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Digital disruption of optimal co-innovation configurations

Esteban Lafuente [a], Yancy Vaillant [b], Rodrigo Rabetino [c,*]

[a] Department of Management, Polytechnic University of Catalonia (UPC Barcelona Tech), Spain
[b] Department of Strategy, Entrepreneurship and Innovation, TBS Education, France
[c] School of Management, University of Vaasa, Finland

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ABSTRACT

We evaluate the co-innovation trajectory of firms adopting different collaborative innovation networks (i.e., vertical, horizontal, and institutional). The results of the empirical applications are obtained from a multilevel regression, and a Nash bargaining model estimated via data envelopment analysis on a sample of 734 enterprises from seven OECD countries form Europe and Latin America. Findings point to important national and firm-level distinctions across the optimal co-innovation configurations: whereas vertical co-innovation strategies are characteristic of firms with the highest innovation efficiency, institutions are frequently found to be optimal for co-innovation success in less developed innovation systems that may be faced with structural deficiencies. However, digital competency is found to disrupt co-innovation configurations for successful innovation, facilitating the development of efficient vertical and horizontal co-innovation trajectories.

1. Introduction

Co-creation has recently been invoked as a decisive strategy to improve business' innovation outcomes by supporting multi-organization collaborations that enhance resource integration and knowledge-sharing processes (Frow et al., 2015; Storbacka et al., 2016; Nambisan et al., 2019; Prahalad and Ramaswamy, 2004). In parallel to these developments, ecosystems are increasingly gaining weight within the strategic management narrative. In this tradition, the literature describes how ecosystems—conceived as coordinated systemic constellations of multiple stakeholders where flows of knowledge and value result in collective social and economic processes—house the design, production, and delivery of products and services (Adner, 2017; Jacobides et al., 2018). Additionally, studies have documented how knowledge-sharing and digitalization processes fuel ecosystems to give rise to innovative business model configurations empowered by digital technologies (Kohtamäki et al., 2019; Autio and Thomas, 2022). In particular, collaborating in knowledge ecosystems (Järvi et al., 2018) to co-innovate with various types of stakeholders—e.g., customers, suppliers, competitors, universities, and research institutions—has been found to equip businesses with external resources, including information, insights, and ideas (Markovic and Bagherzadeh, 2018).

Co-creation and co-innovation can lead to better innovation performance and value creation. Research has repeatedly found that technological networking is among the best predictor of technological innovation (Pennings and Harianto, 1992; Poorkavoos et al., 2016; Arranz et al., 2020). It is theorized that innovation emerges from firms' accumulated stock of technological and networking skills (Pennings and Harianto, 1992). As such, innovation research should not, according to these authors, be limited to a single firm but should be elevated to the system of collaborations within which these are ideated, developed, and implemented (Kohtamäki et al., 2019).

Collaboration is at the basis of advanced innovation (Rothwell, 1991; Fritsch, 2001), but for effective co-innovation to take hold and lead to successful innovations, a conducive innovation system must exist (Van Lancker et al., 2016; Pittaway et al., 2004). An innovation system is characterized by diverse and complex innovation actors that collaborate on the generation, development, and exploitation of innovation while being shaped by formal and informal institutions (Van Lancker et al., 2016). The most common sources of 'innovation' inputs are associated

* Corresponding author.
E-mail addresses: esteban.lafuente@upc.edu (E. Lafuente), y.vaillant@tbs-education.fr (Y. Vaillant), rodrigo.rabetino@uwasa.fi (R. Rabetino).

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with vertical collaborations with suppliers and customers (Ranjan and Read, 2021). Nevertheless, innovative firms may also obtain valuable inputs stimulating effective innovativeness from horizontal collaborations with companies in the same industry. Additionally, co-innovation can be derived from institutional collaborations with higher education, scientific, and technological institutions (Cai et al., 2019).

In this discussion, ambiguity and debate persist in the literature regarding appropriate network configurations for successful innovation (Frow et al., 2015; Voorberg et al., 2015). While research has been conducted on the vertical networking activities that occur between suppliers, customers, and firms (Kohtamäki et al., 2019; Lafuente et al., 2019; Ranjan and Read, 2021), or horizontal innovation collaborations between firms of the same industry (Cozzoni et al., 2021), as well as on how institutions co-innovate to create value by filling in ecosystemic gaps (Ranjan and Read, 2021), little has been research on which co-innovtion configuration leads to the optimal innovation output. Besides innovation-driven collaborations, digitalization also has the potential to compensate for ecosystemic deficiencies, enabling firms to collaborate more actively. Digital tools and services have been found to potentially facilitate the co-innovation process in four main areas (Lember et al., 2019; Storbacka et al., 2016); they can help firms to establish direct interactions to innovate, they can improve the engagement of collaborating actors, they offer ways in which to link these actors' resources better, and they can contribute to facilitating shared decision-making. Digital transformation impacts society so that there are transcendent changes in the trends and formats of related organizations within innovation systems. The popularity of these technologies, which were previously often limited to research centers and large companies, allows for their more widespread use as part of efforts to achieve concerted innovation goals (Hidalgo and Herrera, 2020), which not only result in the co-creation of products but also in smart solutions and digital service innovations enabled by digital platform ecosystems (Huikkola et al., 2021; Jovanovic et al., 2021; Kohtamäki et al., 2020).

Underlying this argument line is the presence of variance across macro-level network deficits or micro-level digital shortfalls. From the point of view of optimal co-innovation network configurations, this suggests that the 'one size fits all' approach would offer limited analytical material. In light of the central role of co-creation for successful innovation, what configurations of innovation-driven collaborations contribute to optimizing firms' innovation efficiency? Moreover, is the connection between co-innovation networks and innovation efficiency affected by the local ecosystem's characteristics and the firm's digital technologies availability?

Against this backdrop, the objective of this study is to assess the optimal co-innovation configuration from a multilevel analysis perspective to determine if and how these optimal innovation network configurations differ across countries and across firms. Special attention is given to the role of digital competencies over optimal co-innovation configurations. Not only will the disparities in optimal co-innovation configurations across a diverse set of OECD economies be contrasted, but the innovation efficiency across firms of different digital capabilities will also be analyzed to identify distinctions and determine whether standardized or customized co-innovation configurations are optimal for successful innovation. In doing so, this study uses a multilevel regression model to confirm country-level effects on businesses' innovation efficiency. Given the networked structure of the proposed co-innovation process, the parametric analysis is followed by a firm-specific assessment rooted in the Nash bargaining problem that allows computing businesses' innovation efficiency via non-parametric techniques—i.e., Data Envelopment Analysis (DEA)—to conduct a comparison of the optimal co-innovation configurations of firms with top- and poor-innovative performance potential. Finally, efficiency comparisons between more and less digitally qualified businesses are also performed.

For the specific purpose of this study, the proposed DEA approach is more suitable for our analysis for at least two interrelated reasons. First, from a methodological viewpoint, the most significant advantage of DEA is that it does not require a pre-specification of the production technology and can also handle different types of variables simultaneously without affecting estimation results (Cooper et al., 2011; Grifell-Tatjé and Lovell, 2015). Second, from a strategic perspective, every business has its own operational and organizational priorities, and what can be considered a desirable strategy for businesses located in a given territory may not be so in another context. The flexibility of the proposed DEA model supports this argument. By computing endogenous (non-arbitrary weights) that we link to strategic priorities, the DEA model not only represents two differentiated and inter-connected stages of the businesses' innovation process but also recognizes organizational heterogeneity and allows businesses to identify the most relevant aspects for enhancing their co-innovation strategy based on their specific internal and market conditions.

The results of our analysis stretch beyond a purely computational exercise and have important implications for academics and strategy makers. The study fills the gap identified by Voorberg et al. (2015), who conclude from their review of the collaborative innovation literature that doubt still exists regarding the appropriate network configuration for successful innovation. It also responds to the call by Lember et al. (2019) for greater research on how co-innovation processes are affected by a business' digital competency level. The multilevel analysis applied to 734 businesses from seven OECD economies point to important national and firm-level distinctions across the optimal co-innovation configurations. However, despite this heterogeneity, clear trends are identified.

Not only is digitalization facilitating collaborative efforts, but contrary to the relatively standardized collaboration configurations that dominate existing literature, digital competency opens the need for a more customized approach to analyzing innovation systems and the multiagent relationships leading to optimal innovation. Whereas the industrial and institutional co-innovation (co-production, co-creation) kinds of literature are being primarily developed independently, with few interactions, the findings of this research emphasize the need to have a much more holistic and multilevel perspective of dynamic innovation systems and collaborative network configurations. The study results show that digital competencies facilitate optimal vertical and horizontal co-innovation practices, replacing the need for institutional collaborations. When analyzing the optimal co-innovation configuration of firms according to their digital capacity, the optimal configuration for successful co-innovation tends towards vertically dominated ones in observed European OECD economies and horizontal ones in those observed from Latin America.

The plan of the paper follows. Section 2 presents the theory that underpins the study, while Section 3 deals with the model used to evaluate businesses' innovative efficiency. The sample and data are depicted in Section 4, while Section 5 presents the results. Section 6 offers the concluding remarks, implications, and future research lines.

2. Background theory and hypotheses

2.1. Co-innovation

External agents are essential for innovation development, where firms must promote co-innovation to generate more meaningful value (Hidalgo and Herrera, 2020). Co-innovation is an innovation paradigm in which new ideas and approaches from various internal and external sources are integrated into a platform (formalized or not) to generate new organizational and shared values. The core of co-innovation includes engagement, co-creation, and compelling experience for value creation (Lee et al., 2012). As such, co-innovation constitutes a direct part of the production process. This circumstance differs from passive clientelism: it is not enough to receive or consume a product or service. External agents must become active players within the innovation process for co-innovation. Akin to the more common co-creation process, mostly centered on vertical collaborations with clients or suppliers in an increasingly customized solution delivery trend, co-innovation is more inclusive as it comprises more diverse innovation network configurations. Le Roy et al. (2022) give examples of vertical co-innovation within the video games industry, where game development innovation is often tightly interknitted between software and hardware industry firms to advance new innovations and technologies synchronously. Co-innovation also includes horizontal, usually more additive, innovation network collaborations with analogous value providers to reach critical mass or cost-sharing objectives (Cozzoni et al., 2021). An example of horizontal co-innovation in which two companies of the same industry collaborate to innovate at the same stage of the value chain is Airbus and Thalès in the satellite manufacturing industry (Fernandez et al., 2018). These two competing aerospace companies share their technology and collaborate to handle innovation projects that are costly, risky, and highly innovative. Similarly, co-innovation collaborations for innovation ideation, development, and implementation can also occur with institutional partners who are often the holders of human and infrastructural resources and capabilities that are key for advanced innovation (Etzkowitz and Klofsten, 2005). The AI-based visual recognition start-up, AllRead, is intricately networked with the university-based Computer Vision Center of Catalonia, with who AllRead partners as part of its institutional co-innovation efforts to remain on the leading edge of Computer Vision technologies despite its relatively small size.

Most firms can find themselves disadvantaged due to low levels of in-house resources and capabilities and managerial opportunity costs associated with conducting successful innovation independently (Rothwell, 1991; Poorkavoos et al., 2016). Seeking appropriate external collaborations for innovation can generate many advantages from the organizational perspective, including better innovation performance (Markovic and Bagherzadeh, 2018). The different agents active in an innovation system often have limited innovation capacity. Still, the synergies unleashed through the mutualization of their competencies expand their collective innovation capability frontier when they co-innovate. Firms gained external innovation capabilities from other companies through obvious mechanisms such as joint R&D and less guided interactions and collaborations that lead to purposeful know-how exchanges and collective reasoning. As such, innovation networking activities are often strategic rather than simply responding to short-term problems (Pennings and Harianto, 1992; Arranz et al., 2020).

The principal benefits of networking for innovativeness beyond the obvious relational capital gains include risk sharing, obtaining access to new markets and technologies, speeding products to market, pooling complementary skills and resources, safeguarding property rights, and/or acting as a key vehicle for obtaining access to external knowledge (Pittaway et al., 2004). Ranjan and Read (2021) have recently analyzed the value derived from co-innovation. From the perspective of customers co-innovating with their supplier(s), tangible gains can be obtained from either better products/services or product/service experiences. These benefits can be objective in nature but are often more the result of subjective perceptions generated because of the co-innovation process itself (Romero and Molina, 2011). From the supplier's perspective, value and superior performance are derived primarily through improved value proposition, pricing, service, and solution delivery (Kohtamäki et al., 2019). For suppliers, co-innovation with clients and users allows for better product/service and market entry innovation, and value communication (Ranjan and Read, 2021). Beyond value chain collaborations, the benefits of co-innovation have been found to come from dyadic problem-solving, knowledge integration, and more holistic networked solution formulation (Romero and Molina, 2011).

2.2. Institutional conditions of countries' innovation system

In this study, the deduction is made that the optimal network configuration for successful co-innovation - *whether co-innovation will lead to more optimal innovation output due to dominant vertical, horizontal, or institutional collaborations* – differs across national innovation systems. National innovation systems (Lundvall, 2007; Malerba, 2002) play an essential role in the diffusion of innovations in terms of how they shape networking activity (Carlsson et al., 2002). The national innovation system is driven by nation-specific institutions and policies and bonded by the interactions between its many agents (Vaillant, 2022). These influence the nation's capacity to generate, produce, and diffuse innovation and define the interrelationship of innovation actors and institutions that enable innovation generation, diffusion, and appropriation (Lafuente et al., 2022; Van Lancker et al., 2016).

National institutional frameworks, which are country-specific, generate the environmental conditions faced by local firms (Acemoglu et al., 2012; Vaillant, 2022). As a result, the optimal co-innovation configurations at the country level are particular to each national economy. This circumstance can be explained from the premises of institutional economic theory (North, 1981, 1990; Williamson, 2000), which suggests that the social and economic conventions of an economy (such as political rules, economic rules, and contracts as well as codes of conduct, attitudes, values, and norms) influence the boundaries that set internal economic activity and development (Williamson, 2000). As such, national institutional frameworks contain all forms of restriction that shape human interaction (North, 1991; Vaillant and Lafuente, 2007) and, consequently, the propensity for co-innovation.

Coase (2005) and Williamson (2000) reinforced the notion of basis-setting institutions as central to macroeconomic evolution, technological change as well as organizational and institutional innovation (Ménard and Shirley, 2014). This idea centers the macro-level analysis on the specific path-dependence of nations bounded by the institutional frameworks leading individual economies on separate development trajectories and influencing internal innovativeness at the micro-level (Lloyd and Lee, 2018). The primary function of institutions in a society is to reduce uncertainty by creating a stable structure for interaction (Lafuente et al., 2007). From a co-innovation point of view, national economies are innate with institutional constraints that affect the national innovative capacity of firms operating within each country (Williamson, 2000) and the likeliness of engaging in collaborative economic efforts.

North (1990) uses an institutional lens to explain how the innovative structure and performance of different national economies can eventually be "radically differential". Institutions determine the opportunities of a national economy and the competency structure of firms created within that economy to take advantage of these opportunities (Vaillant and Lafuente, 2007; Lafuente and Vaillant, 2021). The key components for a functional innovation system are i. Diverse innovation actors, ii. Their openness to work collaboratively, iii. Engagement in all phases of innovation (generation, development, exploitation), and iv. A favorable formal and informal institutional framework for innovation (Van Lancker et al., 2016). Ranjan and Read (2021) added their situational contingency requirements to these essentials based on the presence in an economy's innovation system of adversity, compatibility, complementarity, opportunity, and uniqueness.

Since these determinants of effective co-innovation influence the dominant collaboration configurations adopted in an economy, and these are directly subject to each particular national institutional framework (Lafuente and Vaillant, 2021), the following hypothesis is formulated based on the aforementioned theoretical logic.

H1. *The optimal network configuration for successful co-innovation in a national innovation system is unlikely to follow a standardized transnational pattern.*

2.3. Firm-specific conditions

Similar to the deduction presented in the previous sub-section, at the level of the firm, the optimal network configuration for successful co-innovation is assumed to differ across firms of different innovation potentials based on their resource endowment. The resource-based view (RBV) of the firm states that businesses have specific resources that they can transform into capabilities that ultimately determine their competitiveness and superior performance (Barney, 1991, 2001). From this perspective, a firm's innovation capacity is the result of the amalgamation of a set of complex and heterogeneous resources (what it has) and capabilities (what it can do with what it has) that are specific to each organization (Grant, 1991; Lafuente and Vaillant, 2021). The heterogeneous distribution of resources across firms ultimately forms the building blocks of each venture's innovative capacity. The potential for successful innovation that such a competency may create is a function of its availability and the configuration of the system of competencies accessible to the firm.

A firm can significantly improve its innovative capacity by leveraging the skills of others (Grant, 1991, 2021). Therefore, both internal and external skills are crucial for successful innovation to take hold. The more firms have accumulated networking skills, as inferred from the magnitude of co-innovation activities, the higher the probability of generating effective innovation (Pennings and Harianto, 1992). In the context of this study, the co-innovation configuration refers to a multidimensional trait that differs across firms. These are the extent to which resources can be accessed through different collaborative combinations and intensities to generate contrasting innovative capacity sets (Miller, 1996). Based on the configuration theory developed by Miller (1986), the elements of a system cannot be fully understood in isolation, so the analysis of the complete system is inevitable. If a single item is easy to copy, the competitive advantage comes from the orchestrated complementarities of the system as a "whole" (Miller and Whitney, 1999; Cheng and Wang, 2022).

This argument is consistent with RBV's postulates that firms are a set of interrelated resources and capabilities and that a precise competitive analysis should consider the differentiated role of firm competence configuration (generating strong or poor innovative performance). Kraaijenbrink et al. (2010) offer a comprehensive review and assessment of the literature that uses the RBV postulate to conduct research. From this general line of research, competencies can be understood to fall within the capability frontiers set by the resource strengths or weaknesses of the firm. The position of a firm in the domain within its capability frontier differs across firms based not only on their innovation competency structure but also on their proficiency for exploiting external resources and capabilities accessible through collaborations and network arrangements (Lafuente et al., 2020). An optimal co-innovation configuration would lead the firm to compete at its innovation capability frontier under the chosen collaborative configuration. Consequently, similar firms competing within the same national institutional context can demonstrate relatively different innovative competencies. Thus, firms may vary in their innovative competency levels within an optimum co-innovation configuration and, therefore, achieve different innovation performances.

Therefore, the co-innovation configurations that firms should prioritize to improve their innovation performance are necessarily related to the specific resource strengths or weaknesses limiting their internal innovation capability frontier, which binds their performance potential. An innovation performance analysis based on net-effect logic would emphasize that successful innovation depends on available resources and skills and that the optimal co-innovation configuration is mostly dependent on what can be externally accessed to complement what is internally on hand. This deduction, therefore, leads us to hypothesize that the optimal co-innovation configuration of firms is likely to vary across firms with differing performance potential.

H2. *The optimal network configuration for successful co-innovation in a national innovation system is unlikely to follow a standardized pattern across firms of differing innovation performance levels.*

2.4. The digital effect

Digital technologies, platforms, and infrastructures have changed business innovation processes significantly (Chierici et al., 2020), favoring collaboration and knowledge sharing among firms and other agents within innovation systems (Nambisan et al., 2018, 2019). It has been found that co-innovation increases as more digital tools and platforms are used, increasing the propensity to spread resources and sharing intensity which positively affects the collective capacity to innovate (Chierici et al., 2020).

Digital technologies enable information sharing among the actors of a network or system of innovation, thus supporting the process of knowledge acquisition, dissemination, and exploitation (Scuotto et al., 2017b). As a result of digitalization, innovation has been increasingly based on models of systems integration and co-innovation (Huizingh, 2011). Therefore, the capacity for innovation does not exclusively lie within corporate contexts using firms' resources. The relational behavior interlinking the players involved in co-innovation, from mere access to partners' knowledge platforms to the transfer of information and know-how to the co-production of new knowledge, engenders increasingly complex concerted governance (Klerkx and Aarts, 2013). Hence, the contribution of digital transformation and the use of digital technologies facilitate intra- and inter-organizational collaborations that help firms with their innovation. Digitalization has opened up a wide range of possibilities for firms to interact with stakeholders, especially regarding the search for novel smart solutions, new product-service offerings, or innovation processes (Chierici et al., 2020; Huikkola et al., 2021; Kohtamäki et al., 2020).

However, new technologies could have the opposite effect on co-innovation propensities (Lember et al., 2019). According to Lember et al. (2019), the digitally enhanced capacity of firms to gather, analyze, and employ vast amounts of data through social media, sensor networks, data analytics, and machine learning solutions may diminish the (perceived) need for co-innovation. Still, empirical evidence on the effects of new digital technologies stresses the enormous benefits digital technologies could have for innovation (Parida et al., 2019).

There is, at this point, no systematic approach that shows how optimal co-innovation configurations are affected by digital technologies (Lember et al., 2019). However, Hidalgo and Herrera (2020) concluded that for the generation of added value through ICT-augmented co-innovation, innovation network collaboration with customers, partners (competitors), and suppliers played an important role. This result was not the case with universities and other institutional actors (Hidalgo and Herrera, 2020). The compensatory role of institutions as co-innovation partners fills in when market-based framework deficiencies and/or unavailability of adequate collaborators can be replaced by the impact of digitalization over co-innovation practices. Digitalization can facilitate interaction in many ways, leading firms to self-organize and bypass institutional collaborations (Lember et al., 2019). As such, the following hypothesis emerges.

H3. *Digital technologies influence the optimal co-innovation configuration for successful innovation.*

We show below how the proposed framework—in which business innovation is conditioned by previous decisions linked to the configuration of co-innovation collaborations—can be modeled using the Nash bargaining problem and how innovation efficiency can be estimated via Data Envelopment Analysis (DEA).

3. Estimation strategy: analysis of the (two-stage) business innovation process using data envelopment analysis (DEA) in a nash bargaining model

Underlying the theory that underpins this study (Section 2), two critical assumptions condition the modeling of the connections between co-innovation collaborations and businesses' innovation. On the one hand, businesses can establish multiple collaborations with different parties (i.e., buyers, suppliers, competitors, partner businesses, and institutional agents). The outcomes of such collaborations—i.e., the configuration (relative importance) of participants in the business' network—may or may not be optimal for triggering business innovation efforts. On the other hand, regardless of their efficiency level, the internal configuration of co-innovation collaborations acts as input for the business innovation strategy; that is, the configuration of these collaborations conditions the innovation outcomes achieved by the analyzed businesses.

The proposed framework imposes the assumption of network coordination to the innovation process; therefore, in the presence of co-innovation collaborations for the sampled businesses, innovation efficiency (θ^*) can be modeled as the joint result of the optimality of the configuration of co-innovation collaborations (**z**) (Stage 1: θ^1) and business innovation outcomes (**y**) (Stage 2: θ^2): $\theta^* = \theta^1 \times \theta^2$. Fig. 1 presents the network (two-stage) framework proposed in this study to evaluate the role of co-innovation collaborations on business innovation.

The relationship between the different dominant co-innovation configurations and innovation outputs can be understood as a centralized model characteristic of the bargaining problem developed by Nash (1950, 1953; Collard-Wexler et al., 2019). In the bargaining game, a number of agents (K) participate, and a payoff vector (u) for the agents is part of a two-dimensional Euclidean payoff space (R). A feasible set (T) is a subset of the payoff space, and a breakdown or status quo point (b) is an element of the payoff space.

The bargaining problem can then be specified as a model (K, T, b) consisting of participating individuals (K), a feasible set (T), and a breakdown point (b). Nash (1950) states that the feasible set (T) should be compact, convex, and contain the payoff vector. Nash (1950, 1953) argued that a reasonable solution should satisfy four properties: (1) Pareto efficiency, (2) invariance concerning affine transformation, (3) independence of irrelevant alternatives, and (4) symmetry.

Nash (1950, 1953) showed a unique solution for the traditional bargaining problem—the Nash solution—which satisfies the properties mentioned above. The solution, which is a function (f) associated with each bargaining problem (i.e., $f\,(K, T, b)$), is obtained by solving the following maximization problem:

$$\underset{\vec{u}\in T,\, \vec{u}\geq \vec{b}}{\text{Max}} \prod_{i=1}^{N}(u_i - b_i) \qquad (1)$$

In equation (1) $\vec{u}$ is the payoff vector for the analyzed cases (in our case, businesses: $i = 1, \ldots, N$), $\vec{b}$ is the breakdown point—i.e., starting point or the hypothetical payoff if the business' innovation process excludes bargaining or internal coordination—and u_i and b_i are the i-th elements of the vectors $\vec{u}$ and $\vec{b}$, respectively. In the context of the proposed co-innovation framework, the agents involved in the two stages (Fig. 1) are regarded as the two players in the bargaining game (K = {1, 2}), the efficiency scores are the payoffs ($u = \theta^* = \{\theta^1, \theta^2\}$), the production technology of each production stage (T1, T2) is the feasible set (T = {T1, T2}), and the weights associated with the variables included in the two stages of the centralized model (Stage 1 and Stage 2) are the strategic choices (priorities) that produce the business' payoff.

Under the assumption that efficiency will be the lowest if there is no coordination between the collaboration-building process (Stage 1) and the innovation process (Stage 2), that is, the two agents (Stage 1 and Stage 2) do not negotiate, the breakdown point (b) can be computed by generating a "least-ideal" strategic efficiency score for a fictitious business that, in each stage of the model, consumes the maximum input level and produces the lowest (positive) output (i.e., $\mathbf{z} > 0$ and $\mathbf{y} > 0$). This way, our model assumes that all businesses have a more or less developed innovation process (measured by the stages of our model: $b = \{\theta^1_{min}, \theta^2_{min}\}$).

In the context of this study, the following bargaining model can be used to compute—for each business ($i = 1, \ldots, N$)—a distance function rooted in Data Envelopment Analysis (DEA) (Charnes et al., 1978; Liang et al., 2008) that evaluates businesses' co-innovation strategy distinguishing between the two stages proposed in Fig. 1:

$$\text{Max}\left(\frac{\sum_{d=1}^{D}\gamma_d z_{di}}{\sum_{m=1}^{M}\delta_m x_{mi}} - \theta^1_{min}\right) \times \left(\frac{\sum_{y=1}^{Y}\omega_y y_{yi}}{\sum_{d=1}^{D}\gamma_d z_{di}} - \theta^2_{min}\right) \qquad (2)$$

$$s.t.\ \frac{\sum_{d=1}^{D}\gamma_d z_{di}}{\sum_{m=1}^{M}\delta_m x_{mi}} \geq \theta^1_{min}\ ; \quad \frac{\sum_{y=1}^{Y}\omega_y y_{yi}}{\sum_{d=1}^{D}\gamma_d z_{di}} \geq \theta^2_{min}$$

$$\frac{\sum_{d=1}^{D}\gamma_d z_{di}}{\sum_{m=1}^{M}\delta_m x_{mi}} \leq 1 \quad ; \quad \frac{\sum_{y=1}^{Y}\omega_y y_{yi}}{\sum_{d=1}^{D}\gamma_d z_{di}} \leq 1 \quad i = 1, \ldots, N$$

$$\delta_m, \gamma_d, \omega_y > 0 \quad m = 1, \ldots, M, d = 1, \ldots, D, y = 1, \ldots, Y$$

The drawn technology (T = {T1, T2})—which is represented by the restrictions in equation (2)—is the feasible set for the bargaining problem, exhibits constant returns to scale, is homogeneous of degree +1, and is convex in the outputs. Thus, the function of the bargaining problem (i.e., $f\,(K, T, b)$) can be denoted as $f\,(\{1, 2\}, T, \{\theta^1_{min}, \theta^2_{min}\})$.

By applying the formulation proposed by Du et al. (2011), the DEA Nash bargaining problem analyzed in this study can be solved by transforming equation (2) in the following linear model:

$$\text{Max}\ \theta^1 \sum_{y=1}^{Y}\omega_y y_{yi} - \theta^1_{min}\sum_{y=1}^{Y}\omega_y y_{yi} - \theta^2_{min}\sum_{d=1}^{D}\gamma_d z_{di} + \theta^1_{min}\theta^2_{min} \qquad (3)$$

$$s.t.\quad \sum_{d=1}^{D}\gamma_d z_{di} \geq \theta^1_{min}\ ; \quad \sum_{y=1}^{Y}\omega_y y_{yi} \geq \theta^2_{min}\ ; \quad \sum_{d=1}^{D}\gamma_d z_{di} = \theta^1$$

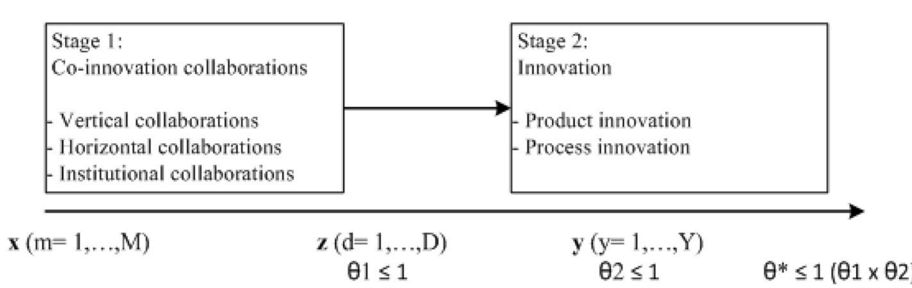

Fig. 1. Co-innovation collaborations and business innovation.

$$\sum_{d=1}^{D}\gamma_d z_{di}-\sum_{m=1}^{M}\delta_m x_{mi}\leq 0 \quad i=1,\ldots,N$$

$$\theta^1\sum_{y=1}^{Y}\omega_y y_{yi}-\sum_{d=1}^{D}\gamma_d z_{di}\leq 0 \quad i=1,\ldots,N$$

$$\theta^1>0,\delta_m,\gamma_d,\omega_y\ >0 \quad m=1,\ldots,M,d=1,\ldots,D,y=1,\ldots,Y$$

In equation (3), collaboration efficiency and innovation efficiency are computed simultaneously. Collaboration efficiency (Stage 1) is $\theta^1 = \sum_{d=1}^{D}\gamma_d\mathbf{z}_{di}$, γ is the vector of endogenous weights that maximizes θ^1 (i.e., weights point to strategic priorities in the configuration of collaborations), and $\theta^1\leq 1$ is estimated through a DEA model with a single constant vector of 1s as input ($\mathbf{x} = 1\forall i$) (see Lovell and Pastor (1999) and Karagiannis and Lovell (2016) for a detailed explanation of DEA models with a single constant input). Innovation efficiency (Stage 2) is $\theta^2 = \sum_{y=1}^{Y}\omega_y\mathbf{y}_{yi}$, ω includes the endogenous weights for the innovation outputs that maximize θ^2, and $\theta^2\leq 1$ is estimated via a DEA model in which the weighted collaborations (outputs of Stage 1: $\mathbf{z}$) are the inputs. For each firm, innovation efficiency (θ^*) is obtained as $\theta^* = \theta^1\times\theta^2$.

Notice that, instead of reflecting the best technical efficiency level common to standard DEA models, the results computed via equation (3) reflect the best achievable efficiency that businesses can realize through negotiation, in our case, by creating more strategically purposeful collaborations and by matching co-innovation collaborations to innovation efforts. Finally, all innovation efficiency estimations (equation (3)) are computed at the country level using the GAMS© software.

4. Research program

4.1. Data

The data set used for the study's empirical design is drawn from an international research project on business competitiveness (Global Competitiveness Project, GCP: www.sme-gcp.org) developed at the Polytechnic University of Catalonia (UPC Barcelona Tech, Spain) and the University of Pecs (Hungary). In 2020, universities from ten European and Latin American countries participated in the GCP (i.e., Bosnia and Herzegovina, Czech Republic, France, Hungary, Spain, Serbia, Brazil, Colombia, Costa Rica, and Mexico). The objective of the GCP is to analyze the factors of business competitiveness by using composite indicators (Lafuente et al., 2020). Recent work by Alonso-Ubieta and Leiva (2019), Bayon and Aguilera (2021), Moreno-Gómez et al. (2021), Lafuente et al. (2021), Lafuente and Vaillant (2021), and Lányi et al. (2021) corroborate the validity of the GCP methodology and databases.

Researchers from the participating universities supervised the entire data collection process. The selection process of the surveyed firms in each country was conducted in two different phases. First, each participating team identified businesses operating in different industries. At this phase, owners and/or top managers are the relevant respondent group. An appointment was arranged after an initial telephone call to gain approval from the owners or a top manager. In the second phase, a face-to-face or virtual interview was held with one of the owners (only if they are part of the top management team) in the case of businesses with less than 20 employees. In comparison, a top manager was interviewed in firms with more than 20 employees.

Self-administrated, structured interviews were conducted during the data collection process in which respondents were asked to answer essentially closed questions. Members of the participating teams conducted the survey, and the data was collected between March and June 2019. The GCP teams use a homogeneous questionnaire to ensure enhanced comparability of results.

The final sample includes information for 734 businesses from seven countries: Colombia (N = 63), Costa Rica (N = 171), Czech Republic (N = 111), France (N = 131), Hungary (N = 90), Mexico (N = 102), and Spain (N = 66). Note that the purpose of the sampling is in no way to reach representativity of any kind, but much the opposite, as is postulated in the theoretical development of the paper and is stated in the study's first hypothesis: *optimal co-innovation configurations are particular to each national innovation system and cannot be standardized/generalized across countries*. Also note that we excluded from the sample extractive and construction businesses so that the final sample includes businesses operating in manufacturing, retail, consumer services, and knowledge-intensive business service sectors.

4.2. Innovation efficiency: input-output set for the proposed two-stage model

Co-innovation collaborations.—In line with the arguments presented in Section 2, we use three types of collaboration to evaluate businesses' collaborative configurations, namely, vertical co-innovation (i.e., collaboration with suppliers and buyers), horizontal co-innovation (i.e., collaboration with partner businesses and competitors), and institutional co-innovation (i.e., collaboration with universities, research centers, technology parks, and local innovation agencies).

As part of the GCP methodology, respondents were asked to rate the importance of each variable related to co-innovation collaborations using a 5-point Likert scale in which 1 represents low relevance, 4 represents high relevance, and 0 indicates that the focal collaboration variable has no strategic value whatsoever for the firm (Douglas and Ryman, 2003). The remaining scale points ensure the uniform evaluation of the variables' importance. Notice that the division of the positive scale values (from 1 to 4) allows a sufficient degree of differentiation in the valuation of the analyzed variables (Lederer et al., 2013). Because for some countries, the sample is relatively small, we employ factor analysis to reduce the dimensionality of the co-innovation collaborations to reduce the potential loss of discriminatory power of output-maximizing linear programs with large numbers of variables (i.e., inputs and outputs) relative to the number of analyzed units (see Adler and Golany (2001) for a detailed description of this approach, while Adler and Yazhemsky (2010) and Lafuente et al. (2021) are examples of empirical applications based on this method).

The results of the information statistics—i.e., Cronbach's alpha test of reliability, KMO test of sampling adequacy, and the Bartlett test of sphericity—presented in Table 1 corroborate the validity of our approach and that the constructs extracted from the factor analysis are internally consistent across variables to measure the underlying co-innovation collaborations.

Business innovation.—Innovation has been analyzed from multiple angles, and innovation outcomes take many forms, including innovative products or services, process innovation, and the innovative dynamics and management of inter-organizational relationships (e.g., Chesbrough, 2010; Foss and Saebi, 2017; Frow et al., 2015; Håkansson and Waluszewski, 2007; Zott and Amit, 2013). We employ four variables to measure business innovation: two variables related to product innovation (new product development and significant amendments to products) and two variables linked to process innovation (novelty of process technology and use of latest developed technologies with less than five years in the market).

Like co-innovation collaborations, respondents weighted the relative importance of each innovation variable using a 5-point Likert scale (from 0 to 4), and factor analysis was used to evaluate how well the four variables reflect the (latent) innovation construct. Again, the findings of the information statistics reported in Table 1 are above the recommended cutoff points and highly significant, thus confirming the validity of the proposed factor model to measure business innovation.

Table 1
Factor analysis: Summary results for the study variables.

	Variables	Variance explained (%)	Cronbach's alpha	KMO test (sampling adequacy)	Bartlett test of sphericity
Panel A) Network					
Vertical	- Buyers - Suppliers	0.6980	0.9237	0.6100	76.49***
Horizontal	- Partners (business group) - Competitors	0.6567	0.8846	0.7461	81.69***
Institutional	- Universities - Research centers - Technology parks - Innovation agencies	0.5878	0.7650	0.7643	441.03***
Panel B) Innovation					
Innovation	- Product (new and significant amendments) - Process (novelty of technology and use of latest developed technologies)	0.7907	0.9117	0.8032	2768.98***

4.3. Variable description: digital competency, firm characteristics, and country-specific effects

This subsection describes the variables used in the parametric (multilevel) analysis evaluating the role of digital competencies on innovation. Descriptive statistics for the selected variables are presented in Table 2.

Because businesses' digital competency is key in understanding the configuration of co-innovation collaborations, we include in our study the 'digital presence' pillar of the competitiveness measure provided by the Global Competitiveness Project (GCP). This aggregate variable—-which ranges between 0 and 1—evaluates three aspects of businesses' digital competency.

a) Technical digital competency, which includes the analysis of output-type connectivity of the business' website (i.e., website size in bytes and loading speed in seconds), complexity (i.e., inner and outer links, images, scripts, and CSS), and appearance (i.e., web appearance in search engines, use of safe communication channels (SSL), use of cookies, integration to external analytical tools such as Google Analytics, and the possibility to visualize the website on mobile devices),
b) Digital connectivity competency that describes the input-type relationship of the website with its environment, that is, the possibility of communicating with the business through different channels (i.e., email, platform systems such as Apple or Google, and social media), and
c) Digital marketing competency that includes the e-marketing tools actively used by the business in the last three years (i.e., website, targeted e-mails, wikis, blogs, social media, web 2.0 applications such as games, web campaigns, chat, link marketing, banners, online guerilla marketing, and mobile marketing).

The firm-level variables used in this study include business size (measured as the logged number of employees), business age (measured as the logged of market experience expressed in years), and a set of industry dummy variables that identify if the sampled businesses operate in knowledge-intensive business services (KIBS), manufacturing, retail, or consumer service sectors.

The country-specific effect is measured through the Digital Platform Ecosystem Index (DPE) for 2020 provided by the Global Entrepreneurship and Development Institute (https://thegedi.org) (Acs et al., 2014, 2022; Szerb et al., 2022). The DPE integrates two ecosystem literatures, namely, the digital ecosystem and entrepreneurial ecosystem, by situating four stakeholders at the core of the digital ecosystem: digital users, technology entrepreneurs, digital platforms, and governments. The DPE works under the assumption that for technology to be successfully developed and introduced, the interactions within the digital ecosystem need to be developed simultaneously (Szerb et al., 2022). By compiling 12 variables linked to 12 individual-level variables properly matched with selected institutional variables related to the country's digital ecosystem, the DPE—which ranges between 0 and 100—measures the quality of countries' digital ecosystem (Acs et al., 2022; Szerb et al., 2022).

5. Results

The results of this study will first present in subsection 5.1 the findings of the multilevel regression model that focuses on the country- and firm-level impacts on overall efficiency. Subsections 5.2 and 5.3 will evaluate the co-innovation configuration choices adopted by the sampled businesses and their contingent connection to innovation efficiency and digital competency, respectively.

5.1. Multilevel regression model: country effects and overall efficiency

The first stage of our analysis is to determine the possible presence of country-level influence over successful firm innovation and the optimal

Table 2
Descriptive statistics and bivariate correlations for the independent variables used in the multilevel model.

	Variables	Avg.	Std. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	Digital competency	0.5138	0.2651	1						
2	Firm size (employees)	47.09	170.47	0.0909	1					
3	Firm age (years)	15.54	12.68	0.0787	0.1803	1				
4	KIBS (dummy)	0.2684	0.4434	0.0988	−0.0709	−0.0663	1			
5	Manufacturing (dummy)	0.1281	0.3344	0.1157	0.1428	0.1747	−0.2321	1		
6	Retail (dummy)	0.1839	0.3877	−0.0614	−0.0181	0.0435	−0.2875	−0.1819	1	
7	Consumer services (dummy)	0.4196	0.4938	−0.0381	−0.0184	−0.0930	−0.5150	−0.3259	−0.4037	1
8	Digital platform ecosystem (DPE index)	42.70	12.54	0.0193	0.0845	−0.0107	0.2553	−0.0376	−0.1183	−0.1109

Note: The table reports, for each variable, the mean value (Avg.), the standard deviation (Std. dev.), and bivariate correlations. Correlations with an absolute value below 0.0614 (i.e., |0.0614|) are not significant, correlations between |0.0614| and |0.0709| are significant at the 10%, correlations between |0.0710| and |0.0930| are significant at the 5%, and correlations higher than |0.0931| are significant at the 1%.

co-innovation configuration adopted by firms. A multilevel mixed-effects linear regression addresses this point, which relates to this study's first hypothesis. Due to the nested nature of the business-level data set by countries, a conventional regression model would likely produce inefficient estimates and biased standard errors (Snijders and Bosker, 2012). A multilevel model is, therefore, preferable and can be presented in the following form:

$$\theta^*_{ic} = \beta_{00} + \beta_{0c} + \beta_1 \text{Firm level variables}_{ic} + \beta_2 \text{DPE}_c + \varepsilon_{ic} \tag{4}$$

In equation (4), i indexes business and c countries, β_{00} is the overall mean of the dependent variable (i.e., overall efficiency scores) and β_{0c} is the randomly distributed country effect, that is, the variance of the mean value of the overall efficiency scores for each country (c) around the overall average efficiency. The firm-level variables include size (ln employees), business age (ln years of market experience), and industry. At the same time, the country-specific effect is measured through the Digital Platform Ecosystem Index (DPE) for 2020.

As a necessary prerequisite, the country effect was verified to ensure that it represents the institutional umbrella backing the innovative activity of businesses in the economy. The between-country variance of the overall efficiency was estimated to determine the appropriateness of the proposed multilevel model (equation (4)). The results of the intercept-only model (Model 1 in Table 3), which captures the proportion of the total variance in the dependent variable between countries, were used to compute the intra-class correlation coefficient (ICC). The results in Model 1 indicate that mean innovation efficiency (θ^*) among countries is 0.2154 (without controlling for business-level covariates), and there is more variation within countries (0.0314) than between countries (0.0016). The ICC value for Model 1 is 0.0485, suggesting that 4.85% of efficiency variations lie between the analyzed countries. Consequently, the results for Model 1 indicate that there is enough between-country variance to justify a multilevel approach.

For the full model (specification 2), the ICC value (0.061)—which lies in the mid-level acceptance area according to the rule of thumb proposed by Hox (2010)—is larger than that reported for the unconditional model (as expected, given that the model controls for some business-level variation). The results in Model 2 indicate that the country-level effect significantly impacts businesses' overall efficiency. These findings agree with our first hypothesis and its argument that there is no dominant cross-country pattern for optimal co-innovation configuration. The national institutional setting where firms are embedded impacts the ideal co-innovation configuration across the analyzed countries meaningfully. This result gives evidence of strong formal institutional path dependency (Acemoglu et al., 2012), thus leading to support this study's first hypothesis (H1), which proposed that *the optimal network configuration for successful co-innovation in a national innovation system is unlikely to follow a standardized transnational pattern.*

Other interesting findings from the multilevel regression results in specification 2 of Table 3 are that, in general terms, larger firms tend to be more efficient at innovation. This is although smaller firms would tend to have the most to gain from co-innovation. Small firms often lack the critical mass and human and financial resources necessary to engage in innovative projects by themselves (Ko et al., 2020). Hence, co-innovation represents a way to overcome this physiological lack of resources. Another telling result is that firms categorized as KIBS demonstrated relatively greater innovation efficiency than those from other industries. Similar findings associating KIBS with increased innovative capability development are found in Lafuente et al. (2018) and from a territorial perspective in Vaillant et al. (2023). KIBS play an important role in the innovation management process, both internally and externally, promoting co-innovation concerning their customers and suppliers (Miles, 2005).

Table 3
Multilevel regression model: Results.

Variables	Model 1:Baseline model	Model 2: Full model
Intercept	0.2154 (0.0162)***	0.1731 (0.0234)***
Firm size (ln employees)		0.0021 (0.0006)***
Firm age (ln years)		−0.0059 (0.0076)
KIBS (dummy)		0.0847 (0.0297)***
Manufacturing (dummy)		0.0378 (0.0224)*
Retail (dummy)		0.0049 (0.0264)
Random effects		
Country intercept variance (DPE index)	0.0016 (0.0008)**	0.0015 (0.0006)**
Residual variance	0.0314 (0.0074)***	0.0231 (0.0063)***
Log likelihood	−21.4260	−11.6958
Goodness of fit statistics		
Wald test (chi2)	–	35.81***
Pseudo R2 (McFadden)	–	0.4541
LR test: full model vs. linear regression		14.41***
LR test: full model vs. null model		40.88***
ICC	0.0485	0.0610
Number of observations	734	734
Number of countries	7	7

All variables are at the business level (level 2) except the DPE index (level 1). Robust standard errors are presented in parentheses. *, **, *** indicate significance at the 10%, 5% and 1%, respectively.

5.2. *Innovation efficiency: identification of strategic co-innovation priorities*

The multilevel analysis focused on the link between digital national frameworks and innovation. To address the study's second hypothesis, this section identifies the collaborations for innovation followed by firms to assess whether the prioritized configurations are conducive to superior innovativeness. Table 4 presents the country-level breakdown of the efficiency results—by country and distinguishes between top- (Q1) and bottom- (Q4) performing businesses based on their resources endowments—and firm-specific weights representing the dominant co-innovation configuration that should be prioritized to optimize firms' innovation success.

The findings for optimal co-innovation—i.e., endogenous weights estimated through equation (3)—show that businesses prioritize different collaborative configurations. At the country level, we have a visual confirmation in Table 4 of the results obtained previously from the multilevel regression that confirmed the lack of transnational trends in optimal co-innovation configuration (H1).

When analyzing the ideal co-innovation configuration among the observed European and Latin American OECD countries, no clear general dominance is found about whether firms should prioritize vertical, horizontal, or institutional collaborations to achieve greater efficiency levels. There seems to be more of a continental pattern, with co-innovation configurations dominated by institutional collaborations being optimal for successful innovation in Latin America, whereas European optimal configurations vary across countries. Therefore, the macroeconomic path-dependency institutional argument upon which this study's first hypothesis is based is mainly prevalent in Europe (Lafuente et al., 2022; North, 1990; Williamson, 2000).

However, to test the study's second hypothesis, considering that a significant difference between optimal co-innovation configurations exists between firms from the same country, Table 4 separates the underperforming ventures (Q1) from the high-performing innovators (Q4). Efficiency results in Table 4 offer a different story from the results obtained from the full sample.

Compared to the full sample, isolating the co-innovation of top performing firms shows how horizontal co-innovation practices are not the dominant observed configuration for optimal innovation output.

Table 4
Efficiency results (equation (3)).

Country	N	Overall efficiency	Stage 2: Innovation	Stage 1: Co-innovation collaborations			
		Efficiency result ($\theta^1 \times \theta^2$)	Efficiency result (θ^2)	Efficiency result (θ^1)	'Pie share: 'Vertical co-innovation	'Pie share': Horizontal co-innovation	'Pie share': Institutional co-innovation
Panel A: Full sample							
Colombia	63	0.1493	0.4775	0.3127	0.0905	0.0919	**0.1304**
Costa Rica	171	0.2092	0.4882	0.4285	0.0465	0.1697	**0.2123**
Czech Republic	111	0.1723	0.4447	0.3873	**0.1955**	0.0987	0.0932
France	131	0.2678	0.6673	0.4012	**0.1562**	0.1239	0.1211
Hungary	90	0.1669	0.4701	0.3550	0.1157	**0.1218**	0.1175
Mexico	102	0.1440	0.4266	0.3377	0.1128	0.0857	**0.1392**
Spain	66	0.2120	0.5197	0.4080	0.0732	0.1625	**0.1723**
Total	734	0.1938	0.5047	0.3840	0.1125	0.1259	0.1456
Panel B: Top performers (upper quartile)							
Colombia	16	0.3987	0.5185	0.7689	0.0864	0.2067	**0.4758**
Costa Rica	43	0.5227	0.5937	0.8804	0.0214	0.2984	**0.5606**
Czech Republic	28	0.3320	0.4062	0.8173	0.2348	0.2507	**0.3318**
France	33	0.7296	0.7988	0.9133	**0.4470**	0.1680	0.2983
Hungary	23	0.4915	0.6097	0.8061	**0.4155**	0.0864	0.3042
Mexico	25	0.4366	0.5108	0.8548	0.1310	0.2093	**0.5145**
Spain	17	0.3921	0.4700	0.8343	**0.4585**	0.0458	0.3300
Total	185	0.4887	0.5748	0.8501	0.2392	0.1984	0.4125
Panel C: Poor performers (bottom quartile)							
Colombia	16	0.0310	0.3994	0.0777	0.0103	**0.0670**	0.0004
Costa Rica	44	0.0239	0.3428	0.0696	0.0092	**0.0600**	0.0004
Czech Republic	29	0.0820	0.4696	0.1746	**0.1692**	0.0045	0.0008
France	34	0.1289	0.6275	0.2054	**0.1980**	0.0063	0.0012
Hungary	24	0.0431	0.3645	0.1183	**0.1143**	0.0035	0.0005
Mexico	26	0.0353	0.354	0.0997	0.0419	**0.0575**	0.0003
Spain	17	0.0589	0.4695	0.1254	**0.1203**	0.0047	0.0004
Total	190	0.0590	0.4457	0.1323	0.1274	0.0043	0.0006

This is contrary to a much more optimizing horizontal co-innovation practice by firms with relatively less performing innovation, and this especially amongst firms from countries that do not necessarily have all the 'fundamental conditions' for successful innovation systems (Van Lancker et al., 2016). In these countries, co-innovation with institutions is key, but only for top-performing firms. The optimal co-innovation networking configuration for firms in the bottom performance quartile does not include institutional collaborations for innovation. For these

Table 5
Mean efficiency comparisons between businesses with high (above average) and low (below average) digital competency.

Country	N	Overall	Stage 2: Innovation	Stage 1: Co-innovation collaborations			
		Efficiency result ($\theta^1 \times \theta^2$)	Efficiency result (θ^2)	Efficiency result (θ^1)	'Pie share: 'Vertical co-innovation	'Pie share': Horizontal co-innovation	'Pie share': Institutional co-innovation
Panel A: Businesses with high (above average) digital competency							
Colombia	28	0.1864	0.4903	0.3801	0.0944	**0.1581**	0.1277
Costa Rica	80	0.2911	0.5329	0.5463	0.0359	**0.3095**	0.2009
Czech Republic	59	0.2034	0.4532	0.4488	**0.2041**	0.1235	0.1213
France	60	0.3100	0.6860	0.4519	**0.1636**	0.1374	0.1509
Hungary	47	0.1808	0.4797	0.3769	**0.1336**	0.1142	0.1292
Mexico	50	0.1931	0.4719	0.4093	0.1168	**0.1515**	0.1409
Spain	37	0.2434	0.5282	0.4609	**0.2213**	0.0696	0.1699
Total	361	0.2378	0.5262	0.4520	0.1239	0.1757	0.1544
Panel B: Businesses with low (below average) digital competency							
Colombia	35	0.1210	0.4674	0.2588	0.0868	0.0405	**0.1315**
Costa Rica	91	0.1459	0.4488	0.3251	0.0543	0.1295	**0.1413**
Czech Republic	52	0.1382	0.4351	0.3176	0.0685	0.0584	**0.1907**
France	71	0.2335	0.6516	0.3584	**0.1515**	0.1128	0.0940
Hungary	43	0.1522	0.4597	0.3310	**0.1158**	0.1137	0.1015
Mexico	52	0.1030	0.3830	0.2688	0.1115	0.0160	**0.1413**
Spain	29	0.1732	0.5088	0.3405	0.0788	0.0843	**0.1774**
Total	373	0.1540	0.4840	0.3182	0.0948	0.0869	0.1366

underperforming firms, vertical or horizontal collaborations optimally lead to more successful innovations.

Only the most efficient co-innovation European economy under analysis, France, consistently maintains a dominant vertical optimal co-innovation configuration. The dominant co-innovation partner for optimal innovation varies across firms of different potential performance levels in all other economies. These results support the study's second hypothesis (H2): *The optimal network configuration for successful co-innovation in a national innovation system is unlikely to follow a standardized pattern across firms of differing innovation performance levels.*

5.3. Digital competency and optimal co-innovation

In this section, firms' digital competency is considered to assess whether digital technologies influence the optimal co-innovation configurations conducive to successful innovation. Table 5 presents the country-level breakdown of the efficiency results and distinguishes between businesses with high (above average) and low (below average) digital competency and firm-specific weights representing the dominant co-innovation configuration that should be prioritized to optimize firms' innovation success.

In doing so, it is clear that digital competency has a crucial influence on the optimal co-innovation configuration of firms. Digital competency are strong enhancers of the impact that vertical, value-chain, and horizontal, cross-industry, co-innovation practices have over the optimization and success of innovation output. Digitalization appears to be particularly influential as an auxiliary of institutional partners to reach optimal co-innovation configuration. Firms with above-average digital competency have optimal co-innovation configurations that do not prioritize institutional partners and are dominated by vertical or horizontal collaborations.

Whereas the sampled European OECD economies see their optimum co-innovation configuration driven towards vertical collaborations by digital competencies, those most digitally capable firms in the observed Latin American OECD countries see their innovation output optimized by horizontal co-innovation configurations. As such, it can be seen in Table 6 below that digital competency is mostly contributing to the innovation optimization of manufacturing firms in European economies. In contrast, for those observed Latin American OECD economies, digital competencies are especially helping business and consumer service industry firms optimize their innovation output. Overall, these results support the study's third hypothesis H3: *Digital technologies influence the optimal co-innovation configuration for successful innovation.*

6. Concluding remarks, implications, and future research lines

6.1. Concluding remarks

This paper analyzed how firms strategize the configuration of their co-innovation collaborations to determine their impact on innovation efficiency and assess if and how these optimal innovation network configurations differ across countries and firms. This answers the call by Voorberg et al. (2015), who, following a systematic review of the collaborative innovation literature, concluded that ambiguity and debate persisted in the literature regarding appropriate network configurations for successful innovation. Special attention was given to the role of digital technologies over optimal co-innovation configurations. This comes in response to Lember et al. (2019)'s review showing the absence of precise approaches to how co-innovation processes are affected by a business' digital competency level. Not only were macro-level disparities in optimal co-innovation configurations across international economies contrasted, but the micro-level innovation efficiency across firms of different innovative potential and firms of divergent digital competency were analyzed to determine whether standardized or customized co-innovation configurations are optimal for successful innovation.

To do so, this study adopted a multilevel regression model to confirm country-specific effects followed by a non-parametric Nash bargaining model to compare the optimal co-innovation configurations of firms with high- and poor-innovative performance, as well as of more and less digitally apt firms. Using a data set from the Global Competitiveness Project of 734 firms of seven OECD countries from Europe and Latin America, the study finds clear distinctions in optimal co-innovation configurations at national and firm levels. Despite this heterogeneity, specific, clear trends are identified. Digital competency is found to disrupt co-innovation configurations for successful innovation as they are clearly associated with the optimal co-innovation configurations dominated by vertical (value chain) and horizontal (industry) collaborations, replacing the need for dominant institutional co-innovation. The study found that co-innovation with institutional partners completely fell from the optimal configuration of digitally apt firms across all studied economies. On the contrary, institutional partnerships were essential for successful innovation in the case of less digitally capable firms.

Table 6
Profile of businesses with high (above average) and low (below average) digital competency.

Country	N	Size (employees)	Firm age (years)	KIBS	Manufacturing	Retail	Consumer services
Panel A: Businesses with high (above average) digital competency							
Colombia	28	181.50***	19.32	0.2500	0.1429	0.0714	0.5357
Costa Rica	80	49.94***	18.73	0.1875*	0.1500	0.2375	0.4250*
Czech Republic	59	36.34***	16.17	0.3051**	0.1525*	0.2373	0.3051
France	60	115.53**	12.98	0.4833	0.1667**	0.0500	0.3000
Hungary	47	19.62*	16.13	0.3191	0.2340	0.2340	0.2128
Mexico	50	24.00**	11.41	0.1600**	0.1600	0.1000	0.5800*
Spain	37	61.62**	24.95	0.2432	0.1351	0.0270	0.5946
Total	361	64.17***	16.84	0.2798	0.1634**	0.1801	0.3767*
Panel B: Businesses with low (below average) digital competency							
Colombia	35	18.91	11.06	0.1714	0.1143	0.1143	0.6000
Costa Rica	91	29.54	17.22	0.0989	0.1099	0.2418	0.5495
Czech Republic	52	16.10	15.10	0.5192	0.0577	0.1731	0.2500
France	71	77.49	12.52	0.4507	0.0423	0.0986	0.4085
Hungary	43	10.44	15.65	0.3953	0.1860	0.1860	0.2326
Mexico	52	11.41	10.40	0.0192	0.0769	0.1731	0.7308
Spain	29	13.07	16.17	0.1379	0.1034	0.0345	0.7241
Total	373	30.76	14.28	0.2574	0.0938	0.1877	0.4611

Note: For each country, the Mann-Whitney *U* test is used to evaluate whether significant differences exist in the distribution of variables between businesses with high vs. low digital competency (*, **, *** = significance at the 10%, 5% and 1%, respectively).

6.2. Implications

Finding the disruptive effects of digital technologies over the optimal co-innovation configurations at the macro and micro levels brings meaningful implications for policy, practice, and academia. The implications discussed in this section emerge from the study results and are strictly connected to our research questions.

Strategic isomorphism is sub-optimal.—In connection to this study's first research question ('what configurations of innovation-driven collaborations contribute to optimizing firms' innovation efficiency?'), the main lesson to take away from the findings of this study is that when it comes to innovation networks, one size does not fit all. This study also highlights the role of digital tools and platforms in helping innovation systems and firms within them reach their optimum innovation possibility frontier. Such tools appear to bridge partners, facilitate collaboration, and compensate for firms' potential systemic deficiencies or resource deficits, aiding them to optimize their innovation potential and consequently helping the entire innovation system in reaching its full innovation capacity. In the presence of digital competences, the surrogate role often filled by institutional partners in innovation systems is no longer necessary, where even less endowed firms can improve their innovation efficiency through direct vertical and/or horizontal co-innovations with value-chain or industry partners within their ecosystem to better optimize their innovation potential.

From a practice and policy viewpoint, this is an important finding since by facilitating the digital transition of industry, public administrations can significantly promote innovative capacity optimization of their economies. The positive impact of digital facilitation would likely be of particular importance in the case of less resource-endowed firms that can better access innovation ecosystems and engage in external co-innovation activities through digital tools. Without digital competencies, firms are often driven toward innovation collaborations with institutional players. Still, these are less accessible within the optimal co-innovation configurations of less-endowed firms. Digitalization, therefore, becomes a better path towards optimal co-innovation practices for these firms, and the role of public policy measures in stimulating and facilitating such digital transition can be key.

Digital technologies open a window of opportunity for co-innovation collaborations.—Because digital transformation is impacting every corner of society, researchers must keep up, question, and revamp existing paradigms that have consolidated themselves in academia but may be affected by digitalization. This is clearly the case for appraising the impact of digital technologies over co-innovation and the collaborative network configurations that lead to optimal innovation outputs. Not only is digitalization facilitating collaborative efforts, but contrary to the relatively standardized collaboration configurations postulated that are overwhelmingly found in past literature, digital competency opens the need for a more customized approach to analyzing innovation systems and the multiagent relationships leading to optimal innovation. It became clear when elaborating on this study that the industrial and institutional co-innovation (co-production, co-creation) literature is being primarily developed in parallel with each other, with few interactions. However, the findings of this research emphasize the need to have a much more holistic and multilevel perspective of innovation system dynamics and collaborative network configurations. This argument line connects to our second research question ('is the connection between co-innovation networks and innovation efficiency affected by the local ecosystem's characteristics and the firm's digital technologies availability?').

6.3. Future research lines

The findings reported in this study are open to further verification. First, as with most efficiency studies, it is impossible to analyze the decision-making process underlying firms' co-innovation configurations directly. Future research could address this issue by exploring micro-foundational and intra-firm resource optimization and the related decision-making processes impacting the innovation efficiency of firms. The innovation indicator used in this study is an indicator extracted from factor analysis. Although this practice is robust and widely used in academic work (e.g., Lafuente et al., 2021), different co-innovation configurations may call for a less balanced measure of innovation when establishing optimal innovation frontiers.

Second, efficiency was used as a theoretically supported proxy for a firm's attainable innovation deployment. However, further research may look to find ways to specifically measure and consider what firms can achieve with their resource endowment and how these are optimized, scaled, and/or complemented through collaboration, resulting in more efficient innovation capacity utilization. Similarly, research has found meso-level institutional framework variations within countries (Vaillant and Lafuente, 2007; Driga et al., 2009). Innovation systems are often multidimensional (Van Lancker et al., 2016) and can fall outside simple geographic parameters to include more precise functional ecosystems (Kohtamäki et al., 2019). Such meso-level delimitations could also be included within the framework of future research. Related, although the properties of non-parametric DEA models—e.g., capacity to handle multiple inputs and multiple outputs to model units' production function without imposing any functional form on the technology—make it a powerful analytical tool, this method is not exempt from weaknesses that might condition estimations. These include, for example: the use of non-paprametric linear programming to compute efficiency scores which complicates statistical hypothesis testing, the inability to separate true inefficiency from estimation error, and its restricted approach that does not allow to make a distinction between different types of efficient (and inefficient) units (Grifell-Tatjé and Lovell, 2015). The obvious recommendation to researchers in the field is to put to the test the robustness of non-parametric efficiency estimations by contrasting the DEA results with alternative methodologies (e.g., parametric frontier models or bootstrapped distance functions).

Third, as the dominant vertical, horizontal, and mainly institutional co-innovation configurations appeared to serve different purposes according to our findings, new research can also be conducted to specify further the specific gains from different co-innovation configurations for firms in the broader innovation system.

Finally, it would be interesting for future research to include a more significant number of countries in its samples, possibly including other continents than those included here. Despite having found significant country-specific heterogeneity in the study sample, including firms from more countries may better capture the inherent diversity of those in Europe and Latin America.

Data availability

The authors do not have permission to share data.

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