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Going all in or spreading your bet: a configurational perspective on open innovation interaction channels in production sectors

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Abstract
Using different interaction channels within open innovation partnerships holds the potential to enhance the chance of success in production sectors. However, our comprehension of how open innovation partnerships are affected by varying combinations of interaction channels, and how this corelates with their level of open innovation output, remains limited. There are discrepancies in the current literature regarding the individual and combined effects of open innovation interaction channels. Our study aims to resolve these inconsistencies by using a configurational perspective, which allows for the identification of multiple successful pathways. Employing fuzzy-set Qualitative Comparative Analysis (fsQCA) to a dataset of European open innovation partnerships in production sectors, we uncover specific combinations of interaction channels that explain high levels of innovation outcomes. Subsequently, we distinguish between two successful pathways. Notably, we observe that the relationship between interaction channels is causally complex, high engagement in open innovation may not guarantee favorable innovation outcomes. This finding highlights the intricate causal dynamics at play. Thus, our study is a significant step toward reconciling the disparate perspectives in the literature concerning the impact of interaction channels on open innovation output.

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1. Introduction

The pursuit of intensified inter-organizational collaborations has emerged as a crucial factor for success in the context of open innovation (OI) (Majchrzak et al., 2023). Within an OI ecosystem, individual actors do not operate in isolation; instead, they engage in collaborative efforts, co-creating knowledge, and continuously adapting their range of interaction channels to generate new value (Ogink et al., 2023). The growing complexity of knowledge necessitates multiple innovation partnerships and diverse interaction channels to increase the potential of addressing appropriate innovation demands (Bogers et al., 2017). Open innovation interactions encompass different inbound, outbound, and coupled processes encompass representing the diversity of functions, relations, and organizational setups (Bogers et al., 2017; Audretsch & Belitski, 2023). These interactions can take many forms, including co-creation of innovation in science-industry partnerships and user innovation, crowdsourcing, patenting and licensing, utilizing open data, among others (Beck et al., 2022) Each of interaction channels has a core purpose to establish an environment that fosters innovation success, however, different interaction channels has distinct explicit and/or implicit impact on OI innovation output (e.g., Bogers et al., 2017; West and Bogers, 2014).

Previous research has approached the assessment of the importance of OI interactions in two distinct ways. The first approach examines the overall impact of OI interactions on innovation results without considering the specificities of each interaction channel (e.g., Rauter et al., 2019; Greco et al., 2016). The second focuses on the outcomes of individual interaction types (e.g., Pollok et al., 2019; Parida et al., 2012). Consequently, much of the nuanced interplay among underlying characteristics of OI interactions remain largely unexplored.

Recent academic papers have underscored the necessity for a deeper comprehension of causal complexity of interactions within OI contexts (Ogink et al., 2023; Radziwon et al., 2023). Researchers point to limited knowledge regarding the factors contributing to low levels of innovation output amidst extensive OI engagement (Brunswicker and Vanhaverbeke, 2015; Marzi et al., 2023). Not every interaction labelled as OI ensures mutual benefit, leading sometimes to hidden failures. Alongside Coad et al. (2021) and Stefan et al., (2022) we argue that this "dark side" of OI interactions, where failures emerge almost as likely as successes, needs further exploration.

Radziwon and Bogers (2019) underscore the significance of conducting comparative studies that encompass diverse ecosystems with distinct strategic profiles and advocate for exploring knowledge flow and governance within these contexts, that might have a weight over the OI effects. Building upon existing research agendas, scholars have stressed the need for additional studies that elucidate the complex processes governing interactions in ecosystems (Suominen et al., 2019; Robaczewska et al., 2019) and the causality that exist between these processes and outcomes (Milagres and Burcharth, 2019). Viewing OI partnerships from an ecosystem perspective reveals how they can extend an organizations's ability to capture resources and enhance the effectiveness of integrating them in the innovation process (West and Olk, 2023). This raises the significance of resource orchestration, which involves restructuring, bundling, and leveraging resources to realize potential (Sirmon et al., 2011). Derived from the resource-based approach, resource orchestration theory explores the competitive advantages gained through resource coordination, combination, and the transformation of these advantages into innovative output (Sirmon et al., 2011). While it is safe to assume that in the context of OI resource orchestration is critical for sustainable development and enhanced competitiveness (Cui et al., 2022), OI has not often been considered from an interdependence perspective (Sedita and Grandinetti, 2023; Barbosa et al., 2021). Some earlier conceptualizations have proposed that combinations of open innovation interactions could be more accurate predictors of innovation output compared to single interactions (Bogers et al., 2017; 2018). It has been observed that OI activities bring diverse effects, interacting in causally complex and synergistic ways (Milagres and Burcharth, 2019). Although there is a possibility that these interactions could be compensatory, with one interaction channel counterbalancing the others, research investigating this aspect remains lacking.

In the realm of empirical research in management discipline, traditional methods have often prioritized analyzing the isolated impacts of individual conditions rather than considering the interactions between multiple conditions (Ragin, 2014). However, to address the constraints of these traditional approaches and to study causal complexity effectively, scholars have turned to fuzzy qualitative comparative analysis (fsQCA) (Schneider and Wagemann, 2012; Ragin, 2014). The fsQCA method is specifically designed to address the mutual influence and interdependence of factors, offering valuable insights into the mechanisms of OI. By focusing on combinatorial effects, this method facilitates a more comprehensive understanding of OI processes. Additionally, fsQCA provides multiple analytical opportunities. One of the capabilities of fsQCA is its ability to examine the adequacy of numerous configurations leading to the same result, examine causal asymmetry, and therefore uncover various paths to OI success (Ragin, 2014; Fiss, 2011; Schneider and Wagemann, 2012; Kumar et al., 2022). In this way, fsQCA enhances our understanding of the complex relationships that drive OI interactions.

In light of the existing research and the calls made by different scholars (Bogers et al., 2017; Milagres and Burcharth, 2019; Ogink et al., 2023; Radziwon and Bogers, 2019; Bertello et al., 2023), this paper aims to contribute both theoretically and managerially by bringing a comprehension of the different combinations of interaction channels that lead to successful OI success. The central research question we address in this study is: "Which configurations of interaction channels are most beneficial in achieving high levels of OI outcomes?" To address this question, a multistage study design was employed. The research began with a thorough literature review and a series of initial background interviews. Subsequently, 29 European inter-organizational OI partnerships were selected for analysis. These partnerships operated within industry clusters and involved a diverse set of international partners. The fsQCA method was used to investigate how OI partners can effectively orchestrate interaction channels to achieve high levels of OI output. Through this analysis, the combined effect of resource orchestration channels on the OI process was examined, and the pathways through which these effects are achieved were identified.

This paper makes a valuable contribution to the OI literature by identifying configurations of interaction channels that facilitate innovation outputs and enrich the understanding of the complex mechanisms involved in choosing OI interactions that align with OI objectives. It stands as one of the first works that presents a framework and comprehensive analysis of the connected and interactive role of interaction channels in fostering high-level OI output, aligning with the emerging literature focused on gaining insights into the drivers of OI outputs (Bogers et al., 2017, 2018; Lee et al., 2019). The study's results highlight multiple pathways leading to OI success, indicating that different configurations of interaction channels can yield superior outcomes compared to relying on a single channel alone. By clarifying the interactive relationship between these successful interactions, the study identifies two types of engagements based on permutations of necessary and sufficient conditions. Additionally, the research sheds light on interactions that lead to low OI output, offering a novel perspective on OI effectiveness as there is a limited understanding about the conditions contributing to reduced innovation output despite high OI engagement (Brunswicker and Vanhaverbeke, 2015; Marzi et al., 2023). Furthermore, the study explores the reciprocal connection between resource orchestration and OI, enhancing the body of knowledge concerning resource orchestration as a multi-dimensional construct in the context of OI (Cui et al,, 2022; Carnes et al., 2017). Methodologically, the introduction of fsQCA into OI research unveils equivalent driving mechanisms of OI output from the causal asymmetry angle, offering the OI field a fresh outlook of studying samples of moderate size. The managerial insights derived from the findings can aid organizations in understanding how to design interaction channels effectively to promote high levels of OI outputs in production sectors, thus providing valuable guidance for real-world OI implementation.

2. Literature review

Open innovation (OI) can be characterized as a decentralized innovation approach that involves the governance of knowledge flows across organizational lines, both inbound and outbound, for financial and non-financial gains, conforming to the organization's commercial approach (Chesbrough et al., 2014). Comprehensive studies on OI has confirmed its significant benefits across various types of innovation (Bogers et al., 2017, 2018). However, the existing body of literature also acknowledges the presence of costs and downsides associated with OI (Dahlander et al., 2021; Stefan et al., 2022).

OI enables inter-organizational partnerships to transcend the constraints imposed by project or partner’s boundaries, allowing them to collaboratively focus on critical issues and develop innovative results. Nevertheless, when viewed from an cross-organizational standpoint, the efficacy of OI extends beyond the exchange of ideas in the initial phases of the innovation processes (e.g., Dahlander et al., 2021; Chesbrough and Bogers, 2014). OI frequently necessitates organizations to coordinate or engage in innovation partnerships through OI interaction channels, which involve a various range of innovation partners for the duration of different phases of the innovation cycle (West and Bogers, 2014). The significance of interaction channels in influencing OI output is well recognized, but their operationalization for years has primarily aimed at behavioral aspects rather than configurational routines. A concept proposed by Majchrzak et al. (2023) introduces "innovation-producing” interactions. In these OI interaction channels, actors are encouraged to share not only solutions but also crucial knowledge about the underlying problems. Interestingly, the best solutions tend to emerge after a diverse range of knowledge is contributed by others within the channel.

OI interaction channels encompass a variety of inbound, outbound, and coupled processes. These channels involve activities such as co-creation of innovation in science-industry user innovation, crowdsourcing, patenting and licensing, utilizing open data, among others (Beck et al., 2022) Bogers et al. (2017) emphasize the significance of OI channels, such as platform-based systems, crowdsourcing communities, and open data, as important contexts for future research on the network level. The requirement for a specific OI interaction type depends on the industry and commercial approach (Chesbrough and Bogers, 2014; Baldwin and Woodard, 2009). As a result, a fundamental inquiry related to the OI performance should revolve around configuring these successful connections.

2.1. Open Innovation interaction channels

One of the core interaction channels of OI is external knowledge sourcing. It involves utilization and aggregation of knowledge at a certain stage of readiness (Radziwon and Bogers, 2019), mainly through traditional market driven interactions i.e. sourcing knowledge from science and non-science partners (Laursen and Salter, 2006; Adner and Kapoor, (2010); Perkmann et al., 2013) It serves as a significant channel for both sharing existing knowledge and acquiring new and original insights. (Beck et al., 2022) This type of OI, involves inter-organizational partnerships, often in the form of university-industry projects. The level of interaction with partners can range from contributory to collaborative (Perkmann et al. 2013). The effect of such a partnership is not limited to formal project interactions; it also arises through less apparent functions such as commision projects, advisory, and staff exchange (D’Este et al., 2013).

Science-industry interactions often manifest as longstanding partnerships that leverage diverse facets for knowledge flow. These are typically founded on direct and non-formal connections between team members (e.g., Hossain and Kauranen, 2016). Personal connection in such partnerships fosters close relations between science and industry actors, stimulating mutually beneficial knowledge flows like training opportunities and resource accessibility (D’Este et al., 2013). Investigative advisory can also play a pivotal role in establishing trust among partners (Perkmann et al., 2013), which can lay the foundation for novel and enduring projects. Despite the potential benefits, the existing literature identifies numerous challenges that impact science-industry interactions. These challenges include organization innovation capability (Howells et al., 2012), partnership expectations (Steinmo and Rasmussen, 2018), and partnership risk (Radziwon and Bogers, 2019).

Platforms and complex systems represent OI formats that facilitate participation and contribution to open and distributed innovation platforms or communities (Baldwin and Woodard, 2009). Platforms are characterized by modular architectures that enable the creation and integration of diverse and interchangeable components, while complex systems are networks of interdependent and heterogeneous agents that interact and co-evolve over time (Schaffers et al., 2011). Interacting through platforms can take various forms, such as designing or adopting a platform architecture that enables modularity and interoperability, joining or creating a platform ecosystem that involves multiple actors and roles, developing or integrating platform components that add value and functionality, and governing or influencing the platform rules and standards that shape the behavior and outcomes of the system (Gawer and Cusumano, 2014). The existing body of research concerning platform-based systems highlights significant governance concerns. These include matters related to intellectual property control, technology access, and social aspects such as the importance of transparent information policies (Boudreau 2010; Bogers et al., 2017; Benlian et al., 2015). Platform innovation can be driven by technological change, market demand, or strategic intent; However, previous research has shown (Baldwin and Woodard, 2009), the platform architecture imposes constraints on conjunctional contingences. Over time, the platform architecture requires updates to ensure its continued relevance and effectiveness. In connection to OI, using platforms as an interaction channel can enhance the innovation performance of organizations by enabling scalability and flexibility, leveraging network effects and collective intelligence, fostering diversity and experimentation, and generating emergent and systemic properties (Gawer and Cusumano, 2014) Thus the effectiveness of utilizing this OI interaction channel depends largely on the size and composition of the platform (Isckia et al., 2020).

Technology transfer is the process of transferring and commercializing internal knowledge for the purpose of innovation (Teece, 1986).It is a type of OI interaction when contractual, intellectual property (IP), and other similar mechanisms play central role in the interaction. This direct control of OI interaction channel is often perceived by managers as the ideal, but it is increasingly difficult to achieve. Technology transfer in relation to OI can take various forms, such as revealing or protecting the knowledge through patents or other mechanisms, negotiating or licensing the knowledge to other parties, selling or spinning off the knowledge to create new ventures, partnering or collaborating with other parties to co-develop or co-exploit the knowledge, and disseminating or diffusing the knowledge to wider audiences (Chesbrough and Crowther, 2006). Organizations may use both formal and informal methods to protect safeguard their innovations and capitalize on its value. Formal methods include patent, copyrights, trademarks, while informal methods may include being the first to market, having a head start, or creating customer loyalty (Bigliardi et al., 2020). Technology transfer can enhance the OI innovation performance of organizations by capturing value from their knowledge assets, creating new revenue streams, reaching new markets or customers, fostering entrepreneurial culture, and stimulating feedback and learning (Nguyen et al., 2023). The IP protection type depends on the character of the collaboration and the kind of knowledge being shared (Bogers et al.,2018; Laursen et al., 2022). The issue at hand is determining the degree to which OI can be augmented with intellectual property protection and the circumstances under which this combination can foster dynamic innovation partnerships. Some of the factors that influence the effectiveness are: the sector's appropriability setup, the access to complementary assets and resources, the level of ambiguity and complexity of the technology, the strength of the relationships with other parties, and the legal and institutional frameworks (Hagedoorn and Zobel; 2015). It this OI interaction channel, it's important to address and handle the compromises that occur in innovative environments. Knowledge leakages, can for example hinder the possibility to obtain patents due to the need for novelty in the patent application. (Bogers et al., 2017).

User innovation is another crucial OI interaction type, where individuals can create or enhance products according to their own needs (von Hippel, 2009). Individuals or groups participate in the innovation cycle and contribute to user-driven innovation (Piller and West, 2014; Bogers et al., 2017). In fact, one of the biggest OI resources for companies is the knowledge and actions of individual or institutional consumers (Laursen and Salter 2006). User innovation can manifest in numerous ways, such as modifying or customizing existing offerings, creating or inventing fresh solutions, sharing or diffusing one's innovations with others, and adopting or commercializing others' innovations (von Hippel, 2009). Users play a vital role in contributing to organisations' OI process by sharing their views, derived from their experiences with the product. Moreover, they might engage in innovating and utilizing the products in fields beyond the scope of the organization (Bogers et al., 2010). Motivated by the enjoyment of the innovation process itself and the potential gains derived from the upgraded solution. Additionally, they are gaining symbolic capital through expressions of gratitude and recognition from their peers (Piller and West, 2014). Users can introduce diverse elements that contribute to the effectiveness of OI. User innovation can enhance the innovation performance of organizations by generating novel and valuable solutions, meeting latent or unmet needs, exploiting user feedback and learning, and creating user loyalty and advocacy (von Hippel, 2009). Another kind of input is motivation of users to contribute to OI interaction. Users exhibit varied capabilities and gains that are associated with significant possibilities in the OI process. These include personas, user interface, the type of innovations, and the IP setup, all of which are closely related to the performance of OI (Bogers et al., 2017). Several elements that influence the effectiveness of user innovation are: the intensity and heterogeneity of user needs, the availability and affordability of user toolkits, the degree of user involvement and empowerment, the protection and appropriation of user innovations, and the integration and collaboration between users and producers (von Hippel, 2009; West and Lakhani, 2008). Despite its great contribution literature shows that organizations often underestimate the potential of user innovation (Bradonjic et al., 2019). This could be attributed to several reasons, including indirect process of user engagement. Additionally, when user-driven solutions are commercialized by organizations, they are inadequately recognized as originating from users. Moreover, organizations may exhibit a bias connected to filtering and minimizing data about user innovation.

Crowdsourcing represents an alternative approach to obtaining knowledge from external stakeholders. It refers to the ability to solicit and utilize ideas, solutions or contributions from an extensive and varied array of individuals, often online (Afuah and Tucci 2012). Crowdsourcing involves organizations seeking solutions outside their organizational bounds by openly sharing the details of a challenge and encouraging stakeholders to engage in bringing ideas for the solution. (Christensen and Karlsson, 2019) Crowdsourcing can take various forms, such as posting or responding to challenges or contests, rating or commenting on ideas or solutions, solving or innovating on problems or tasks, and participating or contributing to communities or platforms (Estelles-Arolas and Gonzalez 2012). Crowdsourcing can enhance the innovation performance of organizations by tapping into the wisdom and creativity of the crowd, reducing costs and time, increasing diversity and quality, and fostering engagement and loyalty (Brabham, 2013). Some of the conditions that influence the effectiveness of crowdsourcing are: the design and attractiveness of the tasks or incentives, the amount and composition of the crowd, as well as the quality and compatibility of the ideas, and the feedback and recognition mechanisms (Majchrzak and Malhotra, 2020). As an OI interaction channel, crowdsourcing necessitates managers to reevaluate their structures of management and governance to stimulate knowledge transfer, inspire stakeholders, and ensure the appropriation of benefits. Organizations must consider how their own management and governance structures align with those of participants, depending on whether the process occurs personally or indirectly and whether it is in a form of competition or collaboration. Given the inclination for knowledge from external stakeholders and the need to attract participants, it becomes crucial to develop processes for efficient evaluation that involve selecting and adopting the suitable solutions (Piezunka and Dahlander, 2014). Empirical research indicates that crowdsourcing could be more suitable for downstream phases of the innovation process and its effectiveness relies on various factors, including the sector and location (Seidel et al., 2016; Bogers et al., 2017).

OI involving partners with the public sector shares similarities with partnerships encountered in the industry. However, there are also new mechanism, like the disclosing public data as open data (Hilgers and Ihl, 2010; Bogers et al., 2017). Open data refers to data disclosed for free by public organizations like local and regional administration or universities and others with some usage limitations but allowing the use of the data for various purposes (Sadiq and Indulska, 2017). For instance, in some countries research projects funded from public sources are obligated to disclose the data, allowing free access, use, and combination for new applications. This type OI interaction can take various forms, such as combining or analyzing data from different sources, creating or sharing data visualizations or applications, and engaging or collaborating with data providers or users. Some of the conditions that influence the effectiveness of open data are: the standard and availability of the data, the usability and interoperability of the data formats, the accessibility and affordability of the data platforms and tools, the awareness and skills of the data users and providers, and the legal and ethical issues related to the data use and reuse (Zuiderwijk and Janssen, 2014).The utilization of open data is often applied in a public-private partnerships, which entails robust set of rules for involvement of public organizations that adhere transparency (Olk and West, 2020). Such partnerships are typically more concentrated on the initial phases of the innovation process when contrasted with participation in a platform ecosystem (Huber et al., 2020).

In sum, the diverse array of OI interactions mentioned in existing literature introduces questions regarding interdependence of the in order to drive OI success. Consequently, various configurations of interaction channels could be similarly effective in explaining OI outcomes (Fiss, 2011). Moreover, significant interdependencies exist between those interactions, suggesting that focusing on one practice might be ineffective. Enhancing inter-organizational OI interaction necessitates employing a variety of approaches that stem from underlying connections (Beck et al., 2022). For example, technology transfer often follows collaborative efforts in science-industry partnerships, rather than being an isolated interaction. Understanding OI interaction channels involve determining how to configure more of these interactions and ensure their effectiveness. Digitization and various forms of orchestration drive these interaction types, requiring new frameworks for managing diverse partners.

2.2. Ecosystem and the resource orchestration

Within the OI framework, it is ecosystems that enable organizations to tap into knowledge form outside (Chesbrough et al., 2006). As a market-driven innovation networks they involve interdependent actors within in specific fiels, addressing their fundamental development (Ritala and Almpanopoulou; 2017). By coordinating the interactions of actors, the ecosystem can generate value more effectively that an individual actor (West and Olk, 2023). OI ecosystems engage multiple partners co-creating and transferring knowledge (Radziwon and Bogers, 2019). A primary objective of this study is to present the inter-organizational OI partnerships as a means for an effective management of an ecosystem and explore how the orchestration of various resources with coinciding OI interaction channels fosters a configurational pathway to achieving high levels of OI outputs.

Regarding ecosystems, the concept of resource orchestration comes into significance, referring to the process of reconfiguring, bundling, and harnessing resources from within the organization as well as from outside, along with the attainment of potential (Sirmon et al., 2011). The resource orchestration approach stems from the resource-based theory. Combining works relating to management of resources and asset orchestration Sirmon et al. (2011) developed a theoretical framework on the significance of resource coordination and combination, ultimately leading to innovation success. The resource orchestration is especially relevant in ecosystems that are based heavily on R&D organizations, which are built to manage multiple Oi interaction channels. Industries that are rooted in science, such as bio and pharma sectors, demonstrate greater capability OI interaction channels, primarily due to the high levels of uncertainties involved in developing complex scientific research (West and Olk, 2023). These firms heavily rely on the co-evolution and opportunities connected to OI interaction channels as contributions to their research and development endeavors, recognizing the need for participation within these channels to benefit from knowledge available in the ecosystem. Most firms are not equipped to work with multiple knowledge flows, rely more on internal R&D (Laursen and Salter, 2014) meaning that industry type (and corresponding firm size) be significant in the choice of OI interaction channels. Small firms may find it challenging to establish inter-organizational ecosystem partnerships with incumbent companies, while they may have more resources to invest in developing partnerships (Chesbrough, 2003).

Existing literature recognizes that OI is the result of the interdependence of inbound, outbound and coupled processes, but the current research often focuses on individual interaction channels neglecting the crucial role of ecosystem resource orchestration. Recent research agendas emphasize the need to analyze interdependencies among conditions to offer a more thorough comprehension of successful OI outcomes (Radziwon et al., 2023). The significant rate of failure in numerous OI projects (Lauritzen and Karafyllia, 2018) may stem from a lack of a comprehension of the successful configuration of conditions (Milagres and Burcharth, 2019). The intricate configurations of interaction channels, leading to various paths for partners to achieve OI, pose challenges when using traditional research methods (Ragin, 2014; Fiss, 2011). To address this, we propose a configurational framework and theorize that high OI output is not solely reliant on an individual channel but rather on the interdependencies between channels and effective resource orchestration. Therefore, they should be considered to enable organizations to achieve OI success.

3. Experimental

Since there is no universally accepted framework providing a theoretical foundation for studying configurations of interaction channels in OI, we conducted a review of existing empirical research to identify interaction channels deemed crucial in the OI process. After analyzing 54 articles, interaction channels were selected for inclusion and aggregated into conditions. Subsequently, we performed a background study to determine the prominent interaction channels in European inter-organizational partnerships. Through semi-structured interviews with seven managers representing such partnerships, we explored the utilized interaction channels and their impact on innovation outcomes. The interviews were recorded, then transcribed, and finally thematically analyzed. To validate the widespread of the identified interaction channels within OI partnerships and to inquire about the OI output effecting from the channels, a questionnaire was sent to selected inter-organizational partnerships operating under industry clusters. These partnerships facilitated a diverse group of international partners. The study was a part of a larger European multinational OI capabilities management research project, that involved partners from Denmark, Poland, and Latvia. In the OI landscape, European firms have deployed numerous successful OI routines that have been adopted globally, providing a solid ground for research in OI field.

The sample was chosen according to the following criteria: a) the multi-partner partnerships was R&D oriented; b) at least one partner was a research institution; c) it is not a new venture; d) the partnership operates in the production sector. The primary data source was a questionnaire sent to 110 partnership managers, 35 of which had decided to fill it in. Ultimately, the study included a total of 29 partnerships.; these were mainly form sectors such as ICT, energy, biotechnology, medica, food processing, metal industry, construction, machinery and aircraft. The chosen sample was considered adequate for reliable fuzzy-set QCA (Fiss, 2011). The participants were selected as experts in inter-organizational engagement based on their extensive experience in managing multi-partner OI projects. Because the effective utilization of QCA relies on the ratio of cases to causal conditions, this number of cases is deemed adequate for reliable fsQCA (Fiss, 2011). Respondents were considered experts in inter-organizational collaboration owing to their robust experience in management of multi-partner OI projects.

The online questionnaire requested respondents to evaluate their engagement in various interaction channels within their partnerships. Further respondents were asked to offer their perceptions of the level of the innovation output resulting from utilizing the interaction channels. To complement the questions on interaction channels, additional prompts were included in the questionnaire, inspired by Bacon et al.'s (2022), to encourage respondents to elaborate on their responses if desired. To guarantee the reliability and validity of the diverse data, we employed triangulation as a verification method. The data source was supplemented with additional official publication material and series of interviews with partnership leaders.

FsQCA, an approach rooted in fuzzy algebra, proves well-suited for examining intricate causality of various interaction channels, garnering significant recognition in the innovation domains (Ragin, 2014). The outcome-driven nature of fsQCA enables the identification if particular conditions are necessary for attaining a particular result. It excels in analyzing pathways, uncovering the configurations of conditions that culminate in the same outcome. FsQCA's strength lies in addressing asymmetric data and has been employed to explore the amalgamation of factors, behaviours, and impressions that foster performance enhancement (Saridakis et al., 2022; Kusa et al., 2021).

FsQCA) offers several benefits in innovation research over quantitative and other qualitative methods. Firstly, fsQCA generates more fine-grained insights into variable relationships and providing a means to reach better managerial conclusions (Rasoolimanesh et al., 2021). It is also effective in examining the complex causal relationships, e.g., in SMEs' radical innovation, contributing to the related literature in a unique way (Tang et al., 2022). Moreover, fsQCA introduces the notion of equifinality and provides new ground for methodological discussions in the field of innovation performance, offering a fresh perspective in innovation research (Cabrilo et al., 2020). FsQCA is globally recognized as an alternative to both quantitative analysis, which often oversimplifies causal complexity, and purely qualitative methods, which lack generalizability (Gligor et al., 2021; Oyemomi et al., 2019).

As an effective analytical method for exploring the interdependence of conditions, in our study the method facilitated the determinantion of specific combinations of interaction channels as conditions that contributed to the high level of outcomes in OI partnerships. The analysis was based on a model that considered six potential conditions representing interaction channels in an OI partnership: sourcing of external knowledge (ExterKnowl), technology transfer (TechTrans), platforms and complex systems (PlatfAndComplSys), engaging users (UserDriv,), crowdsourcing (Crowdsour) and utilizing Open data (OpenData). Only interaction channels that demonstrated theoretical connection with existing literature, as explored in empirical OI studies and confirmed by the initial background, were included in this analysis. Table 1 displays the condition included in the questionnaire. Each construct was defined and aggregated taking foundation in extant literature on OI partnerships.

Table 1. Conditions relating to OI interaction channels included in the model with literature references

Conditions relating to OI interaction channels	Reference
Sourcing of external knowledge (ExterKnowl)	Bogers et al., 2017; Radziwon and Bogers, 2019; Beck et al., 2022; Perkmann et al. 2013; D'Este et.al. 2013; Hossain and Kauranen, 2016; Adner and Kapoor, 2010; Chesbrough and Bogers, 2014
Technology transfer (TechTrans)	Scuotto et al., 2020; Bogers et al., 2017; Lichtenthaler, 2010; Hagedoorn and Zobel 2015; Nguyen et al., 2023; Chesbrough and Crowther 2006; Laursen et al., 2022
Platforms and complex systems (PlatfAndComplSys)	Bogers et al., 2017; 2018; Baldwin and Woodard, 2009; Schaffers et al., 2011; Gawer and Cusumano, 2014; Boudreau, 2010; Benlian et al., 2015; Isckia et al., 2020
User driven activity (UserDriv)	Von Hippel, 2009; Bogers et al., 2010; Bogers et al., 2017; Piller and West 2014; West and Lakhani 2008; Majchrzak and Malhotra, 2020; Bradonjic et al., 2019
Open data (Open Data)	Chesbrough et al, 2014; Zuiderwijk and Janssen, 2014; Bogers et.al., 2017; 2018; Sadiq and Indulska 2017; Olk and West, 2020; Huber et al., 2020; Beck et all., 2022
Crowdsourcing (Crowdsour)	Afuah and Tucci, 2012; Majchrzak and Malhotra, 2020; Estellés-Arolas and González-Ladrón-de-Guevara; 2012; Piezunka and Dahlander, 2014; Seidel et al., 2016; Christensen and Karlsson, 2019; Bogers et al., 2017; Beck et all., 2022

Given the requirement of an outcome measure for fsQCA, our research aimed to evaluate the impact of the six interaction channels as conditions for the success of OI output. This assessment took into account the impact of OI processes on organization's performance, accelerating the advancement of novel products and production methods (e.g., Dodgson, 2020; Bertello et al., 2023). We carefully considered that OI encompasses various aspects of the business model, even though not always resulting in monetary rewards (Dahlander et al., 2021). As OI routines become more widespread, conventional innovation-related measurements are becoming limited. There are significant challenges in establishing clear definitions and monitoring of these novel outputs, evaluating their quality, and providing mechanisms for mangers to derive value from them. Addressing this challenge, we adopted the definition of innovation output from Bacon et al. (2022), which refers to "active interaction between organizations, leading to measurable and effective application by the recipient organization." Such an approach enables us to compare diverse cases across different sectors and geographical locations in OI collaboration, with a focus on innovation performance (Audretsch and Belitski, 2023). In our article, we focus primarily on OI processes with a higher level of impact on the innovation output, dealing with complex, multi-sided problems that require the integration of diverse knowledge domains (Ooms and Piepenbrink, 2021). Such processes facilitate radical innovation and are not limited to the bound of an individual partner, making OI essential in addressing these challenges. We define low innovation output as incremental innovation, which is typically constricted by the product's structure (e.g., modularity) and does not involve revolutionary solutions (Holgersson et al., 2022).

4. Results and discussion

The results of the study reveal the necessary and/or sufficient conditions for achieving a high level of OI output. The analysis was based on a model that considered six potential conditions (ExterKnowl, TechTrans, PlatfAndComplSys, UserDriv, Crowdsour, OpenData).

The data was calibrated before the analysis. During the calibration process, we transformed the variables into "fuzzy" sets membership, which ranges from 0 (full non-membership) to 1 (full membership), with 0.5 denoting the highest level of ambiguity (Ragin, 2014; Kraus et al., 2018; Saridakis et al., 2022). We used already validated scale references to determine the data points for full membership, non-membership, and crossover point. Ordinal scales provided qualitative anchors that informed the calibration benchmarks of set affiliations (Kumar et al., 2022; Fiss, 2011;). Through analysis of existing literature, we aligned the theoretical references with the real distribution of the sample. To overcome potential challenges at the crossover point (0.5) we included a minor constant of 0.001 (Saridakis et al., 2022; Ragin, 2014;). Using similar approach, we defined thresholds for each of the variables. This calibration process ensured that the variables were converted into memberships within "fuzzy" sets, spanning between full non-membership and full membership.

Descriptive statistics were used to indicate that the six conditions in the model vary across cases, with ExterKnowl having the highest mean and TechTrans having the highest standard deviation (Table 2). The results therefore highlight the variability of the conditions across cases.

Table 2. Descriptive statistics of variables

Variable	Mean	Std. Dev.	Minimum	Maximum	N
ExterKnowl	0.7372414	0.203061	0.33	1	29
TechTrans	0.5637931	0.3179179	0	1	29
PlatfAndComplSys	0.7248276	0.3285771	0	1	29
UserDriv	0.5065517	0.3469103	0	1	29
Crowdsour	0.2868966	0.39855	0	1	29
OpenData	0.3793103	0.313368	0	1	29
LevelofInnovOutput	0.5282759	0.2257718	0.33	1	29

The calibrated data was analyzed using fsQCA3.0 software. We followed confirmed research practices, including conducting a sufficiency analysis with a minimum case frequency of

≥2 and a raw consistency of ≥0.8. (Saridakis et al., 2022; Kumar et al., 2022; Fiss, 2011). By employing these rigorous routines, we identified the configurational pathways that meet the requirements.

FsQCA provides three distinct approaches to handle ambiguous cases: parsimonious, complex, and intermediate solutions. Each approach varies in the assumptions made regarding the observations that do not perfectly align with any of the defined membership categories. The parsimonious solution includes all logical remainders, while the intermediate solution involves partial logical remainders. On the other hand, the complex solution encompasses no logical remainders (Schneider and Wagemann, 2012; Ragin, 2014) These solutions are essential for interpreting the fsQCA results, as they provide different perspectives on the relationships between conditions and outcomes. In our study the intermediate solution includes the same three configurations as the complex solution, but with weaker assumptions, and has the same solution coverage and solution consistency as the complex solution, therefore it is not presented in a separate table. The combination of parsimonious and complex solutions is often recommended as the main point of reference for interpreting the fsQCA results. Table 3 provides a concise overview of the complex solution to a high level OI outcome, including raw coverage and levels of consistency (for the solution and for each of the configurations in the solution). The solution coverage indicates the practical significance of the solution, while the consistency underscores the degree to which cases with the same configuration exhibit consistent outcome (Fiss, 2011).

Table 3. fsQCA complex solution for high levels of OI outputs using interaction channels as conditions.

Model: HighOIOutput = f(ExterKnowl, TechTrans, PlatfAndComplSys, UserDriv, Crowdsour, OpenData) **Algorithm:** Quine-McCluskey		
Frequency cut-off: 2 **Consistency cut-off: 0.885906** **Solution coverage: 0.760444** **Solution consistency: 0.830956**	Raw coverage	Consistency
ExterKnowl * TechTrans * PlatfAndComplSys * UserDriv	0.565274	0.895553
ExterKnowl * ~TechTrans * PlatfAndComplSys * ~UserDriv * ~Crowdsour	0.388381	0.853658
ExterKnowl * PlatfAndComplSys * ~UserDriv * ~Crowdsour * OpenData	0.302872	0.87218

The complex solution revealed three configurations strongly related to a significant increase in the number of implemented innovations. The solution coverage of 0.76 indicates that it applies to 76% of the cases, and the solution consistency of 0.83 indicates that it is present in 83% of the cases where a high level of OI output occurred. The necessary condition analysis for the high level of OI output is displayed in Table 4.

The parsimonious solution provided only one variable. In the context of fsQCA, when there is only one variable in a parsimonious solution, it is considered both necessary and sufficient for the outcome due to the nature of the method. The variable that is necessary and sufficient to increase the number of implemented innovations: PlatfAndComplSys (Raw coverage: 0.890992; Consistency: 0.649382). This parsimonious solution has a higher coverage of 0.89, indicating that it applies to a higher proportion of cases than the complex solution, but a lower consistency of 0.65, indicating that it is present in a smaller proportion of cases where a high level of OI output occurred.

Table 4. Results of necessary conditions analysis for high level of OI outcome

Model: HighOIOutput = f(ExterKnowl, TechTrans, PlatfAndComplSys, UserDriv, Crowdsour, OpenData)		
	Consistency	Coverage
ExterKnowl	0.956919	0.685688
~ExterKnowl	0.430809	0.866142
PlatfAndComplSys	0.890992	0.649382
~PlatfAndComplSys	0.367493	0.705514
TechTrans	0.847911	0.794495
~TechTrans	0.561358	0.679842
UserDriv	0.760444	0.793056
~UserDriv	0.605744	0.648498
Crowdsour	0.456266	0.840144
~Crowdsour	0.672977	0.498549
OpenData	0.608355	0.847273
~OpenData	0.714752	0.608333

To identify necessary and peripheral conditions we compared results of the complex and parsimonious solutions as advised in the literature (Saridakis et al., 2022; Kumar et al., 2022; Fiss, 2011). The distinct impact of each causal condition to a high level of OI output in each configuration is statistically significant (Schneider and Wagemann, 2012). We determined three configurations that may result in a high level of OI output. Solution a1 has a relatively higher raw coverage value, indicating greater empirical significance in comparison to a2 and a3. The results of the fsQCA analysis are displayed in Table 5.

Configuration a1 implies that utilizing multiple interaction channels: sourcing of external knowledge, technology

Table 5. Results of fuzzy set QCA analysis

	High level of OI output			**Low level of OI output**	
Conditions	a1	a2	a3	b1	b2
ExterKnowl	•	•	•	•	•
PlatfAndComplSys	●	●	●	Ø	Ø
TechTrans	•	Ø		Ø	
UserDriv	•	Ø	Ø	•	Ø
Crowdsour		Ø	Ø	Ø	Ø
OpenData			•	Ø	•
Consistency	0.895553	0.853658	0.87218	0.91456	0.87218
Raw coverage	0.565274	0.388381	0.302872	0.291667	0.339181
Unique coverage	0.306789	0.0861619	0.0652742	0.14693	0.0730994
Solution consistency	*0.830956*			*0.834818*	
Solution coverage	*0.760444*			*0.753655*	

Note(s): Black circles ("•") indicate presence of the condition, cross circles ("Ø") absence of the condition and blank spaces "do not care" condition; larger circles denote core conditions, while smaller circles indicate peripheral conditions transfer, platforms and complex systems and engaging users in the inter-organisational OI partnerships may be responsible for high levels of OI outputs with or without the presence of the two remaining channels. Configuration a2 posits that concentrating on sourcing of external knowledge and using platforms and complex systems without engaging in technology transfer, user driven activity or crowdsourcing may lead to high levels of innovation outputs. Configuration a3 implies that, similarly to configuration a2, sourcing of external knowledge and using platforms and complex systems but also utilizing open data without regards to user driven activity or crowdsourcing results in high levels of OI outputs.

For cases involving low levels of OI outputs, Table 5 displays two configurations characterized by dependable solution consistency (≥0.8) and raw coverage surpassing the standard threshold of 0.2 concerning the full membership in the outcome (Saridakis et al., 2022). The distinctive impact of each configuration holds statistical significance. Both configurations align with the context of low innovation outputs, as their consistencies surpass the benchmark of 0.8 (Saridakis et al., 2022; Kumar et al., 2022). Configuration b1 makes it apparent that relying solely on external knowledge sourcing and user-driven activity may result in low level of OI outputs. Furthermore, configuration b2 indicates that the utilization of external knowledge sourcing in conjunction with open data may also yield low levels of innovation output when all other conditions are either absent or irrelevant.

In conclusion, the results suggest that utilizing platforms and complex systems (PlatfAndComplSys) is a necessary and sufficient condition for a higher levels of innovation output. One other condition identified in the solutions: sourcing of external knowledge (ExterKnowl) may also contribute significantly to this outcome in many cases. The rest of the conditions, namely engaging in technology transfer (TechTrans), user driven activity (UserDriv), utilizing open data (Open Data) and crowdsourcing (Crowdsour) are of a much less significance and in some cases engagement in those interaction channels without utilizing platforms and complex systems (PlatfAndComplSys) might lead to lower levels of innovation output.

To ensure the robustness of our analysis, we employed established standards, which include resetting the calibration and consistency threshold, removing cases (Kumar et al., 2022; Fiss, 2011). We followed the approaches proposed by Schneider and Wagemann (2012). Initially, after decreasing the consistency benchmark from to 0.75 the configurations were still valid. Next, we randomly removed two cases and reanalyzed the solutions, which showed that the findings remained unchanged.

5. Summary and conclusion

The examination of how OI partnership actors interact with each other in production sectors is of paramount importance, encompassing aspects related to their behavior, strategic choices, and the institutional context that shapes the cross-boundary nature of OI activities (Bogers et al., 2017). By taking into account the impact of various combinations of interaction channels, this study underscores how diverse OI interaction pathways can guide organizations toward achieving high levels of innovation outputs. The findings from the fuzzy-set QCA provided insights into the diversity of outcomes in inter-organizational OI partnerships, highlighting various combinations that result in either high or low levels of innovation output.

First, the parsimonious solution underlined that a necessary condition of utilizing platforms and complex systems needs to be present for high levels of innovative results. In the context of fsQCA, when there is only one variable in a parsimonious solution, it is considered both necessary and sufficient for the outcome due to the nature of the method.

Second, the complex solution examined three distinct configurations that lead to high innovation output, thereby addressing the research question. We utilized the logic scheme proposed by Ragin (2014) to further condense the configurations from a theoretical standpoint. Based of permutations of necessary and sufficient conditions, we identified two types of engagement in OI that have different core characteristics but are both leading to an OI success. First type of engagement (configuration a1) represents a broad approach to OI interactions in inter-organizational partnerships. Multiple OI interaction channels are particularly important for high technology and science-based sectors that greatly rely on such input. Therefore, OI implementing companies in these sectors should formulate approaches that capitalize on the exchange of knowledge, encompassing both the inflow and outflow of insights within these knowledge-rich ecosystems. (West and Olk, 2023). Second type of engagement (configuration a2 and a3) encompasses two variations that similarly result in high levels of innovation output. These two share the necessary conditions (using platforms and complex systems; sourcing of external knowledge) and only differ on the presence of a condition connected to utilizing open data. In fact, the findings offer more nuanced details about the non-core interactions since the solutions include absence of conditions and not only an “do not care” option. The proposed solutions imply that in many cases it’s not only enough to organize OI efforts around using platforms and complex systems, but it is beneficial to actually limit the engagement in any other interactions and thus optimize resource and time allocation. The role of using platforms and complex systems holds specific significance as it is a common factor in each of the three paths leading to high open innovation output. It suggests a more robust connection with OI than what previous empirical work had presumed. In an expanding trend, numerous industries are structuring their operations around core platforms, which are further accompanied and complemented by networks or constellations of partner organizations. These auxiliary entities rely heavily on the platform (Gawer and Cusumano 2014). In the present-day landscape, the influence of digital transformation has further intensified the adoption of platform-centric approaches (Bogers, et al. 2017). Hence, platformization emerges as a crucial facilitator for OI by simplifying the onboarding and collaboration of diverse new participants. It also serves as a pertinent variable influencing the efficiency of OI.

Concerning low innovation output, sufficiency analysis has identified two distinct configurations. They both point to sourcing of external knowledge, and one other condition when all other characteristics are absent. The role of sourcing of external knowledge was highlighted as this type of interaction channel was always treated as a underlying foundation of OI projects. This suggests that the rest of the conditions, namely engaging in technology transfer (TechTrans), user driven activity (UserDriv), utilizing open data (Open Data) and crowdsourcing (Crowdsour) are of a much less significance and in some cases engagement in those interaction channels without utilizing platforms and complex systems (PlatfAndComplSys) might lead to lower levels of innovation output. These findings are noteworthy as they underscore the significance of strategizing the OI effort. They reveal that, even at elevated levels of a specific type of OI interaction, low innovation outputs can be obtained when crucial conditions are lacking (Brunswicker and Vanhaverbeke, 2015; Marzi et al., 2023). In this respect, the results align with previous research concerning the asymmetries in the impacts between the multiple resource orchestration dimensions (Cui et all, 2022). It has to be noted however, that despite evidence of contribution of singular OI interaction channels to OI performance, decision-makers often underestimate the share of each contribution as a source of innovation and that error can have severe consequences for firms' competitiveness and for innovation policies. (Bradonjic et al. (2019).

This study emphasizes the complexity and inefficiencies that may be present in resource orchestration through multiple OI interaction channels connected to innate complexity of innovation ecosystems (Robaczewska et al., 2019). Without careful analysis and cost/benefit consideration, there is the potential for overlap or even cannibalization of engagement in different OI interaction channels. Although overlap can generate abundance and potentially enhance overall output, it also has the potential to introduce inefficiencies when limited resources are distributed too extensively (Xie et al., 2023). These results indicate that the configurations of OI interaction channels can differ in their capacity to efficiently and effectively coordinate resources within specific OI partnerships. Embracing the somewhat risky adoption of OI interaction pathways compels organizations to make present commitments and resource allocations, even when the benefits may be realized in the long term (Bigliardi et al., 2020).

Organizations engaging in OI partnerships must remember that utilizing an effective interaction channel is not enough. Seizing the effect of organizational learning on innovative behaviour typically involves the combined evaluation of various factors that include the support of managers and boundary-spanning leadership, employee training, promoting experimentation, fostering risk-taking, and cultivating attitude that values self-efficacy (Mignon et al., 2020)

Theoretical contributions

In our paper, we introduce a novel framework for the analysis of OI that takes into account the interdependence of OI interaction channels. This framework enables a more in-depth investigation into the management of OI interactions, resulting in a nuanced classification of interaction channels beyond the conventional dichotomy of single interaction types versus aggregated OI activity. The alternative engagement pathways to achieving high innovation output highlight that, in specific combined circumstances, OI can yield innovation effects through synergistic interactions, thus reinforcing the concept of interdependent causality. As a result, we respond to recent calls for a deeper comprehension of how interactions unfold in OI contexts (Ogink et al., 2023; Radziwon and Bogers, 2019) and contribute to the OI literature by shedding light on the intricate process of selecting OI interactions that best align with OI objectives.

Additionally, the findings uncover various routes to success in OI, where distinct combinations of channels can yield superior outcomes compared to a single channel. This study stands as one of the pioneers in delivering an in-depth examination of the combined and interactive roles of interaction channels in promoting high-level OI output. This contribution aligns with the growing body of literature focused on comprehending the determinants of OI outputs (Bogers et al., 2017, 2018; Lee et al., 2019). Significantly, we elucidate the interplay between these successful interactions, identifying two types of engagement based on permutations of necessary and sufficient conditions. Furthermore, the study provides insights into interactions leading to low innovation output, with sufficiency analysis identifying two such configurations. This introduces a fresh perspective to OI effectiveness research, as limited knowledge exists regarding the factors contributing to low levels of innovation output amidst extensive OI engagement (Brunswicker and Vanhaverbeke, 2015; Marzi et al., 2023).

Thirdly, we delve into the intricate interplay between resource orchestration and OI. This research makes a valuable contribution to the field of resource orchestration by treating it as a multilayered concept and advancing the theory of resource orchestration within the context of OI. While innovation is propelled by the interplay between uncertainty and resource orchestration (Carnes et al., 2017; Cui et al., 2022), our investigation centers on how the specific aspects of resource orchestration, specifically the interaction channels, influence OI outputs. Consequently, we unveil the interdependent dynamics of resource orchestration and OI. Our results corroborate the assertions made by Cui et al. (2022), who advocate for the integration of OI into the resource orchestration field and the expansion of resource orchestration theory to accommodate the contemporary digitally transformed landscape.

Fourthly, we corroborate the propositions that inter-organizational OI partnerships serve as a means of indirectly governing an ecosystem (Radziwon and Bogers, 2019). We elucidate how the coordination of multiple resources through intersecting OI interaction channels offers a distributed approach conducive to achieving high levels of OI outputs.

Fifthly, our research introduces novel concepts regarding the selection of OI research methods. FsQCA method examines various alternative causes, deals with complex linkages, nonlinear relationships, and explains the configuration pattern of variables. Through the incorporation of fsQCA our study holds substantial potential for bridging the gap between theory and methods, facilitating in-depth examinations of various combinations of causal factors leading to both low and high OI outputs. We uncover comparable operational mechanisms for OI output, considering causal asymmetry. This innovative approach opens up new avenues for conducting research on limited and medium-sized samples in the OI domain.

Practical contributions

From a pragmatic point of view, our results give valuable perspective that can assist companies in production sectors in comprehending how interaction channels should be structured to foster high levels of OI outputs. OI strategies geared towards augmenting the innovative activity of companies should prioritize the enhancement of interaction channels. Our findings reveal that certain setups of interaction channels are more effective in stimulating OI output compared to others. It's important to note that even at elevated levels of a single type of interaction, low innovation outputs can result when the essential conditions are lacking. While it's crucial to acknowledge that these conditions constitute a configurational aspect of the solution, their core nature underscores the need for practitioners to consider implementing strategies to ensure their presence. E.g. The results underline the necessity of platforms and complex systems and confirm their relative advantage over other OI interactions. In recent years, the innovation landscape has witnessed an unprecedented transformative shift characterized by the rise of platforms, the complex systems, and the pervasive influence of digitalization. Such transitions have profound implications for the practice of OI. Through this study we support the comprehensive view that OI interactions can adapt, thrive, and drive value creation amid the dynamic forces of platforms and complex systems, even though there might be different performance outcomes of innovation strategies that co-exist in the same platform ecosystem at the same time. (Cenamor and Frishammar, 2021). In sectors reliant on technology and science, adopting a targeted approach to OI interactions through platforms and knowledge-rich ecosystems might be not only crucial but also unavoidable. Embracing distributed resource coordination might help to recognize inter-organizational OI partnerships as a means of indirectly governing a platform or an ecosystem. On the other hand, practitioners should beware of isolated OI interactions leading to low innovation output. Focusing solely on user- driven activity, open data utilization, and crowdsourcing, may not give expected results. Companies have to carefully navigate resource orchestration in OI, considering the potential for overlap or cannibalization of engagement in different OI interaction channels. While overlap can sometimes enhance overall output, it may introduce inefficiencies when resources are distributed too extensively.

For long-term OI practitioners, it's essential to stay attuned to trends in organizational change and harness advanced technologies. However, it's crucial for executives to steer clear of adopting a 'one-interaction-type-fits-all' strategy and instead choose a pathway that aligns with their available resources and capabilities to support OI. Utilizing an effective interaction channel is not sufficient for OI success. Prioritizing organizational learning by evaluating factors such as manager and boundary-spanning leadership support, employee training, experimentation, risk-taking, and fostering an attitude that values self-efficacy. Each entity should also develop resource orchestration capabilities that align with the unique conditions of their industry (Pundziene et al., 2023).

Though this research gives noteworthy contributions, it is crucial to acknowledge a number of limitations that should be considered in future research efforts. Firstly, our case selection encompassed diverse industries, each potentially facing distinct conditions and resource constraints. In future studies, it would be beneficial to analyse and compare the variances in OI interaction channels based on industry characteristics. This could lead to a more nuanced understanding of our findings and enhance their applicability across industries. Secondly, the majority of our sample cases involved partnerships originating from Denmark, Poland, and Latvia, with partners primarily coming from the European Union. Expanding the sample to include cases from developing countries and other developed nations in the analysis can further enrich our insights. Thirdly, we relied on subjective perceptions to evaluate conditions and outcomes. A notable enhancement would involve the incorporation of objective metrics to measure innovative output, even though the diversity of business sectors might complicate cross-case comparisons. Fourthly, our research primarily concentrated on the influence of interaction channels on OI. Future investigations could construct a more generalized framework, to delve deeper into the combinations of various factors collectively influencing OI.

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