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Systematizing Barriers to Open Innovation Adoption: A Multi-Method Approach Based on Meta-Synthesis, Fuzzy Interpretive Structural Modeling, and MICMAC Analysis

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ABSTRACT

Open innovation, as a dominant paradigm in innovation management, encourages organizations to deliberately leverage inbound and outbound knowledge flows to accelerate innovation and create value; however, its adoption and implementation are confronted with multifaceted barriers that are interwoven, multi-level, and dynamic. The central problem of this study is that although the existing literature has identified numerous barriers to open innovation, it has provided limited attention to the causal structure, hierarchical ordering, and the extent of mutual influence among these barriers. Accordingly, this study aims to identify, categorize, and model the structural dynamics of barriers to open innovation adoption. This research employs a sequential multi-method design. In the first phase, a systematic literature review grounded in the PRISMA 2020 framework was integrated with a meta-synthesis approach; relevant studies were extracted and analyzed from six reputable scientific databases. From 612 initial records, after removing duplicates and applying inclusion and exclusion criteria, 24 articles were selected for the final meta-synthesis. This phase yielded 23 barriers organized into six overarching dimensions: individual/behavioral, cultural, structural/managerial, knowledge/capability, relational/governance, and infrastructural/environmental barriers. In the second phase, Fuzzy-ISM and Fuzzy-MICMAC analysis were conducted, drawing on judgments from a panel of 14 academic and industrial experts. The findings reveal that weak knowledge absorptive capacity, misalignment between reward and motivation systems, and insufficient support from top management occupy the lowest hierarchical level, functioning as fundamental root drivers. A control-oriented and low-trust culture, weak learning and knowledge-sharing culture, and insufficient inter-organizational trust constitute linkage variables. By contrast, intellectual property concerns, difficulty in selecting appropriate partners, and limitations in financial and time resources emerge primarily as dependent outcome variables. The resulting structural framework provides managers with a prioritized intervention map, directing focus toward root-level levers rather than surface-level symptoms.

Keywords: *Open innovation; adoption barriers; meta-synthesis; Fuzzy-ISM; MICMAC*

1. Introduction

In contemporary competitive environments, innovation has become one of the most critical determinants of organizational survival, growth, and long-term value creation. Rapid technological change, globalization, increasing customer expectations, and the emergence of digital ecosystems have fundamentally altered how organizations generate, acquire, and exploit knowledge. Under these conditions, traditional innovation models based exclusively on internal research and development activities have become increasingly insufficient for addressing complex market demands and technological uncertainty. Organizations are now expected to collaborate with a wide range of external actors, including customers, suppliers, universities, research institutes, start-ups, competitors, and governmental agencies, to access complementary knowledge and accelerate innovation processes. This transformation has led to the widespread adoption of the open innovation paradigm, which emphasizes purposeful inflows and outflows of knowledge across organizational boundaries to improve innovation performance and competitive advantage (Chesbrough & Brunswicker, 2014; West & Bogers, 2014). Over the past two decades, open innovation has evolved from a novel theoretical concept into a dominant framework for understanding how organizations create, share, and commercialize knowledge in increasingly interconnected environments (Bigliardi et al., 2021; Bogers et al., 2017).

The growing relevance of open innovation is closely associated with broader economic and technological transformations. Organizations increasingly operate within innovation ecosystems characterized by distributed knowledge sources, collaborative networks, and dynamic interdependencies among stakeholders. These developments have diminished the effectiveness of closed innovation approaches and reinforced the need for external collaboration as a strategic necessity rather than a discretionary choice. Research has demonstrated that organizations capable of effectively leveraging external knowledge sources are more likely to accelerate product development, reduce innovation costs, improve market responsiveness, and achieve superior innovation outcomes (Greco et al., 2016; West & Bogers, 2014). Furthermore, open innovation contributes to organizational flexibility and enables firms to access resources and expertise that would be difficult or costly to develop internally. Consequently, open innovation has become a central theme in innovation management research, attracting substantial attention from scholars across multiple disciplines and industrial sectors (Bigliardi et al., 2021; Bogers et al., 2017).

The increasing integration of digital technologies into organizational processes has further strengthened the importance of open innovation. Digital transformation has fundamentally altered how organizations communicate, collaborate, and exchange knowledge both internally and externally. Emerging technologies such as cloud computing, artificial intelligence, big data analytics, blockchain, and digital platforms facilitate real-time information sharing and enable new forms of collaborative innovation. The convergence of digital transformation and open innovation has created opportunities for organizations to access distributed knowledge networks on an unprecedented scale, allowing them to co-create value with external stakeholders and develop more agile innovation processes (Hanelt et al., 2021; Nambisan et al., 2019). Recent scholarship has highlighted that digital transformation and open innovation are increasingly interdependent phenomena, with digital technologies serving as critical enablers of knowledge integration, collaboration, and innovation ecosystem participation (Natalicchio et al., 2024). As organizations continue to digitalize their operations, the ability to effectively implement open innovation practices becomes essential for sustaining competitiveness and fostering long-term growth.

From a strategic perspective, open innovation is increasingly viewed as a dynamic capability that enables organizations to sense, seize, and transform opportunities arising from external knowledge environments. Dynamic capability theory suggests that organizations must continuously reconfigure their resources and competencies in response to environmental changes. Open innovation facilitates this process by providing access to diverse knowledge sources and fostering organizational learning across boundaries. In this context, firms are not merely passive recipients of external knowledge but active participants in collaborative innovation networks that enhance their adaptive capacity and strategic flexibility (Bogers et al., 2019). Moreover, employee diversity, knowledge heterogeneity, and organizational openness have been shown to positively influence innovation outcomes by expanding the range of ideas and perspectives available for problem solving and opportunity recognition (Bogers et al., 2018). Consequently, open innovation is increasingly recognized as a strategic mechanism for enhancing organizational resilience, adaptability, and innovation performance.

The benefits of open innovation extend beyond traditional economic and technological outcomes. Recent studies have demonstrated its positive effects on sustainability, corporate social responsibility, and societal value creation. Open innovation practices facilitate the development of environmentally sustainable solutions by enabling organizations to access external expertise and collaborate with stakeholders addressing complex societal challenges. The integration of open innovation with sustainability initiatives has become particularly important in addressing global concerns related to environmental degradation, resource scarcity, and social inequality (Luthra et al., 2015; Strazzullo et al., 2025). Additionally, open innovation has been linked to improved corporate social responsibility performance, suggesting that collaborative approaches to innovation can generate benefits for both organizations and society at large (Strazzullo et al., 2025). These findings underscore the broader significance of open innovation as a mechanism for achieving sustainable and socially responsible development.

Despite its considerable promise and widespread recognition, the implementation of open innovation remains challenging for many organizations. Although firms increasingly acknowledge the importance of external collaboration and knowledge exchange, numerous obstacles continue to hinder the successful adoption of open innovation practices. Existing research indicates that organizations frequently encounter difficulties related to organizational culture, leadership, governance structures, technological capabilities, knowledge management systems, and inter-organizational relationships (Bigliardi et al., 2021; Chesbrough & Brunswicker, 2014). These challenges are often multidimensional and interconnected, making them difficult to address through isolated interventions. Consequently, many organizations struggle to realize the full benefits of open innovation despite substantial investments in collaborative initiatives and innovation programs.

One of the most extensively studied barriers to open innovation is organizational resistance to external knowledge. Employees and managers frequently exhibit reluctance to adopt ideas originating outside their organizations, a phenomenon commonly referred to as the "not invented here" syndrome. This cognitive and behavioral bias can reduce the willingness of organizational members to engage with external partners and limit the effective utilization of externally generated knowledge. Research has shown that such attitudes can significantly impede knowledge integration and weaken the effectiveness of collaborative innovation initiatives (Antons & Piller, 2015). Furthermore, concerns regarding loss of control, knowledge leakage, and uncertainty about collaboration outcomes often reinforce resistance to open innovation practices, creating substantial obstacles to organizational openness and learning.

Another critical challenge concerns organizational capabilities related to knowledge acquisition, assimilation, and exploitation. Effective open innovation requires firms to possess strong absorptive capacity, enabling them to identify valuable external knowledge, integrate it into existing organizational processes, and transform it into innovative outcomes. Organizations lacking such capabilities may struggle to benefit from external collaborations even when opportunities for knowledge exchange are readily available. The importance of absorptive capacity extends beyond innovation performance and has been identified as a microfoundation of organizational resilience, supporting firms' ability to adapt to changing environments and respond to external disruptions (Duchek, 2019). Similarly, knowledge management capabilities play a crucial role in facilitating knowledge sharing, learning, and innovation across organizational boundaries (Ferraris, Mazzoleni, et al., 2020; Ferraris, Santoro, et al., 2020). Without effective mechanisms for managing knowledge flows, organizations may fail to capitalize on the opportunities created through open innovation initiatives.

The challenges associated with digital transformation further complicate the adoption of open innovation. While digital technologies provide important enablers of collaboration and knowledge exchange, organizations often face significant barriers in implementing and integrating these technologies into their innovation processes. Factors such as technological complexity, inadequate digital infrastructure, lack of technical expertise, cybersecurity concerns, and organizational resistance to technological change can limit the effectiveness of digital transformation efforts (Hanelt et al., 2021; Raj et al., 2022). Since digital transformation and open innovation are increasingly intertwined, barriers affecting one domain frequently influence the other. Organizations that struggle to adopt Industry 4.0 technologies and digital platforms may encounter difficulties in participating effectively in innovation ecosystems and managing collaborative innovation activities (Natalicchio et al., 2024; Raj et al., 2022).

Inter-organizational relationships represent another important source of challenges for open innovation adoption. Successful collaboration requires trust, effective governance mechanisms, aligned objectives, and clear communication among partners. However, organizations often encounter difficulties in establishing and maintaining such relationships, particularly when collaborating with diverse stakeholders possessing different priorities, cultures, and expectations. Partner selection, intellectual property management, contractual arrangements, and coordination mechanisms frequently emerge as significant barriers to collaborative innovation (Lakemond et al., 2016; West & Bogers, 2014). In addition, communication failures and hidden forms of organizational resistance can undermine collaboration and reduce the effectiveness of innovation partnerships. Recent research has emphasized the importance of understanding silent resistance and communication dynamics within organizational networks, highlighting their implications for open innovation success (Deif et al., 2025).

The contemporary business environment has also introduced new strategic challenges that influence open innovation adoption. Firms increasingly operate in volatile and uncertain contexts characterized by rapid technological disruption, shifting customer preferences, and intensified competition. Under such conditions, organizations must continuously develop new products, services, and business models to maintain competitive advantage. Strategic foresight, knowledge management, and collaborative innovation have therefore become essential drivers of innovation success and organizational renewal (Mubarak et al., 2025). Moreover, the integration of digitalization, ambidexterity, and green innovation has emerged as a critical area of interest, particularly for small and medium-sized enterprises seeking to balance exploration and exploitation while pursuing sustainable growth objectives (Kokubun, 2025). These developments further reinforce the strategic importance of understanding the factors that facilitate or hinder open innovation adoption.

Although the literature has extensively documented the benefits and challenges associated with open innovation, significant gaps remain in understanding how various barriers interact and influence one another. Existing studies have generally focused on identifying individual obstacles or examining specific aspects of open innovation implementation. Consequently, limited attention has been devoted to exploring the structural relationships among barriers, their hierarchical importance, and their causal interdependencies. Yet organizations rarely experience barriers in isolation; instead, these obstacles form complex systems in which certain factors may act as root causes while others emerge as downstream consequences. Understanding such relationships is essential for designing effective managerial interventions and allocating organizational resources efficiently (Chauhan et al., 2021; Raj et al., 2022).

Furthermore, contemporary research increasingly emphasizes the need to integrate open innovation with broader organizational objectives related to performance, competitiveness, sustainability, and social impact. Open innovation has been associated with improved business performance, enhanced competitive advantage, and increased innovation capacity, yet the realization of these benefits depends on organizations' ability to overcome adoption barriers and establish supportive organizational conditions (Farida & Setiawan, 2025; Greco et al., 2016). Similarly, the growing importance of technological innovation in addressing economic and social challenges underscores the need for organizations to develop effective innovation systems capable of leveraging external knowledge and collaboration networks (Asaleye & Ncanywa, 2025). Consequently, a comprehensive understanding of the barriers affecting open innovation adoption has important implications for both theory and practice.

Given the increasing strategic importance of open innovation, the accelerating pace of digital transformation, and the persistent challenges organizations face in implementing collaborative innovation practices, there is a clear need for a systematic investigation of the barriers that hinder open innovation adoption and the structural relationships among them. Therefore, the aim of this study is to identify the barriers to open innovation adoption and to model their hierarchical structure, causal relationships, driving forces, and dependency patterns through an integrated multi-method approach.

2. Methods and Materials

This research follows a sequential multi-method design implemented in two analytically connected phases. The design reflects the dual objective of the study: to extract and synthesize evidence on barriers to open innovation adoption from the existing literature, and subsequently to model the structural and causal relationships among those barriers through expert judgment. A single method cannot address both objectives simultaneously—systematic evidence synthesis provides the empirical breadth required for comprehensive barrier identification, while structural modeling provides the causal depth necessary for understanding how barriers interact and which ones occupy foundational positions in the system. Figure 1 presents the overall research workflow.

Phase One: Systematic Review and Meta-Synthesis. To ensure rigor and replicability in study selection, the review process adhered to the PRISMA 2020 framework (Page et al., 2021). Searches were conducted across six major scientific databases—Scopus, Web of Science Core Collection, ScienceDirect, Emerald Insight, SpringerLink, and Wiley Online Library—using a structured Boolean search string that combined open innovation terminology with barrier-related language:

(*"open innovation" OR "collaborative innovation" OR "inbound innovation" OR "outbound innovation" OR "coupled innovation"*) AND (*barrier* OR obstacle* OR challenge* OR inhibitor* OR resistance OR constraint* OR failure**) AND (*adoption OR implementation OR management OR organization**)

Inclusion was restricted to peer-reviewed empirical and conceptual articles published in English that directly addressed barriers, challenges, or limitations of open innovation adoption and provided sufficient methodological transparency for evidence extraction. Review articles without extractable analytical evidence, books, theses, editorials, and studies without accessible full text were excluded.

As summarized in Table 1, the search returned 612 initial records. After duplicate removal, 464 records were screened at the title and abstract level, yielding 93 candidates for full-text review. Following eligibility assessment, 24 articles met the threshold for inclusion in the final meta-synthesis.

Table 1

PRISMA 2020 Screening and Selection Summary

Stage	Records
Identified from databases	612
After removing duplicates	464
Removed at title/abstract screening	371
Full-text articles assessed	93
Removed after full-text review	69
Included in meta-synthesis	24

To ensure methodological consistency across the 24 selected articles, a quality assessment checklist was applied. As detailed in Table 2, each article was evaluated against five criteria—clarity of the research problem, methodological fit, adequacy of data, analytical transparency, and relevance to the topic—each scored on a three-point scale. Only studies reaching the minimum acceptable aggregate score were retained.

Table 2

Quality Assessment Criteria and Scoring Scale

Criterion	Description	Scale
Clarity of research problem	Clear statement of problem and objective	1–3
Methodological fit	Alignment between design and objective	1–3
Adequacy of data	Sufficient empirical or analytical evidence	1–3
Analytical transparency	Detailed explanation of analysis process	1–3
Relevance to the topic	Direct focus on open innovation barriers	1–3

Qualitative analysis of the retained articles proceeded through open, axial, and selective coding. Barrier-related statements were first extracted and converted into initial codes; similar codes were then consolidated into conceptual categories; and categories were grouped into broader thematic dimensions. This process yielded 23 barriers organized across six dimensions: individual/behavioral, cultural, structural/managerial, knowledge/capability, relational/governance, and infrastructural/environmental. These 23 barriers serve as the analytical units of the second phase.

Phase Two: Fuzzy Interpretive Structural Modeling and MICMAC Analysis. The second phase was designed to move beyond enumeration and reveal the causal architecture underlying the 23 identified barriers—specifically, how they influence one another, which occupy root positions, and which are downstream consequences. This required a method capable of handling the complexity of interdependencies among a moderately large set of variables while accommodating the inherent imprecision of expert judgment. Fuzzy Interpretive Structural Modeling (Fuzzy-ISM), combined with Fuzzy-MICMAC analysis, satisfies both requirements (Warfield, 1974; Luthra et al., 2015).

An expert panel of 14 specialists from academic and industrial settings was convened to assess the pairwise influence relationships among the 23 barriers. Selection criteria required a research or practical background in open innovation, technology management, or inter-organizational collaboration, with a minimum of five years of professional experience and direct familiarity with open innovation projects or technology transfer initiatives. As shown in Table 3, the panel comprised eight academic experts and six industrial practitioners, with a mean professional experience of 10.1 years.

Table 3

Expert Panel Characteristics

Characteristic	Value
Total number of experts	14
Academic experts	8
Industrial/managerial experts	6
Mean professional experience (years)	10.1

Because expert judgments about the strength of influence between barriers are inherently vague, linguistic variables were used to elicit assessments, each mapped to a corresponding Triangular Fuzzy Number (TFN). A TFN is formally defined as $\tilde{A} = (l, m, u)$, where $l$is the lower bound, $m$the most plausible value, and $u$the upper bound, with the membership function:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \dfrac{x-l}{m-l}, & l \leq x \leq m \\ \dfrac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x > u \end{cases}$$

Table 4 presents the six-point linguistic scale and its fuzzy equivalents used in the expert questionnaire.

Table 4

Linguistic Scale and Triangular Fuzzy Equivalents

Linguistic Variable	Symbol	Triangular Fuzzy Number
No influence	NI	(0.0, 0.0, 0.1)
Very low influence	VLI	(0.0, 0.1, 0.3)
Low influence	LI	(0.1, 0.3, 0.5)
Medium influence	MI	(0.3, 0.5, 0.7)
High influence	HI	(0.5, 0.7, 0.9)
Very high influence	VHI	(0.7, 0.9, 1.0)

Expert judgments were aggregated by computing the fuzzy arithmetic mean across all panel members. For each ordered pair of barriers (i, j), if the judgment of expert $k$is $\tilde{x}_{ij}^{(k)} = (l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)})$, the aggregated value is:

$$\tilde{x}_{ij} = \left(\frac{1}{K}\sum_{k=1}^{K} l_{ij}^{(k)}, \frac{1}{K}\sum_{k=1}^{K} m_{ij}^{(k)}, \frac{1}{K}\sum_{k=1}^{K} u_{ij}^{(k)}\right)$$

where $K = 14$. This produces the Fuzzy Structural Self-Interaction Matrix (FSSIM). To convert fuzzy values into crisp form, the centroid defuzzification method was applied:

$$x_{ij}^{*} = \frac{l_{ij} + m_{ij} + u_{ij}}{3}$$

A threshold of $\alpha = 0.50$was then used to transform the crisp matrix into a binary initial reachability matrix:

$$r_{ij} = \begin{cases} 1, & x_{ij}^{*} \geq \alpha \\ 0, & x_{ij}^{*} < \alpha \end{cases}$$

Transitivity was subsequently applied to complete indirect relationships: if barrier $B_i$influences $B_j$and $B_j$influences B_k, then $B_i$is taken to indirectly influence B_k. The resulting final reachability matrix serves as the basis for level partitioning. For each barrier B_i, a reachability set $R(B_i) = \{B_j \mid r_{ij} = 1\}$, an antecedent set $A(B_i) = \{B_j \mid r_{ji} = 1\}$, and their intersection $I(B_i) = R(B_i) \cap A(B_i)$were identified. Barriers satisfying $R(B_i) = I(B_i)$were assigned to the highest hierarchical level and removed iteratively until all barriers were positioned.

The Fuzzy-MICMAC phase used the same final reachability matrix to compute driving power (DP_i) and dependence power (DeP_i) for each barrier:

$$DP_i = \sum_{j=1}^{n} r_{ij}\,, DeP_i = \sum_{j=1}^{n} r_{ji}$$

Plotting each barrier in the *DP*–*DeP* space (Figure 2) yields the four-quadrant MICMAC classification. Autonomous variables exhibit low driving and low dependence; dependent variables show low driving and high dependence; linkage variables combine high driving with high dependence; and driver variables demonstrate high driving power alongside low dependence. Driver variables are of particular strategic significance because they propagate influence broadly through the system while remaining relatively insulated from the effects of others, making them the natural entry points for organizational intervention.

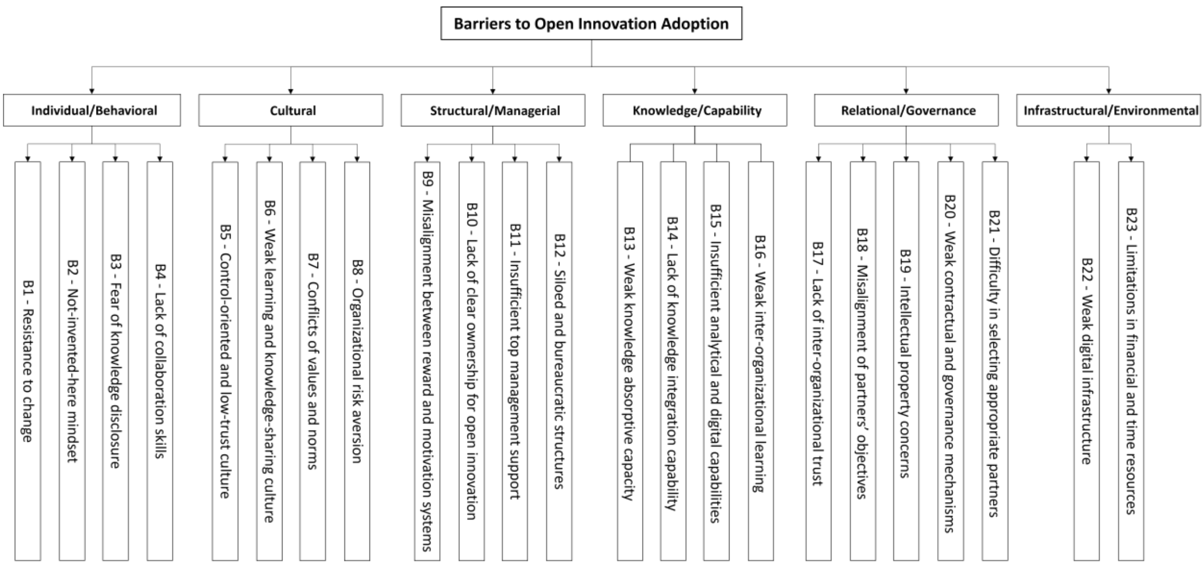
The complete analytical sequence—from meta-synthesis to FSSIM construction, defuzzification, initial reachability matrix formation, transitivity completion, level partitioning, and MICMAC classification—constitutes an integrated methodological chain in which each step is a direct prerequisite for the next.

3. Findings and Results

Qualitative analysis of the 24 retained studies through open, axial, and selective coding produced 23 distinct barriers to open innovation adoption. These barriers were organized into six thematic dimensions reflecting the nature and locus of each impediment within organizational systems. Figure 1 presents the complete taxonomy.

Figure 1

Dimensions and Codes of Barriers to Open Innovation Adoption



The dimensional distribution is notable: five of the six barriers in the relational/governance dimension (B17–B21) involve inter-organizational dynamics, suggesting that the boundary-spanning character of open innovation generates a structurally distinct cluster of impediments not present in closed innovation contexts. Similarly, the four structural/managerial barriers (B9–B12) each involve internal governance mechanisms whose misalignment with open innovation logic constitutes a systemic, rather than incidental, source of resistance.

Fourteen expert panelists assessed the pairwise directional influence among all 23 barriers using the six-point linguistic scale described in Section 3. Individual linguistic judgments were converted to their corresponding triangular fuzzy numbers (TFNs) and aggregated via fuzzy arithmetic mean across all $K = 14$panelists, yielding the FSSIM. Given the 23×23dimensionality of the complete matrix, Table 5 presents a representative submatrix for six theoretically central barriers spanning four dimensions.

Table 5

Representative Submatrix of the FSSIM (Six Selected Barriers)

	B5	B6	B9	B11	B13	B17
B5	—	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)	(0.3, 0.5, 0.7)	(0.5, 0.7, 0.9)
B6	(0.3, 0.5, 0.7)	—	(0.3, 0.5, 0.7)	(0.1, 0.3, 0.5)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)
B9	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)	—	(0.5, 0.7, 0.9)	(0.7, 0.9, 1.0)	(0.3, 0.5, 0.7)
B11	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)	(0.7, 0.9, 1.0)	—	(0.7, 0.9, 1.0)	(0.5, 0.7, 0.9)
B13	(0.3, 0.5, 0.7)	(0.5, 0.7, 0.9)	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)	—	(0.5, 0.7, 0.9)
B17	(0.5, 0.7, 0.9)	(0.1, 0.3, 0.5)	(0.1, 0.3, 0.5)	(0.3, 0.5, 0.7)	—	

Several patterns in this submatrix merit attention prior to defuzzification. B11 (insufficient top management support) registers the linguistic category *Very High Influence* (0.7, 0.9, 1.0) toward both B9 and B13, indicating that expert consensus positions managerial commitment as a strong upstream condition for both incentive alignment and absorptive capacity. By contrast, B17 (lack of inter-organizational trust) exerts only *Low Influence* (0.1, 0.3, 0.5) toward B9 and B11, consistent with its subsequent classification as a relationally-driven rather than organizationally-driven barrier.

Centroid defuzzification was applied to each TFN in the FSSIM according to:

$$x_{ij}^{*} = \frac{l_{ij} + m_{ij} + u_{ij}}{3}$$

This transforms each pairwise fuzzy assessment into a single scalar representing the central tendency of expert judgment. Table 6 presents the resulting crisp influence values for the selected submatrix.

Table 6

Defuzzified Crisp Influence Matrix (Selected Submatrix)

	B5	B6	B9	B11	B13	B17
B5	—	0.70	0.50	0.30	0.50	0.70
B6	0.50	—	0.50	0.30	0.70	0.70
B9	0.70	0.70	—	0.70	0.87	0.50
B11	0.70	0.70	0.87	—	0.87	0.70
B13	0.50	0.70	0.70	0.50	—	0.70
B17	0.70	0.70	0.30	0.30	0.50	—

The defuzzified values confirm the directional asymmetries visible in the FSSIM. The B11→B9 and B11→B13 values of 0.87 are the highest entries in this submatrix, reinforcing the primacy of top management support as a structural upstream variable.

Applying the threshold criterion $\alpha = 0.50$ to the defuzzified matrix:

$$r_{ij} = \begin{cases} 1, & x_{ij}^{*} \geq 0.50 \\ 0, & x_{ij}^{*} < 0.50 \end{cases}$$

converts the crisp influence matrix into a binary initial reachability matrix. Entries at exactly the threshold value ($x_{ij}^{*} = 0.50$) are assigned 1, consistent with the inclusion convention adopted in prior ISM applications (Warfield, 1974). Table 7 presents the resulting binary matrix for the selected submatrix.

Table 7

Initial Reachability Matrix (Selected Submatrix)

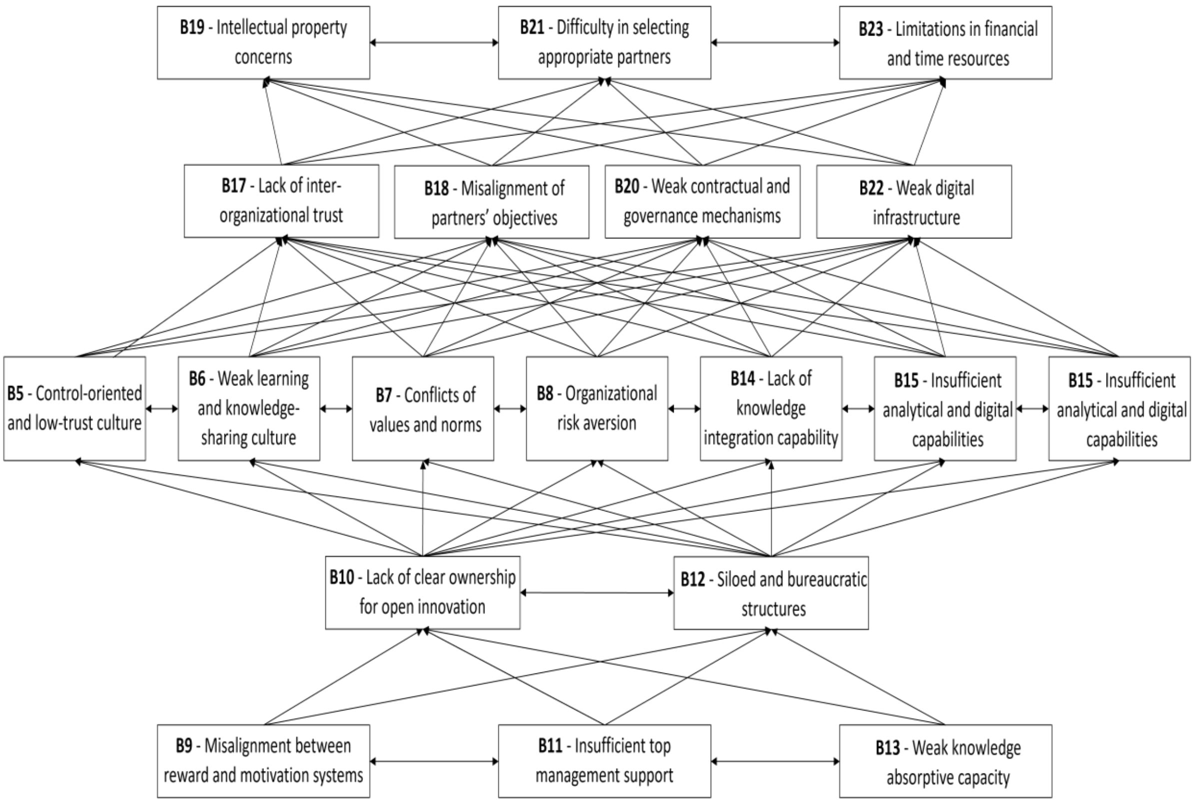
	B5	B6	B9	B11	B13	B17
B5	1	1	1	0	1	1
B6	1	1	1	0	1	1
B9	1	1	1	1	1	1
B11	1	1	1	1	1	1
B13	1	1	1	1	1	1
B17	1	1	0	0	1	1

The near-complete connectivity visible in this submatrix—B9, B11, and B13 each influence all other barriers in the selection—is characteristic of driver-cluster variables and anticipates their position in the lowest hierarchical level of the ISM digraph.

Transitivity was enforced over the full 23×23 initial reachability matrix to obtain the final reachability matrix, ensuring that all indirect influence pathways are explicitly captured. Level partitioning then proceeded iteratively: for each barrier B_i, the reachability set $R(B_i)$, antecedent set $A(B_i)$, and intersection $I(B_i) = R(B_i) \cap A(B_i)$were computed. Barriers satisfying $R(B_i) = I(B_i)$were assigned to the current highest level, removed from the matrix, and the procedure repeated until all 23 barriers were positioned. Figure 2 presents the final level structure.

Figure 2

ISM Hierarchical Level Partitioning of All 23 Barriers



The five-level hierarchy reveals a logically coherent stratification: organizational capabilities and managerial commitments occupy the foundation, structural configurations occupy an intermediate position, and relational/governance outcomes emerge at the apex as downstream consequences of unresolved lower-level deficiencies. This architecture implies that interventions targeting apex barriers—such as intellectual property concerns (B19) or partner selection difficulties (B21)—without addressing the base-level drivers will produce limited and transient effects.

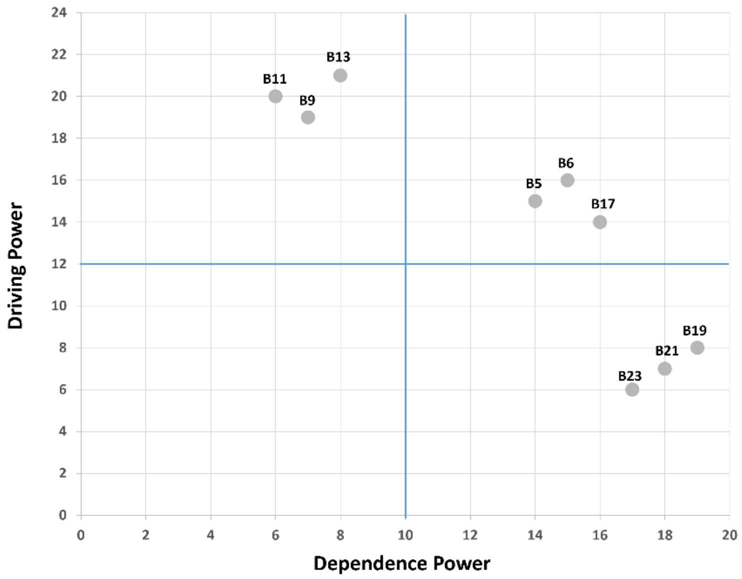
Driving power (DP_i) and dependence power (DeP_i) were computed from the final reachability matrix as the row sums and column sums, respectively:

$$DP_i = \sum_{j=1}^{23} r_{ij}\,, DeP_i = \sum_{j=1}^{23} r_{ji}$$

Figure 3 plots these values for a representative selection of barriers, spanning three MICMAC quadrants.

Figure 3

MICMAC Driving Power and Dependence Power (Selected Barriers)



The MICMAC results are fully consistent with the ISM level structure. B13, B11, and B9 occupy the driver quadrant (high DP, low DeP), confirming their status as root variables whose effects propagate broadly through the system while remaining minimally conditioned by other barriers. Their driving power scores—21, 20, and 19, respectively, out of a maximum of 23—indicate near-system-wide influence reach.

B5, B6, and B17 fall in the linkage quadrant (high DP, high DeP), indicating that they simultaneously propagate influence to other barriers and absorb influence from below. This dual sensitivity renders linkage variables analytically and managerially pivotal: they amplify perturbations in both directions, meaning that improvements in root drivers will cascade positively through linkage variables before reaching apex barriers, while unresolved linkage variables can sustain dysfunction even when some root conditions improve.

B19, B21, and B23 occupy the dependent quadrant (low DP, high DeP). Their low driving scores indicate limited systemic leverage; their high dependence scores confirm that their manifestation is substantially determined by the state of lower-level barriers. From a strategic standpoint, these barriers are more accurately described as symptoms than causes.

No barriers in this study were classified as autonomous (low DP, low DeP), indicating that all 23 identified barriers are structurally integrated into the influence network—a finding that validates the comprehensiveness of the barrier taxonomy derived from the meta-synthesis phase.

The convergence of Fuzzy-ISM and MICMAC results across both analytical dimensions—hierarchical position and influence topology—produces a robust structural portrait of the open innovation barrier system. Three principal findings emerge.

First, the barrier system is hierarchically stratified, not flat. A three-tier architecture is evident: a foundational tier comprising managerial, motivational, and capability factors (B9, B11, B13); an intermediate tier of cultural and learning mediators (B5, B6, B7, B8, B14, B15, B16); and an apex tier of relational, governance, and resource constraints (B17–B23). This architecture means that the observed severity of surface-level barriers—IP disputes, partner misalignment, resource scarcity—is, in part, a structural outcome of unresolved conditions at lower levels.

Second, the three driver-cluster barriers exhibit a logically interrelated pattern of root causation. Weak knowledge absorptive capacity (B13) limits an organization's ability to recognize the value of, and strategically engage with, external knowledge—the central mechanism of open innovation. Insufficient top management support (B11) deprives open innovation initiatives of the strategic legitimacy, resource allocation, and organizational protection required for sustained engagement. Misaligned reward systems (B9) produce incentive structures that actively discourage the knowledge-sharing, cross-boundary collaboration, and risk tolerance that open innovation demands. Together, these three conditions constitute an organizationally self-reinforcing failure mode in which the absence of capability, commitment, and incentive alignment mutually perpetuates the other deficiencies.

Third, the linkage cluster demands particular attention in intervention design. Because B5, B6, and B17 are simultaneously high-influence and high-dependence, they function as transmission nodes within the barrier network. Addressing root drivers without engaging these cultural and relational variables risks incomplete diffusion of improvements; conversely, addressing linkage variables in isolation—without reforming the root conditions—will produce unstable gains that revert as root pressures persist. Effective intervention therefore requires a sequenced approach: root-driver reform as a precondition, followed by systematic attention to linkage variables.

4. Discussion and Conclusion

The purpose of this study was to identify the barriers to open innovation adoption and to examine their structural relationships through a sequential multi-method approach integrating meta-synthesis, Fuzzy Interpretive Structural Modeling (Fuzzy-ISM), and MICMAC analysis. The findings revealed that barriers to open innovation adoption do not operate independently but instead form a complex and interconnected system characterized by hierarchical relationships, varying degrees of influence, and mutual dependencies. Twenty-three barriers were identified and organized into six dimensions, including individual/behavioral, cultural, structural/managerial, knowledge/capability, relational/governance, and infrastructural/environmental barriers. More importantly, the structural modeling results demonstrated that weak knowledge absorptive capacity, insufficient top management support, and misalignment between reward and motivation systems occupy the deepest levels of the hierarchy and function as primary driving forces influencing numerous downstream barriers. In contrast, concerns related to intellectual property, partner selection difficulties, and resource constraints were positioned at higher hierarchical levels and exhibited strong dependence characteristics. These findings suggest that many of the visible barriers organizations experience during open innovation implementation are manifestations of more fundamental organizational deficiencies.

A central finding of this study is the dominant role of knowledge absorptive capacity as a foundational driver of open innovation adoption barriers. The Fuzzy-ISM results positioned weak absorptive capacity at the lowest hierarchical level, while MICMAC analysis classified it as one of the strongest driver variables. This finding is highly consistent with the broader open innovation literature, which has repeatedly emphasized the importance of absorptive capacity in enabling organizations to recognize, assimilate, transform, and exploit external knowledge. Open innovation fundamentally depends on the ability of organizations to effectively utilize knowledge originating beyond their boundaries, and therefore insufficient absorptive capacity undermines the entire logic of openness. Previous studies have argued that organizations lacking strong learning capabilities often fail to derive value from collaborative innovation arrangements because they cannot effectively integrate external expertise into internal innovation processes (Bogers et al., 2019; Duchek, 2019). Similarly, research examining the interaction between knowledge management and innovation performance has demonstrated that knowledge acquisition alone is insufficient unless firms possess the organizational routines and capabilities necessary to transform information into actionable knowledge (Ferraris, Mazzoleni, et al., 2020; Ferraris, Santoro, et al., 2020). The present findings extend this literature by demonstrating that absorptive capacity is not merely one barrier among many but rather a foundational condition that shapes the emergence of numerous cultural, structural, and relational barriers.

The results also revealed that insufficient support from top management functions as a major root barrier influencing the broader open innovation system. This finding supports previous research suggesting that leadership commitment plays a critical role in determining whether open innovation initiatives receive adequate resources, legitimacy, and organizational attention (Bogers et al., 2019; Chesbrough & Brunswicker, 2014). Open innovation often requires significant changes in organizational culture, governance mechanisms, performance measurement systems, and external relationship management. Such transformations are unlikely to occur without visible commitment from senior leadership. The present findings indicate that weak managerial support contributes to a chain of secondary barriers, including inadequate incentive systems, poor knowledge-sharing cultures, and limited organizational learning capabilities. This aligns with digital transformation research emphasizing that strategic leadership is essential for overcoming organizational inertia and enabling successful change initiatives (Hanelt et al., 2021; Nambisan et al., 2019). Therefore, organizations attempting to strengthen open innovation practices must recognize leadership commitment as a prerequisite rather than a consequence of successful implementation.

Another important finding concerns the role of reward and motivation systems. The results demonstrated that misalignment between organizational incentives and collaborative innovation objectives acts as a significant driver barrier. This finding provides further support for research indicating that employees' willingness to engage in knowledge sharing and external collaboration is strongly influenced by the organizational context in which behavior is rewarded and evaluated (Antons & Piller, 2015; Bogers et al., 2018). Traditional performance management systems often prioritize individual achievements, internal knowledge creation, and short-term outputs, inadvertently discouraging collaboration with external stakeholders. When employees perceive that sharing knowledge or engaging in external partnerships offers little personal or professional benefit, resistance to open innovation naturally emerges. This interpretation is consistent with studies highlighting the behavioral foundations of open innovation and emphasizing the importance of aligning organizational incentives with collaborative goals (Antons & Piller, 2015). The present study extends these insights by demonstrating that incentive misalignment serves as an upstream factor that contributes to numerous downstream cultural and relational barriers.

The analysis further identified several linkage variables, including a control-oriented culture, weak learning and knowledge-sharing culture, and insufficient inter-organizational trust. These barriers exhibited both high driving power and high dependence, indicating that they simultaneously influence other barriers while also being influenced by root-level conditions. Such findings highlight the critical mediating role of organizational culture in the adoption of open innovation. Previous studies have consistently emphasized that open innovation requires cultures characterized by openness, trust, collaboration, experimentation, and continuous learning (Bigliardi et al., 2021; Lakemond et al., 2016). Organizations with highly hierarchical structures and control-oriented norms often struggle to develop the flexibility and trust necessary for effective external collaboration. Similarly, cultures that discourage knowledge sharing or penalize experimentation can significantly reduce employees' willingness to engage with external partners. The present findings support these arguments by demonstrating that cultural barriers occupy strategic positions within the broader barrier network. Their classification as linkage variables suggests that they function as transmission mechanisms through which deeper structural and capability-related deficiencies influence relational and governance outcomes.

Trust emerged as another critical factor within the barrier system. Insufficient inter-organizational trust was identified as a key linkage barrier connecting internal organizational conditions to external collaboration challenges. This finding aligns with extensive open innovation research emphasizing that trust serves as the foundation of successful knowledge exchange, collaboration, and partnership formation (Greco et al., 2016; West & Bogers, 2014). Organizations engaged in open innovation frequently exchange sensitive knowledge, technological expertise, and strategic information, creating concerns regarding opportunistic behavior, intellectual property protection, and unequal value appropriation. In the absence of trust, organizations may restrict knowledge sharing, limit collaboration intensity, or avoid potentially beneficial partnerships altogether. The findings suggest that trust-related challenges are not isolated relational problems but are deeply connected to organizational culture, leadership support, and knowledge management capabilities. Consequently, efforts to strengthen inter-organizational trust should be accompanied by broader organizational reforms addressing the underlying drivers identified in this study.

The findings concerning intellectual property concerns, partner selection difficulties, and resource constraints provide additional insights into the nature of open innovation barriers. These variables were classified as dependent barriers, indicating that they are largely influenced by other factors within the system rather than functioning as independent drivers. This result challenges the common managerial tendency to focus primarily on contractual arrangements, intellectual property protection mechanisms, and partner evaluation procedures when addressing open innovation challenges. Although such issues are undoubtedly important, the structural model suggests that they often represent symptoms of deeper organizational problems rather than primary causes. Similar observations have been reported in prior research, which has argued that governance and partnership challenges frequently emerge when organizations lack the capabilities, culture, and strategic alignment necessary to support effective collaboration (Lakemond et al., 2016; West & Bogers, 2014). Therefore, addressing these dependent barriers without simultaneously tackling root-level drivers is unlikely to produce sustainable improvements in open innovation performance.

The study also contributes to the growing literature examining the relationship between digital transformation and open innovation. Recent research has increasingly emphasized the convergence of these two phenomena, arguing that digital technologies serve as key enablers of collaborative innovation and knowledge exchange (Nambisan et al., 2019; Natalicchio et al., 2024). The present findings support this perspective by highlighting the importance of knowledge capabilities, organizational learning, and management commitment in facilitating open innovation adoption. Organizations lacking the capabilities required to absorb external knowledge may face similar challenges when attempting to implement digital transformation initiatives. Likewise, leadership support and organizational culture have been identified as critical success factors in both domains (Hanelt et al., 2021). The structural relationships identified in this study therefore suggest that digital transformation and open innovation share common organizational foundations, reinforcing recent calls for more integrated approaches to studying these phenomena (Natalicchio et al., 2024).

Furthermore, the findings have implications for sustainability, green innovation, and corporate social responsibility. Contemporary research increasingly recognizes open innovation as an important mechanism for addressing complex societal challenges through collaborative problem-solving and stakeholder engagement (Kokubun, 2025; Strazzullo et al., 2025). However, the present results suggest that organizations can only fully realize these broader benefits when foundational barriers are effectively addressed. Weak absorptive capacity, inadequate leadership support, and misaligned incentives not only hinder innovation performance but may also restrict organizations' ability to participate in sustainability-oriented innovation networks and cross-sector collaborations. This observation aligns with research emphasizing the strategic role of innovation capabilities in achieving sustainable competitive advantage and societal impact (Farida & Setiawan, 2025; Strazzullo et al., 2025).

Finally, the study contributes methodologically by demonstrating the value of integrating meta-synthesis, Fuzzy-ISM, and MICMAC analysis for investigating complex organizational phenomena. Previous open innovation research has primarily focused on identifying barriers through qualitative reviews or ranking their importance using survey-based methods (Bigliardi et al., 2021; Bogers et al., 2017). While such approaches provide valuable descriptive insights, they often fail to reveal the underlying causal architecture of barrier systems. By combining systematic evidence synthesis with structural modeling techniques, this study provides a more comprehensive understanding of how barriers interact and influence one another. The findings support arguments that complex innovation challenges should be examined as systems of interconnected factors rather than isolated variables (Chauhan et al., 2021; Raj et al., 2022). This systems perspective offers a stronger foundation for both theoretical development and managerial decision-making.

This study has several limitations that should be considered when interpreting the findings. First, the structural model was developed using expert judgments, and although the selected experts possessed substantial academic and practical experience in innovation management, their assessments inevitably reflect subjective interpretations. Second, the barriers identified through the meta-synthesis were derived from studies published in selected databases and English-language sources, which may have excluded relevant findings from other contexts and publication outlets. Third, the study adopted a cross-sectional perspective and therefore could not capture how barrier relationships evolve over time as organizations gain experience with open innovation practices. Finally, while the findings provide a comprehensive conceptual model, empirical validation using organizational-level data from different industries and countries would strengthen the generalizability of the proposed framework.

Future studies should empirically test the proposed hierarchical model using quantitative approaches such as structural equation modeling and longitudinal research designs. Researchers may also compare barrier structures across different industries, organizational sizes, and national contexts to identify potential variations in causal relationships. Additional studies could investigate the influence of emerging technologies such as artificial intelligence, blockchain, and digital platforms on open innovation barriers and their structural dynamics. Future research should also explore the role of institutional environments, innovation ecosystems, and public policy factors in shaping barrier configurations. Finally, longitudinal investigations examining how organizations progressively overcome barriers and develop open innovation capabilities would provide valuable insights into the dynamic nature of innovation adoption processes.

Organizations seeking to strengthen open innovation adoption should prioritize interventions targeting root-level barriers rather than focusing exclusively on visible symptoms. Building absorptive capacity through employee development, knowledge management systems, and organizational learning initiatives should be considered a strategic priority. Senior leaders should actively champion open innovation initiatives by providing resources, communicating clear strategic objectives, and creating an environment that supports experimentation and external collaboration. Performance evaluation and reward systems should be redesigned to encourage knowledge sharing, partnership development, and collaborative problem-solving. Organizations should also invest in cultivating trust-based cultures that support learning, openness, and cross-boundary interactions. Finally, managers should adopt a systems perspective when addressing open innovation challenges, recognizing that sustainable improvements require coordinated interventions across leadership, culture, capabilities, governance, and external relationship management.

Authors’ Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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