

Designing the Cognitive Map of Key Actors in the Innovation Ecosystem: An Exploratory Study Using the Fuzzy Cognitive Modeling Approach

Zahra Shahsavari¹ , Mahmoud Moradi² , Mohammad Rahim Ramazanian³ , and Reza Asadifard⁴ 

1. Corresponding author, Ph.D. Candidate, Department of Management, Faculty of Management and Economics, University of Guilan, Rasht, Iran. E-mail: zar_shahsavari@webmail.guilan.ac.ir
2. Associate Prof., Department of Management, Faculty of Management and Economics, University of Guilan, Rasht, Iran. E-mail: m.moradi@guilan.ac.ir
3. Associate Prof., Department of Management, Faculty of Management and Economics, University of Guilan, Rasht, Iran. E-mail: ramazanian@guilan.ac.ir
4. Associate Prof., Department of Innovation Policy and Foresight, Technology Studies Institute, Tehran, Iran. E-mail: reza_asadifard@tsi.ir

Article Info

Article type:
Research Article

Article history:
Received June 16, 2026
Received in revised form
July 08, 2026
Accepted September 21,
2026
Available online October
01, 2026

Keywords:
Fuzzy cognitive mapping,
innovation ecosystem,
ecosystem actors,
laboratory industry.

ABSTRACT

Objective: Innovation ecosystems are complex, multilayered structures comprising diverse actors such as universities, industries, investors, policymakers, and researchers. Identifying and analyzing the interconnections among these actors is paramount for advancing innovation and improving ecosystem performance. This study investigates the relationships among actors within the innovation ecosystem of the laboratory industry using Fuzzy Cognitive Mapping (FCM) to analyze their causal relationships and mutual influences.

Methodology: Based on a literature review, field data, and interviews with academic and industry experts, seventeen key actors were identified. A 17×17 interaction matrix was developed to determine the influence of each actor on others within the ecosystem. The FCM analysis was used to model the network structure of these actors and to evaluate the strength of their interactions.

Results: The cognitive map analysis identified 17 actors and 268 causal relationships within the laboratory industry innovation ecosystem, indicating a highly interconnected structure. Centrality analysis shows that the LabsNet network, accelerators, platforms, and coordinating units play the most influential roles in shaping ecosystem dynamics.

Conclusion: The findings highlight that the performance of the laboratory industry innovation ecosystem depends on the coordinated functioning of multiple interdependent actors. In particular, facilitative and coordination oriented structures—such as accelerators, platforms, and coordinating units—play a critical role in enabling interaction, knowledge exchange, and collaborative innovation. Strengthening these components can therefore support the sustainable development and dynamism of the ecosystem.

Cite this article: Shahsavari, Z., Moradi, M., Ramazanian, M., & Asadifard, R., (2026). Designing the cognitive map of key actors in the innxovation ecosystem: An exploratory study using the fuzzy cognitive modeling approach, *Industrial Management Journal*, 18(4), 48-77. <https://doi.org/10.22059/imj.2026.413648.1008314>



© The Author(s).

Publisher: University of Tehran Press.

DOI: <https://doi.org/10.22059/imj.2026.413648.1008314>

Introduction

Innovation is the most effective pathway to value creation (Adner & Kapoor, 2010). In today's competitive environments, it is recognized as a critical source of competitive advantage and long-term organizational success. Organizations with greater innovation capacity can respond more rapidly to environmental changes and challenges (Asgari et al., 2025). In the innovation literature, an innovation ecosystem is defined as a network of organizations and individuals that interact over time and co-evolve to create value through innovation (Nylund et al., 2019; Paasi et al., 2023). Ecosystems are heterogeneous assemblages in which actors develop their capabilities in a co-evolutionary manner through processes of value co-creation (Moore, 1996; Adner & Kapoor, 2010; Autio & Thomas, 2014; Coletto et al., 2024). These ecosystems consist of complementary actors connected through interdependencies, shared resources, and reciprocal interactions (Adner, 2017; Granstrand & Holgersson, 2020; Tanveer et al., 2026). Accordingly, the performance of an innovation ecosystem depends not only on the presence of diverse actors but also on the quality and structure of the relationships among them (Dedehayir et al., 2018; Baldwin et al., 2024).

In such an environment, firms achieve competitive advantage by identifying the latent value embedded in the products and services they offer to customers (Ethiraj & Posen, 2013; Mäkinen & Dedehayir, 2013). However, no single firm can provide all the resources required for the development and commercialization of innovation; therefore, organizations must interact with other actors within the innovation ecosystem to create value (Talmar et al., 2020; Granstrand & Holgersson, 2020). This issue becomes even more significant in complex innovation environments, where value creation depends on the combination of complementary resources, interorganizational collaboration, and the alignment of roles among different actors (Paasi et al., 2023; Baldwin et al., 2024; Neto et al., 2024). Recent studies in the field of innovation systems also indicate that innovation outcomes emerge from interactions among institutional structures, policy mechanisms, and both formal and informal relationships among diverse actors (Ranjbar et al., 2026).

Strategic research activities provide a fundamental foundation for the acquisition of new knowledge and technologies. Conducting rigorous and credible research requires access to reliable laboratories to ensure the validity and reliability of test results (Azadi & Zahir-Mirdamadi, 2016). Universities and research institutions across various scientific fields typically maintain their own dedicated laboratories, and many industries also rely on laboratory services to assess product quality and support production processes. Therefore, laboratories are considered one of the essential infrastructures of scientific and research systems (Nersessian et al., 2003). In knowledge-based and technology-driven industries, laboratory infrastructures are not merely collections of technical equipment; rather, they function as intermediary links between scientific knowledge, industrial applications, quality assurance, and the development of innovation.

Despite the significant importance of laboratories, our understanding of the ecosystem of this industry—particularly in the context of innovation—remains limited. Complex socio-technical systems often require approaches capable of representing interdependencies and feedback relationships among system components (Kokkinos & Nathanail, 2023).

Managing the laboratory industry ecosystem is highly complex due to the large number of actors involved, the diversity of their roles, the interdependencies among them, and the breadth of their interactions. In such systems, innovation outcomes depend not only on the presence of different actors but also on how they interact and how roles are distributed across the system (Valkokari et al., 2016; Paasi et al., 2023; Neto et al., 2024). However, many previous studies have primarily focused on identifying actors or providing general descriptions of the relationships among them, while paying less attention to analyzing the causal structure of interactions among these actors. In other words, although the existing literature has examined the roles of different actors in innovation ecosystems, our understanding of how these actors influence one another and how their relationships form a causal structure—particularly in contexts such as the laboratory industry—remains limited. This research gap suggests that, to better understand the dynamics of such ecosystems, it is necessary to move beyond merely identifying actors and instead analyze the structure of influence relationships among them.

Accordingly, the main objective of this study is not only to identify the actors within the laboratory industry ecosystem but also to analyze the causal relationships among them and examine the extent of their mutual influence on ecosystem dynamics. In this regard, the following research questions are proposed:

- ✓ Who are the main actors in the innovation ecosystem of the laboratory industry?
- ✓ How are the causal influence relationships among these actors structured?
- ✓ Which actors exert the greatest influence on the dynamics of the ecosystem?

To address these questions, this study employs Fuzzy Cognitive Maps (FCM) as a modeling approach for representing causal relationships among complex system elements (Kosko, 1986; Özesmi & Özesmi, 2004). FCM is particularly useful in complex and uncertain settings. It can integrate expert knowledge and support interpretable causal analysis (Sovatzidi & Iakovidis, 2026). This method enables the representation of the direction and strength of relationships among concepts, the identification of influential elements, and the analysis of system dynamics. By identifying the key actors in the laboratory industry ecosystem and analyzing the relationships among them, this study seeks to provide a clearer picture of interaction structures and key points of influence within this ecosystem. In doing so, it contributes to the development of the innovation ecosystem literature and advances understanding of the dynamics of this industry. This study also provides practical insights for policymakers and industry stakeholders involved in the development and management of laboratory infrastructures.

Literature Background

In the innovation management literature, traditional perspectives that viewed innovation as the outcome of the independent activities of individual organizations have gradually given way to network-based approaches. Research shows that innovation, in many cases, results from the interaction and collaboration of diverse actors operating within a shared institutional, technological, and economic environment (Moore, 1993). Under such conditions, organizations must interact with external actors to develop and commercialize innovation, as the resources, knowledge, and capabilities required for innovation are typically distributed across different actors (Adner & Kapoor, 2010; Autio & Thomas, 2014). Accordingly, the concept of the “innovation ecosystem” has emerged to describe a set of interconnected organizations and institutions that participate in the process of value creation through interaction, knowledge exchange, and the combination of resources (Jacobides et al., 2018). In such an ecosystem, firms, universities, research centers, governmental institutions, and other stakeholders are connected through a network of formal and informal relationships, and through these interactions the flow of knowledge, technology, and resources within the system takes shape (Granstrand & Holgersson, 2020; Liu et al., 2026).

One of the fundamental characteristics of innovation ecosystems is the heterogeneity and interdependence among actors. Each actor provides a portion of the resources, capabilities, or infrastructures required for the development of innovation, and innovation typically emerges through the combination and synergy of these resources (Talmar et al., 2020). Accordingly, the performance of an ecosystem largely depends on the quality of interactions among actors and the way relationships among them are structured (Granstrand & Holgersson, 2020). Recent studies also describe the innovation ecosystem as a complex network of heterogeneous actors that, through multidimensional interactions, facilitate the flow of knowledge and technology and provide the conditions for the development of innovation and industrial growth (Compagnucci et al., 2025; Liu et al., 2026).

The importance of this network-based logic becomes more evident in industries that rely on scientific and research infrastructures. The laboratory industry represents an example of such systems, in which laboratories, universities, research centers, industries, knowledge-based firms, equipment suppliers, and standardization bodies interact with one another. Laboratory networks in many countries play an important role in scientific advancement and business development; the presence of advanced research laboratories and well-developed laboratory infrastructures can accelerate technological progress and enhance economic competitiveness (Namdarian, 2016). In addition, by providing a platform for testing ideas and conducting research activities, laboratories create conditions for the development of innovation and the cultivation of creative thinking, and

they can contribute to increasing organizations' innovation capacity in a manner similar to innovation platforms (Santarsiero et al., 2020).

Furthermore, many universities, research centers, and industries rely on laboratory services to conduct research activities, evaluate product quality, and develop technologies; therefore, laboratories are regarded as one of the key infrastructures of scientific and research systems (Nersessian et al., 2003). In the innovation ecosystem literature, a considerable portion of research has focused on identifying actors and examining their roles in the value creation process. For example, the Triple Helix model introduces the interaction among university, industry, and government as one of the main mechanisms for the production and diffusion of knowledge (Etzkowitz, 2003). However, recent studies show that, in practice, innovation ecosystems include a much broader range of organizations and institutions, and the relationships among them extend beyond the Triple Helix framework (Jacobides et al., 2018; Compagnucci et al., 2026). In this regard, Hoveskog et al. (2026) view the innovation ecosystem as a framework for explaining collaboration among heterogeneous actors in the processes of value creation and capture. Within this framework, the overall value of the ecosystem is not the outcome of the activities of a single actor but rather the result of the synergy among the resources and activities of multiple actors. Accordingly, concepts such as resource complementarity, interdependence, and the coordination of activities are highlighted as key elements in the functioning of innovation ecosystems (Hoveskog et al., 2026).

Despite these advances, a considerable portion of the existing research has primarily focused on identifying key actors or examining the limited relationships among some of them. However, in many innovation ecosystems, the overall performance of the system stems from a network of reciprocal interactions among different actors. Therefore, merely identifying actors without analyzing the influence relationships among them cannot provide a comprehensive picture of ecosystem dynamics. This issue becomes even more significant in industries such as the laboratory industry, which are characterized by a high diversity of actors and strong interdependencies. In recent years, some studies have attempted to analyze the network structure of relationships among actors within ecosystems. In this approach, the position of each actor in the network and the extent of its connections with other actors can influence access to knowledge resources and opportunities for collaboration. For example, Mohammadi et al. (2024) in a study on absorptive capacity in the innovation ecosystem of Sharif University of Technology showed that analyzing the pattern of relationships among actors can help identify the degree of each actor's influence on the flow of knowledge and innovation. However, many of these methods primarily focus on the structure of connections and are less capable of modeling causal relationships and the strength of influence among actors. In complex socio-technical systems, understanding system dynamics often requires approaches capable of representing causal interactions and feedback relationships among multiple

factors (Kokkinos & Nathanail, 2023). Therefore, to achieve a better understanding of the dynamics of innovation ecosystems, it is necessary not only to identify the actors but also to analyze the structure of causal relationships among them. Such an analysis can reveal how interactions among different actors lead to the emergence of patterns of influence within the ecosystem and which actors play more central roles in this structure. One of the methods used to model such complex systems is Fuzzy Cognitive Maps (FCM). This method was first introduced by Kosko (1986) and was developed to model systems with complex causal relationships among variables. Such graph-based representations allow researchers to capture the causal structure of complex systems and analyze how different components influence one another (Sovatzidi & Iakovidis, 2026; Kosko, 1986; Özesmi & Özesmi, 2004). This feature makes it possible to model influence relationships among system components and is particularly useful in situations where knowledge about the system is largely derived from expert judgments and qualitative assessments (Sovatzidi & Iakovidis, 2026).

Various studies have shown that FCM can be used to analyze complex socio-technical systems and to explore the influence relationships among different actors and system components (Kokkinos & Nathanail, 2023). For example, Quiñones et al. (2019) employed a combination of the Delphi method and FCM to analyze barriers to technology transfer in universities, and Falana et al. (2022) applied FCM to examine the roles of key stakeholders in delivering net-zero carbon buildings and to analyze the influence relationships among actors involved in the system. In domestic studies, Ahmadi et al. (2026) showed that FCM is capable of revealing both direct and indirect pathways of influence among variables and clarifying the structure of relationships in complex systems. Unlike quantitative social network analysis, which primarily reveals network structure through numerical representations, these methods may not fully explain the meaning, context, and dynamics of relationships and may overlook elements such as content, process, change, and awareness (Çakır, 2026). Therefore, methods capable of representing causal influence structures among actors can provide deeper insights into ecosystem dynamics and the roles of different participants (Sovatzidi & Iakovidis, 2026). Despite the growing body of research on innovation ecosystems, the analysis of the causal structure of relationships among actors remains limited in some domains, and this issue is particularly evident in the laboratory industry.

In this regard, FCM is especially suitable because it captures weighted and directional causal relationships, incorporates expert judgment, and helps reveal both direct and indirect pathways of influence within complex systems (Karatzinis & Boutalis, 2025). Therefore, the present study employs Fuzzy Cognitive Maps to model the influence relationships among actors in the laboratory industry ecosystem and, based on the structure of these relationships, to identify the key actors of the ecosystem.

Overall, the reviewed literature suggests that innovation ecosystems should be understood not only as sets of actors but also as systems of relationships through which actors influence one another. However, two gaps remain evident in studies of the laboratory industry ecosystem. First, while previous research has identified actors and described their roles, scant attention has been paid to the causal structure of relationships among these actors and how such interdependencies shape ecosystem dynamics. Second, despite the central importance of laboratories as scientific and research infrastructure, the laboratory industry has received limited attention in innovation ecosystem research. In response, the present study focuses on the laboratory industry ecosystem and applies Fuzzy Cognitive Mapping (FCM) to examine the structure of influence relationships among its actors. By doing so, the study moves beyond mere actor identification to provide a relational analysis of the ecosystem. Based on the reviewed literature, the main actors considered in this study are summarized in Table 1.

Table 1. Literature-based identification of innovation ecosystem actors

Variable	Subgroup	
C1	Suppliers and Manufacturers	(Adner & Kapoor, 2011; Autio & Thomas, 2014; Zeng et al., 2017; Talmar et al., 2020; Yin et al., 2020; Dedehayir et al., 2022; Pushpanathan & Elmquist, 2022; Li-Ying et al., 2022; Baldwin et al., 2024; Wang et al., 2024)
C2	Commercial Companies	(Autio & Thomas, 2014; Oh et al., 2016; Granstrand & Holgersson, 2020; Talmar et al., 2020; Beliaeva et al., 2019)
C3	Developers	(Adner & Kapoor, 2011; Nambisan & Baron, 2013; Kapoor & Furr, 2015; Jacobides et al., 2018; Talmar et al., 2020; Yin et al., 2020; Klimas & Czakon, 2022))
C4	Industry	((Adner, 2017; Audretsch et al., 2022; Dedehayir et al., 2018; Granstrand & Holgersson, 2020; Gu et al., 2021; Gulati et al., 2012; Oh et al., 2016; Pushpanathan & Elmquist, 2022; Su et al., 2018; Yin et al., 2020; Zeng et al., 2017)
C5	Researchers	(Autio & Thomas, 2014; Li-Ying et al., 2022; Oh et al., 2016; Paasi et al., 2023; Robaczewska et al., 2019; Stam, 2015; Su et al., 2018; Talmar et al., 2020)
C6	Specialists	((Autio & Thomas, 2014; Dedehayir et al., 2018; Su et al., 2018; Beliaeva et al., 2019; Granstrand & Holgersson, 2020)
C7	University	(de Vasconcelos Gomes et al., 2018; Guerrero et al., 2016; Iansiti & Levien, 2004; Kapoor & Furr, 2015; Liu & Stephens, 2019; Oh et al., 2016; Stam, 2015)
C8	Investors and Financial Providers	(Beliaeva et al., 2019; Guerrero et al., 2016; Iansiti & Levien, 2004; Neto et al., 2024; Su et al., 2018; Tamtik, 2018; Yin et al., 2020)
C9	Government	(Dedehayir et al., 2018; Gu et al., 2021; Guerrero et al., 2016; Li-Ying et al., 2022; Oh et al., 2016; Oliveira & Rua, 2025; Stam, 2015)
C10	Entrepreneurs	(Dedehayir et al., 2018; Guerrero et al., 2016; Li-Ying et al., 2022; Neto et al., 2024; Robaczewska et al., 2019; Su et al., 2018)
C11	Competitors	(Adner, 2017; Adner & Kapoor, 2011; Dedehayir et al., 2022; Granstrand & Holgersson, 2020; Jacobides et al., 2018; Liu & Stephens, 2019; Pushpanathan & Elmquist, 2022; Wang et al., 2024)

C12	Central Actor	(Iansiti & Levien, 2004; Adner & Kapoor, 2011; Adner, 2017; Jacobides et al., 2018; Dedehayir et al., 2018; Granstrand & Holgersson, 2020; Talmar et al., 2020; Baldwin et al., 2024)
C13	Accelerators	(Dedehayir et al., 2018; Granstrand & Holgersson, 2020; Guerrero et al., 2016; Robaczewska et al., 2019; Neto et al., 2024; Jütting, 2024)
C14	Innovation Intermediaries & Facilitators	(Baldwin et al., 2024; Guerrero et al., 2016; Jütting, 2024; Li-Ying et al., 2022; Lin, 2018; Neto et al., 2024; Tamtik, 2018)
C15	Coordinating Units	(Adner & Kapoor, 2011; Autio & Thomas, 2014; Baldwin et al., 2024; Carrara & Freisinger, 2024; Dedehayir et al., 2022; Pushpanathan & Elmquist, 2022; Su et al., 2018)
C16	Support Roles	(Baldwin et al., 2024; Dedehayir et al., 2018; Frow et al., 2016; Neto et al., 2024; Robaczewska et al., 2019; Tamtik, 2018; Yin et al., 2020)
C17	Platform	(Autio & Thomas, 2014; Dattée et al., 2018; Dedehayir et al., 2018; Jacobides et al., 2018; Oh et al., 2016; Pushpanathan & Elmquist, 2022; Su et al., 2018; Wang et al., 2024; Yin et al., 2020; Zeng et al., 2017)

Materials and Methods

This study followed a structured multi-stage methodological framework to systematically identify, validate, and model the key actors of the laboratory innovation ecosystem. The overall operational procedure of the study, spanning from initial identification to final scenario analysis, is illustrated in Figure 1.

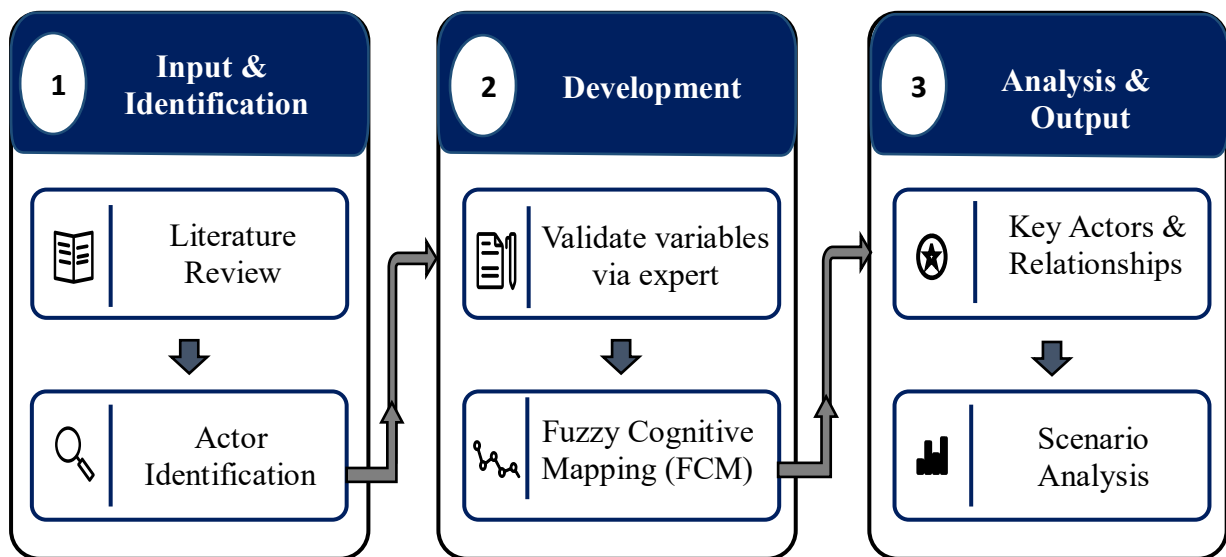


Figure 1. Research methodology framework of the study

The research process consisted of four sequential stages, each corresponding to a distinct component of the study design:

Identification of Ecosystem Actors from the Literature

The research process began with a systematic review of English-language scholarly publications indexed in Scopus and Web of Science to identify a preliminary set of actors within innovation ecosystems. The review focused on studies addressing innovation ecosystems, value cocreation, coevolutionary interactions, and the roles of organizations and individuals in innovation processes. This stage produced an initial pool of candidate actors reflecting the conceptual foundations of the innovation ecosystem literature.

Validation and Refinement of Ecosystem Actors

Because the initial extraction generated a relatively broad set of codes, the preliminary list was subsequently evaluated through consultation with domain experts to enhance content validity. During this stage, overlapping concepts were merged and conceptually weak or less relevant items were removed based on expert judgment. This iterative refinement process ensured that the resulting set of actors was coherent and theoretically grounded. Following this validation process, a final set of 17 ecosystem actors was confirmed. With the assistance of academic and industry experts, these actors were subsequently contextualized and categorized in relation to the laboratory industry to provide greater analytical clarity. Their corresponding roles within the laboratory innovation ecosystem were identified to facilitate clearer interpretation of their roles. The classification of ecosystem actors and their laboratory industry equivalents is presented in Table 2.

Fuzzy Cognitive Mapping

Fuzzy Cognitive Mapping (FCM) is a causal modeling approach originally introduced by Kosko (1986) to represent complex systems composed of interconnected concepts. FCM is particularly valuable for analyzing complex problems in unstable or uncertain environments, where concepts may be loosely defined, and the relationships among them are holistic and nonlinear. Its inherent flexibility makes FCM well suited for high-level policy research, as it can accommodate macro-level constructs without requiring highly precise empirical inputs. FCM has proven especially effective in domains characterized by structural uncertainty, particularly when complemented by descriptive analytical tools (Kokkinos & Nathanail, 2023). Recent studies also highlight that FCM allows the incorporation of expert knowledge to model causal relationships in complex systems where precise quantitative data are unavailable (Cousins et al., 2024). Moreover, FCM enables the integration of expert knowledge in defining system concepts and causal relationships, making it particularly suitable for contexts where empirical data are limited but expert understanding is available (Sovatzidi & Iakovidis, 2026).

In contrast, System Dynamics typically requires the quantitative specification of stock–flow structures to model how systems evolve through feedback loops and dynamic behavior (Karunathilake et al., 2020), while network analysis represents systems as interconnected nodes

and edges and focuses on examining structural relationships among actors (Soleimanian et al., 2024). In this study, FCM was prioritized over Social Network Analysis (SNA). According to recent methodological discussions, quantitative SNA often reduces complex social relations to numerical data and focuses primarily on the existence of ties, failing to capture whether interactions are positive or negative or to fully explain the dynamics of relationships (Çakır, 2026). As the innovation ecosystem involves intricate causal feedback loops and qualitative shifts, FCM provides a more robust framework. Unlike SNA, which may lead to misleading results in small-scale networks due to inflated centrality ratios, FCM enables the integration of expert-based qualitative insights into a semi-quantitative model, allowing for the simulation of system behavior under various scenarios (Karatzinis & Boutalis, 2025). Consequently, while static network analysis is limited to mapping existing structural connections at a single point in time, FCM is more suitable for this study because it captures the dynamic, causal relationships that govern ecosystem behavior. In such contexts, FCM enables the modeling of causal influence relationships among actors based on expert knowledge. Similar expert-based FCM approaches have been applied to analyze the influence relationships among stakeholders in complex socio-technical systems (Falana et al., 2022).

To capture interactions within the innovation ecosystem, an online questionnaire was administered to the expert panel. Experts were identified through purposive sampling, beginning with known contacts in academia and the laboratory industry and expanding through referrals from the initial participants. To ensure that the expert panel possessed comprehensive knowledge of both laboratory systems and the innovation ecosystem, candidates were selected based on their professional or research background in laboratory management, technical operations, or innovation-related fields. In total, 13 experts—including industry managers, technical specialists, and university faculty—participated in the study. The demographic characteristics of the expert panel are summarized in Table 2. Experts evaluated the influence of each actor on the innovation performance of other actors. These causal influences were expressed using linguistic variables and subsequently converted into numerical values ranging from -1 to $+1$ (strong positive influence: $+1$; moderate positive influence: $+0.5$; no influence: 0 ; moderate negative influence: -0.5 ; strong negative influence: -1). To facilitate this process, the researchers arranged the online questionnaire as a 17×17 cross-impact matrix. For each cell (i, j) in the matrix, experts were asked to answer the following standardized question: To what extent and in what direction does the performance or activity of Actor i directly influence Actor j ? If no causal link existed, they selected No influence (0). Otherwise, they chose the corresponding linguistic term representing the direction and intensity of the relationship.

Table 2. Demographic profile of the experts

	Education	Research/Industry Experience	Expert Role
E1	Ph.D. in Technology Management	More than 7 years	Faculty Member & Head of Laboratory Network
E2	Ph.D. in Industrial Management (Production and Operations)	More than 7 years	Faculty Member & Senior Laboratory Manager
E3	Ph.D. in Industrial Management (Production and Operations)	More than 7 years	Industry Practitioner & Adjunct Professor
E4	Ph.D. in Industrial Management (Production and Operations)	More than 7 years	Industry Practitioner & Adjunct Professor
E5	Ph.D. in Industrial Management (Strategy)	3–7 years	Industry Practitioner & Researcher
E6	Ph.D. in Information Technology	3–7 years	Industry Practitioner & Researcher
E7	Ph.D. Candidate in Industrial Management (Production and Operations)	3–7 years	Researcher & Adjunct Professor
E8	Ph.D. Candidate in Industrial Management (Production and Operations)	1–3 years	Researcher
E9	Ph.D. Candidate in Entrepreneurship	More than 7 years	Industry Practitioner
E10	M.Sc. in Nanotechnology	More than 7 years	Researcher & Senior Laboratory Specialist
E11	M.Sc. in Nanotechnology	3–7 years	Laboratory Specialist
E12	M.Sc. in Nanotechnology	1–3 years	Researcher
E13	B.Sc. in Biology	More than 7 years	Laboratory Specialist

Thirteen experts evaluated the causal relationships among the 17 identified actors of the innovation ecosystem. The level of agreement among experts was assessed using Kendall's coefficient of concordance (W), calculated as Equation 1:

$$W = \frac{12S}{m^2(n^3 - n)} \quad (1)$$

where m represents the number of experts, n denotes the number of ranked variables (17 actors), and S is the sum of squared deviations of the rank totals from their mean. The statistical significance of the concordance was examined using Equation 2:

$$X^2 = m(n - 1)W \quad (2)$$

The results indicate a moderate to substantial level of agreement among experts ($W = 0.524$). The chi-square test confirmed statistical significance ($\chi^2 = 1846.15$, $p < 0.001$), indicating a consistent perception among experts regarding the causal relationships within the innovation

ecosystem. To further assess the robustness of the results, a leave-one-out sensitivity analysis was performed. In this procedure, Kendall's coefficient of concordance (W) was recalculated by sequentially removing each expert from the dataset. The results showed that the value of W varied only slightly across the iterations, ranging from 0.511 to 0.533, compared with the original value of 0.524. The largest change occurred when Expert 2 was excluded, resulting in $W = 0.511$ ($\Delta W = -0.013$). Overall, the small variation in W indicates that expert agreement remains stable and that the results are not significantly influenced by any single expert.

Following the collection of expert opinions, the individual cognitive matrices from 13 participants were aggregated by averaging. Specifically, if A_k represents the 17×17 adjacency matrix corresponding to expert k (where $k = 1, 2, \dots, 13$), the final aggregated matrix (A_{avg}) was calculated as Equation 3:

$$A_{avg} = \frac{1}{13} \sum_{k=1}^{13} A_k \quad (3)$$

This aggregation allowed the resulting model to reflect the collective judgment of the panel while reducing the influence of individual bias. The resulting final matrix was then returned to three participating experts for validation, and all three experts confirmed the results. Subsequently, the relationships among ecosystem actors were modeled using FCM, a qualitative-quantitative approach that captures causal relationships among complex elements in a visual and analytical network format. Analysis and visualization were conducted using FCMapper and Pajek software, which enabled the examination of structural interactions, network characteristics, and dynamic dependencies among ecosystem actors. Technical details of the FCM implementation are provided in the following sections.

Results

For analytical clarity, the actors were classified into five categories: (1) industrial and manufacturing actors, (2) science and knowledge-based actors, (3) governmental and resource-providing actors, (4) interactive and entrepreneurial actors, and (5) facilitating and coordinating actors. Although these categories provide a useful conceptual structure, many actors perform multiple functions depending on their position and the nature of their interactions within the ecosystem. For instance, a university may simultaneously operate as a knowledge producer, a resource provider, and—in certain collaborations—even as a customer. All actors in the laboratory industry ecosystem are considered stakeholders whose actions are driven by the pursuit of improved innovation outcomes. Their roles and interactions collectively shape the dynamics of the ecosystem. A detailed list of these actors is presented in Table 3. The collected data were

subsequently analyzed using FCM to model the causal relationships and identify the most influential actors within the system.

Table 3. Innovation ecosystem actors and their dynamics in the laboratory industry

Group	Variable	Subgroup	Laboratory Industry Equivalent
Industrial and manufacturing	C1	Suppliers and Manufacturers	Laboratory equipment and chemical manufacturers
	C2	Commercial Companies	Active laboratory-based knowledge enterprises
	C3	Developers	Engineers and technologists enhancing technological capacity
	C4	Industry	Laboratory industry
Science and knowledge-based	C5	Researchers	Researchers from research centers and universities specializing in laboratory sciences
	C6	Specialists	Laboratory science specialists
	C7	University	University of Tehran, Sharif University, medical sciences universities, etc.
Governmental and resource-providing	C8	Investors and Financial Providers	Innovation financing funds (e.g., Health Research & Technology Fund)
	C9	Government	National Standards Organization, Food & Drug Organization, Office of Science & Technology, Ministry of Science, Ministry of Industry, Mine and Trade (relevant governmental sections)
Interactive and entrepreneurial	C10	Entrepreneurs	Founders of technology-based companies linked to universities and science parks
	C11	Competitors	Other networks or independent laboratories outside LabsNet
	C12	Central Actor	LabsNet Network ¹
Facilitating and coordinating	C13	Accelerators	Emerging specialized accelerators and health-tech incubators with laboratory-focus potentials
	C14	Innovation Intermediaries & Facilitators	Technology transfer offices in universities and science parks
	C15	Coordinating Units	Laboratory networks and ecosystem coordinating bodies
	C16	Support Roles	Network support staff and university technical groups
	C17	Platform	LabsNet.ir platform for managing laboratory services, Nota and Mahamax platforms

Table 4 presents the aggregated expert judgments regarding the causal influence of the actors on one another. The values represent the final weighted scores assigned by the experts and form the 17×17 interaction matrix used for subsequent FCM analysis.

¹ - Iranian Laboratory Network

Table 4. Matrix of relationship strengths

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1																	
C2	0.00																
C3	0.95	0.93															
C4	1.00	0.98	0.98														
C5	0.48	0.55	0.95	0.53													
C6	0.48	0.53	0.95	0.55	0.55												
C7	0.85	0.50	0.93	0.48	0.13	0.00											
C8	0.45	0.58	0.50	1.00	0.10	0.90	0.00										
C9	0.38	0.80	0.85	0.83	0.43	0.43	0.00	0.03									
C10	0.90	0.58	0.18	0.55	0.13	0.08	1.00	0.00	0.43								
C11	- 0.48	0.25	0.00	0.35	0.03	0.03	0.05	- 0.03	0.00	- 0.48	0.00	0.28	0.43	0.03	- 0.05	- 0.03	0.00
C12	0.95	0.98	0.55	0.58	0.95	0.53	0.95	0.15	0.45	0.58	- 0.08	0.00	0.88	0.58	0.95	0.95	0.98
C13	0.45	0.93	0.90	0.45	0.43	0.43	0.48	0.95	0.43	0.95	0.40	0.88	0.00	0.50	0.45	0.45	0.48
C14	0.50	0.55	0.53	0.53	0.15	0.08	0.95	0.50	0.43	0.55	0.38	0.58	0.93	0.00	0.93	0.88	0.50
C15	0.53	0.95	0.53	0.55	0.93	0.48	0.93	0.50	0.83	0.53	0.03	0.98	0.88	0.95	0.00	0.90	0.93
C16	0.05	0.50	0.53	0.50	0.50	0.48	0.48	0.03	0.43	0.50	0.38	0.98	0.85	0.90	0.53	0.00	0.53
C17	0.55	0.50	0.53	0.55	0.88	0.88	0.90	0.48	0.85	0.93	0.40	0.98	0.90	0.50	0.53	0.50	0.00

The cognitive-map analysis conducted using FCMapper indicates that the configuration of actors within the laboratory-industry innovation ecosystem consists of 17 components and 268 causal links, with a network density of 0.927. The relatively high network density suggests a strong level of interdependence and interaction among the actors, indicating that the ecosystem is structurally interconnected. At the same time, this high density may reflect a small-world-like pattern, in which actors are closely connected and separated by only a few relational steps. This pattern may arise either from the industry's inherent interconnectedness or from the shared professional context in which the expert panel formed its judgments.

The values in the defuzzified matrix represent the aggregated expert judgments and quantify the influence that each variable exerts on the others. Following the integration of expert opinions, the degrees of influence and dependence for each factor were analyzed in the FCMapper environment. These results are presented in Table 3. In this context, influence refers to the extent to which a concept affects other factors, dependence represents the amount of influence received from others, and centrality denotes the sum of influence and dependence. A higher centrality score indicates the relative structural importance of that component within the network. Table 5 also reports the ranking of the factors based on their relative importance and centrality.

Table 5. Influence–dependence degree and factor centrality

Component	Outdegree	Indegree	Centrality	Rank
C1	7.45	9.88	17.32	9
C2	8.65	10.33	18.98	6
C3	7.72	9.88	17.60	8
C4	9.08	10.38	19.45	5
C5	5.73	7.20	12.93	16
C6	6.20	6.88	13.08	14
C7	8.70	9.25	17.95	7
C8	7.58	5.38	12.95	15
C9	9.23	5.95	15.18	12
C10	7.58	8.35	15.93	10
C11	2.48	5.45	7.93	17
C12	11.05	10.53	21.57	1
C13	9.55	10.35	19.90	2
C14	8.93	6.13	15.05	13
C15	11.38	8.25	19.63	4
C16	8.10	7.15	15.25	11
C17	10.85	8.93	19.77	3

Scenario analysis

The scenario analysis constitutes the dynamic dimension of this research. Scenarios are formulated by changing the values of the three components with the highest centrality. The resulting variations and behavioral responses of the remaining components are then examined. In this study, four

scenarios are proposed. The first is the baseline scenario, in which all factors are assumed to be active with a value of 1. The changes and impacts of the remaining scenarios are then evaluated against this baseline. In the second scenario, a situation is simulated in which the central actor—the LabsNet network—is present, but no coordination efforts are undertaken. Accordingly, the central actor is considered active (1), while the coordinating components and the accelerator are considered inactive (0). In the third scenario, both the central actor and the coordinating component are assumed to be active (1), while the accelerator remains inactive (0). This scenario represents the current state of the industry’s ecosystem in the country. It is used to examine the consequences of the absence of the accelerator while the other two key components remain active. In the fourth scenario, all three components are assumed to be semi-active (0.5). This scenario enables the model to capture the system’s intermediate behavior. The results of these scenarios presented in Table 4.

Centrality indices indicate the extent to which a particular concept is significant relative to others. Such concepts occupy a critical position in the model and exert the greatest direct influence on the other concepts. More specifically, the results indicate that components C12, C13, C17, and C15 occupy structurally prominent positions within the ecosystem and appear to exert relatively strong influence on other actors in the innovation network.

According to the FCM results, the LabsNet (C12) has the highest centrality and functions as a major connector among actors in the ecosystem. The Iranian Laboratory Network (LabsNet) serves as a national coordination platform established to optimize laboratory infrastructure efficiency. It functions as a hub for equipment sharing, service standardization, and capacity building (Iranian Laboratory Network, n.d.). Accelerators (C13) also play an essential role; however, given that no specialized accelerator currently exists in the country, this gap may represent an important opportunity to strengthen the ecosystem. The platform (C17) strengthens the technical infrastructure, and the coordinating units (C15) are responsible for operational and executive functions. The higher the centrality value of these roles, the greater their influence on the innovation ecosystem. Accordingly, these components were used for the “what-if” scenario analysis, consistent with the approach adopted in the studies by Gan et al. and Shouchenko et al.

Table 6 .Scenario analysis results

Conc epts	Policy Measure				Results				Scenario Comparison			Chan ges		
	No Cha nges (1)	Sc ene 2	Sc ene 3	Sc ene 4	Scene 1	Scene 2	Scene 3	Scene 4	2&1	3&1	3&4	2	3	4

C1	1				0.999 97	1.00	0.9999 5134	1.00	- 0.0000 5183	- 0.0000 1785	- 0.0000 5034	9	9	9
C2	1				0.999 9845	0.999 8986	0.9999 6101	0.9999 35553	- 0.0000 8590	- 0.0000 2353	- 0.0000 4899	9	9	9
C3	1				0.999 981	0.999 9204	0.9999 5318	0.9999 48808	- 0.0000 6062	- 0.0000 2783	- 0.0000 3221	9	9	9
C4	1				0.999 9838	0.999 9556	0.9999 7454	0.9999 64221	- 0.0000 2819	- 0.0000 0923	- 0.0000 1955	9	9	9
C5	1				0.999 7182	0.998 9103	0.9995 6881	0.9991 08867	- 0.0008 0791	- 0.0001 4941	- 0.0006 0935	8	8	8
C6	1				0.999 61	0.999 0381	0.9994 0323	0.9992 03407	- 0.0005 7187	- 0.0002 0678	- 0.0004 0660	8	8	8
C7	1				0.999 9628	0.999 848	0.9999 4006	0.9998 79002	- 0.0001 1473	- 0.0000 2271	- 0.0000 8377	8	9	9
C8	1				0.998 250	0.992 516	0.9954 7157	0.9960 99	- 0.0057 3409	- 0.0027 7879	- 0.0021 5124	7	7	7
C9	1				0.999 041	0.996 560	0.9984 9494	0.9977 25	- 0.0024 8019	- 0.0005 4573	- 0.0013 1578	7	8	7
C10	1				0.999 858	0.999 372	0.9996 3058	0.9996 02	- 0.0004 8654	- 0.0002 2774	- 0.0002 5593	8	8	8
C11	1				0.021 294	0.032 665	0.0318 02	0.0273 76	0.0113 7044	0.0105 0754	0.0060 8222	2	2	3
C12	1	1	1	0.5	0.999 987	1.000 000	1.0000 00	0.5000 00	0.0000 1297	0.0000 1297	- 0.4999 8703	1	1	1
C13	1	0	0	0.5	0.999 982	0.000 000	0.0000 00	0.5000 00	- 0.9999 8209	- 0.9999 8209	- 0.4999 8209	0	0	1
C14	1				0.999 174	0.996 460	0.9986 35	0.9977 20	- 0.0027 1371	- 0.0005 3821	- 0.0014 5351	7	8	7
C15	1	0	1	0.5	0.999 899	0.000 000	1.0000 00	0.5000 00	- 0.9998 9859	0.0001 0141	- 0.4998 9859	0	1	1
C16	1				0.999 703	0.998 847	0.9995 33	0.9990 60	- 0.0008 5576	- 0.0001 6973	- 0.0006 4358	8	8	8
C17	1				0.999 951	0.999 800	0.9999 21	0.9998 39	- 0.0001 5142	- 0.0000 3002	- 0.0001 1242	8	9	8

Scenario 1 (Baseline Scenario)

In Scenario 1, all concepts were initialized with an activation value of 1, representing a condition in which all actors in the ecosystem are simultaneously active. The simulation results indicate that the system converges to a stable state, with the values of most concepts remaining very close to their initial levels. This finding indicates that when all ecosystem actors are active, the modeled structure can maintain overall system stability.

Scenario 2

In Scenario 2, the accelerator (C13) was removed from the network by assigning it an activation value of 0, while all other concepts retained their initial values. The simulation results show that the value of C13 decreased from 0.999982 in the baseline scenario to 0.000000, corresponding to a change of -0.99998209 . In addition to this direct change, several other concepts also show reductions compared with the baseline scenario. In particular, the values of investors (C8), government institutions (C9), and innovation intermediaries (C14) decrease. Smaller reductions are also observed in several other concepts, including researchers (C5), experts (C6), entrepreneurs (C10), support institutions (C16), and other actors (C17). In contrast, competitors (C11) increase, with their value rising from 0.021294 to 0.032665.

Scenario 3

In Scenario 3, the coordinating unit (C15) remained active, while the accelerator (C13) continued to be inactive. The results show that the value of C13 remained at 0.000000, corresponding to a change of -0.99998209 compared with the baseline scenario. Across the remaining concepts, the differences relative to the baseline scenario are generally smaller than those observed in Scenario 2, and most changes remain limited in magnitude. As in Scenario 2, competitors (C11) show an increase.

Scenario 4

In Scenario 4, the activation levels of three key actors—the central actor (C12), accelerators (C13), and coordinating units (C15)—were reduced from full activation to 0.5. The simulation results show that the values of these three concepts decrease noticeably compared with the baseline scenario. Among the remaining concepts, most changes are negative but relatively small. The largest indirect reductions among the non-manipulated concepts are observed in investors and financial providers (C8), innovation intermediaries and facilitators (C14), and government institutions (C9). In contrast, competitors (C11) show an increase.

Network Visualization of the Innovation Ecosystem

The data generated by FCMapper were imported into Pajek to visualize the innovation ecosystem network. The resulting model is presented in Figure 2. In this figure, the central actor is positioned at the core of the network, while the competitors—identified as the least influential components in this ecosystem—appear at the periphery with smaller node sizes and negative effects on the ecosystem cycle.

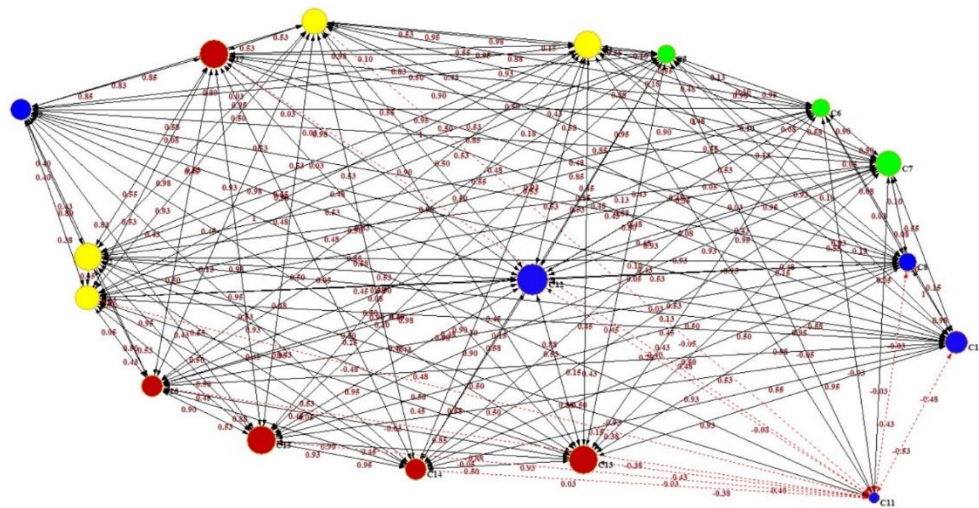


Figure 2. Cognitive mapping of innovation components in the laboratory industry

Discussion

The findings indicate that the innovation ecosystem of the laboratory industry cannot be viewed merely as a collection of independent actors; rather, it consists of a set of interdependent roles that influence one another through reciprocal relationships. The model results show that none of the variables function purely as causes or effects; instead, all components of the system simultaneously play both influencing and influenced roles. Such a pattern suggests that ecosystem performance depends less on the isolated presence of individual actors and more on the quality of interactions, coordination mechanisms, and the complementarity of roles among different actors. This result is consistent with perspectives in the innovation ecosystem literature that move beyond the level of individual firms and emphasize interdependencies, complementary roles, and alignment among actors (Baldwin et al., 2024; Granstrand & Holgersson, 2020; Jacobides et al., 2018; Talmar et al., 2020). From a methodological perspective, the use of Fuzzy Cognitive Mapping (FCM) in this study made it possible to model the perceived causal influence relationships among actors in the ecosystem.

FCM is particularly suitable for analyzing complex systems in which relationships among actors are multidirectional, interdependent, and largely based on expert knowledge. For example, the study by Ghasemnia Arabi et al. (2026) on the older adult health ecosystem shows that FCM analysis can identify actors with important structural roles and reveal how they influence other components of the system. One of the key findings of this study is the prominent structural position of C12, namely the LabsNet network, within the ecosystem. According to the centrality analysis results, this component has the highest level of centrality in the network and functions as a key connector among different ecosystem actors. Within the framework of innovation ecosystem studies, such a position typically indicates a coordinating or orchestrating role in the network. These roles can facilitate interaction, knowledge exchange, and the alignment of activities among different actors (Adner, 2017; Autio, 2022; Paasi et al., 2023; Moeenian et al., 2024).

Alongside this central actor, several other components also occupy structurally prominent positions. In particular, the components C13 (accelerators), C15 (coordinating units), and C17 (the platform) exert a relatively strong influence on other actors in the network. The results indicate that the ecosystem examined in this study relies not only on productive or knowledge-based actors but also on a set of facilitating and intermediary roles. This interpretation is consistent with the findings of Hernández Chea et al. (2021), who show that intermediary organizations, such as accelerators and incubators, do not merely play a connecting role. Rather, they contribute to the formation and functioning of entrepreneurial ecosystems by configuring the ecosystem structure, facilitating service provision, brokering resources, and guiding collaborations. In the same vein, Mamès et al. (2025) introduce these actors as guardians of the value creation process, who strengthen connections among heterogeneous actors by using coordination tools and facilitating interactions. Various studies have also shown that intermediary institutions, such as accelerators, technology transfer centers, and coordinating units, can contribute to ecosystem cohesion by reducing coordination frictions and facilitating interactions among heterogeneous organizations (Neto et al., 2024; Paasi et al., 2023; Tabarés & Boni, 2026). From this perspective, these actors can be considered part of the soft infrastructure that supports ecosystem performance.

The high centrality ranking of the platform (C17) indicates that platform infrastructures within this ecosystem serve functions that extend well beyond simple communication. In innovation ecosystems, platforms often govern interaction rules, manage resource access, and orchestrate connections among complementary actors. This finding aligns with the platform governance literature, which positions platforms as mechanisms for reducing coordination costs and facilitating access to complementary capabilities (Baldwin et al., 2024; Jacobides et al., 2018). In the ecosystem examined here, the platform helps identify and connect dispersed laboratory capacities. Furthermore, as Barile and Secundo (2026) demonstrate, digital platforms can transcend their role as passive infrastructure to become active mechanisms for ecosystem coordination.

The industrial and manufacturing sector emerges as the core of economic value creation in the ecosystem. Within this group, C4 (industry) and C2 (commercial companies) exhibit higher centrality and dependency values, indicating that economic value creation in the ecosystem is closely linked to productive capacities and the commercialization of laboratory services and equipment. Such a pattern is consistent with the view that value creation in innovation ecosystems depends on the integration of complementary resources and capabilities across diverse organizations (Adner & Kapoor, 2016; Granstrand & Holgersson, 2020). However, the results also indicate that the activities of these actors are embedded in a broader ecosystem comprising scientific, institutional, and intermediary entities. This finding further supports the emphasis on interdependence and complementarity in innovation ecosystems (Tanveer et al., 2026).

Similarly, the scientific and knowledge group—comprising universities, researchers, and specialists—plays a critical role. Innovation in the laboratory industry is inherently dependent on specialized knowledge and technical capabilities, a point also emphasized in prior innovation ecosystem research (Adner, 2017; Coletto et al., 2024). At the same time, this study suggests that knowledge production alone is not sufficient to sustain ecosystem dynamism; innovative outcomes emerge only when knowledge is activated through interactions with industry, intermediary institutions, and commercialization mechanisms. This observation is consistent with studies that stress the co-evolution of actors and the interplay among scientific, industrial, and institutional domains in the value creation process (Neto et al., 2024).

Conversely, C11, representing competitors, exhibits the lowest level of influence among the network components. The limited interaction of this component with other elements of the ecosystem suggests that competitive actors do not play a prominent role in the studied network structure. However, this does not necessarily imply that competition is unimportant; rather, it may indicate that competitive actors are less involved in coordinated interactions or collaborative mechanisms within the ecosystem. Ecosystem literature also suggests that relationships among actors are not purely collaborative, and that various forms of competition and coopetition may coexist as part of the natural dynamics of innovation ecosystems (Ritala & Thomas, 2025; Dedehayir et al., 2022). Under such conditions, a lower level of coordination among the main actors may create greater space for competitive behaviors, thereby increasing the potential influence of competitors in ecosystem dynamics.

Scenario analysis adds a dynamic dimension to the study by showing the ecosystem's sensitivity to changes in key components. In the third scenario, which reflects the current state of the country's laboratory industry ecosystem, C13 (the accelerator) remains inactive, with a value of zero. This may reflect the absence of a specialized acceleration mechanism, which could hinder entrepreneurship and the emergence of innovative businesses in this domain. This finding is

consistent with entrepreneurial ecosystem research emphasizing that the absence of intermediary actors can limit resource mobilization, the management of interdependencies, and the development of structured collaboration patterns (Hernández Chea et al., 2021).

The results further show that decreases in C12, C13, and C15 produce substantial declines relative to the baseline scenario, along with indirect reductions in several other components, especially C8 (investors and financiers), C14 (intermediaries and innovation facilitators), and C9 (government). This pattern indicates that the ecosystem is highly sensitive to changes in its coordinating core, with a weakening in this structure generating ripple effects across the network. Meanwhile, the increase in C11 (competitors) in some scenarios may reflect a shift in ecosystem balance as the influence of coordinating actors declines. This interpretation is consistent with research showing that ecosystem stability depends on the quality of relationships among complementary actors and the continuity of connecting mechanisms (Cobben et al., 2023; Paasi et al., 2023). This result also aligns with the findings of Sultana and Turkina (2023), who show that intermediary institutions play an important role in shaping collaborative relationships and diffusing innovation within ecosystems by facilitating encounters among actors, matching potential partners, and supporting the implementation of collaborations.

Overall, the results of this study indicate that the laboratory industry innovation ecosystem exhibits a relatively coordinated and semi-centralized structure. Although a limited number of key actors occupy pivotal positions, the system's performance ultimately depends on extensive interactions among a diverse set of complementary actors. In this context, the LabsNet network, accelerators, coordinating units, and the digital platform emerge as critical elements for maintaining the ecosystem's structural cohesion. At the same time, industrial and scientific actors play essential roles in knowledge production and economic value creation. Consequently, the dynamics of this ecosystem can be understood as the outcome of interactions among productive, knowledge-based, and facilitative roles that collectively underpin the emergence and development of innovation. This conclusion is consistent with perspectives that conceptualize innovation ecosystems as dynamic and evolving systems in which the roles and relationships among actors change over time, thereby requiring active coordination and governance mechanisms (Coletto et al., 2024; Jütting, 2024).

Practical and Policy Implications

The findings of this research indicate that certain intermediary actors, particularly the LabsNet network, play a crucial role in connecting different actors within the laboratory industry innovation ecosystem. Strengthening and further developing such coordinating institutions can therefore

enhance interactions among universities, firms, equipment suppliers, and other ecosystem participants, thereby enabling more effective utilization of scientific and technological capacities.

Developing and strengthening these intermediary mechanisms can contribute to more effective collaboration and support the transformation of knowledge and technology into applied innovations. Developing and strengthening these intermediary mechanisms can contribute to the formation of more effective collaborations and support the transformation of knowledge and technology into applied innovations.

At the policy level, the findings suggest that policies focusing solely on individual actors are insufficient to support the laboratory industry. Instead, policymakers can foster more favorable conditions for the development and dynamism of this ecosystem by adopting an ecosystem-based approach that emphasizes strengthening connections among actors, facilitating access to financial resources, and reducing innovation-related risks.

Conclusion

The objective of this study was to analyze the structure of relationships among actors in Iran's laboratory industry innovation ecosystem using Fuzzy Cognitive Mapping (FCM). The results indicate that the performance of this ecosystem is shaped not by the actions of a single actor but by a network of interdependent relationships among scientific, industrial, and facilitating actors. The findings show that although the LabsNet network occupies a central position within the ecosystem structure, the ecosystem's dynamism and functioning do not depend solely on this actor. Alongside LabsNet, actors forming the ecosystem's soft infrastructure—including accelerators, coordinating units, and platforms—play an important role in facilitating knowledge flows, strengthening interactions, and reducing barriers to collaboration. Scenario analysis further indicates that weakening these actors can reduce the ecosystem's overall dynamism and efficiency. Overall, the results suggest that the laboratory industry innovation ecosystem exhibits a semi-centralized structure in which system performance depends largely on the quality of coordination and interaction among complementary actors. By modeling the causal structure of these relationships through FCM, this study contributes to a better understanding of how actor interdependencies shape innovation dynamics in industry-specific ecosystems. Ultimately, for policymakers and practitioners, fostering innovation in the laboratory industry requires shifting the focus from a single central hub toward strengthening interdependent ties and coordinating mechanisms that transform individual contributions into a coordinated and efficient network.

Research Limitations and Suggestions for Future Research

Despite efforts to provide a coherent framework for analyzing relationships among actors in the laboratory industry innovation ecosystem, this study has several limitations that may guide future research. First, given the breadth and complexity of this ecosystem, the study focused primarily on identifying and analyzing relationships among key actors. As a result, a comprehensive examination of the structural, institutional, and technological barriers affecting innovation processes in this ecosystem was beyond the scope of the research. Future studies could address these dimensions to provide a deeper understanding of the challenges facing innovation development in the laboratory industry.

Second, because the analysis centers on the laboratory industry innovation ecosystem, the findings are most directly applicable to this specific industrial context. Comparative studies examining innovation ecosystems in other technological or knowledge-based industries could help identify common and distinctive patterns of interaction among ecosystem actors.

Third, the scenarios developed in this research were designed to assess the effects of changes in the status of selected key actors. Future research could extend this approach by designing more diverse scenarios, including simultaneous changes in multiple actors or variations in broader environmental conditions such as policy, financial, and technological changes.

Finally, given the prominent role of coordinating and intermediary actors identified in this study, future research could further explore the mechanisms through which these actors facilitate collaboration among scientific, industrial, financial, and governmental sectors and contribute to the overall functioning of innovation ecosystems.

Data Availability Statement

Data available on request from the authors.

Acknowledgements

The authors would like to thank all participants of the present study.

Ethical considerations

The authors avoided data fabrication, falsification, plagiarism, and any form of misconduct.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

The authors declare no conflict of interest.

References

- Adner, R. (2004). A demand-based view of sustainable competitive advantage. *Strategic Management Journal*, 25(8–9), 779–799. <https://doi.org/10.1002/smj.398>
- Adner, R. (2006). Match your innovation strategy to your innovation ecosystem. *Harvard Business Review*, 84(4), 98–107. <https://hbr.org/2006/04/match-your-innovation-strategy-to-your-innovation-ecosystem>
- Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, 43(1), 39–58. <https://doi.org/10.1177/0149206316678451>
- Adner, R., & Kapoor, R. (2010). Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic Management Journal*, 31(3), 306–333. <https://doi.org/10.1002/smj.821>
- Adner, R., & Kapoor, R. (2011). Innovation ecosystems and the pace of substitution: Re-examining technology S-curves. *Strategic Management Journal*, 32(7), 667–689. <https://doi.org/10.1002/smj.930>
- Ahmadi, F., Janbozorgi, M., Esfandiar, S., & Sadat Mirdadashi, S. (2026). Investigating the factors affecting the development of the wisdom component: Application of cognitive-physical roles. *The Quarterly Journal of Revealed Ethics*, 4(37), 115–138. <https://doi.org/10.22034/re.2025.552035.2120>
- Asgari, N., Babaei, R., Rahimi, A. and Ghorani, S. . F. (2025). Restudying Prerequisites and Outcomes of Organizational Innovation: A Systematic Literature Review. *Industrial Management Journal*, 17(1), 163-203. doi: 10.22059/imj.2025.374168.1008140
- Audretsch, D. B., Belitski, M., & Guerrero, M. (2022). The dynamic contribution of innovation ecosystems to schumpeterian firms: A multi-level analysis. *Journal of Business Research*, 144, 975–986. <https://doi.org/10.1016/j.jbusres.2022.02.037>
- Autio, E. (2022). Orchestrating ecosystems: A multi-layered framework. *Innovation*, 24(1), 96–109. <https://doi.org/10.1080/14479338.2021.1919120>
- Autio, E., & Thomas, L. (2014). Innovation ecosystems: Implications for innovation management. In M. Dodgson, D. Gann, & N. Phillips (Eds.), *The Oxford handbook of innovation management* (pp. 204–228). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199694945.013.012>
- Autio, E., Kenney, M., Mustar, P., Siegel, D., & Wright, M. (2014). Entrepreneurial innovation: The importance of context. *Research Policy*, 43(7), 1097–1108. <https://doi.org/10.1016/j.respol.2014.01.015>
- Azadi, P., & Zahir Mirdamadi, A. (2016). Introducing the international laboratory accreditation cooperation. *Danesh-e Azmayeshgahi Iran*, 4(2). <https://ijlk.ir/archive/20>

- Baldwin, C. Y., Bogers, M. L., Kapoor, R., & West, J. (2024). Focusing the ecosystem lens on innovation studies. *Research Policy*, 53(3), 104949. <https://doi.org/10.1016/j.respol.2023.104949>
- Barile, D., & Secundo, G. (2026). Orchestrating an open innovation ecosystem enabled by an AI-based platform: A case study of collaboration between NTT DATA and start-ups. *Journal of Innovation and Knowledge*, 17, 101036. <https://doi.org/10.1016/j.jik.2026.101036>
- Beliaeva, T., Ferasso, M., Kraus, S., & Damke, E. J. (2019). Dynamics of digital entrepreneurship and the innovation ecosystem: A multilevel perspective. *International Journal of Entrepreneurial Behavior and Research*, 26(2), 266–284. <https://doi.org/10.1108/ijebr-06-2019-0397>
- Çakır, E. (2026). Operationalizing graph theory and social network analysis in mixed methods research: A cyclical integration model. *Türkiye İletişim Araştırmaları Dergisi*, (49), 384–408. <https://doi.org/10.17829/turcom.1598035>
- Carrara, F., & Freisinger, E. (2024). Actors' activities and interactions in innovation ecosystems: A systematic literature review and typology. *International Journal of Innovation Management*, 28(03n04), 2430002. <https://doi.org/10.1142/s1363919624300022>
- Cobben, D., Ooms, W., & Roijakkers, N. (2023). Indicators for innovation ecosystem health: A Delphi study. *Journal of Business Research*, 162, 113860. <https://doi.org/10.1016/j.jbusres.2023.113860>
- Coletto, C., Caliar, L., Bernardes-de-Souza, D., & Callegaro-de-Menezes, D. (2024). Dynamics of actors in innovation ecosystems' analytical structures. *Innovation and Management Review*, 21(4), 244–259. <https://doi.org/10.1108/inmr-11-2022-0150>
- Compagnucci, L., Spigarelli, F., Perugini, F., Iacobucci, D., & Cobis, F. (2026). Does the hub and spoke model matter for university-industry engagement in innovation ecosystems?. *The Journal of Technology Transfer*, 51(1), 243–274. <https://doi.org/10.1007/s10961-025-10234-6>
- Cousins, M., Parmley, E. J., Greer, A. L., Neiterman, E., Lambraki, I. A., Graells, T., ... & Majowicz, S. E. (2024). Using a fuzzy cognitive map to assess interventions to reduce antimicrobial resistance in a Swedish One Health system context under potential climate change conditions. *Research Directions: One Health*, 2, e6. <https://doi.org/10.1017/rdh.2024.6>
- Dattée, B., Alexy, O., & Autio, E. (2018). Maneuvering in poor visibility: How firms play the ecosystem game when uncertainty is high. *Academy of Management Journal*, 61(2), 466–498. <https://doi.org/10.5465/amj.2015.0869>
- de Vasconcelos Gomes, L. A., Facin, A. L. F., Salerno, M. S., & Ikenami, R. K. (2018). Unpacking the innovation ecosystem construct: Evolution, gaps and trends. *Technological Forecasting and Social Change*, 136, 30–48. <https://doi.org/10.1016/j.techfore.2016.11.009>
- Dedehayir, O., Mäkinen, S. J., & Ortt, J. R. (2018). Roles during innovation ecosystem genesis: A literature review. *Technological Forecasting and Social Change*, 136, 18–29. <https://doi.org/10.1016/j.techfore.2016.11.028>
- Dedehayir, O., Mäkinen, S. J., & Ortt, J. R. (2022). Innovation ecosystems as structures: Actor roles, timing of their entrance, and interactions. *Technological Forecasting and Social Change*, 183, 121875. <https://doi.org/10.1016/j.techfore.2022.121875>
- Ethiraj, S. K., & Posen, H. E. (2013). Do product architectures affect innovation productivity in complex product systems? In J. E. Oxley, B. Silverman, & R. Adner (Eds.), *Advances in strategic management: Collaboration and competition in business ecosystems* (Vol. 30, pp. 127–166). Emerald. [https://doi.org/10.1108/s0742-3322\(2013\)0000030008](https://doi.org/10.1108/s0742-3322(2013)0000030008)

- Etzkowitz, H. (2003). Innovation in innovation: The triple helix of university-industry-government relations. *Social Science Information*, 42(3), 293–337. <https://doi.org/10.1177/05390184030423002>
- Falana, J., Osei-Kyei, R., & Tam, V. W. Y. (2022). Roles of key stakeholders in delivering net zero carbon building: A fuzzy cognitive mapping approach. *Journal of Cleaner Production*, 338, 130536. <https://doi.org/10.1016/j.jclepro.2022.130536>
- Frow, P., McColl-Kennedy, J. R., & Payne, A. (2016). Co-creation practices: Their role in shaping a health care ecosystem. *Industrial Marketing Management*, 56, 24–39. <https://doi.org/10.1016/j.indmarman.2016.03.007>
- Ghasemnia Arabi, N. , Sadeghi Moghadam, M. R. , Valipour Khatir, M. and Soltani Neshan, M. (2026). Analyzing the Elderly Healthcare Ecosystem: A Hybrid Stakeholder Salience and Fuzzy Cognitive Mapping Approach. *Industrial Management Journal*, 18(1), 250-278. doi: 10.22059/imj.2026.409152.1008280
- Granstrand, O., & Holgersson, M. (2020). Innovation ecosystems: A conceptual review and a new definition. *Technovation*, 90–91, 102098. <https://doi.org/10.1016/j.technovation.2019.102098>
- Gu, Y., Hu, L., Zhang, H., & Hou, C. (2021). Innovation ecosystem research: Emerging trends and future research. *Sustainability*, 13(20), 11458. <https://doi.org/10.3390/su132011458>
- Guerrero, M., Urbano, D., & Fayolle, A. (2016). Entrepreneurial activity and regional competitiveness: Evidence from European entrepreneurial ecosystems. *Journal of Business Research*, 69(11), 555–562. <https://doi.org/10.1007/s10961-014-9377-4>
- Gulati, R., Puranam, P., & Tushman, M. (2012). Meta-organization design: Rethinking design in interorganizational and community contexts. *Strategic Management Journal*, 33(6), 571–586. <https://doi.org/10.1002/smj.1975>
- Hernández-Chea, R., Mahdad, M., Minh, T. T., & Hjortsø, C. N. (2021). Moving beyond intermediation: How intermediary organizations shape collaboration dynamics in entrepreneurial ecosystems. *Technovation*, 108, 102332. <https://doi.org/10.1016/j.technovation.2021.102332>
- Hoveskog, M., Holmén, M., Ernest, A., & Bergquist, M. (2026). How automotive firms enable value creation within mature innovation ecosystems: The case of Polestar. *Technology in Society*, 103218. <https://doi.org/10.1016/j.techsoc.2026.103218>
- Iansiti, M., & Levien, R. (2004). Strategy as ecology. *Harvard Business Review*, 82(3), 68–78. <https://hbr.org/2004/03/strategy-as-ecology>
- Iranian Laboratory Network. (n.d.). *About LabsNet*. <https://labsnet.ir/>
- Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic Management Journal*, 39(8), 2255–2276. <https://doi.org/10.1002/smj.2904>
- Jütting, M. (2024). Introducing the lifecycle perspective to innovation ecosystem design: The innovation ecosystem clock model. *Journal of Cleaner Production*, 483, 144262. <https://doi.org/10.1016/j.jclepro.2024.144262>
- Kapoor, R., & Furr, N. R. (2015). Complementarities and competition: Unpacking the drivers of entrants' technology choices in the solar photovoltaic industry. *Strategic Management Journal*, 36(3), 416–436. <https://doi.org/10.1002/smj.2223>
- Karatzinis, G. D., & Boutalis, Y. S. (2025). A review study of fuzzy cognitive maps in engineering: applications, insights, and future directions. *Eng*, 6(2), 37. <https://doi.org/10.3390/eng6020037>

- Karunathilake, H., Bakhtavar, E., Chhipi-Shrestha, G., Mian, H. R., Hewage, K., & Sadiq, R. (2020). Decision making for risk management: A multi-criteria perspective. In *Methods in Chemical Process Safety* (Vol. 4, pp. 239–287). Elsevier. [10.1016/bs.mcps.2020.02.004](https://doi.org/10.1016/bs.mcps.2020.02.004)
- Klimas, P., & Czakon, W. (2022). Gaming innovation ecosystem: Actors, roles and co-innovation processes. *Review of Managerial Science*, 16(7), 2213–2259. <https://doi.org/10.1007/s11846-022-00518-8>
- Kokkinos, K., & Nathanail, E. (2023). A fuzzy cognitive map and PESTEL-based approach to mitigate CO₂ urban mobility: The case of Larissa, Greece. *Sustainability*, 15, 12390. <https://doi.org/10.3390/su151612390>
- Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*, 24(1), 65–75. [https://doi.org/10.1016/s0020-7373\(86\)80040-2](https://doi.org/10.1016/s0020-7373(86)80040-2)
- Lin, S. (2018). The structural characteristics of innovation ecosystem: A fashion case. *European Journal of Innovation Management*, 21(4), 620–635. <https://doi.org/10.1108/ejim-09-2017-0115>
- Liu, F., Zheng, D., Zhao, D., & Wen, B. (2026). Spatiotemporal differentiation and evolution of associated networks of China's agricultural innovation ecosystem. *Agricultural Systems*, 231, 104537. <https://doi.org/10.1016/j.agsy.2025.104537>
- Liu, W., He, Y., Liang, Y., & Lim, M. K. (2024). A theoretical framework for platform-to-platform cooperation: A multi-case study from China. *International Journal of Physical Distribution and Logistics Management*. <https://doi.org/10.1108/ijpdlm-07-2023-0242>
- Liu, Z., & Stephens, V. (2019). Exploring innovation ecosystem from the perspective of sustainability: Towards a conceptual framework. *Journal of Open Innovation: Technology, Market, and Complexity*, 5(3), 48. <https://doi.org/10.3390/joitmc5030048>
- Li-Ying, J., Sofka, W., & Tuertscher, P. (2022). Managing innovation ecosystems around big science organizations. *Technovation*, 116, 102523. <https://doi.org/10.1016/j.technovation.2022.102523>
- Mäkinen, S. J., & Dedehayir, O. (2013). Business ecosystems evolution: An ecosystem clockspeed perspective. In J. E. Oxley, B. Silverman, & R. Adner (Eds.), *Advances in strategic management: Collaboration and competition in business ecosystems* (Vol. 30, pp. 99–125). Emerald. [https://doi.org/10.1108/s0742-3322\(2013\)0000030007](https://doi.org/10.1108/s0742-3322(2013)0000030007)
- Mamès, M., Donner, M., & de Vries, H. (2025). Partnerships for sustainable food and bioeconomy systems in Europe: Exploring the role of intermediaries. *Sustainable Futures*, 10, 101361. <https://doi.org/10.1016/j.sfr.2025.101361>
- Moeenian, M., Ghazinoory, S., & Yaghmaie, P. (2024). Analysing the performance of a health innovation ecosystem in the COVID-19 crisis: Complexity and chaos theory perspective. *Health Research Policy and Systems*, 22(1), 59. <https://doi.org/10.1186/s12961-024-01136-4>
- Mohammadi, M., Elyasi, M. and Savehshemshaki, A. (2024). A Framework for Analyzing Absorptive Capacity Using Social Network Analysis (Case Study: Sharif University Innovation Ecosystem). *Industrial Management Journal*, 16(1), 99–116. doi: 10.22059/imj.2024.357800.1008049
- Moore, J. F. (1993). Predators and prey: A new ecology of competition. *Harvard Business Review*, 71(3), 75–86. <https://hbr.org/1993/05/predators-and-prey-a-new-ecology-of-competition>
- Moore, J. F. (1996). *The death of competition: Leadership and strategy in the age of business ecosystems*. Harper Business.

- Nambisan, S., & Sawhney, M. (2011). Orchestration processes in network-centric innovation: Evidence from the field. *Academy of Management Perspectives*, 25(3), 40–57. <https://doi.org/10.5465/amp.2011.63886529>
- Namdarian, L. (2016). A review of the role of laboratories in science and technology and innovation policymaking. Paper presented at the Second International Conference on Management and Economics in the 21st Century. <https://sid.ir/paper/833253/fa>
- Nersessian, N. J., Kurz-Milcke, E., Newstetter, W. C., & Davies, J. (2003). Research laboratories as evolving distributed cognitive systems. In *Proceedings of the 25th Annual Cognitive Science Society* (pp. 857–862). Psychology Press. <https://escholarship.org/uc/item/3g45c6wx>
- Neto, J. R., Figueiredo, C., Gabriel, B. C., & Valente, R. (2024). Factors for innovation ecosystem frameworks: Comprehensive organizational aspects for evolution. *Technological Forecasting and Social Change*, 203, 123383. <https://doi.org/10.1016/j.techfore.2024.123383>
- Nylund, P. A., Ferras Hernandez, X., & Brem, A. (2019). Strategies for activating innovation ecosystems: Introduction of a taxonomy. *IEEE Engineering Management Review*, 47(4), 60–66. <https://doi.org/10.1109/emr.2019.2931696>
- Oh, D. S., Phillips, F., Park, S., & Lee, E. (2016). Innovation ecosystems: A critical examination. *Technovation*, 54, 1–6. <https://doi.org/10.1016/j.technovation.2016.02.004>
- Oliveira, J. P., & Rua, O. L. (2025). Innovation ecosystems and open innovation on micro-enterprises. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(1), 100443. <https://doi.org/10.1016/j.joitmc.2024.100443>
- Özesmi, U., & Özesmi, S. L. (2004). Ecological models based on people's knowledge: A multi-step fuzzy cognitive mapping approach. *Ecological Modelling*, 176(1–2), 43–64. <https://doi.org/10.1016/j.ecolmodel.2003.10.027>
- Paasi, J., Wiman, H., Apilo, T., & Valkokari, K. (2023). Modeling the dynamics of innovation ecosystems. *International Journal of Innovation Studies*, 7(2), 142–158. <https://doi.org/10.1016/j.ijis.2022.12.002>
- Pushpanathan, G., & Elmquist, M. (2022). Joining forces to create value: The emergence of an innovation ecosystem. *Technovation*, 115, 102453. <https://doi.org/10.1016/j.technovation.2021.102453>
- Quiñones, R., Caladcad, J. A., Quiñones, H., Caballes, S. A., Abellana, D. P., Jabilles, E. M., Himang, C., & Ocampo, L. (2019). Open innovation with fuzzy cognitive mapping for modeling the barriers of university technology transfer: A Philippine scenario. *Sustainability*, 11(23), 6715. <https://doi.org/10.3390/joitmc5040094>
- Ranjbar, A., Tarighi, S. and Nateghipour, N. (2026). Analyzing the Role of Funding Sources in Research and Development in Driving Global Innovation. *Industrial Management Journal*, 18(1), 189-213. doi: 10.22059/imj.2026.404515.1008267
- Ritala, P., & Thomas, L. D. W. (2025). Innovation ecosystems. In P. Eriksson, T. Montonen, P.-M. Laine, & A. Hannula (Eds.), *Elgar encyclopedia of innovation management*. Edward Elgar Publishing. <https://doi.org/10.4337/9781035306459>
- Robaczewska, J., Vanhaverbeke, W., & Lorenz, A. (2019). Applying open innovation strategies in the context of a regional innovation ecosystem: The case of Janssen pharmaceuticals. *Global Transitions*, 1, 120–131. <https://doi.org/10.1016/j.glt.2019.05.001>

- Santarsiero, F., Schiuma, G., & Carlucci, D. (2020). Entrepreneurability: Innovation labs as engines of innovation capacity development. In *Innovative entrepreneurship in action: From high-tech to digital entrepreneurship* (pp. 115–127). Springer. https://doi.org/10.1007/978-3-030-42538-8_8
- Soleimanian, M., Pourshahbaz, A., & Shackelford, T. K. (2024). The personality architecture of online aggression: A network analysis integrating HEXACO, the dark tetrad, and life history strategy in Iranian adolescents. *Journal of Adolescence*, 101, 1–13. <https://doi.org/10.1016/j.adolescence.2024.01.001>
- Sovatzidi, G., & Iakovidis, D. K. (2026). A review of fuzzy cognitive maps and their perspectives for explainable decision making. *Neurocomputing*, 134038. <https://doi.org/10.1016/j.neucom.2026.134038>
- Stam, E. (2015). Entrepreneurial ecosystems and regional policy: A sympathetic critique. *European Planning Studies*, 23(9), 1759–1769. <https://doi.org/10.1080/09654313.2015.1061484>
- Su, Y. S., Zheng, Z. X., & Chen, J. (2018). A multi-platform collaboration innovation ecosystem: The case of China. *Management Decision*, 56(1), 125–142. <https://doi.org/10.1108/md-04-2017-0386>
- Sultana, N., & Turkina, E. (2023). Collaboration for sustainable innovation ecosystem: The role of intermediaries. *Sustainability*, 15(10), 7754. <https://doi.org/10.3390/su15107754>
- Tabarés, R., & Boni, A. (2026). Towards responsible innovation ecosystems through social labs: Lessons from the field. Available at SSRN 5262432. <https://doi.org/10.2139/ssrn.5262432>
- Talmar, M., Walrave, B., Podoyntsina, K. S., Holmström, J., & Romme, A. G. L. (2020). Mapping, analyzing and designing innovation ecosystems: The ecosystem pie model. *Long Range Planning*, 53(4), 101850. <https://doi.org/10.1016/j.lrp.2018.09.002>
- Tamtik, M. (2018). Innovation policy is a team sport: Insights from non-governmental intermediaries in Canadian innovation ecosystem. *Triple Helix*, 5(1), 1–19. <https://doi.org/10.1186/s40604-018-0062-8>
- Tanveer, U., Hoang, T. G., Ishaq, S., Kamal, M. M., & Attri, R. (2026). Enhancing supplier innovation capabilities through digital technology integration: A relational perspective. *Technological Forecasting and Social Change*, 223, 124426. <https://doi.org/10.1016/j.techfore.2025.124426>
- Valkokari, K., Amitrano, C. C., Bifulco, F., & Valjakka, T. (2016). Managing actors, resources, and activities in innovation ecosystems: A design science approach. In *Working Conference on Virtual Enterprises* (pp. 521–530). Springer. https://doi.org/10.1007/978-3-319-45390-3_44
- Wang, K., Feng, Y., & Liu, S. (2024). Analyzing the innovation ecosystem of China's major science and technology projects: From the ecological and systems science perspective. *Project Leadership and Society*, 5, 100156. <https://doi.org/10.1016/j.plas.2024.100156>
- Yin, D., Ming, X., & Zhang, X. (2020). Sustainable and smart product innovation ecosystem: An integrative status review and future perspectives. *Journal of Cleaner Production*, 274, 123005. <https://doi.org/10.1016/j.jclepro.2020.123005>
- Zeng, D., Hu, J., & Ouyang, T. (2017). Managing innovation paradox in the sustainable innovation ecosystem: A case study of ambidextrous capability in a focal firm. *Sustainability*, 9(11), 2091. <https://doi.org/10.3390/su9112091>