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Measuring the Connection Between Open Innovation, Dynamic Capabilities, and LinkedIn in Tech-Based Companies

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Abstract

Organizations face challenges in acquiring the necessary expertise and dynamic capabilities (DCs) to rapidly develop products and services due to the current technological environment. Open innovation (OI) offers greater flexibility by enabling cooperation with external partners and motivating personnel to adopt new business approaches. Social media can play a crucial role in this strategy, providing valuable information that can enhance the performance of innovation projects by accessing market insights and innovative technical solutions. The article aims to analyze how social media and OI strategy, integrated with DCs, can enhance business opportunities and challenges. This research proposes an analytical framework contributing to literature and theory on using social media analysis to gauge innovation strategy implementation and contrast it with DC theory. It provides a comprehensive framework addressing essential characteristics to navigate changing scenarios by using an innovative method (netnography) to understand and measure companies' interaction on social media, utilizing primary data (surveys on openness to innovation) and secondary data (LinkedIn data analyzed through machine learning and natural language processing). The empirical section of the paper quantifies the strategic advantages of OI and DCs with a focus on eight innovative multinational tech-based corporations, analyzing their "degree of openness" and adaptability. Organizations that are more open and accumulate integrated knowledge gain competitive advantages, enhancing their ability to innovate, coordinate, rapidly market, and respond to market changes, demonstrating the development of DC alongside OI. Managerial implications relate to the need to match OI strategy with DCs associated with social media.

Keywords Social media · LinkedIn · Text mining · Business strategy · Open innovation · Dynamic capabilities

JEL Classification L14 · L25 · M14 · O31 · O32 · O36

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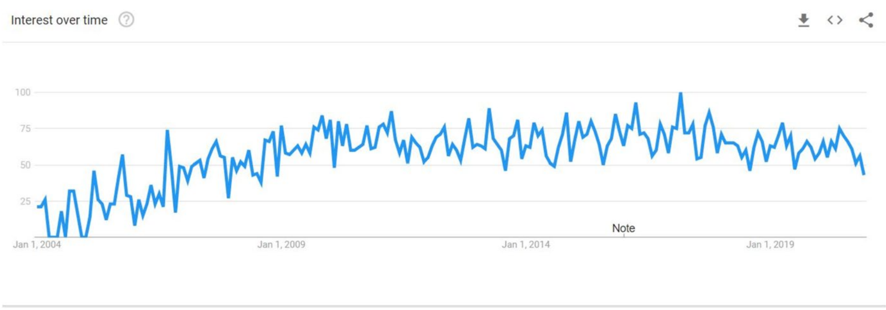


Fig. 1 Open innovation term interest over time (source: Google Trends)

Introduction

Organizations acknowledge that they could not gain by themselves all the expertise needed to develop products and services on time in a new technological context. Therefore, the concept of open innovation (henceforth "OI") provides us with more flexibility to identify and leverage complementary results and opportunities that can be achieved by cooperating with external partners and motivating their personnel to introduce new business forms. Besides, corporate incubators and accelerators play a preponderant role in the OI paradigm (Moschner et al., 2019; Shankar & Shepherd, 2019), where start-ups constitute a significant source of external innovation (Kohler, 2016).

In the last years, organizations realized the growing importance of implementing the OI strategy in their planning activities (Vanhaverbeke et al., 2017). For example, a simple search of the term "open innovation" on Google obtained approximately 676.000.000 results (June 24, 2022). The vast number of these results implies the wide diffusion of this term, and its evolution over the years (between 2004 and 2020) has been increasing, as shown in Fig. 1. According to Google Trends,[1] the peak popularity of the term occurred in March 2017. Nevertheless, some differences and subtle variations are hidden behind OI, mostly related to organization types; for example, the most related topics are enterprise, management, and technology.

This study focuses on a specific aspect: social media, OI, and dynamic capabilities (hereinafter DCs) to boost companies' capabilities, assuming the importance of the opportunities and challenges for organizations to transform their business in the light of social media analysis. In this line, Dong and Wu (2015) stated: "OI is growing rapidly with the emergence of social media technologies." Moreover, social media is one more tool, and of great importance today, of technology watch—an innovation management (IM) technique and part of the IM process in many models, which can create long-lasting advantages for firms (Albors-Garrigos et al., 2018). Du et al. (2016) mentioned that social media drove the OI concept, dedicating resources to cultivating a firm's sustainability orientation and integrating it into

[1] See https://trends.google.es/trends/

the new product development process. In other words, at a strategic level, we need a model (OI), but at an operational level, tools (IM) are necessary to allow actions for innovation to be carried out. According to Roberts et al. (2016), social media "can provide access to novel information about customer needs and technological solutions unknown to the firm." Indeed, utilizing inputs from social media could increase innovation project performance, as firms obtain access to novel market insights and innovative technical solutions.

Owing to the high volatility in today's economy, the prosperity of companies depends on their capacity to rapidly adapt to situational changes (Spanuth et al., 2020), and the adoption of new technologies influences organizational processes to stimulate the recognition and development of new skills and capabilities (Mention et al., 2019, 2020). From a strategic perspective, we position social media in and for innovation as an overlapping interaction between DCs (sensing, seizing, and reconfiguration). In this context, DCs play an essential role in the strategy combined with OI. From this perspective, these capabilities are considered an organization's ability to purposely create, extend, or modify their resource base (Helfat & Peteraf, 2009; Helfat et al., 2007). To establish a comprehensive discussion framework that addresses changing scenarios, DCs bring organizations the ability to integrate, build, and reconfigure their abilities to tackle changing circumstances in which there is deep uncertainty (Teece et al., 1997). Hence, in some situations where changes are much faster than in traditional business (e.g., technological start-ups, entrepreneurial ventures, FinTech firms, among others), the support of a model based on the combination of OI and DCs, might be a handy tool. In addition, Lee and Yoo (2019) pointed out the links of both paradigms to innovation performance to secure competitive organizational vantage.

Social media in innovation-driven companies as a business strategy has been continuously growing, especially under the umbrella of the OI context, leveraging digital communication and community tools (Tirabeni & Soderquist, 2019). The culture of the business world is evolving. As part of the communication channel of companies implementing the OI strategy, social media is a critical way to obtain valuable information (Sundström et al., 2020). Hence, sharing ideas will be better for those companies, which may be why the LinkedIn network works so well for some players who seem to be using this strategy more on an individual rather than an institutional level. In this regard, Dai et al. (2018) pointed out that LinkedIn "is distinctly known as a powerful professional networking tool that enables its users to display their curricular information and to establish connections with other professionals."

The research gap derives from the fact that academic research has paid little attention to the relation between OI and social media (Mount & Martinez, 2014)—albeit not at a more general level within the umbrella of technology watch—which may result in a limited understanding of how organizations can be benefited from the application of opinion mining across the innovation process, and role of DCs in this context has been largely ignored. Additionally, Teece (2020) indicates that there is little literature on how OI can contribute to organizational success.

The purpose of the paper is to understand the use of OI and DCs in technology-based companies and measure its strategical abilities in social media through primary and secondary sources. This research proposes a comprehensive mixed method to build a DCs framework focused on the behavior of companies implementing OI on LinkedIn. In addition, for large companies, practical implications and actionable recommendations are crucial. Decision-makers can use quantitative data to evaluate OI strategy, providing evidence of their effectiveness and efficiency (Bouteraa et al., 2024). To design and refine strategies that are feasible and acceptable within the company's specific context, qualitative insight from secondary sources can provide detailed information on the implementation process, organizational culture, and stakeholder perspectives.

The central argument is that OI needs to be oriented to social media integrating DCs in this orientation. This builds on the fact that once the benefits of social media are acknowledged, organizations might be willing to create a strategy that emphasizes the contribution of innovation and resources, sharing a vision and goals, and providing an appropriate framework for change (Hitchen et al., 2017). Moreover, this framework could be obtained by digging into the discourse on social media. Corral de Zubielqui et al. (2019) addressed leveraging new mechanisms to access information from outside actors, customers, and other social media users to facilitate innovation and firm performance. In addition to social media sources, in conjunction with OI and DCs for the advantage of organizational performance, we consider developing a new framework to obtain insights about trends that could help managers and organizations in decision-making.

The discussion regarding the old and new features of the OI term suggests defining and using the concept of openness degree compared to companies' discourse in social media. Additionally, this research examines how social media helps to define their DCs and OI dimensions. Moreover, related to data management, analyzing a vast amount of data from social media can yield an invaluable source of information, that cannot only be obtained through traditional outlets (Farzindar, 2014). Foremost, dealing with extensive text collections can result in a complicated assignment and involves the context, problem domain, and certain actors to do adequate research and application techniques (Jurafsky & Martin, 2008; Sohangir et al., 2018).

In this research, the exploratory approach is based on primary and secondary sources from companies of diverse activities that implemented OI. Firstly, a comprehensive documentary review of some companies has been done based on secondary sources. For the primary data, a survey regarding the innovation openness degree has been conducted; then, data coming from LinkedIn applied machine learning (ML) techniques, which involved text mining and natural language processing (NLP) to carry out the analysis on large quantities of text.

The contribution of this paper is an analytical framework, supported by empirical testing, contributing to literature and theory on using social media analysis to gauge OI implementation and contrast it with DCs theory. Through the combination of mixed methods, it is feasible to obtain quantitative findings from ML analysis of LinkedIn updates and could inform the development of new qualitative research questions and guide the selection of secondary sources for in-depth analysis.

After this introduction, the paper is structured as follows. The "Literature Review" section examines some aspects of the key literature related to OI, DCs, and the concepts related to text mining with a focus on social media analysis. The "Methods" section describes the quantitative and qualitative approaches to secondary and primary sources. The "Results" section illustrates the outcomes of the mixed method applied and the key features of companies' strategic approach. The "Discussion, Implications, and Concluding Remarks" section focuses on the analytical intersection findings, and the concluding remarks are presented in the last section.

Literature Review

The use of DCs enables organizations to adapt to new situations (Teece, 2020; Teece et al., 1997), which is of vital importance in a time like the present, marked by a rapid technological transition, with recent examples such as the current developments in artificial intelligence (AI) and generative AI (Magni et al., 2024), among others. This requires the adoption of knowledge management practices and the improvement of social innovation capabilities, which allow organizations to face such crucial challenges (Fait et al., 2023). It is here where OI plays a significant role, presenting itself as a highly relevant tool in building knowledge-based capabilities.

On the one hand, Abdulkader et al. (2020) explored OI ecosystems to capture firm value, developing a framework to map the interactions to understand value co-creation through the integration of OI principles and mechanisms of value systems, which is crucial to business process management. Furthermore, DCs can contribute to digitization and organizational creativity as well as enhance significant and evolving capabilities, which are providing solutions, seizing opportunities, and adapting to change (Scuotto et al., 2022a; b). On the other hand, according to the systematic literature review conducted by Rumanti et al. (2021), most of the organizational performance is determined by internal innovation factors. However, as the authors conclude, there is an important relationship between OI and organizational performance, since the application of innovative capabilities and practices significantly influences the achievement of a clear improvement in an organization's performance (Rumanti et al., 2021).

Indeed, many large entities currently believe that increasing their visibility to potential partners, as well as improving their international positioning in a specific business sector, becomes a key factor in driving the adoption of OI models in the organization's non-core activities (Tejero & León, 2021). This view is deeply rooted in companies within high-tech business sectors such as ICT, industry (automotive, space, aeronautics), chemical, and pharmaceutical, to name a few (Schuhmacher et al., 2018). The justification for adopting OI models is similar in all cases: many entities, both public and private, realized that they could not find all the knowledge they needed internally to develop successful advanced products and services in time to maintain their competitiveness in a rapidly evolving technology and market context. Their goal was to achieve greater flexibility in internal innovation management processes to identify and leverage disruptive results and market opportunities by cooperating with external entities (partners) and to reduce associated risks. The same approach was also applied, with less emphasis, to motivate and support their own workforce in launching new tech companies that would exploit the generated results in new markets or sectors.

The OI paradigm describes how collaborations transform organizations with other organizations (Greco et al., 2016). Henry W. Chesbrough coined the OI term “the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation, respectively” (Chesbrough, 2003; Chesbrough et al., 2006). In other words, it is a novel path to understanding the evolution of many companies looking for external skills and collaborators to conduct their work more efficiently and flexibly. Moreover, OI is a broad approach for exploring how knowledge flows across organizational boundaries and how the innovation process can have benefits and weaknesses (Carmona-Lavado et al., 2021). Indeed, leading companies are tapping this new approach to continue innovating their sector by adopting this model. According to Carayannis and Meissner (2016), innovation is much more than research and development. The feature of OI is to be a more open process that crosses geographical, institutional, and disciplinary boundaries, posing challenges to organizations in managing their internal innovation capabilities. Government innovation policy also impacts the management of public research institutes and the national innovation framework.

Some authors (Naqshbandi & Jasimuddin, 2018; West & Bogers, 2014, 2017; West et al., 2014) categorized the approaches regarding OI in organizations. Hence, relying on a case-based methodology, Tirabeni and Soderquist (2019) identified engagement practices in leading innovation-driven companies in the ICT sector. They recognize how operational integration interacts between internal and external resources in a dynamic environment through examples. In this sense, there are two types related to the orientation of knowledge flows across the firm’s boundaries, both outside-in (inbound innovation) and inside-out (outbound innovation) actions to stimulate internal change and to increase business possibilities for external use of creation, in conjunction (Chesbrough, 2003). On the one hand, inbound activities involve investigating the environment and combining outer information for technology improvement and acquisition from outside system associates. On the other hand, OI outbound activities include utilizing technology to commercialize inside-generated ideas or technologies through external channels. In addition, another type resulting from the combination of inbound and outbound OI activities is known as “coupled OI,” which describes an active collaboration with partners to innovate and involves combining purposive inflows and outflows of knowledge to develop and commercialize innovation collaboratively (Gassmann & Enkel, 2004; Greco et al., 2016).

Profiles for OI Degrees

The profiling method implies that some dimensions are more relevant than others to increase the activity’s success, and prior knowledge constitutes the basis for good management. The concept behind this profiling is the “openness degree,” which refers to measuring the level of open activities in one organization (Lazzarotti et al., 2010).

The concept implemented by León et al. (2020) to profile university-driven open ecosystems and proposed in the work of Öberg and Alexander (2018) is synthesized

Table 1 Dimensions of "openness" (source: Öberg & Alexander, 2018)

Openness	Description	Scholars	The paper is defined as
Breadth	The more different the competences, the more open	Idrissia et al. (2012)	Heterogeneity in skills of contributors (they are not the same type of actors)
Depth	The deeper the knowledge, the more open	Idrissia et al. (2012)	The expertise of contributors is high
Freedom, lack of formalization	The freer the collaboration, the less formalized and the more open	Herzog (2008), Aslesen and Freel (2012)	Arrangement based on voluntary participation. Contracts are not the main deal
Number of phases	The more phases the parties are included in, the more open	Lazzarotti and Manzini (2009)	More than one phase is covered in the innovation process
Number of actors	The more parties, the more open	Lazzarotti and Manzini (2009)	More than two actors were involved

in Table 1. The "openness" combines several low-level dimensions (Chesbrough & Appleyard, 2007; Henkel et al., 2014) and is feasible to be measured by contrasting sources retrieved from organizations and performing quantitative or qualitative analysis.

In addition to the five dimensions described in Table 1, three additional dimensions (León et al., 2020) are proposed to assess the impact of the use of OI schemes on one given organization, which are not included in the previous five ones:

- Percentage of external funding sources. It refers to the money source to work in an OI approach. Typically, this occurs when one company is "forced" to work on OI projects due to constraints imposed by public administrations funding the project.
- Percentage of R&D projects framed in OI projects. It refers to the relative importance of the firms' activity. If only 1% of projects follow the OI logic, the impact on the whole company is meager.
- Percentage of R&D economic resources. It complements the previous one from the economic volume involved. Only one OI project could affect a large percentage of the R&D resources; its impact will be high.

DCs Insight

The DCs theory has received considerable attention in the business strategy literature (Eisenhardt & Martin, 2000; G. P. Pisano, 2017; Teece, 2007, 2020; Teece et al., 1997; Zollo & Winter, 2002). The concept of DCs (Teece et al., 1997) has evolved from a resource-based view (RBV), an organizational framework used to determine the strategic resources a firm can exploit to achieve sustainable competitive advantage (Barney, 1991; Wernerfelt, 1984). This theory has powered the RBV arguments by transforming the essentially static view of creating a more strategic improvement (Barney, 2001).

The DCs imply how companies can adapt to new situations to expand, modify, or create standard dimensions through the access and recombination of expertise, allowing success over time (Teece et al., 1997). Therefore, some studies (Eisenhardt & Martin, 2000; Zollo & Winter, 2002) acknowledged that DCs are essential resources in organizations and conjunction with OI, are relevant to secure competitive advantage (Lee & Yoo 2019). For this reason, sustaining organizational competence depends mainly on the ability of companies to integrate and internalize, both explicitly and tacitly, their knowledge that constitutes a fundamental resource to contribute to the strategy, encompassing the acquisition of skills, learning, and accumulation of intangible and indivisible assets in the organization (Teece, 2007).

Model-Based on OI and DCs

According to Cheng et al. (2016), OI activities influence the effectiveness of ventures and toward radical innovation performance, building on knowledge-based capabilities. Furthermore, regarding DC implementation, Teece and Leih (2016) pointed out, "with deep uncertainty, good management must include the art of imagining a future and endeavoring to build it. Reason and analysis are only one element of the process. Awareness of available opportunities is important, and it is often aided by imagination."

Since the emergence of the OI concept (Chesbrough, 2003), it has become one of the critical strategies for technology management. A high percentage of technological-based organizations have implemented, in one way or another, OI to conduct their corporate activities (or part of them) in cooperation with other external partners (Bogers et al., 2019; Teece, 2020). Specifically, this knowledge management process allows the development of organizational routines that implement OI. Nevertheless, Teece (2020) indicates that there is surprisingly scarce literature regarding how OI provides outcomes in the broader strategic management of organizations.

A model based on DCs underlies the learning process and the evolutionary cycle of organizational knowledge. It started from creating and developing organizational routines, from the co-evolution between accumulation, integration, and knowledge codification (Zollo & Winter, 2002). In the model proposed by Teece (2007, 2020), this process is the result of the interaction of three sets of organizational processes: sensing (opportunity detection), seizing (opportunity valuation), and transforming (execution) capabilities (see Table 2). These three clusters of DCs can help companies effectively reap the full benefits of OI (Bogers et al., 2019).

Alternatively, Garzón Castrillón (2015) proposed a model that establishes three basic approaches: building, innovation, and contingency, and illustrates the strategic impact of DCs. In this model, which arrived after a process of integration, union, and fusion, to establish four DCs: "absorption capacity," "innovation capacity," "learning capacity," and "adaptability." All these capabilities converge into a new configuration to boost the impact of innovation. It is visible the importance of R&D where the novel value proposition could be announced or promoted through social media channels. In this model, it is noticeable that on the left side, the organization reveals its "value creation process," on the top, the DC strategic impact, and on the right side, arriving at consumers through the market the value proposition.

The conceptual model of OI presented by Chesbrough is presented in Fig. 2 (Chesbrough, 2003). The "holes" exemplify the organization's borders to allow entering and exiting information, technology, and ideas to capture opportunities in the market (both current and new markets). This idealization could be problematic if the company has a single exit point for its activity, as usually happens in traditional

Table 2 Strong DCs make OI effective (source: Teece (2020))

Sensing	Recognizing external know-how opportunities
	Learning from external sources of know-how
Seizing	Agile decision-making once an external source is identified
	Initiating combinatorial activities
	Adopting hybrid business models
Transforming	Selecting governance mode for external linkage
	Integrating internal and external knowledge

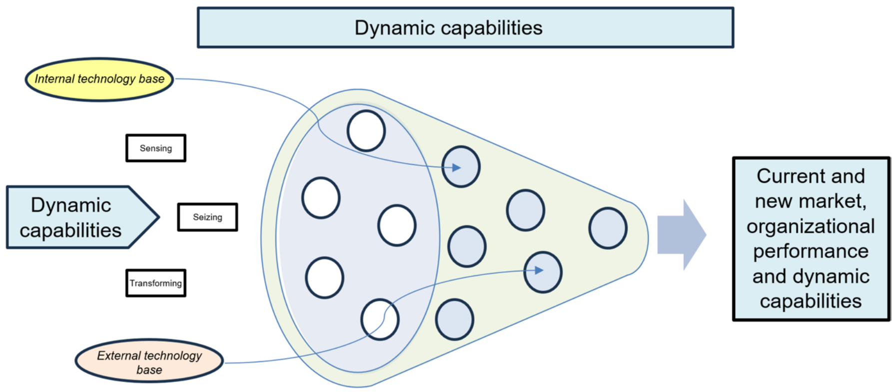


Fig. 2 Open innovation model and dynamic capabilities approach (source: adapted from Chesbrough (2003)

companies. Furthermore, companies can exploit their intellectual property (IP) by licensing to pre-existent companies or start-ups or promoting and funding the creation of spinouts embedding the ideas of their employees. We also included the components of DCs presented by Teece (2007, 2020), where the result of the interaction of three sets of organizational processes sensing, seizing, and transforming, effectively affect the market, the organizational performance, and the business capacities of a certain organization.

The Analytical Intersection

DCs were initially associated with positively changing technological environments (Teece, 2007); however, they could involve diverse business activities as a versatile approach. In the DC scene, a solution to continuously growing is the capacity to set changing configurations, resources, and organizational compositions as the business evolves and as markets and technologies develop (Bogers et al., 2019). The process entails changing, extending, and aligning tangible and intangible assets and claims, moving resources such as expertise, knowledge, and other values to address the most significant advantage. Consequently, the rationale, types, experience, and potentiality of applying OI models in organizations to conduct their R&D and related activities, might be possible with the help of social media analysis and the DCs theory (see Fig. 3).

Addressing the intersection of the previously referred OI and DCs, social media such as LinkedIn is changing the corporative world. It has become a powerful networking instrument for companies and people associated with the labor market. It enables users to display their knowledge and connect with other professionals (Dai et al., 2018; Franco-Riquelme, 2020; McCabe, 2017). Additionally, DCs could be linked to the activity on this social media platform, opening through this research another way to measure, for instance, discussing the effectiveness and potential of its exploration.

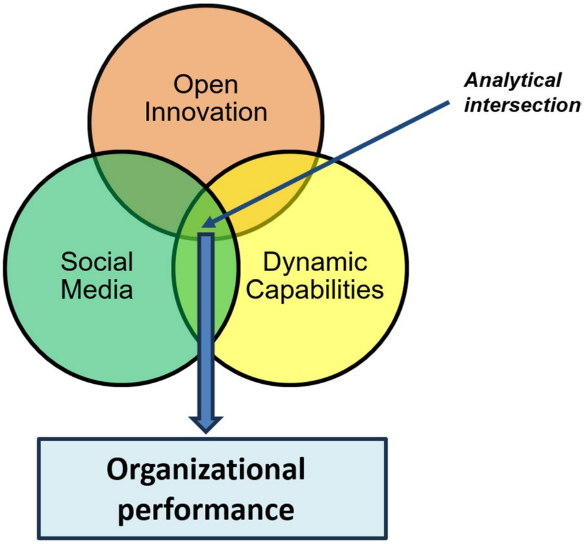


Fig. 3 The research connection between three domains: OI, social media, and DCs resulting in organizational performance (source: own elaboration)

According to Gold et al. (2001), effective knowledge management through capacity development is essential for improving organizational performance. Together, OI, DCs, and social media as knowledge are organized, knowledge management activities are coordinated, and the extent to which knowledge management practices are embedded in the work processes influence the effectiveness and efficiency of organizational performance (W. Zheng et al., 2010).

Social Media Analysis on LinkedIn

Gartner, Inc. describes social media analysis[2] as "the process of measuring, analyzing, and interpreting the results of interactions and associations among people, topics, and ideas." This process comprises four distinct steps, data discovery, collection, preparation, and analysis (Stieglitz et al., 2018). It includes a series of specialized analysis techniques such as social filtering, social-network analysis, sentiment analysis, and other analysis that circulate through them and the study of social media users. These tools help explore social composition and relationships, aside from the behavioral patterns of individuals and organizations.

X (formerly Twitter), LinkedIn, and interactive blogs are capable platforms for distributing informal knowledge and innovative ideas within and across organizations through establishing expertise, socializing, and networking (Jarrahi & Sawyer, 2013). Understanding actual media content may provide significant discoveries to bring new opportunities concerning markets, business, politics, and many other sectors. New tools and algorithms are helping to discover meanings from the source of

[2] See https://www.throttlenet.com/blog/the-cloud/gartner-identifies-the-top-10-strategic-technologies-for-2011/

data flows, and research in this area is expanding swiftly. Notably, social media has been converted into a source of high interest to be considered in several disciplines (computer science, humanities, and social sciences) and the academic world.

Along the same line, the analysis of people's opinion on social media has been increasingly attracting the attention of academic and industry researchers interested in their advantages and scope. Furthermore, the investigation of social media comments has overflowed due to the enormous data treatment capacity that has completely altered how to analyze social phenomena. The research in this field has created a new communication path, providing more value in quantitative analysis than traditional methods to obtain helpful comprehension of the new paradigm in the socio-technological transformation in recent years (Rathore et al., 2016; Toscani et al., 2018).

LinkedIn is a social media focused on business and employment services that operate via websites and mobile applications. LinkedIn was created in December 2002 by Reid Hoffman and was officially launched on May 5, 2003; as of January 2021, LinkedIn had 722 million registered members in over 200 countries and territories.[3] It has more than 16,000 full-time employees with offices in more than 30 cities worldwide.[4] In the 2019 fiscal year, LinkedIn brought in US$ 6.8 billion worth of revenue, contributing to US$ 38.1 billion of commercial cloud revenue for Microsoft, making up part of US$ 126 billion in total revenue.[5]

Compared with professional network sites such as LinkedIn, Xing, and beBee, the first is the largest professional social media site globally (Bridgstock, 2019; Tifferet & Vilnai-Yavetz, 2018; Utz & Breuer, 2019). Unlike FB, Instagram, X, and other social media sites, these are employed for leisure objectives. LinkedIn allows people to find a job and connect with others beyond organizational barriers, unlike companies-internal networks. Therefore, users can invite anyone to become a contact and join colleagues within and outside their professional networks (Papacharissi, 2009). LinkedIn is mainly used for professional networking—including employers posting positions and job seekers posting their resumes—allowing workers and employers to generate profiles and create a network in an online environment representing real-world professional associations. Notwithstanding the growing diffusion of LinkedIn as a communication tool, Pisano and colleagues suggested that (in the case of European) firms still have not been able to exploit the full potential of communication via LinkedIn (S. Pisano et al., 2017). Despite the potential opportunities offered by this platform, companies essentially use it for recruitment.

LinkedIn is an attractive platform for obtaining data from companies and users. For instance, some reasons for using LinkedIn include researching people and companies (77%), reconnecting with past colleagues (71%), uncovering potential job opportunities (41%), networking (39%), and increasing marketing presence (39%) (Breitbarth, 2017). Still, LinkedIn has not been extensively examined (Kluemper et al., 2016), as in the case of X and other social media in diverse scenarios

[3] https://blog.hootsuite.com/linkedin-statistics-business/

[4] https://news.linkedin.com/about-us#statistics

[5] https://www.businessofapps.com/data/linkedin-statistics/

(Franco-Riquelme et al., 2019). However, massive amounts of data from LinkedIn allow scientists and data-oriented researchers to extract insights and create outcome highlights (Sumbaly et al., 2013).

Text Processing on LinkedIn

On LinkedIn, Dai et al. (2018) implemented unsupervised learning to classify profiles according to their professional background, to find the trends of the workforce professional orientation from an online viewpoint. In the same way, other researchers (Piedboeuf et al., 2019) were able to extract the personality from profiles with reliable precision, using two personality models in a way to understand employees or co-workers better: Myer-Briggs (also known as MBTI) and DiSC (dominance, influence, steadiness, and conscientiousness).

Vinothini et al. (2018) performed sentiment analysis to define the polarity and investigate whether LinkedIn updates' text is positive, negative, or neutral. However, they were aware of the difficulty of analyzing all posts and evaluating public opinion about the topic discussed on this platform. This type of analysis is more common to be carried out on X or companies' websites such as TripAdvisor, Amazon, or YouTube (Ordieres-Meré & Franco-Riquelme, 2017).

Source Categorization

Text classification, also known as text categorization (Rusell & Norvig, 2010), is one of the first steps in an NLP system. It is a primary and common application in opinion mining, topic classification, and user profiling (Johnson & Zhang, 2017; Tellez et al., 2018; Wang, 2018). By implementing these NLP tasks, text classifiers can automatically decompose a large amount of text and allow a set of defined labels based on its content. Here, it is described two functions implemented in this research to extract the features from data from social media sources:

- Unigrams: The one-word representation to be used for term frequencies.
- Bigrams: The two-word cluster is used to capture more context in general instead of a single word (unigram).

The text categorization of many words resulted in the extraction procedures, allowing us to establish a set of techniques to deal with the information behind ML implementations.

Unsupervised Learning

Wang (2016) describes unsupervised learning "as a discipline of ML that aims to discover patterns in large data sets or classify the data into several categories without being trained explicitly." Algorithms such as hierarchical clustering, K-means, and topic modeling are used to determine inputs with no pre-existing labels and minimum human supervision (Ansari et al., 2021).

Furthermore, this algorithm implementation is performed by partitioning disjoint K clusters after several iterations grouped by centroids. Hence, it consists of a data reduction approach used to identify homogeneous case groups based on selected features (Jain, 2010). Besides, this type of clustering is often used for classification to discover competitive differentiation patterns in the information behind data based on a defined corpora text.

K-means clustering has computational advantages for large datasets but must be defined as the number of clusters (Steinley, 2006). Utilizing the K-means algorithm to discover groups in LinkedIn public profiles (Dai et al., 2018) describes that this algorithm is helpful "in determining the point where the graph represents the number of clusters versus the percentage of variance explained by clusters starts to rise slower."

Methods

In order to address the research gap on the intersection between OI, DCs, and social media, and to test the previously developed theoretical framework, we propose an empirical section based on eight selected tech-based companies. We analyzed LinkedIn posts quantitatively, yielding valuable insights into open innovation practices and trends. This data-driven approach identifies broad patterns and relationships across a large sample, allowing the findings to be generalized more easily.

Quantitative data alone, however, often lacks the context and depth required to understand the underlying mechanisms and reasons behind these patterns. This is where qualitative methods come into play (Creswell & Plano Clark, 2017; Tashakkori & Teddlie, 2010). Researchers use secondary sources such as case studies, interviews, and academic articles to gather rich, detailed information about people's experiences, motivations, and challenges in open innovation. Based on these sources, we can understand how companies implement and perceive specific strategies and why certain patterns emerge. Combining both methods allows authors to leverage each other's strengths, leading to more robust and reliable findings.

Research Application

We considered the examination of companies that alleged that they are currently using the OI strategy. From an initial number of thirty companies, and having conducted documentary research, based on their LinkedIn activity, the surveys answered, technological-based organization, and diverse origins, it was determined to focus on eight companies: Accenture, BBVA, IBM, Intel, LG, NASSCOM, Telefonica, and Vodafone. Moreover, due to documentary research, these eight companies were selected for their relevance and innovative activities in 2019 and 2020. Accordingly, given that the focus was to study diverse cases with diverse profiles, the sample sizes have an intrinsic limitation to make the work understandable and accessible. With the chosen sample, it is possible to include situations with different actors and behaviors. Hence, it is intended to use a small piece from other regions with relative importance because they are the most representative of their use of the OI strategy.

We conducted a mixed method, starting with a social media analysis and implementing an ML approach. The qualitative approach consisted of a survey to compare their "openness profile" regarding the information provided by the LinkedIn profiles of each company. The discussion framework was centered on the DCs theory to find a comprehensive answer to the strategy together with OI. Two sources have determined the analysis: the primary sources—surveys and LinkedIn posts (i.e., updates); and secondary sources—based on the web, and reports, among others.

Some studies have been used as sources of inspiration for the method adopted in our research, namely, the dynamic governance of social network is a new perspective of AI systems by Chen et al. (2020) which focuses on optimizing the active evolution of entrepreneurial social media using a dynamic optimization algorithm-based AI system, which enhances dynamic governance and efficiency in exploring AI roles in entrepreneurial social media. Also, a relevant paper from Zheng et al. (2011) utilizes a Likert questionnaire and structural equation modeling in a survey of Chinese manufacturing firms to reveal significant relationships between dynamic capabilities and innovation performance, with knowledge combination capability mediating this relationship.

Indeed, Nisioti et al. (2022) studied the impact of social media structure on innovation in dynamic settings, demonstrating that experience sharing within a dynamic structure achieves high levels of innovation, particularly for tasks with deceptive nature and large search space, while Verma et al. (2023) addressed how ML techniques can be used to forecast user behavior on social media such as Facebook, X, and LinkedIn, which can inform strategies for analyzing social media in companies who implemented OI.

This context provides a blend of ML techniques and qualitative survey approaches, focusing on social media analysis in the context of OI and DC theory. By extracting data from LinkedIn updates, it could be compared with the literature regarding DCs, thereby establishing the dimensions indicated in this theory. Then we applied such a combined approach in our study.

Quantitative Approach: LinkedIn as a Primary Source

Regarding the quantitative analysis on LinkedIn, we performed text mining on the eight selected companies, starting with the corporative page on this social media. After applying the LinkedIn scraper, a total amount of 1104 updates have been retrieved. The social media analysis was conducted for one year, between February 2019 and February 2020.

Table 3 lists the company names, the country of origin (HQ), their main activity, and the number of updates retrieved during the research period. We focused on the text for this database, extracting all the information for the analysis of LinkedIn accounts.

Table 3 The list of eight companies analyzed HQ, activity, and the number of updates retrieved from LinkedIn (source: own elaboration)

#	Company name	HQ	Activity	Updates
1	Accenture	Ireland	Consulting services	75
2	BBVA	Spain	Banking	208
3	IBM	USA	IT services	139
4	Intel	USA	Microelectronic	104
5	LG	South Korea	Manufacturer	60
6	NASSCOM	India	Innovation services	209
7	Telefonica	Spain	Telco operator	209
8	Vodafone	UK	Telco operator	100
Total				**1104**

Variable's Definition

It has been retrieved by searching on companies' public profiles and saving the searches using the Python language through the library LinkedIn Scraper, which is used to extract the post, known as "updates," in LinkedIn jargon.

In this case, it has considered building the LinkedIn database focusing on four variables (see Table 4): the head of the news feed, the subhead (which usually is metadata: video, quiz, picture), the time of post, and the number of likes—which was not incorporated in this research. Indeed, the latter has not been considered because we focus on the discourse rather than the analysis of comments weighting.

Text Mining

To perform text mining, we first chose post-dates to define the periods under study. Second, we focused on the text, extracting all the information for our analysis based on LinkedIn updates. The comments are essential in providing the material basis and a testbed for building NLP systems.

Once periods were established, the text cleaning task from the tweets database and LinkedIn updates were carried out to establish the text corpora. After that, and having selected the computational programs for data processing, automated tools are available to perform some or all pre-processing steps (Ghiassi et al., 2013).

We structured the pre-processing steps based on the following tasks (Jurafsky & Martin, 2008): regular expressions, normalization, tokenization, filtering, stemming (i.e., stripping off words' endings), lemmatization (it is the replacement of common

Table 4 LinkedIn variables definition (source: own elaboration)

#	Variables	Description
1	Head	Plain text corpus to be analyzed
2	Subhead	Metadata source embedded in the post
3	Timestamp	Original date post
4	Likes	The accumulated number of likes

terms for the same lemma), and other pre-processing, which constitutes secondary tasks such as eliminating repeated words or characters, stopwords, numbers, and blank spaces; correcting the grammatical errors; and converting the entire text to lowercase, avoiding misalignments in the analysis with capitalized words.

Text Classification

A collection of sentences consists of words, and in linguistics and probability, an N-gram is a contiguous sequence of N words from a given sample of text (Liu & Strauss, 2021). Here, it describes the main tasks implemented in our quantitative approach to extract the features from data. In this research, we focused on dealing with the combination of the two-word cluster (bigrams) to remove the LinkedIn post's main features.

Bag-of-Words (BoW)

The information retrieval (IR) method is best represented concisely with the help of visualization tools. Hence, the Bag-of-Words (BoW) model is a simplified version of the NLP approach. The BoW models represent a multiset of words and, in our research case, are divided by bigrams.

Qualitative Approach: Secondary and Primary Sources

In the qualitative part of this study, we performed through data obtained, in the first place, from secondary sources of information. The organizational information was collected from the company's websites and reports, among other sources. This also includes the comparison of DCs theory by documentary research through the approach on companies' profiles.

Comparison of OI Models of the Companies

The profiling process means that some dimensions are more relevant to increase the activity's success, and prior knowledge constitutes the basis for proper management. Therefore, it has been assumed that the innovation profile dictates the most appropriate management structure. One of the intuitive concepts behind this profiling is the "openness degree," which we refer to as quantifying the level of open activities found in a determined organization. This profiling concept could be suggested that openness is a combination of several low-level dimensions.

Based on eight dimensions previously identified in the literature (León et al., 2020), the "open innovation profile" of a specific R&D department or entire organization can be represented due to the values assigned to the variables. The values associated with each dimension correspond to the result of a qualitative process; for instance, these values could be obtained using a standard method where several persons with different backgrounds and positions could provide their views.

Primary Sources

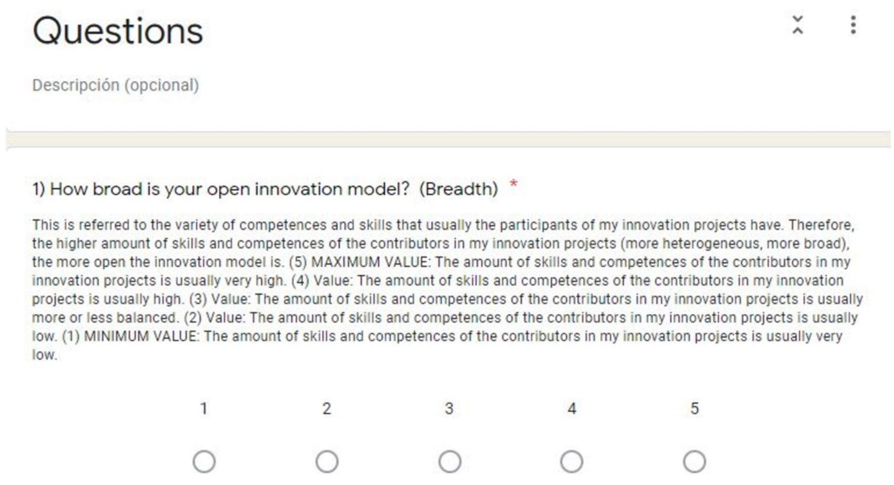
We determined to conduct a brief survey to enrich the knowledge—and get a more accurate picture from the inside—about the OI approach that companies implementing this innovation paradigm use. Besides, it implied receiving better information about their implemented OI models compared with the data from LinkedIn. For primary sources, a questionnaire was designed to be submitted to CEOs or Innovation Managers (see Fig. 4). Eight replies were received from the initial number of companies (thirty samples) considered for qualitative research, which are finally designated to be implemented for the quantitative approach.

Accordingly, the openness dimensions described in the background section and based on the work of (León et al., 2020), who facilitated the "openness degree" development, where the definition of the variables and the measuring values are detailed as follows:

- Breadth

It refers to an assortment of competencies and know-how that usually have the participants in innovation projects. Thus, the higher the competences and know-how of the contributors in innovation projects (e.g., more heterogeneous or broader), the more open the innovation model is.

- Maximum value = 5; The number of skills and competences of the contributors in innovation projects is usually very high.
- Minimum value = 1; The number of skills and competences of the contributors in innovation projects is usually deficient.



Questions

Descripción (opcional)

1) How broad is your open innovation model? (Breadth) *

This is referred to the variety of competences and skills that usually the participants of my innovation projects have. Therefore, the higher amount of skills and competences of the contributors in my innovation projects (more heterogeneous, more broad), the more open the innovation model is. (5) MAXIMUM VALUE: The amount of skills and competences of the contributors in my innovation projects is usually very high. (4) Value: The amount of skills and competences of the contributors in my innovation projects is usually high. (3) Value: The amount of skills and competences of the contributors in my innovation projects is usually more or less balanced. (2) Value: The amount of skills and competences of the contributors in my innovation projects is usually low. (1) MINIMUM VALUE: The amount of skills and competences of the contributors in my innovation projects is usually very low.

1 2 3 4 5

Fig. 4 Sample of questions belonging to the survey (source: own elaboration)

- Depth

It is described as the level of expertise of the contributors to innovation projects; when they are specialized, they have more knowledge, thereby having more options to participate in the project. Hence, the higher the expertise of the contributors in innovation projects are more in-depth, the more open the innovation model is.

– Maximum value = 5; The expertise of the contributors to innovation projects is usually very high.
– Minimum value = 1; The expertise of the contributors to innovation projects is usually shallow.

- Freedom

The freer the collaboration in innovation projects, the more open the OI model is. It means the arrangement is based on voluntary participation when they are less formalized.

– Maximum value = 5; Innovation projects are usually formalized at a very high level.
– Minimum value = 1; Innovation projects are usually formalized at a deficient level.

- Number of R&D phases covered.

The more phases the parties are included in innovation projects, the more open is the innovation model.

– Maximum value = 5; The number of phases included in innovation projects is usually very high.
– Minimum value = 1; The number of phases included in innovation projects is usually very low.

- Number of actors involved.

The more parties involved in innovation projects, the innovation model is more open.

– Maximum value = 5; The number of actors involved in innovation projects is usually very high.
– Minimum value = 1; The number of actors involved in innovation projects is usually very low.

- Percentage (%) of external funding sources.

It refers to the source of the money to work in an OI way. Generally, this case occurs when one company is "forced" to work on OI projects due to constraints imposed by public administrations funding the project (e.g., putting as a compulsory condition to be supported to conduct the research work in cooperation with an academic institution).

- Maximum value = 5; external funds in innovation projects are usually very high.
- Minimum value = 1; The amount of external funds in innovation projects is usually very low.

• Percentage (%) of economic resources.

It complements the previous one from the economic volume involved. Only one OI project could affect a large percentage of the R&D resources; its impact will be high (the OI model is more open).

- Maximum value = 5; The percentage of the R&D resources framed in OI projects is usually very high.
- Minimum value = 1; The percentage of the R&D resources framed in OI projects is usually very low.

• Percentage (%) of R&D projects.

It implies the relative importance of the firm's activity. If only 1% of projects follow the OI logic, the impact on the company is very low (so, the OI model is less open).

- Maximum value = 5; The percentage of R&D projects framed in OI projects is usually very high.
- Minimum value = 1; The percentage of R&D projects framed in OI projects is usually very low.

Once the variables and the values are defined, they can be assigned to the dimensions of each company; their respective profiles are drawn using the information gathered from the survey.

Secondary Sources: Documentary Analysis

The qualitative part of this study also included secondary sources of information, and the rationale, types, experience, and models applied by organizations. Hence, it has been analyzed that OI and DCs were implemented according to the selected companies who embraced this paradigm to serve as inputs and compare other approaches. Moreover, corporate information was extracted from public sources, like the companies' websites, reports, and other sources.

Results

This section analyses the OI profiles based on eight companies selected for their relevance and activity regarding their innovative-related activities in 2019 and 2020. By comparing the profile of a given emblematic organization, the purpose is to understand their openness degree, compared with social media outcomes, and establish their DCs in their context. The results are shown in two segments: the quantitative approach was based on LinkedIn updates, where the implementation involved

ML techniques. Then, the qualitative approach, based on information coming from the comparison of a survey conducted to CEOs and innovation managers, and the secondary source, which consists of data collected from websites, reports, and articles mainly about the selected companies.

We illustrate the "openness degree" visualizations, comparing both sources: primary and secondary. Besides, terms frequency analysis was performed to interpret the discourse of the analyzed companies in social media, in conjunction with OI and the DCs theory, which is explained based on the three sets of the organizational process: sensing, seizing, and transforming capabilities.

LinkedIn Frequency Terms

The evaluation of LinkedIn updates allows us to compare and remark on the companies' discourse, showing perceptions of how they can communicate with their clients and the terms they use more frequently. The text mining application to the LinkedIn database consisted of 1104 updates retrieved. Once performed, the text classification resulted from the analysis of each company; it has obtained the BoW representation. To capture more context, we choose the bigrams implementation instead of a single word. Moreover, the compound terms make more sense to understand the reason and correlation among the concepts to be analyzed (Lemus-Aguilar et al., 2017).

To proceed with the measurement regarding the selected companies, we started the exploration of the term's frequencies, which is a basic, but exciting rapprochement to look at the most frequent terms scale. For this reason, we counted the number of bigrams based on their appearances to seek the orientation of their discourse on social media. Due to the analysis performed for one year, the frequency is divided by each company as an indication of the main topics for these companies. In addition, we considered the implementation of the algorithm K-means to carry out a text-based clustering experiment that has a considerable advantage in exploring large quantities of data coming from our LinkedIn source.

Frequency Terms Analysis

This segment explored the simple frequencies of bigrams associated with the LinkedIn updates database of each company. To visualize frequencies (see Fig. 5), we implemented barchart graphic representation, wherein an ascending scale order is defined as the most cited bigrams coming from each company database and the number of times that appeared.

In Fig. 5A, corresponding to Accenture, more appearances are related to the name of the CEO (Pedro Moreno) and other collaborators (such as Gloria Lomana and Mercedes Oblanca), also having terms such as "agile competitive," "investments value," "United Nations," "digital transformation," and "human resources." Regarding BBVA, in Fig. 5B, the list of bigrams frequencies is listed, leading the name of managers, and terms such as "artificial intelligence," "big data," "talent and culture," "sustainable finance," "open innovation," and "quantum computing." Fig. 5C shows the bigrams related to IBM, and the most frequencies

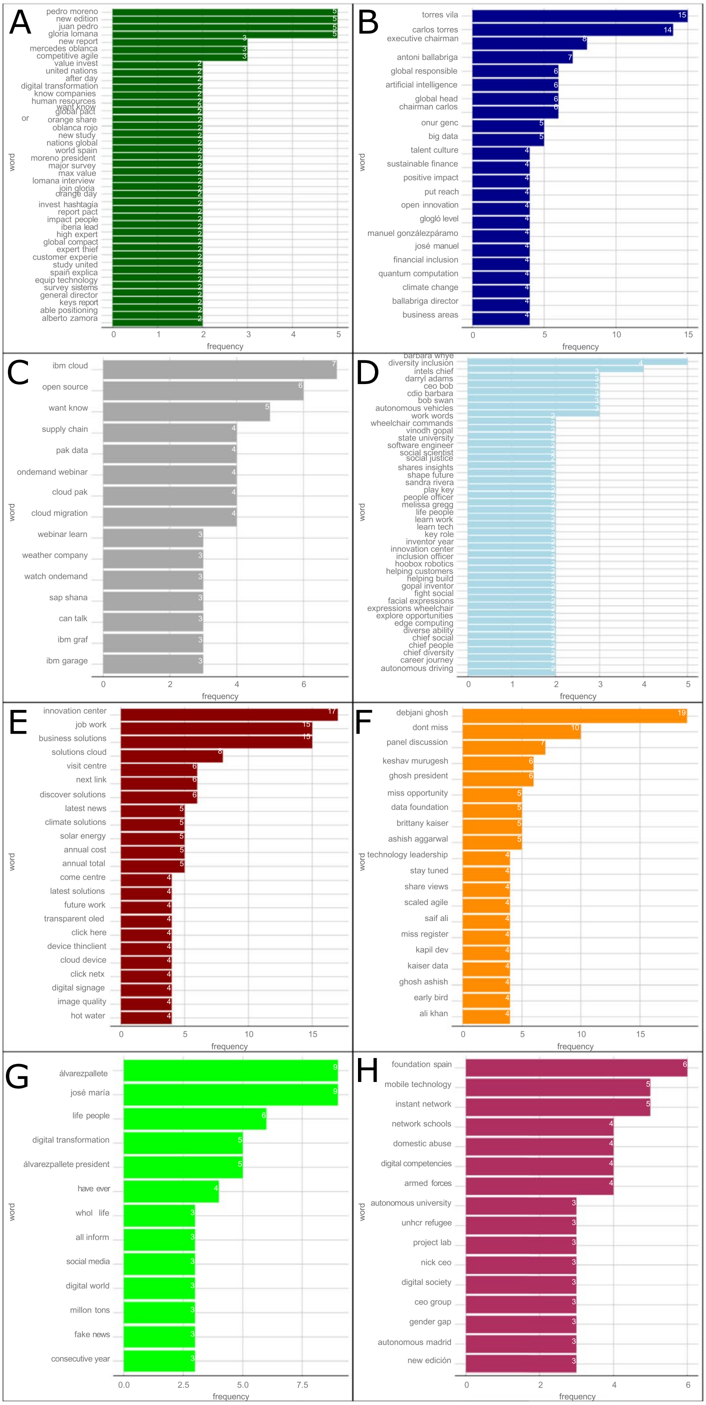


Fig. 5 Bigram's frequencies of corporate LinkedIn sites of evaluated companies (source: own elaboration)

are “IBM cloud,” “open source,” “supply chain,” “on-demand webinar,” “cloud migration,” and “sap hana.” In the case of Intel, Fig. 5D illustrates the most frequent bigrams, starting with “diversity inclusion” and CEOs and collaborators. Also appears “autonomous vehicles,” “state university,” “software engineer,” “social justice,” “shares insight,” “learn tech,” “innovation center,” and “edge computing,” among other terms. Regarding Fig. 5E, the most frequent bigrams related to LG are “innovation center,” “workplace,” “business solutions,” “LG cloud,” “solar energy,” “future work,” and the brand products. Figure 5F presents the frequencies of NASSCOM bigrams in order of appearances, such as the president Debjani Ghosh and other collaborators, “panel discussion,” “data foundation,” “technology leadership,” and “scaled agile,” among other terms. As can be seen, in Fig. 5G, the recurrence of the term Telefonica LinkedIn corporate site is mainly referring to the CEO, followed by “digital transformation,” “news Telefonica,” “social media,” “digital work,” “Telefonica foundation,” and “fake news.” And finally, Fig. 5H displays in order of appearance the most frequent terms related to Vodafone, such as “Vodafone foundation,” “mobile technology,” “instant network,” “network schools,” “domestic abuse,” “digital competences,” “armed forces,” “autonomous university,” “project lab,” “digital society,” and “gender gap.”

Affinity of Words Implementation

Table 5 shows the concept of the clustering K-means coming from LinkedIn updates. The K-means algorithm grouped the terms by clusters representing the proximity between each other. In order to have a concise explanation of the clustering algorithm, we focused on a few samples and considered the most representative terms from the eight groups ($k = 8$), which was the grouping designed number. For each company, the text updates have been analyzed, showing the following results:

In the case of Accenture, the clusters are representatively defined as “companies,” “future concern,” “people (Gloria Lomana),” “world,” and “Spain.” BBVA, clusters present more focus on “finance” and “business,” “development,” “digital,” “data,” “people (Carlos Torres Vila),” and “global.” IBM terms group has a strong presence of two concepts: “cloud” and “enterprise.” Also, “webinar,” “development,” and “learning” are present in the clusters. According to the cluster in Intel, the terms are more spread in their nature, reflecting terms such as “data,” “computer,” “team,” “technology,” “inclusion,” and “diversity” as relevant words in the text of the LinkedIn updates. LG showed the terms “solutions” and “work” as a primary interest. Also appeared “energy,” “center,” and “sustainability” in the clusters.

The NASSCOM updates texts were more focused on “digital” and “technology,” and some terms that appeared are “business,” “start-ups,” and “people (Debjani Ghosh).” Regarding the clusters, Telefonica is referred mainly to as the “Internet,” “people,” and “data,” and names such as the CEO “José Álvarez Pallete,” and

Table 5 K-means cluster of affinity words based on LinkedIn companies' accounts (source: own elaboration)

#	Accenture	BBVA	IBM	Intel	LG	NASSCOM	Telefonica	Vodafone
1	companies shares-painfuture major	global responsible business financial head	cloud explore business day register	computing data business experience experiences	cloud lg solutions annual cost	data digital world chairman forum	telefonica spain data internet world	network vodafone support foundation country
2	study ceos new keys companies	data business part data talent	data cloud business day ibm	helping future learn team technologies	solar lg energy panels discover	digital global leadership shares chairman	digital telefonica spain world key	equipment we want edition tecnology digital
3	keys discover report future technology	data business development director spain	learn research data helped ibm	learn work make technology software	job position solutions lg business	india discussion industry day future	life people technology whole world	lives technology part education mobile
4	lomana gloria new edition world	bank spain equipment strategy year	watch webinar applications cloud learn	chief officer people technology world	solutions center innovation lg visit	register business dont industry miss	telefonica digital álvarezpallete spain josé	vodafone today spain world digital
5	world companies-digital spain business	digital customers business global world	ibm services register business development	employees opportunities work company culture	center air conditioning lg business	experience hear share forum tech	time key world people internet	technology partnership working access country
6	report companies keys spain ceos	business investment director employees discover	cloud business ibm applications services	inclusion barbara whye chief culture	lg sustainable information business link	technology hashtag business ceo future	year data spain maría technology	vodafone project spain foundation university
7	tech juan moreno pedro world	discover team year people madrid	webinar join data time development	diverse workday culture inclusion	job position lg solutions cloud	tech technology day visit world	be data internet news álvarezpallete	vodafone digital vodafones million technology
8	hashtag ia value ceos future companies	carlos torres vila chairman sustainable	ibm learn business cloud know	experience learn leadership team love	lg solutions discover business solutions	debjani ghosh startups technology catch	josé telefonica álvarezpallete maría spain	vodafone women people technology access

location: “Spain.” Finally, Vodafone is primarily mentioned in the clusters, terms such as “technology,” “access,” “woman,” “Spain,” “university,” and “foundation.”

“Openness Degree” Outcomes Visualization

This process started with data collected from secondary sources. In this stage, from an initial number of thirty worldwide companies implementing OI strategy. The number decreased to eight, who were the companies that answered the survey. This documentary task was based on corporate data from public sources, like the companies’ websites, reports, blogs, and articles.

In the second stage of the data-collecting process, primary sources of information have been used to make the process more objective and adjusted to the reality of the evaluated companies. Once all the data coming from the questionnaire has been collected, a matrix with numerical values was assigned based on the responses collected.

Furthermore, the definition of the comparison of the company’s profiles was established on the eight variables considered in this study, as follows:

1. Breadth
2. Depth
3. Freedom
4. Number of R&D phases covered.
5. Number of actors involved.
6. Percentage (%) of external funding sources
7. Percentage (%) of economic resources
8. Percentage (%) of R&D projects

We proceed to represent in a “radar chart,” where the values associated with each variable are in function of the performed qualitative process. The company’s profile is meant by this depiction, where the comparison resulted from superposed primary and secondary sources. Based on these variables, the eight companies can be seen in Fig. 6 to determine the contrast between sources and, therefore, to assess their openness degree.

Companies’ Profile Comparison

Regarding the results coming from primary and secondary sources (surveys and documentary research, respectively), in the first place, Fig. 6A portrays Accenture; discrepancies were noticed between both sources. Indeed, the profile is coherent, indicating that it is more oriented to various skills, with higher expertise, in the half path of formalized collaboration, and similarly with more phases and parties involved in innovation projects.

Second, in Fig. 6B, the comparison of BBVA based on both sources is slightly similar, showing above midterm-based organization regarding innovation, less

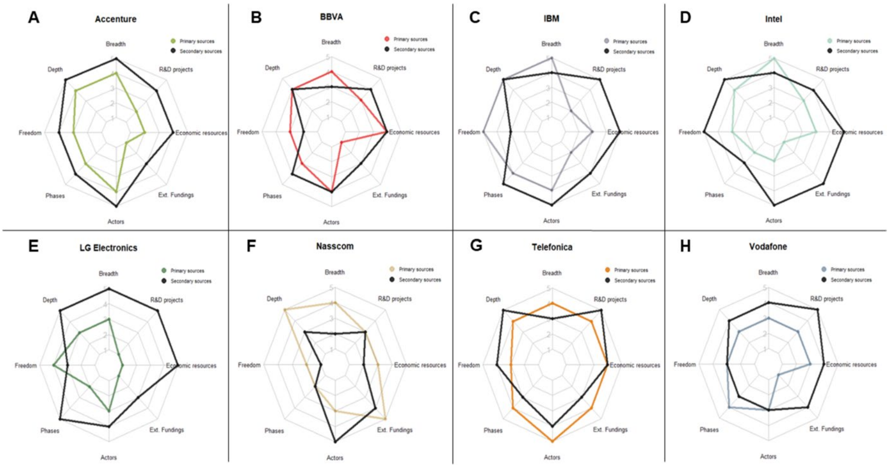


Fig. 6 Radar charts of the eight companies and their openness degree comparison of primary and secondary sources (source: own elaboration)

oriented to external funding, but having more resources assigned to projects with skills and expertise many actors involved.

Third, in the case of IBM, depicted in Fig. 6C, it is noticed as a company oriented to a range of competencies, with a high level of expertise among its collaborators and a less formalized approach, regarding its projects, according to primary sources. However, secondary sources are more oriented to R&D projects, economic resources, and multiple actors and phases involved.

Fourth, regarding Intel, as shown in Fig. 6D, the information from primary sources has dramatically changed, establishing an organization focused on its OI collaborator's capabilities and skills with limited external funding. On the contrary, the secondary sources display an organization more oriented to economic resources, external financing, and actors involved, in the same line with their freedom and the expertise of contributors.

Fifth, in Fig. 6E, about LG, discrepancies between sources are evident. Based on primary sources, it seemed to be a less formalized organization, having average skills and levels of expertise based on its collaborators. However, secondary sources depicted a company oriented to R&D projects, with more economical sources, more professional, and a high level of knowledge among its collaborators, in the same line with the phases involved.

Sixth, in Fig. 6F regarding NASSCOM, the differences between sources are not noticeable, but according to primary sources, they focus on their collaborator's expertise and external funding. Secondary sources show an organization more oriented to the multiple actors involved in OI projects.

Seventh, in Fig. 6G, Telefonica shows a very similar comparison of primary and secondary sources, with an orientation to the level of workers' expertise and high impact on R&D projects and multiple actors involved in the OI ambit.

Finally, in Fig. 6H, in the case of Vodafone, the difference among sources is relatively equivalent, with an average openness degree in almost all variables. According to secondary sources, it is more oriented to R&D projects.

Dynamic Capabilities Approach

Through the examination of DCs theory (Teece et al., 1997), as detailed in the background chapter, this framework gave us the base to find the capacity of organizations to change and adapt their primary resources. According to this perspective, aptitude must be tailored to new situations, and attitude should be very active regarding changing scenarios. In short, this framework must be assumed by the entire organization for its evaluation, the necessary actions, and, consequently, its success.

Thus, based on this premise, it has been considered to associate three batches of DCs where can be summarized the organizational processes: sensing, seizing, and transforming capabilities (Teece, 2007). To recap, the concepts disaggregated from this theory are enlightened in Table 2, which briefly explains these concepts. Hence, this scheme helps to perceive opportunities and threats—sensing—, take advantage of these opportunities—seizing—, and finally, maintain the competitiveness of the company by improving, combining, protecting, and, when necessary, reconfiguration the business and its intangible and tangible assets—transforming—(Bogers et al., 2019; Teece, 2007, 2020).

Table 6 summarizes the DCs batches, the findings of the text classification by companies, represented on each set by two words associated (bigrams), after its organizational processes' definition. To this end, after looking at the unigrams (i.e., single word) charts and the bigrams charts, we decided to present the results of the bigrams because the compound terms made more sense to understand the reason and their relation among the concepts presented in the database.

The outcomes are resumed by enumerating the process and pointing out each company's sensing, seizing, and transforming capabilities. Accenture is defined by social values, human resources responsibility, and technological competencies. The case of BBVA shows the orientation to new technologies, sustainability, and culture. IBM's case to supply chain, their current business model, and—possibly—new business perspectives. Intel displayed social responsibility, technology, and innovation.

Regarding LG, its strategy focuses on its business, solutions, and innovation. NASSCOM showed tech-based skills. Telefonica, social media, and relation to the digital world. Finally, Vodafone focused on digital society, mobile tech, and projects.

Discussion, Implications, and Concluding Remarks

In this paper, we aim to introduce an innovative mixed approach to explore OI (Chesbrough, 2003) and DCs (Teece et al., 1997) strategical advantages by accomplishing a new framework that proposes to measure their organizational performance in social media through primary and secondary sources. It is worth mentioning that our research method implements quantitative research-based surveys and qualitative

Table 6 The bigrams of the selected companies retrieved from LinkedIn and classified according to DCs batches (source: own elaboration)

Company name	Sensing	Seizing	Transforming
Accenture	"Global pact", "customer experience"	"Investment value", "human resources"	"Competitive agility", "digital transformation"
BBVA	"Artificial intelligence", "big data", "quantum computing", "climate change"	"Sustainable finance", "open innovation", "global level" "financial inclusion"	"Global head", "cultural talent", "positive impact", "business areas"
IBM	"supply chain"	"IBM cloud", "open source", "webinar learn"	"Cloud migration", "watch OnDemand"
Intel	"Diversity inclusion", "explore opportunities", "autonomous driving"	"Autonomous vehicles", "software engineer", social scientist", "diverse ability"	"Innovation center", "edge computing"
LG	"LG business", "solar energy"	"business solution", "LG solutions", "LG cloud"	"Innovation center", "cloud device"
NASSCOM	ND	"Technology leadership"	"Data foundation", "scaled agile"
Telefonica	"Social media"	"Digital world"	"Digital transformation"
Vodafone	"Digital society"	"Mobile technology"	"Digital skills", "project lab"

research using questionnaires. Our study poses an innovative research mix method known as netnography (Nakara et al., 2012), which aims at understanding social interaction in contemporary digital communications contexts such as LinkedIn.

In the first part of our method, we validated eight selected organizations' "openness degree" based on primary and secondary sources to perform their "innovation profile." This profile helped us to understand their attitude towards changes oriented to improve the organizational performance. At an organizational level, Huggins et al. (2020) suggest that openness is engendered as existing relationships mature and become more fruitful. Therefore, the connection is more likely to have systems and frameworks to manage the knowledge flowing through these channels effectively. Indeed, regarding the "openness degree" association with companies' shape (see Fig. 6), we found different outcomes, considering that companies with a more "open" attitude are expected to be more susceptible to changes, leveraging their resilient ability faced with changing scenarios, and expanding the options to increase the organizational performance.

We previously identified in the literature, that the OI implementation process needs essential requirements such as time and corporative culture, so the difference in the perception of top managers could be a factor in mitigating the innovation process (Mortara & Minshall, 2011). In this sense, Carayannis and Meissner (2016) defined OI as a paradigm that has been practiced for a long time, and the primary efforts must be targeted at continuously developing companies' organization and managerial models to meet the innovation challenges. Also, diverse approaches and internal constraints could harm the entire vision to face the willingness to change, characterized by bureaucratic processes or lack of resources, expertise, etc. (Kratzer et al., 2017). It is worth mentioning, that documentary research revealed that there are more companies compromised in the OI strategy. However, the survey conducted on the eight companies showed more conservative attitudes in the variables assigned, considering their innovation profile (see Fig. 6).

Through the K-means implementation (Steinley, 2006), it can be inferred that the capacity of organizations' adaptation to new situations shows evidence, as the arguments appeared in the eight proximity clusters regarding each company analyzed. These findings follow the frequency application, and the bigrams classified to the strategical capabilities evaluated in each company (see Table 5).

This research is based on extensive literature on the innovation management area regarding DCs (Eisenhardt & Martin, 2000; Helfat et al., 2007; Teece, 2007, 2020; Teece et al., 1997; Zollo & Winter, 2002). According to the theory and findings, OI and DCs are complementary. An overlap interrelates them and is divided into three categories scrutinized along with this study (Bogers et al., 2019; Teece, 2020). Furthermore, the concept of OI embraces a wide range of possible models. During the implementation process, individual entities should define their approach and determine the proper internal structures and management procedures.

Thus, learning from both theoretical facets, the results obtained are based on previous research regarding the ability to adapt to changes for the acquisition of new skills, learning, initiatives, and even new business models in organizations (Teece, 2007; Teece et al., 1997), and unfailingly to be benefited from external partners that contribute value-added knowledge (Badawy, 2004; Chesbrough, 2003; Chesbrough

& Appleyard, 2007). Therefore, with DCs, organizations can adapt to new situations, which is crucial in today's age of rapid technological progress, with recent examples such as the development of AI and generative AI (Magni et al., 2024). Moreover, as a tool for building knowledge-based capabilities, OI plays a crucial role here. As Scuotto et al. (2022a) pointed out, it is evident the importance of the use of disruptive technologies like AI to achieve more efficient and effective use of such expanding solutions in the leveraging of disruptive technologies in the digital transformation era.

Our findings align with the literature and the corporative discourse on LinkedIn, emphasizing that information management is vital in achieving managerial effectiveness (Gold et al., 2001; Zheng et al., 2010). Thus, in the most open organizations, the processes of accumulation and integration of knowledge promote the creation of competitive advantages based on learning that improves their ability to innovate, coordinate efforts, quickly market new products or services, and thus respond to market changes and maintaining the ability to anticipate unexpected changes (Nonaka et al., 2000). According to Teece (2007, 2020), these processes are evidence of the development of the DCs in conjunction with OI.

We contribute an analytical framework, supported by empirical tests, to the literature and theory concerning social media analysis for gauging OI implementation and comparing it to DC theory to improve organizational performance. ML analysis of LinkedIn updates can be combined with mixed methods to generate quantitative findings and guide the selection of secondary sources for in-depth analysis based on qualitative research questions. Through our proposed method, we aim to scale this experience to other companies or diverse organizations that have a presence on LinkedIn.

Despite its limitations, this study provides valuable insights and lays the groundwork for future research. There is a restriction to capturing the diversity of the OI strategy in the large multinational corporations' field due to the small sample of companies considered for this research. Besides, OI implemented by firms worldwide are very different, and it is impossible to cover all of them. To make the work understandable and accessible, the sample sizes have inherent boundaries since the studies aimed to study diverse cases with diverse profiles. It was necessary to focus on the reliability limitation in using LinkedIn posts for different approaches—such as sentiment analysis—because there is a risk of information bias. Also, people tend to post more positive comments since it is not a usual complaint channel.

Managerial Implications

In our proposed framework for technological-based companies, practical implications, and actionable recommendations are crucial. Decision-makers can use quantitative data to evaluate open innovation strategies, providing evidence of their effectiveness and efficiency. To design and refine strategies that are feasible and acceptable within the company's specific context, qualitative insight from secondary sources can provide detailed information on the implementation process, organizational culture, and stakeholder perspectives.

This investigation gave us hints to prepare the scenario where DCs could be a crucial strategy in conjunction with OI (see Table 6). Therefore, highlighting three visible cases showed coherent outcomes: the case of BBVA, with a consistent discourse from its internal and exogenous sources, evolved from a financial institution to embarking on tech and innovative projects. Alternatively, IBM is an old computer manufacturer, leading tech services and open-source solutions. Moreover, Telefonica has evolved from the Telco sector to offering technological-based services, producing films and series, and implementing their AI technology integration—Aura.[6] Conversely, a disparity in their profile results is that LG, from white line and electronic manufacturer, opened its innovation center, oriented to the service. Nevertheless, this could be explained, considering that the person in charge only depends on the latter business orientation. These findings are consistent with Hussain et al. (2024) who showed evidence digital innovations deliver through the mechanism of digital infrastructure linkage and contribute to improved high-innovation performance practices.

Other studies (Grimaldi et al., 2013; Lee and Yoo 2019) addressed that companies with robust sensing, seizing, and transformation capabilities are more inclined to implement OI as a strategy to use it as a competitive advantage. Although, we considered that this also could be valid in the reverse mode. Our research findings also provided some evidence that in the LinkedIn database, specifically in the scale of frequencies (see Fig. 5), the outcomes showed several terms referred primarily to the top managers or references of Accenture, BBVA, Intel, NASSCOM, and Telefonica, that means the influential personality who is in charge to lead the process. Also, their business orientation and their new features are presented (IBM), or even some recent developments are diverged from their original sector (BBVA), displaying terms such as “AI” and “big data.” In the case of the new direction of strategy (Telefonica), it could be found “digital transformation,” or the fact of a different business opportunity (LG), represented by the “innovation center” that is offered to the B2B sector, rather than to the same to traditional customers or final consumers. The reference to social responsibility is also presented in the case of foundations and gender gap (Vodafone), diversity inclusion and social justice (Intel), or the incursion of new technologies like autonomous vehicles and quantum computing (BBVA).

Concluding Remarks

The sum up of the empirical section of this research can be summarized in this way: The most significant findings of this study are in line with the OI measurement from diverse sources and determining the analytical intersection between DCs and social media—LinkedIn. It can be summarized that when organizations are more open, by their “openness degree,” they can include the OI and the business model process configurations and culture to stimulate ideas generation, autonomous teams, and innovation accomplishments. DCs should be aligned with OI strategy to maximize

[6] https://aura.telefonica.com/es/

the chances to increase organizational performance, although, it requires scope for integrating the structural nature of the knowledge networks underpinning the innovation environment.

This study provided evidence that profile comparison describes the main aspects of companies' OI implementation from internal and external sources and aligns with their discourse in social media and its adaptation capabilities. Indeed, it is helpful to analyze the situation in some selected companies that have heralded their OI strategy as part of their positioning in the market from LinkedIn and surveys.

The eight selected companies for this study are large technological-based companies, but it does not mean that their size is a pre-condition for the present study. Some SMEs have been active in this field, even when their rationale differs. In this sense, the OI strategy recognizes that smaller firms are increasingly prominent in the contemporary innovation landscape (Vrande et al., 2009), and its activities foster product and process innovation, although outbound activities have a greater impact (Madrid-Guijarro et al., 2020). However, they do not have internal R&D departments like large multinational companies (Lee et al., 2010).

In the case of non-technological base organizations, innovative process configurations are imperative that they can be continuously adapted. Thus, this study's contribution to the literature and theory construction regarding the use of social media analysis to measure the application of strategies and evaluate in contrast to DCs theory.

The analysis made in this work reflects some additional features:

- The interest lies in identifying some themes and revealing some cutting-edge elements present throughout the LinkedIn updates, such as AI and big data.
- The idea that the companies' services/products and corporate image associated with references and CEOs might attract the interest of potential clients and partners is widely used.

The results contribute to the literature by showing that OI (Chesbrough, 2003) and DCs (Teece et al., 1997) can be measured on LinkedIn (and compared with surveys and documentary research). They complimented and coexisted as a referent strategy in the companies that adopted it to face changing scenarios—sometimes even reinventing their traditional business model.

To boost the benefits of social media and to obtain knowledge from the DCs (Teece et al., 1997), firms need to consider acquiring new skills, procedures, and competences to interpret and evaluate the information derived from these sources (Roberts et al., 2016). Thus, exploring social media without having these capabilities might reduce its performance, and they might need it to be fully part of their strategy (Du et al., 2016; Roberts et al., 2016).

In terms of further research, having investigated the OI and the links with DCs, we have found that this domain is vast and would require more studies and a more significant number of companies to be analyzed, given the complexity in which organizations that have adopted this paradigm operate. Moreover, it would be interesting to know how social media could benefit corporations and start-ups and how it could attract new ideas for activities in upcoming research.

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Declarations

Ethics Approval Not applicable.

Conflict of Interest The authors declare no competing interests.

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