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Tweeting innovation: Exploring the dissemination of open innovation initiatives

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ABSTRACT

The open innovation (OI) paradigm is gaining public favor and can lead to positive brand associations. In this vein, in line with the institutional theory, formal and informal societal pressures drive the dissemination of OI initiatives, which is becoming a marketing tool for firms. Surprisingly, OI in communication and marketing is an under-researched area. This study addresses this gap in knowledge by analyzing the dissemination of OI initiatives on Twitter (X). It examines OI-related tweets to verify whether the presence of the term "open innovation" and the accuracy of an OI initiative's description contribute to increasing the tweet interactions. This article shows that the term "open innovation", as a keyword or hashtag, is beneficial only when associated with firms' actual OI initiatives. Furthermore, it highlights that more transparent and specific tweets are more effective. Last, it provides recommendations to enhance the impact of OI communication and suggests future research opportunities.

1. Introduction

Open innovation (OI) describes how firms collaborate with external partners to access knowledge and expertise beyond their organizational boundaries (Chesbrough, 2003a). This paradigm recognizes that knowledge is widely distributed and that firms cannot rely solely on their internal capabilities to maintain a competitive edge (Chesbrough, 2006). Indeed, by leveraging inbound and outbound flows of ideas, technologies and talent, firms can enhance innovation outcomes (Gassmann & Enkel, 2004).

Drawing on institutional theory (DiMaggio & Powell, 1983), we argue that coercive, mimetic and normative pressures can induce firms to adopt the OI paradigm and disseminate OI initiatives. Such institutional pressures describe how firms are induced to act in response to the formal requests or expectations of policymakers and customers (coercive), the desire to imitate successful firms (mimetic), or the willingness to conform to established professional norms (normative).

Indeed, society may appreciate firms that show an "open" approach to innovation (informal coercive pressure). In addition, most public subsidies to innovation, such as the Horizon Europe program, require collaboration between two or more complementary partners (Greco et al., 2017), triggering OI endeavors (formal coercive pressure). Regarding mimetic forces, countless leading companies, such as IBM, Merck (Chesbrough, 2003a) and Procter & Gamble (Dodgson et al., 2006), transitioned from closed to OI, becoming aspirational models for their competitors. Finally, in terms of normative forces, innovation management courses increasingly cover OI (Mention et al., 2016) and several professional roles (e.g., OI manager, OI director) are emerging (Dabrowska & Podmetina, 2018).

Once firms react to these pressures by implementing OI initiatives, they are incentivized to communicate their alignment with societal expectations. Therefore, firms may publicly disseminate their OI initiatives to show their adherence to societal pressures, thereby gaining marketing benefits from OI, such as legitimacy, brand awareness, brand likability, and potentially increased sales.

Social media platforms are ideal for disseminating OI initiatives. On this matter, the literature mainly focuses on social media as an OI enabler, primarily as means to collect external knowledge (Barlatier et al., 2023; Corral de Zubielqui et al., 2019; Du et al., 2016; Marion et al., 2014; Mount & Martinez, 2014; Nijssen & Ordanini, 2020; Patroni et al., 2022; Roberts & Candi, 2014) or as a tool to elicit how different OI-related topics are perceived (Saura et al., 2023). Only a few studies

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recognize the marketing and communication potential of OI initiatives (Antonelli et al., 2022; Greco et al., 2022). Notably, to the best of our knowledge, no studies have examined how OI initiatives are disseminated on social media, nor whether such communication efforts are beneficial. These gaps are relevant because the OI paradigm, typically considered a source of industrial benefits (e.g., new products, processes, or access to new markets), can also yield direct marketing and communication benefits from the appeal of the "openness" concept. Consequently, we formulated the following research question (RQ):

RQ1: Does the public engage more with social media communication that includes the term "open innovation"?

We responded to this question by analyzing tweets related to OI in 2018 and 2023 and verifying whether those explicitly mentioning "open innovation" or "#openinnovation" received more interactions than others. We measured interactions as the total number of likes, comments, and retweets, which are considered the main actions of interest on Twitter (Muñoz-Expósito et al., 2017).

Interestingly, as with other catchwords such as "sustainable", "eco-friendly", "social", or "ethical" (Berger-Grabner, 2018), users may mistrust OI tweets when their credibility is unverifiable. Indeed, credibility depends on whether shared information is believable and factual (Bae et al., 2017). The Signaling theory helps explain the factors that influence the credibility and effectiveness of a message (Connelly et al., 2025), pointing out that the power and credibility of a signal lie in its cost (Connelly et al., 2025). Therefore, a "low-cost signal" – i.e., firms casually using the term "open innovation" in their communication activities without describing the underlying initiative in depth – might compromise the credibility of the message and the impact of OI communication. However, in the case of OI communication, it is unclear whether, as signaling theory suggests, more accurate and credible descriptions are needed or whether the OI catchword is sufficient to trigger positive public reactions on social media. Thus, we formulated the following RQ:

RQ2: Does the impact of OI communication on social media increase with the credibility of the shared content?

To address RQ2, we first conducted a semantic analysis of tweets that presented OI initiatives, assessing their transparency and specificity. Transparency and specificity are considered measures of communication accuracy that, in turn, shapes the credibility of the shared content. In particular, we conducted a regression analysis to investigate the links among transparency, specificity, and the impact of each tweet (measured by the number of interactions). Based on this analysis, this article provides recommendations to enhance social media communication on OI.

The rest of the article is structured as follows. Section 2 presents the theoretical background. Section 3 details the methodology adopted. Section 4 presents the results, which are discussed in Section 5. Section 6 concludes the article.

2. Background

2.1. Open innovation and communication

OI encompasses several approaches that organizations can adopt to engage with external stakeholders and exchange know-how. The earliest classifications of these approaches distinguish them based on the direction of knowledge flows: inbound, outbound, and coupled OI (Chesbrough, 2003c; Gassmann & Enkel, 2004). Inbound OI leverages external expertise and resources to enhance internal innovation processes. It includes acquiring external technologies, ideas and solutions through technology scouting and open-source collaborations (Chesbrough, 2003a; Lakhani & Wolf, 2003). Outbound OI leverages internal knowledge and assets by licensing, selling, or sharing them with external partners for further development and commercialization (Chesbrough, 2003c). Coupled OI combines inbound and outbound OI, emphasizing the importance of collaboration and knowledge exchange between organizations to co-develop innovation (Gassmann & Enkel, 2004).

Since 2003, OI has evolved as an umbrella term encompassing numerous approaches that share a commonality in the flows of ideas, knowledge and technologies that permeate organizational boundaries. Inter-organizational collaboration is the cornerstone of dyadic B2B OI (Chesbrough, 2003c). These may evolve into joint ventures (Enkel et al., 2009), where collaboration is more formal and structured. In other cases, projects or organizational units stem from an existing company becoming a spin-off or a startup that develops and commercializes innovative ideas (Chesbrough, 2003c).

As the number of partners increases and orchestration mechanisms become more complex, inter-organizational collaborations may turn into OI networks (e.g., Enkel et al., 2009; Schepis et al., 2021), OI platforms (Osorno & Medrano, 2022), or OI ecosystems (e.g., Xie & Wang, 2020). Similarly, open-source initiatives are considered a form of OI (Lakhani & Wolf, 2003), in which individuals and organizations collaboratively share knowledge, code, or data to create and enhance products and services.

Increasingly popular approaches to OI imply one-to-many relationships. Among them, a firm may resort to innovation contests, where individuals or teams propose ideas, prototypes, and solutions to overcome innovation challenges, with the opportunity to win prizes (Enkel et al., 2009). These contests may take the form of crowdsourcing initiatives (Boudreau & Lakhani, 2013; Vermicelli et al., 2024) or hackathons (Bertello et al., 2021), involving a large group of people to generate ideas, solve problems, or complete tasks. A firm may also establish innovation labs, incubators, or accelerators — physical or virtual — to facilitate collaboration among internal and external stakeholders (Blume, 2020). Some organizations, such as venture capital firms, specialize in accelerating promising startups (Blume, 2020).

Previous studies explored how communication and marketing can support OI. Set aside one article that observed that superior marketing capabilities can inhibit the ability to leverage OI (Jang & von Zedtwitz, 2023), the literature often highlights that effective communication facilitates OI initiatives, fostering knowledge sharing, collaboration, and network building (Chesbrough & Appleyard, 2007; West & Gallagher, 2006). Communication in OI extends beyond traditional boundaries, with organizations actively involving external stakeholders, particularly customers, as co-creators (Sharma et al., 2014). This customer-centric approach empowers organizations to externalize their marketing efforts by engaging customers in innovation (e.g., through contests and crowdsourcing), fostering a sense of co-ownership and collaboration. A relevant aspect of this relationship is the integration between marketing and R&D functions (Joueid & Coenders, 2018). Indeed, by involving customers in the innovation process, organizations can gain valuable insights into customer needs, preferences and behaviors, informing the development of new products and services (Joueid & Coenders, 2018).

Diverse communication channels, including online platforms and OI contests, enable organizations to harness the collective intelligence of their customers and external communities (Dahlander & Gann, 2010; West & Gallagher, 2006). These communication channels facilitate effective knowledge dissemination, collaboration and engagement, enhancing OI outcomes. Furthermore, several studies analyzed the extent to which firms can leverage social media to access knowledge from external actors, yielding mixed results (Corral de Zubielqui et al., 2019; Du et al., 2016; Marion et al., 2014; Roberts & Candi, 2014). In a more recent study, Barlatier et al. (2023) showed how different activities on social media can contribute to defining distinct social media-enabled strategies for OI.

Only very few studies have addressed OI as a communication subject to some extent. In particular, Antonelli et al. (2022) showed that the Open COVID Pledge – an OI initiative aimed to publicly share intellectual property free of charge to tackle the COVID-19 pandemic – achieved great media resonance. Furthermore, Greco et al. (2022) examined the motivations underlying innovation projects tackling the COVID-19 challenge, noting marketing potential among the reasons for initiating the projects. Outside the peculiar COVID-19 context, to the best of our knowledge, no study has investigated the potential of OI as a marketing tool. However, some insights can be drawn from the neighboring literature on open data, where reputation and legitimacy are among the key reasons to invest in open data (Temiz et al., 2022; Yang & Wu, 2016). Interestingly, Temiz et al. (2022) found that organizations primarily invest in open data for legitimacy reasons, either to imitate their competitors or to be perceived favorably by the media and public.

The debate on how reputation benefits can contribute to value capturing through OI is in its early stage, and future research should consider it, as Toroslu et al. (2023) pointed out.

2.2. *Institutional forces inducing open innovation and its dissemination*

In line with the Resource-Based View (Wernerfelt, 1984), OI initiatives are often driven by the need to access and leverage critical resources that are beyond the organization's boundaries to innovate. In designing this study, we focused instead on the institutional motivations leading a firm to adopt OI and publicly communicate this choice, highlighting the roles of coercive, mimetic and normative processes.

Coercive processes include the pressures to comply with regulations and social norms (Mizruchi & Fein, 1999). On the one hand, firms are encouraged to collaborate with others to obtain public subsidies (Greco et al., 2017), a formal source of coercive pressure. On the other hand, society favors firms that invest in innovation (Kunz et al., 2011), which serves as an informal source of coercive pressure. Consistently, boosting corporate image is among the primary motives driving firms to patent (Holgersson & Granstrand, 2017). The openness of an innovation process particularly pleases society. For instance, this is the case of open source communities, where firms contribute to nurturing public relationships and gaining legitimacy rather than generating revenue streams (Lerner & Tirole, 2002). Thus, since a declared openness in the approach to innovation may enhance a firm's corporate image (Grimaldi et al., 2021), the coercive pressure exerted by society may urge firms to embrace the OI paradigm.

Mimetic processes entail imitating the successful practices of others to enhance performance and reduce uncertainty (DiMaggio & Powell, 1983). As more and more "champions" in their respective industries publicly sponsor OI initiatives (Aloini et al., 2017; Dodgson et al., 2006; Toldbod & Laursen, 2024), mimetic forces may encourage other firms to follow their lead.

Last, professional communities shape normative processes since formal education and networks influence the adoption of legitimate practices (DiMaggio & Powell, 1983). OI is now widely discussed in the innovation management modules of Master's and Ph.D. programs (Mention et al., 2016), triggering a normative force that encourages managers to leverage OI in their firms.

Overall, firms have solid institutional motivations to embrace OI. While industrial motivations for OI are self-rewarding, with OI contributing to industrial goals such as product and process innovation, firms pursuing OI to respond to societal pressure are likely to disseminate their initiatives and gain legitimacy by showing that they are meeting expectations. Naturally, the strategic response to institutional pressures can differ markedly from firm to firm, including acquiescence, compromise, avoidance, defiance, and manipulation (Oliver, 1991). In other words, firms may fully embrace OI, adopt it selectively, avoid using it while disguising nonconformity, ignore it, or actively manipulate institutional forces to enhance legitimacy. Environmental protection, another context where institutional pressure is intense, clearly shows that firms' strategies can range from "substantial" to "symbolic" use of sustainable practices, with the latter giving rise to the greenwashing phenomenon (Testa et al., 2018).

As in the case of green innovation strategies, whose adoption and disclosure send a "signal" to customers and can enhance firms' likability (Khan et al., 2021), similar outcomes can be expected after the disclosure of OI initiatives. This signaling process can reduce information asymmetry between the firm and its stakeholders (Spence, 2002) regarding how it embraces the OI paradigm. However, according to the signaling theory (Connelly et al., 2011), cheap signals (i.e., in our context, merely mentioning an OI initiative without an accurate description) are likely to be less credible and impactful than high-cost signals (i.e., signals characterized by a thorough description of the initiative).

3. Methodology

This section describes the methodology used to address the RQs, detailing how we collected and analyzed tweets about OI.

3.1. *Data collection*

Our reasoning about the institutional forces pushing firms' decisions to launch and disseminate OI initiatives influenced the query design. In particular, if a firm believes that disseminating OI helps show its alignment with societal expectations, it will want to explicitly mention "open innovation" in its social media posts. Therefore, this study does not target tweets that mention possible synonyms for OI, such as inter-organizational collaboration, because the purposeful communication of OI initiatives would not be guaranteed. Furthermore, we included only English-language tweets to ensure comparability and analyzed those published in 2018 and 2023. The 2018 dataset aimed to avoid the potential effects of the COVID-19 pandemic in subsequent years. Indeed, the COVID-19 pandemic could have significantly enhanced society's appreciation for firms pursuing OI to address COVID-related issues, disproportionately incentivizing firms to disseminate these initiatives. The 2023 dataset enriched the analysis with more recent data, no longer affected by the communication hype of the COVID-19 period.

Based on these considerations, we implemented the following two queries.

Query A[1] for 2018, implemented in 2023, returned 14′269 tweets. The search string returned both data that explicitly included the word open innovation and tweets related to the topic. Therefore, we implemented a subsequent filtering process, detailed in Fig. 1.

Query B for 2023, implemented in 2024, suffered from the more recent limitations of X's standard APIs, which did not allow the complete download of coherent tweets but returned tweets "relevant" to the query. Consequently, replicating Query A for the year 2023[2] returned only 476 results that included the term "open innovation" and hundreds more – either sponsored or potentially related to the term – that did not include it. To mitigate the sudden change in this policy, we expanded our initial query to include #openinnovation[3] and relevant synonyms of OI identified in a literature review[4] (Toroslu et al., 2023). In other words, using synonyms in query B enabled the collection of a larger number of potentially relevant tweets about OI, resulting in 8'166 tweets.

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[1] Query A: "*open innovation" lang:en since:2018–01-01 until:2018–12-31*.

[2] Query B1 "*open innovation" lang:en since:2023–01-01 until:2023–12-31*.

[3] Query B2 "*#openinnovation" lang:en since:2023–01-01 until:2023–12-31*.

[4] Query B3 "distributed innovation" OR "external innovation" OR (co-creation innovation) OR (cocreation innovation) OR (crowdsourcing innovation) OR "user innovation" OR ((coopetition OR coopetitor) AND innovation) OR ((co-opetitor OR co-opetition) AND innovation) OR ("open source" innovation) OR "R&D collaboration" OR (cooperation innovation) OR (cooperative innovation) OR "innovation partnership" OR "supplier collaboration" innovation OR "customer collaboration" innovation OR "university collaboration" innovation OR "university industry collaboration" innovation OR "B2B collaboration" innovation OR "joint venture" innovation OR "interfirm innovation" OR "inter-organizational innovation" OR "interorganisational innovation" OR hackathon innovation OR "co-innovation" OR "R&D alliance" *"lang:en since:2023–01-01 until:2023–12-31*.

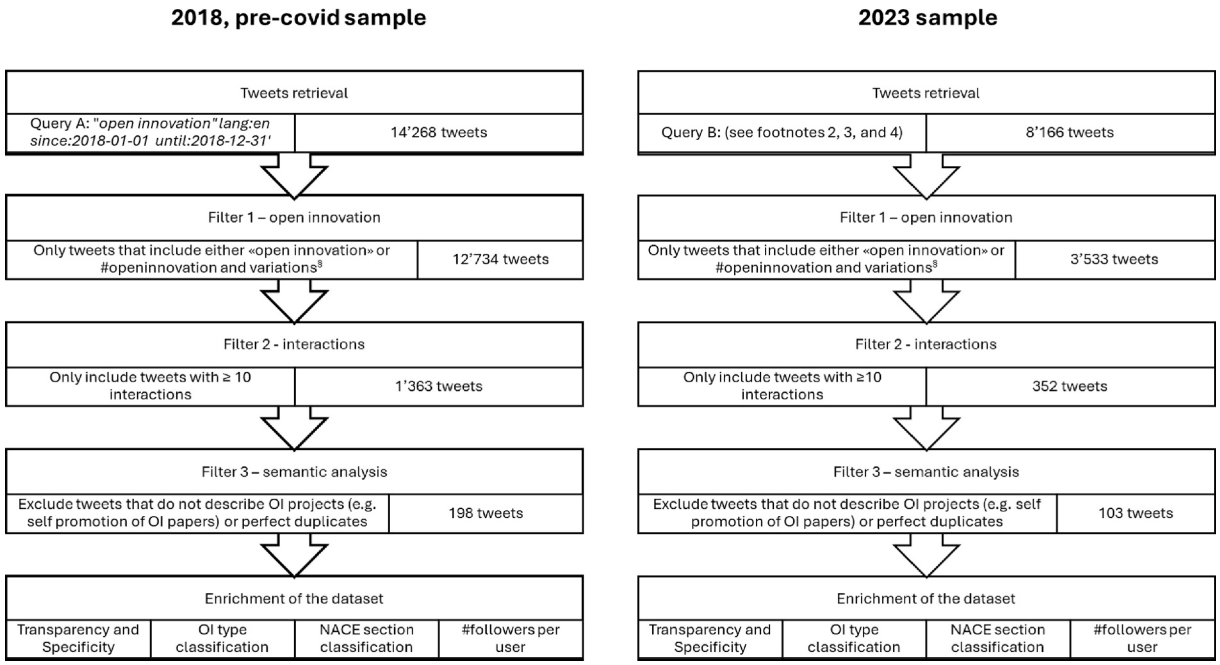

Fig. 1. Research protocol. Notes: § Variations including different capitalization of the words and hybrids, such as open #innovation or open-innovation, were also considered in Filter 2.

We used the *snscrape* Python library to extract relevant tweet data by leveraging the Twitter API.

Fig. 1 summarizes the research protocol we followed to capture relevant OI tweets. First, we applied Filter 1 to both the 2018 and 2023 datasets to exclude tweets that did not explicitly cite OI. Unsurprisingly, based on X’s new policy, a larger percentage of tweets in 2023 were discarded in this stage. Importantly, Filter 1 helped make the two samples comparable, since only tweets explicitly citing OI were kept.

Second, we applied Filter 2, restricting the sample to tweets that received 10 or more interactions. This approach ensured that the dataset was: 1. manageable, considering the manual and time-consuming nature of the analysis; 2. heterogeneous, including an ample array of tweets whose interactions span from 10 to over 300′000; and 3. relevant, as it includes those tweets that triggered at least a minimum degree of engagement. We assessed the total number of interactions by summing the likes, retweets, and comments for each tweet. This comprehensive approach captures user engagement, including likes as endorsements, retweets for dissemination, and comments for interactive dialogues. These metrics measure the impact and resonance of tweets, facilitating a thorough analysis and interpretation.

Third, we analyzed each tweet to exclude those that did not describe firms’ OI initiatives, such as scholarly tweets promoting articles, research projects, or conferences on OI, as well as tweets describing public programs or general news on OI. The core dataset of relevant tweets consists of 301 tweets.

3.2. Data analysis

Two main phases characterized the data analysis: content analysis and regression analysis.

3.2.1. Content analysis

We conducted a content analysis of the tweets. Content analysis entails categorizing and coding textual data to identify patterns and trends (Stemler, 2009). Content analysis aligns with our goal of assessing the credibility of the OI information shared on Twitter. We considered the accuracy of the OI initiative description as a proxy for a tweet's credibility. We operationalized two nuances of accuracy using the variables transparency and specificity, defined with four-level Likert-scale items, removing the intermediate level to avoid neutrality in the analysis.

We evaluated the *transparency* variable by assessing to what extent a tweet enabled the collection of clear information about the shared OI initiative, at least through external informative URLs if not in the tweet’s text. Instead, the *specificity* variable gauged the level of detail and precision in the information presented along three dimensions that characterize OI initiatives: 1. their aim, 2. their underlying activities, and 3. the partners involved. Therefore, we conceived one item for *transparency* and three items for *specificity*, as shown in Table 1.

We preferred using such novel OI-specific items rather than resorting to more generic scales, such as those assessing the credibility of online content (Bae et al., 2017), which directly ask to what extent the online content is reliable, truthful and credible. We believe that a more specific framing of the item improves the accuracy, validity and reliability of the variables.

At the beginning of the process, we created a codebook with exemplary tweets and guidelines to ensure consistency across the assessments of different researchers. Each tweet was initially coded by at least one researcher or research assistant and then reviewed by a senior researcher with more than a decade of experience in the OI field. In the case of discrepancy, the latter amended the coding to ensure consistency. We chose to conduct this analysis manually since we aimed to identify the perceived transparency and specificity of the tweets, which require nuanced human judgment. A non-manual approach would have required massive training for artificial intelligence and would have been

Table 1
Transparency and specificity items.

Construct	Description
transparency	The tweet allows for gathering detailed information about the shared OI initiative (e.g., via a link).
specificity(aim)	The tweet provides details about the OI initiative's goal.
specificity (activities)	The tweet provides details on specific activities or projects that the OI partnership is undertaking.
specificity (partners)	The tweet indicates the partners in the OI initiative.

beyond the reach of other automated classification systems, such as Latent Dirichlet Allocation. In addition, analyzing OI tweets can require watching and interpreting videos or animated images, scrolling through the event photos attached to the tweets, or visiting the linked URLs, which significantly increases the complexity of an automated approach.

Table 2 shows examples of extreme values of *specificity* and *transparency*. Specificity focuses on the tweet's core content, while transparency also considers the information in linked web pages. Even though some correlation between the two constructs is expected, cases with comparatively low specificity and high transparency may occur; for example, when most relevant information is conveyed through an external URL. The opposite – low transparency with high specificity – is less common since a very specific tweet inherently offers reasonably transparent information.

We assigned a NACE code for each OI initiative (see Table A1 in the Appendix). The NACE code, derived from the EU nomenclature of economic activities, provides a standardized classification system for economic activities (Eurostat, 2008). Through this process, we identified the industry affiliation of each OI initiative to gain insights into the distribution of tweets across sectors.

Table 2

Tweets with very high or very low scores in Transparency and Specificity.

Type of value	Tweet	Rationale
High *specificity* and *transparency* (4 in each item)	The countdown officially started ⏰ one week left to participate in the Open Innovation Challenge! Read more here ▶ https://fire-res.eu/open-innovation-challenge/Link : https://x.com/FIRERESProject/status/1724108645183447458	The purpose of the OI challenge and who organizes it are apparent. A figure in the tweet also provides additional information about the challenge. An external URL offers more detailed information for complete transparency.
Low *specificity* (1 in each *specificity* item) and low *transparency* (1)	Looking forward to finding out the winner of Ferrovial's Open Innovation Challenge today! @ferrovial Enhorabuena @guiadeonda https://t.co/c3Fe7VQT8A	We understand this is an OI challenge, but we are unsure who participated or what its purpose was. We need to search for Ferrovial to realize that the challenge probably focuses on the construction industry.
High *transparency* (3), low *specificity* (1, 1, 3)	"We are unequivocally putting a stake in the ground that innovation is our future". Richard Zane @UCHealth will open innovation lab in Denver's @Catalyst HTI (Health Tech Innovation) building #healthinnovation https://dpo.st/2JGE8oV Link: https://twitter.com/Cascadia/status/1006974232276766720	We understand that the tweet promotes an OI lab by UCHealth, but we are unsure of its purpose or how it will function. However, an external URL provides more thorough information. By reading the latter, we find that other organizations are involved, which were not mentioned in the tweet.
Low *transparency* (2), high *specificity* (4, 3, 4)	.@Blackboard's Open Innovation Initiative is now supported via Amazon Web Services AMI. http://amzn.to/2D6v6it Link: https://x.com/AWS_Edu/status/950398195808591874	Thanks to an image in the tweet, we understand that Amazon licensed a technology to Blackboard Learn. Therefore, we understand which parties are involved, the purpose of the initiative, and (roughly) how the technology works. However, neither the tweet nor the external URL describes the OI initiative; rather, they focus on how Blackboard Learn will utilize the licensed technology.

Based on our review of the literature, we identified nine categories of OI initiatives to classify the tweets (Table 3); in this article, we refer to these as "OI categories". Of note, during the coding, we remained open to adding categories; however, all the tweets were classified into the proposed categories.

3.2.2. *Regression analysis*

We conducted a Poisson regression analysis to examine the relationship between the number of tweets' interactions (a count variable) and the presence of the term "open innovation" in their content. Indeed, Poisson regressions are particularly suitable for count variables (Wooldridge, 2009).

First, we examined the relationship between tweets' interactions and the presence of "open innovation" or "#openinnovation" in them, using our initial sample of 22,434 tweets, without applying any filters. Such preliminary research (Model 0) aimed to verify whether using the two terms was associated with a higher likelihood of the tweet being liked, regardless of its transparency and specificity (i.e., credibility), and the type of initiative described in the tweet. In this model, we also included control variables likely to affect interactions, such as the use of emojis, images, videos, and URLs in the tweet (Li & Xie, 2020; Xu & Chawla, 2017). These binary variables were assigned a value of 1 for tweets containing embedded emoji, images, videos, or external URLs, and 0 otherwise. The regression was performed with robust standard errors.

Second, in Model 1, we focused on our core sample of 301 tweets describing OI initiatives with at least 10 interactions[5] to identify any significant differences from Model 0.

In Model 2, we added the *transparency* and *specificity* variables to assess their link with the tweets' impact.

Table 3

Categories of OI initiatives.

Categories of OI initiatives	Description	Source
Corporate innovation labs/incubators/accelerators	Virtual or physical programs to incubate or accelerate initiatives	(Blume, 2020)
Innovation contests, hackathons, crowdsourcing, and technology scouting	Competitions or contests to gather ideas or technical solutions	(Boudreau & Lakhani, 2013; Chesbrough, 2006; Enkel et al., 2009)
Innovation networks, platforms, and ecosystems	Platforms or networks involving many organizations that pursue a common goal	(Enkel et al., 2009; Osorno & Medrano, 2022; Schepis et al., 2021; Xie & Wang, 2020)
Innovation partnerships	Two or more organizations collaborating on an OI initiative	(Chesbrough, 2003a)
Joint ventures	Two or more organizations incorporating a new venture to pursue an OI initiative	(Enkel et al., 2009)
Licensing and technology transfer	A firm licensing its IP to others	(Blume, 2020; Chesbrough, 2003c)
Open source	OI applied to open-source projects	(Lakhani & Wolf, 2003)
Spin-offs and startups	Other OI initiatives involving startup companies or spin-offs	(Chesbrough, 2003c; Enkel et al., 2009)
Venture capital	Venture capital initiatives triggering OI	(Blume, 2020)

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[5] These correspond roughly to the first decile of the tweets in our sample, interactions-wise.

Lastly, in Model 3, we introduced a variable to assess the user's number of followers, which we retrieved separately for each username, since having more followers is likely to increase interactions. To do so, we utilized Social Blade, a specialized third-party site that archives public Twitter metadata over time. When data on the user's number of followers were unavailable for the tweet's reference year (usually from the 2018 data set), we used the closest available data. In a few cases, for instance, we resorted to the number of followers available in 2023 for tweets shared in 2018. We mitigated the risk associated with this source of inaccuracy by standardizing the variable, which, from a range of 0–325,264 (std. dev. 4,288), was transformed into a variable with a unitary standard deviation in the range of (-0.19,12.5), where differences in thousands of followers are negligible. Such a transformation was also useful for reducing heteroskedasticity. Data on three user followers in the 2018 dataset were unavailable; therefore, we treated the corresponding observations as missing.

4. Results

This section first presents a descriptive analysis of the tweets, providing insights into the distribution of the variables. It presents the regression results and concludes with a discussion of robustness checks.

4.1. Descriptive analysis

We calculated Cronbach's alpha coefficients for the three *specificity* items to verify whether they could be aggregated in a single *specificity* variable. The Cronbach's alpha value was 0.917, which is high and well above the desirable thresholds of 0.7–0.8, indicating that the three nuances of specificity are coherent and can be analyzed together. Table 4 presents the descriptive statistics of the variables.

Fig. 2 is a heatmap illustrating the tweets' distribution by OI category and NACE section; the numbers in each cell indicate the number of retrieved tweets for each combination. Of note, most tweets pertain to the "M – Professional, scientific, and technical activities" and "J – Information and communication" sectors, while innovation contests and hackathons dominate the OI categories, followed by "Corporate innovation labs/incubators/accelerators", "Innovation networks, platforms and ecosystems", and "Innovation partnerships". Some OI categories were very scarcely observed, such as "Joint ventures" and "Licensing and technology transfer". Possibly, these were not explicitly advertised as OI initiatives, suggesting that, even though the OI literature considers them fundamental forms of OI, the industry may view them differently, perhaps because they convey practices that are much older than OI. Another interpretation would be that such initiatives are more delicate from a communication perspective, and firms may not want to disseminate them on social media.

Many NACE sections were scarcely cited. On the one hand, this may suggest that OI tweets are more frequent in sectors with higher digital maturity. For instance, OI technological solutions and IoT are often sought for or presented even in comparatively more traditional sectors such as "A – Agriculture", where tweets are fewer than in IT-intensive sectors. On the other hand, industry-specific communication patterns may shape how OI is discussed on social media.

4.2. Regression analysis

Table 5 shows Model 0, which yields a surprising result: the explicit presence of OI, either as a keyword or a hashtag, is negatively associated with the number of interactions. We replicated the regression model by splitting the sample by year of the tweet to identify any significant shifts. Interestingly, while in 2018 the negative effect was much weaker for #openinnovation and not even statistically significant for open innovation as a keyword, the relationship is very strong in 2023.

Table 6 presents Poisson regression models limited to the core sample of tweets that described actual OI initiatives and received at least 10 interactions. The results differ markedly from those of Model 0. First, the presence of an OI hashtag or keyword is positively associated with the number of interactions. The latter's coefficient and statistical significance depict a much stronger effect than the former. Second, the *transparency* coefficient is positive and statistically significant, while *specificity* is positive and weakly statistically significant. Among the OI categories, Open source, Innovation partnerships, and Innovation contests garner more interactions than the reference category (Corporate innovation labs), whereas, somewhat surprisingly, tweets related to the construction industry (F) are comparatively more successful.

More intuitively, the variable describing the standardized number of followers has a positive impact on the number of interactions. In contrast, the presence of an image, emoji, or video is not statistically significant. Another surprising result is the weakly negative statistical significance of external links attached to the tweet. Such a result may be explained by the fact that some of the potentially positive impact of a URL is captured by the transparency variable, which is influenced by it; externally provided URLs enhance transparency when they are relevant, but not when they are irrelevant.

4.3. Robustness checks

We replicated Model 0 using a Zero-inflated Poisson regression, which is appropriate for count variables with many zeroes, as in the case of tweets' interactions, obtaining consistent results. We also performed a standard OLS regression after applying a logarithmic transformation to the variable *interactions*, obtaining consistent results.

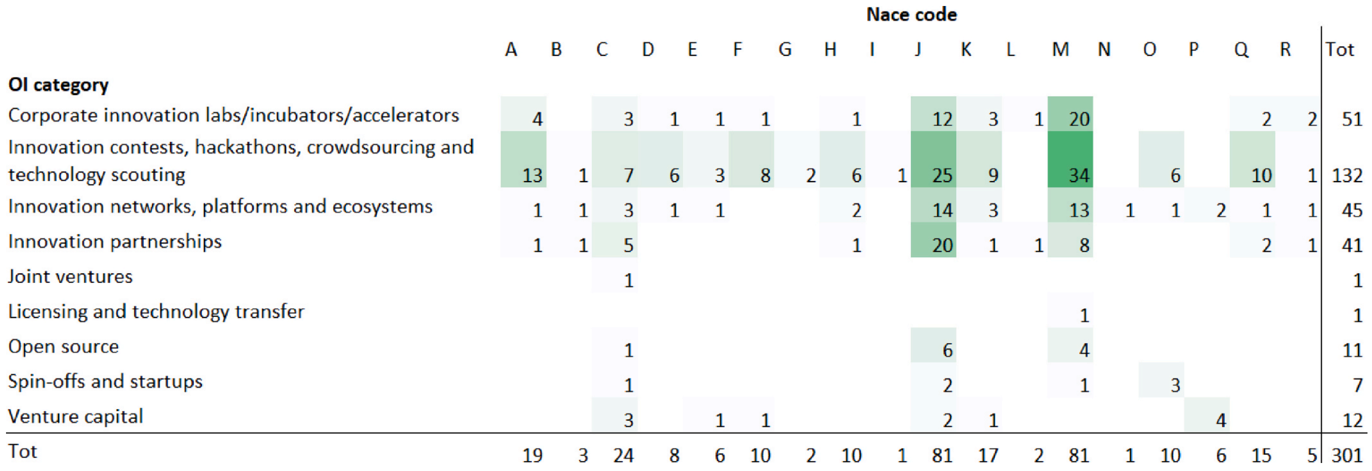
We replicated Model 3, splitting it by year of the tweets: Model 3a (2018) and Model 3b (2023). Both models support the role played by *transparency,* whereas Model 3′s findings on OI keywords are only supported by Model 3b. The lack of statistical significance is likely due to the small number of observations compared to the number of variables. We also replicated Model 3 using a Zero-inflated Poisson regression, which supports the role played by *transparency* and the two OI keywords, whereas *specificity* is not statistically significant.

Furthermore, we replicated Models 2 and 3 using an overall accuracy measure that integrates the three items of specificity with transparency (Cronbach's Alpha of the construct is 0.9404). The *accuracy* variable

Table 4

Descriptive statistics and Pearson's correlation matrix.

	Variable	obs	Mean	St.Dev.	Min	Max	1	2	3	4	5	6	7	8	9
1	*interactions*	22,434	108.03	4288.34	0	325,264									
2	*transparency*	301	2.81	0.88	1	4	0.27								
3	*specificity*	301	2.72	0.87	1	4	0.19	0.70							
4	*followers (std)*	295	−0.01	1.00	−0.19	12.52	0.16	0.05	−0.06						
5	*#openinnovation (keyword)*	22,434	0.08	0.27	0	1	0.01	0.04	0.04	−0.03					
6	*open innovation (keyword)*	22,434	0.71	0.45	0	1	0.06	−0.02	−0.06	0.02	−0.47				
7	*image*	22,434	0.14	0.34	0	1	−0.31	−0.14	−0.10	−0.04	0.03	−0.09			
8	*emoji*	22,434	0.14	0.35	0	1	−0.07	0.11	0.16	−0.05	0.20	−0.06	0.15		
9	*video*	22,434	0.02	0.12	0	1	−0.02	−0.02	0.06	−0.03	−0.04	0.02	−0.21	0.03	
10	*URL*	22,434	0.37	0.48	0	1	−0.08	0.50	0.34	0.05	0.05	−0.06	0.06	0.16	−0.06



	Nace code																		
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	Tot
OI category																			
Corporate innovation labs/incubators/accelerators	4		3	1	1	1		1		12	3	1	20				2	2	51
Innovation contests, hackathons, crowdsourcing and technology scouting	13	1	7	6	3	8	2	6	1	25	9		34		6		10	1	132
Innovation networks, platforms and ecosystems	1	1	3	1	1			2		14	3		13	1	1	2	1	1	45
Innovation partnerships	1	1	5					1		20	1	1	8				2	1	41
Joint ventures			1																1
Licensing and technology transfer													1						1
Open source			1							6			4						11
Spin-offs and startups			1							2			1		3				7
Venture capital			3		1	1				2	1					4			12
Tot	19	3	24	8	6	10	2	10	1	81	17	2	81	1	10	6	15	5	301

Fig. 2. Heatmap of the number of tweets. Grouped by OI category and NACE Sector (see Table A1 for the sector legend). Note: a brighter green corresponds to a higher number of tweets in the cell.

Table 5
Model 0, Poisson regression on the interactions count (robust standard errors). Bold coefficients are statistically significant, at least at the 0.1 level.

	Model 0 (baseline)			Model 0a (2018 only)			Model 0b (2023 only)		
	Coef.	St. E.	p	Coef.	St. E.	p	Coef.	St. E.	p
#openinnovation (keyword)	**−2.92**	0.529	0.000	**−0.54**	0.088	0.000	**−3.43**	0.825	0.000
open innovation (keyword)	**−3.59**	0.368	0.000	−0.04	0.096	0.68	**−3.51**	0.451	0.000
image	0.60	0.527	0.257	**2.31**	0.562	0.000	0.32	0.548	0.56
emoji	**1.19**	0.463	0.010	**0.33**	0.158	0.036	**0.99**	0.480	0.039
video	**1.97**	0.660	0.003	**3.11**	0.722	0.000	**1.70**	0.672	0.012
URL	−0.73	0.510	0.151	**0.34**	0.093	0.000	−0.78	0.525	0.137
R-squared	0.2437			0.0912			0.15		
Observations	22,434			14,268			8166		

confirms its positive effect on interactions, and all other results remain consistent.

5. Discussions

This article was driven by the following rationale: institutional pressures may induce firms to communicate their alignment with society's expectations and obtain legitimacy (DiMaggio & Powell, 1983). In turn, legitimacy could affect firms' likeability, as in the case of firms that disclose green innovation strategies (Khan et al., 2021). Our research focused on a specific means to convey a firm's commitment to OI: its Twitter (X) communication activity. In particular, to address our first RQ, "Does the public engage more with communication activities that include the term "open innovation" than others?", we focused on an engagement-related variable that indicates users' appreciation: the number of interactions a tweet receives. Our initial findings in Model 0 suggest that using the term "open innovation" or its corresponding hashtag in a tweet does not increase interactions. Instead, Models 1–3 show opposite results and support a positive relationship. These contradictory results have a reasonable explanation. The expanded sample in Model 0 includes thousands of tweets that use OI to promote articles, conferences and speeches, which have been removed from this article's core sample. Indeed, the core sample focuses on "actual" OI involving organizations rather than articles and conferences, and it is better suited to address the first RQ.

Notably, Model 3 provides insights into the interactions gathered by different OI activities. On the one hand, the positive performance of open source and innovation contexts may be reasonably explained by their inherent ability to mobilize broader groups of people into the initiatives, who are then more likely to engage with posts. On the other hand, the significant relationship between Innovation partnerships and tweet interactions seems less likely to be affected by reactions from people directly involved in the OI initiative, which are usually fewer than in open-source communities. Therefore, the result may hint at informal coercive pressure from society: the public appreciates innovation partnerships and rewards them with more interactions.

The discrepancy between the results in Model 1 and Model 3 allows for a nuanced answer to the research question, which we formulate as two propositions.

> *P1: Using the term open innovation in a social media post is not sufficient to increase public engagement.*
> *P2: Combining the term open innovation with the description of an actual OI initiative in a firm's social media post increases its credibility and is associated with a higher level of public interaction.*

The second proposition paves the way for addressing the second RQ: "Does the effectiveness of OI communication on social media increase with the credibility of the shared content?". Indeed, while all tweets in the core sample focused on an OI initiative, they differed significantly in terms of how accurately they were described. As aforementioned, we considered the accuracy of the OI initiative description as a proxy for a tweet's credibility. We used two novel variables, *transparency* and *specificity*, to assess such accuracy. From a signaling theory perspective, the firms' tweets can be considered signals. The cost of these signals is essential for their impact (Connelly et al., 2011). Intuitively, low transparency and specificity would describe a cheaper, less accurate signal, which would be less credible and impactful than high-quality ones in terms of likeability. Models 1–3 strongly support the positive effect of *transparency*, whereas the positive impact of *specificity* was somewhat weaker, as indicated by its coefficient, statistical significance, and robustness. Therefore, we propose that:

Table 6

Models 1–3: Poisson regression models on the interactions count (robust standard errors). Factor variables (OI categories and NACE sections) are described in relation to the reference category. OI categories and NACE sections with fewer than 10 observations were grouped into a residual “Other” class.

	Model 1			**Model 2**			**Model 3**		
	Coef.	St.Er.	p	Coef.	St.Er.	p	Coef.	St.Er.	p
transparency				**1.20**	0.370	0.001	**0.95**	0.218	0.000
specificity				0.19	0.217	0.372	**0.39**	0.233	0.097
#openinnovation (keyword)	**2.00**	0.871	0.021	**1.67**	0.716	0.019	**1.65**	0.717	0.022
open innovation (keyword)	**4.33**	1.013	0.000	**3.91**	0.890	0.000	**3.91**	0.886	0.000
image	0.39	0.336	0.248	0.59	0.366	0.105	0.55	0.357	0.122
emoji	−0.43	0.565	0.447	−0.32	0.451	0.479	−0.24	0.441	0.590
video	−0.45	0.809	0.574	−0.53	0.521	0.305	−0.30	0.475	0.534
URL	0.43	0.332	0.195	−0.85	0.453	0.061	**−0.78**	0.410	0.056
followers (std)							**0.29**	0.077	0.000
OI category (w.r.t. corporate inn labs)									
Innovation contests, hackathons, …	0.73	0.552	0.186	1.11	0.836	0.183	**1.06**	0.622	0.087
Innovation networks, platforms, …	0.38	0.576	0.512	0.69	0.782	0.376	0.37	0.646	0.569
Innovation partnerships	**1.26**	0.612	0.039	1.23	0.820	0.132	**1.27**	0.738	0.086
Open source	**1.53**	0.618	0.013	**1.54**	0.818	0.060	**1.54**	0.738	0.037
Other	−0.33	0.714	0.647	0.18	0.849	0.830	0.44	0.770	0.565
NACE section (w.r.t. A)									
C	**2.48**	0.611	0.000	3.01	**0.601**	0.000	**2.69**	0.621	0.000
D	0.86	0.591	0.147	1.27	**0.669**	0.058	**1.35**	0.633	0.033
F	**4.59**	0.905	0.000	4.97	**0.774**	0.000	**4.54**	0.548	0.000
H	0.20	0.685	0.772	0.97	**0.562**	0.084	**0.99**	0.563	0.078
J	**2.16**	0.483	0.000	2.82	**0.513**	0.000	**2.66**	0.479	0.000
K	**1.15**	0.553	0.038	1.68	**0.558**	0.003	**1.74**	0.546	0.001
M	**2.14**	0.558	0.000	2.10	**0.432**	0.000	**2.11**	0.427	0.000
O	0.48	0.474	0.307	1.43	**0.585**	0.014	**1.39**	0.506	0.006
P	1.03	0.707	0.144	1.14	0.762	0.135	1.10	0.756	0.146
Q	**1.12**	0.554	0.043	1.54	**0.483**	0.001	**1.34**	0.466	0.004
Other	**1.30**	0.574	0.023	1.47	**0.576**	0.011	**1.61**	0.552	0.004
R-squared	0.396			0.551			0.606		
Observations	301			301			295		

> *P3: A higher accuracy in the description of OI initiatives increases public interaction.*

The results of this study contribute to the literature presented in Section 2. Indeed, they show that tweets including information about OI initiatives outperform others. This suggests the existence of informal coercive pressures (DiMaggio & Powell, 1983) from society on OI, as firms that signal their openness are “rewarded” by the public for their alignment. However, the term “open innovation” is not sufficient to foster appreciation. Indeed, consistent with signaling theory (Connelly et al., 2011), cheaper signals (i.e., using the OI term without providing accurate information) are less likely to elicit public action. Notably, since these results align with the signaling theory, we are confident they will also apply to other media. However, the extent to which transparency and specificity influence the effectiveness of OI communication may vary across media; for instance, based on the medium's features (e.g., character limitations or constraints on URLs, videos, and images) or the public’s characteristics.

Since this study used 2018 and 2023 data, we replicated all models, splitting the sample into two. Model 0b (year 2023) showed a stronger adverse effect of both OI as a keyword and as a hashtag. In contrast, in Model 0a (year 2018), the negative effect was much weaker for #openinnovation and not even statistically significant for OI. Such a result can stem from OI having reached its maturity 20 years after Chesbrough’s seminal studies (Chesbrough, 2003a, 2003b). Such maturity can be observed in the number of journal articles published on the topic, which peaked in 2021 and has remained substantially constant since, as well as in Google Trends, where peak interest was in 2017 and has gradually decreased since.

Interestingly, Model 3b (year 2023) showed a positive and statistically significant effect of OI as a keyword and hashtag on interactions, highlighting how P3 (and the need to describe OI projects accurately) is more relevant as the hype around the term “open innovation”, more than two decades after its conception, may be less intense. Therefore, practitioners are advised to craft their tweets with care. To support them in the effort, Table 7 presents guidelines to improve a tweet’s transparency and specificity, based on which practices made the tweets in our sample more transparent or specific. For instance, consider a tweet mentioned in Table 2: “*Looking forward to finding out the winner of Ferrovial's Open Innovation Challenge today! @ferrovial Enhorabuena @guiadeonda https://t.co/c3Fe7VQT8A*”. The tweet could have been improved by specifying its name (i.e., Build Up!, which can only be spotted in a picture), including a URL describing the contest, mentioning the participating teams, the purpose or scope of the contest (i.e., construction or, more specifically, safety in road maintenance), and how the competition was run (e.g., in a video or figure).

6. Conclusions and future research opportunities

This article analyzed a sample of tweets on OI to analyze whether mentioning OI in a firm’s communication activities is beneficial per se, in terms of the interactions it elicits, and whether more accurate and credible descriptions of OI initiatives in a firm’s communication

Table 7

Guidelines to improve *transparency* and *specificity*.

Transparency	Specificity
Articulate the purpose of the contents, objectives, or outcomes.	Provide details, such as names, affiliations, objectives, or focus on specific geographic areas to add depth and credibility to tweets.
Include further links or resources to enable access to additional information.	Use domain-specific information, such as industry-related terms, to cater to the targeted audience and establish expertise, but avoid overly complex sentences.
Avoid using excessive technical jargon, as it may make the tweet less understandable.	Offer contextual information to comprehensively present the topic, including background, motivations, and potential impacts of the OI initiative.

activities are needed to obtain such benefit. We found that the term "open innovation" positively affects the public's interactions only when it appears combined with an actual firm's OI initiative; it does not, for instance, in tweets disseminating news, articles, or conference announcements. We also found that a more accurate description of the OI initiative positively influences its communication impact, as measured by the number of interactions it receives. Interactions, though, represent just a means to assess how the public reacts to a firm's signals, leaving space for further questions. Are people more likely to appreciate firms that gather more interactions? Will they be buying more of their products? Will they want to work for them? Exploring the link between OI and firm likeability paves the way for a new, almost unexplored reason to embrace OI, which could impact its success and diffusion, while posing new threats in terms of the improper use of the OI catchword to obtain unwarranted communication benefits.

This study triggers several implications for scholars and practitioners, which are described in the following subsections, along with the limitations of this study.

6.1. Implications for scholars

This article leaves much space for future research. First, from a marketing perspective, future research could examine whether OI initiatives are associated with any "reward" in terms of brand awareness, brand likability, loyalty, or sales. For instance, a broad issue to address is the extent to which embracing and communicating OI enables the attainment of additional benefits beyond traditional industrial ones (e.g., new product and process development).

Second, from an institutional perspective, future research could investigate the nature and strength of institutional pressures, rather than industrial pressures (e.g., the need to solve a technological issue), that could induce a firm to embrace and disseminate OI initiatives. In other words, can institutional pressures be the primary motivation for organizing or joining an OI initiative?

Third, future research could investigate to what extent firms are induced to pretend they are embracing OI, for instance, by organizing OI initiatives aimed at engaging customers with no serious interest in the innovation outcomes. To this end, our measures for transparency and specificity can be considered proxies for the reliability of an OI initiative: the more transparent and specific the description, the more likely the OI initiative has solid industrial roots and has not been established primarily for communication purposes. In this vein, a new stream of research on "*open innovation washing*" – mimicking what happened with whitewashing or greenwashing – could stem from this study.

Fourth, while this study utilizes Twitter to address its research questions, its results could be tested in other social media outlets, or even in traditional media (e.g., by analyzing press releases). Understanding how the peculiarity of each medium affects the relationships among OI, interactions, transparency, and specificity would be important, with useful implications for practitioners.

Fifth, future research could investigate the impact of specific interventions to enhance the transparency and specificity of information shared on social media platforms, ultimately developing best practices for effectively communicating OI initiatives. Furthermore, the usefulness of more transparent and specific tweets could be analyzed outside the OI scope.

Sixth, while we assessed the impact of tweets on users by summing the number of likes, retweets, and comments, other studies could include additional engagement metrics, such as the sentiment and length of comments.

Seventh, future research on OI maturity could focus on verifying the possible link between actual OI initiatives and their dissemination on social media, as well as whether different industries have different preferred means and patterns for disseminating OI.

Lastly, conducting longitudinal studies to track changes in the transparency and specificity of information on social media would provide valuable insights into the evolving nature of the OI discourse.

6.2. Implications for practitioners

This study suggests communicating OI initiatives more thoroughly to better engage stakeholders. Indeed, merely mentioning "open innovation" may even be counterproductive if the communication is poorly crafted. Based on this, we provided recommendations for writing more impactful tweets. While these recommendations stem from analyzing successful tweets in the context of OI, they could also be applied more broadly to improve the effectiveness of tweet presentations across various domains and subject matters. Finally, although our results derive from the analysis of tweets, they are likely to apply more generally to firms' communication activities. Therefore, we encourage practitioners to use transparent and specific messages to leverage OI more effectively.

6.3. Limitations

This research presents at least two limitations. First, we analyzed only a fraction of the tweets on OI. Future studies could expand our analysis vertically, including tweets with fewer interactions, or horizontally, covering more years. Second, the article retrieved data from Twitter using two different methods in 2018 and 2023. We applied filters to make the two samples comparable and consistent, but we acknowledge that our approach may have influenced the results.

CRediT authorship contribution statement

Marco Greco: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Antonio Giovanni Yury Di Russo:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benito Mignacca:** Writing – review & editing, Writing – original draft, Methodology. **Amedeo Pata:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Industry type by NACE code letter.

Code	Industry Sector
A	Agriculture, forestry, and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam, and air conditioning supply
E	Water supply, sewerage, waste management, and remediation
F	Construction
G	Wholesale and retail trade; repair of motor vehicles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific, and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment, and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organizations and bodies

Table A2
Guidelines for consistent content analysis.

Variable	Value	Description
transparency	1	The tweet is uninformative on the OI initiative; no external URL is provided
transparency	2	Some information on the OI initiative is provided; no external URL is present; or, if present, it does not add much information
transparency	3	A provided external URL is needed to understand the OI initiative in full
transparency	4	Very detailed tweet and/or external URL
specificity (aim)	1	No aim is mentioned
specificity (aim)	2	The aim is generally “OI”
specificity (aim)	3	The aim is specified, but unclear
specificity (aim)	4	The aim is very clear
specificity (activities)	1	The activities are not mentioned
specificity (activities)	2	Some activities are vaguely mentioned
specificity (activities)	3	Most relevant activities are cited
specificity (activities)	4	The activities are described thoroughly
specificity (partners)	1	The partners are not mentioned
specificity (partners)	2	Only some partners are mentioned
specificity (partners)	3	Information on the partners can be retrieved with difficulty (e.g., they may be present in an attached video)
specificity (partners)	4	All the partners are mentioned

Data availability

Data will be made available on request.

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