0.001, Squared root of AVE on the diagonal

Table 4. Multiple regression of hypothesized relationships

	Outcome				
	Mediators		Innovation Performance		
Variables	Model I Knowledge sharing	Model II Innovation strategy	Model III	Model IV Total effect	Model V Direct effect
Mediators					
Knowledge sharing		**H6: 0.442*** **			**H4: 0.226** **
		(0.09)			(0.089)
Innovation strategy					**H5: 0.615*** **
					(0.095)
Independent variable					
Outside-in OI	**H2: 0.498*** **	**H3: 0.211** **		0.245**	**H1: -0.073**
	(0.098)	(0.107)		(0.127)	(0.107)
Control variables					
Number of employees					
			-0.006	0.067	0.094
1-500			(0.283)	(0.285)	(0.215)
			-0.033	0.016	-0.015
500-1000			(0.387)	(0.391)	(0.296)
			-0.045	-0.024	0.117
1000-5000			(0.259)	(0.255)	(0.197)
			-0.032	0.024	0.034
5000-15000			(0.216)	(0.218)	(0.165)
OI duration					
< 1 year			-0.236*	-0.225*	0.05
			(0.257)	(0.252)	(0.203)
1 - 3 years			-0.301**	-0.294**	-0.01
			(0.246)	(0.241)	(0.193)
3- 5 years			-0.114	-0.097	0.045
			(0.236)	(0.232)	(0.179)
5 - 10 years			-0.08	-0.081	0.075
			(0.227)	(0.222)	(0.176)
Outside in OI intensity over the last 3 years					
0-20%			0.182	0.282	0.262*
			(0.294)	(0.297)	(0.224)
21-40%			0.131	0.153	0.153
			(0.322)	(0.317)	(0.239)
41-60%			0.034	0.003	0.074
			(0.324)	(0.319)	(0.242)
61-80%			0.207*	0.201*	0.166*
			(0.402)	(0.394)	(0.298)
Industry dummies (7 dummies)			Yes	Yes	Yes
Intercept	1.706***	1.407***	3.516***	2.512***	0.334
	(0.292)	(0.317)	(0.392)	(0.607)	(0.527)
ΔR^2	0.248	0.333	0.279	0.034	0.304
Δ F-statistic	36.199***	27.173***	1.87**	4.562**	35.369***

Note: Standardized coefficients are reported. Standard errors are in parentheses. Bold numbers indicate the standardized coefficient for each hypothesis (H1 – H6).
Two-tailed test: * p<0.1; ** p<0.05; *** p<0.001

Table 5. The indirect effects of outside-in OI on innovation performance

Indirect effects	Standardized coefficient (Bootstrap standard errors)	95% CI*
I) Outside-in OI → Knowledge sharing → Innovation performance	0.113 (0.058)	[0.025; 0.247]
II) Outside-in OI → Knowledge sharing → Innovation strategy → Innovation performance	0.135 (0.055)	[0.069; 0.291] +
III) Outside-in OI → Innovation strategy → Innovation performance	0.13 (0.061)	[0.033; 0.274]

Note: The indirect effects are estimated based on the product of regression coefficients shown in Table 4.
* 5000 bootstrap samples for bias-corrected bootstrap confidence intervals
+ Bias-corrected bootstrap confidence intervals at 99% based on 5000 bootstrap samples: (0.047; 0.346).