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Beyond One-Size-Fits-All: A Configurational Typology of Symbiosis Circular Innovation Industrial Ecosystems

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Abstract

This study advances understanding of industrial symbiosis (IS) by developing a configurational typology of circular ecosystems based on resource-flow patterns. Drawing on data from 68 documented IS ecosystems across 48 countries, the paper applies cluster analysis to five flow-intensity dimensions—material, energy, water, logistics, and knowledge—to identify archetypal configurations. Four stable configurations emerged: low-flow, material-dominant, energy–knowledge, and water-oriented systems. Multinomial logistic regression indicates that sectoral composition and regional context significantly predict configuration membership, while performance analyses confirm that coordinated, contextually aligned ecosystems achieve superior environmental outcomes. Energy–knowledge and water-oriented configurations exhibit strong ecological performance, whereas material-dominant ecosystems show efficiency gains under heavy-industry conditions. Cox's survival analysis further shows that balanced, coordinated systems achieve greater resilience and longevity. Robustness checks across alternative clustering methods, operationalisations, and sub-samples confirm the stability of these patterns. Results are directionally stable; magnitudes vary slightly across specifications. By applying configurational theory to IS, this paper demonstrates that circular, innovation-oriented ecosystem effectiveness depends on the fit between internal flow structures and contextual environments, thereby moving beyond universal models and offering an empirically grounded framework for policy and design in circular-economy practice and sustainable development.

Keywords: industrial symbiosis; configurational theory; cluster analysis; circular economy; resource flows; environmental performance; contextual fit; ecosystem resilience

1. Introduction

Industrial symbiosis (IS) has emerged as a pivotal mechanism for advancing the circular economy by fostering collective exchanges of materials, energy, water, and by-products among

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independent firms. Despite its growing prominence in sustainability policy and practice, IS research continues to rely on universal models that assume homogeneous structures and drivers across contexts. Yet real-world ecosystems differ profoundly in sectoral composition, geographical conditions, and coordination mechanisms, producing highly diverse configurations that existing theories fail to capture. This lack of differentiation constrains both analytical precision and policy effectiveness, as strategies designed for one archetype—such as the spontaneous, multi-flow exchanges in Kalundborg—may not translate to planned, energy-dominant systems like Ulsan. Addressing this conceptual gap is essential for understanding how circular ecosystems organise, operate, and evolve under varying conditions, and for developing targeted frameworks that enhance the global circular transition.

The Kalundborg Symbiosis in Denmark, with its network of material, energy, and water exchanges among industries spanning six decades, differs significantly from the Ulsan Eco-Industrial Park in South Korea, where petrochemical flows dominate [1,2]. Similarly, the Port of Rotterdam's resource exchange platform operates through mechanisms distinct from water-centric symbioses driven by resource scarcity in the Mediterranean [3,4]. Despite this heterogeneity, industrial symbiosis (IS) research has often treated these ecosystems as variations on a single phenomenon, focusing on universal drivers and barriers while overlooking their configurational differences [5–7].

Industrial symbiosis—defined as "a collective approach to competitive advantage involving the physical exchange of materials, energy, water, and by-products" amongst traditionally separate industries [8]—has emerged as a critical strategy for implementing circular economy (CE) principles at the industrial level [9]. As a subset of industrial ecology [10], IS engages multiple organisations in synergistic cooperation, optimising resource utilisation whilst creating economic value and advancing sustainability objectives [11]. The field has witnessed substantial growth since Kalundborg was documented in the late 1980s [12], with industrial symbiosis initiatives proliferating globally across diverse geographical, sectoral, and institutional contexts [13].

However, this geographical and institutional diversification has created a paradox: whilst the number of documented cases has expanded considerably—with recent databases cataloguing over 150 ecosystems across 48 countries [14]—the analytical frameworks used to understand these systems have remained comparatively homogeneous in their dominant analytical framing. The extant literature often examines individual case studies (e.g., Kalundborg, Ulsan) or aggregates statistics across cases, but still lacks widely adopted classification schemes that account for structural heterogeneity among ecosystems [11,15]. This creates a significant knowledge gap: researchers and practitioners often operate without a widely accepted framework for distinguishing ecosystem types, understanding context-specific success factors, or developing targeted intervention strategies.

Recent systematic reviews have identified several persistent gaps in IS research [7,16,17]. First, whilst studies have comprehensively documented enablers and barriers to IS implementation—cataloguing economic, technological, regulatory, and social factors—they typically offer generic recommendations applicable across contexts, "neglecting the wider configuration of connections between actors within the system" [4]; p. 3. This universalistic approach implicitly assumes that mechanisms facilitating symbiosis operate uniformly across contexts, an assumption increasingly challenged by empirical evidence of context-dependent performance [9].

Second, existing typologies in the IS literature remain limited in scope and analytical depth. Chertow's [8] seminal taxonomy distinguished IS initiatives by geographical scale (within facilities, amongst co-located firms, across regions), whilst Boons et al. [18] developed a process-oriented typology based on emergence dynamics (self-organised versus planned). Whilst valuable, these classificatory schemes focus on either spatial proximity or developmental processes rather than the substantive content of symbiotic relationships—specifically, the patterns of resource flows that constitute the structural essence of industrial ecosystems. As Fraccascia and Giannoccaro [19]; p. 2 observe in their comprehensive review of IS indicators, research has primarily examined individual flow types "in isolation," with "no comprehensive framework that considers how different resource flows interact and combine to create distinct ecosystem configurations."

Third, the challenge of quantification in IS research remains unresolved. Kastner et al. [19] and Martin [20] note that measurement efforts have focused on "physical facts such as how much waste, energy, etc., is exchanged rather than a collective effort to include all aspects of synergies" [14], p. 37. This fragmented approach to quantification reflects—and reinforces—the conceptual limitation of treating resource flows as independent rather than interdependent. Without understanding how flows of material, energy, water, logistics, and knowledge interact synergistically, the field cannot develop predictive models or evidence-based design principles for ecosystem development.

To address these gaps, this study adopts a configurational perspective grounded in organisation theory [22–24]. Configurational theory conceptualises organisational phenomena as "multidimensional constellations" of interdependent attributes that combine to produce outcomes [21]. This approach offers three conceptual advantages over traditional variance-based theories that have dominated IS research.

First, configurational theory explicitly recognises *conjunctural causation*—the principle that attributes produce effects through their combinations rather than independently [24,25]. In the context of industrial ecosystems, this suggests that material flows may interact synergistically with energy flows and knowledge-exchange mechanisms, creating emergent properties that cannot be reduced to individual flow types. This aligns with calls in the IS literature to examine "how multiple resource flows interact" rather than studying them "in isolation" [11].

Second, configurational approaches embrace equifinality—the premise that multiple distinct configurations can achieve equally effective outcomes [26,27]. This principle fundamentally challenges the implicit "one-best-way" assumption underlying much IS prescription. Rather than seeking universal success factors applicable to all ecosystems, configurational theory focuses on identifying distinct viable patterns, each adapted to specific contextual conditions. As Fiss [24]; p. 394 demonstrates in his analysis of organisational typologies, "alternative combinations of attributes may be equally effective," suggesting that different flow configurations may constitute multiple pathways to ecosystem success.

Third, configurational theory acknowledges *causal asymmetry*—the recognition that factors that facilitate an outcome may differ fundamentally from those that prevent it [25]. Moreover, "variables found to be causally related in one configuration may be unrelated or even inversely related in another" [22]; p. 1178. Applied to IS, this suggests that whilst knowledge flows may be critical enablers in one type of ecosystem configuration, they may prove less consequential—or even detrimental—in alternative configurations where different coordination mechanisms prevail.

Extending configurational theory to industrial symbiosis offers theoretical advantages beyond IS literature. Recent applications of configurational approaches have illuminated complex phenomena in business ecosystems [28], strategic management [29], and circular economy business models [29]. However, these frameworks have not been systematically applied to understand structural heterogeneity in industrial ecosystems. By conceptualising IS ecosystems as configurations of resource flows—material, energy, water, logistics, and knowledge—this study provides a novel analytical lens that captures both the internal coherence of ecosystem types and their contextual embeddedness.

This study addresses the following research questions:

RQ1: What distinct configurations of industrial ecosystems exist based on patterns of resource flow combinations?

RQ2: What contextual factors (sectoral composition, geographic characteristics, institutional environment) predict ecosystem membership in each configuration?

RQ3: Do different ecosystem configurations exhibit differential performance outcomes in terms of economic efficiency, environmental effectiveness, and organisational resilience?

To answer these questions, we analyse 156 industrial symbiosis ecosystems documented across 48 countries, employing cluster analysis to identify archetypal configurations based on five resource flow dimensions: material exchange intensity, energy sharing intensity, water circulation intensity, logistics and infrastructure coordination intensity, and knowledge exchange intensity. We then use multinomial logistic regression to examine predictors of configuration membership and analyse performance differences across identified clusters through analysis of variance and survival analysis.

This study makes several contributions to industrial ecology and organisation theory. First, we develop an empirically grounded typology of IS ecosystems that moves beyond spatial [8] or process-based [13] classifications to capture the substantive structure of resource interdependencies. By demonstrating that ecosystems cluster into distinct flow configurations rather than forming a continuum, we provide evidence for configurational theory in industrial ecology. In this context, it has been underutilised despite its conceptual relevance.

Second, we provide the first large-N quantitative evidence for equifinality in industrial symbiosis. By identifying multiple configurations associated with high performance—each exhibiting distinct strengths and operating through different mechanisms—we challenge the universalistic assumptions that have implicitly guided IS policy and practice. Our findings suggest that effectiveness depends on *fit* between flow configuration and contextual factors (sector, geography, institutions), a theoretical claim consistent with contingency-configurational perspectives [26,31] but not previously tested in IS research.

Third, we contribute methodologically by operationalising resource flows as measurable, comparable dimensions across diverse contexts. This responds to Fraccascia and Giannoccaro's [19] call for standardised measurement frameworks whilst advancing beyond single-flow analyses that have dominated quantification efforts [20,21]. Our multi-flow measurement approach provides a template for future comparative IS research.

Fourth, we extend configurational theory itself by demonstrating its applicability to inter-organisational ecosystems characterised by multiple resource interdependencies. Whilst prior configurational research has focused predominantly on intra-organisational phenomena [22,24], our study shows how configurational principles—conjunctural causation, equifinality, and asymmetry—operate at the ecosystem level, where coordination challenges and institutional complexity introduce distinctive dynamics.

Practically, our typology provides three tools for IS stakeholders. First, we develop a diagnostic framework that enables ecosystem coordinators to classify their current configuration and benchmark their performance against comparable systems. Second, we identify configuration-specific success factors, offering context-sensitive guidance rather than generic recommendations. Third, we map typical developmental trajectories, showing how ecosystems evolve between configurations over time—information valuable for strategic planning in both greenfield developments and brownfield transformations.

The remainder of this paper proceeds as follows. Section 2 reviews relevant theoretical literature on industrial symbiosis and configurational theory, developing hypotheses. Section 3 details our research methodology. Section 4 presents results, describing identified configurations, their distinguishing characteristics, contextual antecedents, and performance outcomes. Section 5 discusses the theoretical implications, compares our findings with existing typologies, and explores boundary conditions. Section 6 concludes by identifying limitations and proposing directions for future research.

2. Literature Review

2.1. Industrial Symbiosis: From Concept to Complexity

Industrial symbiosis emerged as a distinct research domain in the late 1980s following documentation of the Kalundborg case in Denmark, where spontaneous exchanges of materials, energy, and water amongst co-located firms demonstrated the practical feasibility of industrial ecology principles [12,32]. Chertow's seminal definition conceptualised IS as "engaging traditionally separate industries in a collective approach to competitive advantage involving physical exchange of materials, energy, water, and by-products" [8]; p. 314, establishing the field's intellectual foundations whilst delineating its boundary conditions.

The subsequent two decades saw substantial theoretical development. Chertow [1] introduced the influential "3-2 heuristic"—stipulating that industrial symbiosis requires at least three distinct entities exchanging at least two different resources—to distinguish genuine symbiotic systems from bilateral transactions or single-firm circular initiatives. This heuristic, whilst debated [18], provided operational clarity and facilitated comparative research. Contemporaneously, scholars began examining IS through diverse theoretical lenses: network theory [33,34], evolutionary economics [13], institutional theory [35], and systems thinking [36].

However, as Neves et al. [11] demonstrate, this theoretical proliferation has occurred alongside persistent empirical fragmentation. The literature comprises predominantly case studies of individual ecosystems—with Kalundborg alone generating over 50 publications [10]—or national surveys documenting IS prevalence in specific jurisdictions [37,38]. Comparative analyses across contexts remain scarce, and systematic efforts to classify ecosystem types by structural characteristics are virtually absent [7].

Recent systematic literature reviews [11,16,17] reveal both the field's maturation and its persistent blind spots. On the achievement side, research has comprehensively catalogued enablers and barriers to IS implementation across multiple dimensions:

- Economic factors include cost savings through waste [39], access to cheaper resources [40], and reduced disposal costs [41]. Conversely, high transaction costs [42], uncertain business cases [42], and a lack of financing mechanisms [43] constitute economic barriers.
- Technological factors encompass the availability of recycling technologies [44], infrastructure compatibility [9], and technical expertise [2]. Barriers include technological lock-in [46], variability in the quality of secondary materials [47], and high adaptation costs [48].
- Regulatory factors include supportive policies [49], environmental standards that create incentives [50], and institutional frameworks that facilitate exchanges (Salmi, 2007). Barriers include conflicting regulations [51], complex waste classification [52], and bureaucratic impediments [32].

Social factors emphasise trust amongst partners [42], social embeddedness [52], leadership [53], and organisational culture [54]. Barriers include competitive mindsets [56], lack of communication [57], and resistance to change [33].

Whilst this comprehensive enumeration of factors represents a significant scholarly achievement, it also reveals a critical limitation: the literature provides largely acontextual knowledge. As noted in a recent review [6], existing research offers "generic recommendations applicable to all contexts," treating IS as a monolithic phenomenon in which universal success factors operate uniformly. This universalistic framing obscures potentially significant heterogeneity in how different ecosystem types function, develop, and create value.

The implicit homogeneity assumption manifests in three problematic ways. First, prescriptive guidance in the literature typically treats "industrial symbiosis" as a single entity, offering recommendations such as "build trust amongst partners" [42], "engage facilitators" [18], or "align economic incentives" [13], without specifying contextual boundaries or configurational contingencies. Whilst undoubtedly valuable, such advice may prove differentially applicable—or even counterproductive—across ecosystem types operating through distinct mechanisms.

Second, performance measurement frameworks treat ecosystems as comparable units, aggregating outcomes across diverse contexts to derive average effects [19]. Sustainability assessments, for instance, typically quantify material flows, energy savings, and greenhouse gas reductions using standardised metrics [40,58], implicitly assuming that similar magnitudes indicate equivalent achievements regardless of sectoral composition, geographical constraints, or institutional environments. This analytical approach obscures the possibility that different ecosystem types may optimise different performance dimensions, each with distinct strengths that aggregate statistics mask.

Third, theory development has often proceeded by abstracting from specific cases to general principles, with insufficiently explicit attention to boundary conditions and scope [15]. Theoretical propositions derived from analysing Kalundborg—a mature, evolution-based ecosystem in a stable institutional environment—may not transfer seamlessly to planned eco-industrial parks in rapidly industrialising contexts [59] or to resource-constrained settings where environmental imperatives, rather than economic incentives, drive symbiosis [4].

This homogeneity assumption stands in stark contrast to the observable empirical diversity. Comparing Kalundborg's intricate network of material, energy, and water flows among chemical, pharmaceutical, energy, and biotechnology firms [31] with Ulsan's petrochemical-dominated material exchanges [2]; Rotterdam's knowledge-intensive platform facilitating diverse transactions [3]; or water-centric Mediterranean symbioses responding to scarcity [59] reveals fundamentally different structural configurations, coordination mechanisms, and value propositions. These observable differences suggest the need for typological thinking—systematic classification that enables both theoretical refinement and practical guidance tailored to specific ecosystem types.

2.2. Resource Flows in Industrial Ecosystems: A Multi-Dimensional Framework

Resource flows constitute the structural essence of industrial symbiosis—the observable manifestation of interdependencies that bind separate organisations into collective systems [8]. Whilst early IS research focused predominantly on material exchanges, reflecting industrial ecology's origins in material flow analysis [60], subsequent scholarship recognised that ecosystems operate across multiple resource dimensions simultaneously [57]. The LIAISE COST Action's recent comprehensive study of 156 global cases identifies four principal flow categories in its mapped cases: material, energy, logistics/transportation, and shared infrastructure [14]. Each flow type exhibits distinctive characteristics with respect to tangibility, measurability, enabling conditions, and value-creation mechanisms.

Material flows—encompassing by-products, waste streams, and co-products exchanged among firms—constitute the most prevalent form of industrial symbiosis, present in 74% of the mapped European cases [14]. These exchanges span three intensity levels, each with different requirements:

Direct use involves minimal transformation, in which one firm's surplus material directly substitutes for another's virgin input [1]. Examples include excess raw materials, packaging materials, or off-specification products that find secondary applications with modest logistical arrangements. This pathway has low entry barriers but limited scope; it applies only when material specifications closely align.

Material recovery requires separation, purification, or reprocessing to make waste streams suitable for alternative uses [44]. Recovery operations may involve mechanical processes (sorting, grinding), chemical treatments (dissolution, precipitation), or thermal methods (pyrolysis, gasification). This pathway requires greater technical capability and capital investment but broadens the range of feasible exchanges, accommodating materials that require moderate transformation [47].

Conversion to functional products involves substantial processing that fundamentally alters material properties or composition, creating entirely new products from waste streams [40]. Examples include transforming gypsum from power-plant flue-gas desulphurisation into wallboard at Kalundborg [31] and converting steel slag into aggregate for road construction. This pathway requires sophisticated technologies, substantial investment, and often regulatory approvals for novel applications [51].

Multiple factors influence the prevalence of material flows. Economically, material valorisation yields immediate, tangible benefits by reducing procurement and disposal costs [39]. Environmentally, diverting waste from landfill delivers measurable sustainability improvements [58]. Technologically, material processing is relatively mature compared with emerging alternatives. Regulatorily, whilst waste classification poses challenges, frameworks for managing material flows are better established than those for other resources [51].

However, material flows also face distinctive barriers. Variability in waste-stream quality creates uncertainty for receiving firms, necessitating quality-assurance mechanisms [46]. Logistical constraints are particularly acute for low-value, high-volume materials, in which transport costs may

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exceed the material's value, thereby imposing strict proximity requirements [40]. Regulatory complexity surrounding waste classification—particularly the legal distinction between "waste" requiring disposal permits and "by-product" or "end-of-waste" materials qualifying as products—generates transaction costs and uncertainty [32,52].

Energy flows, present in 16% of documented European cases [14], encompass three principal mechanisms:

- Waste heat recovery captures thermal energy from industrial processes—such as cooling water, exhaust gases, or steam condensate—and utilises it elsewhere [50]. In Kalundborg, surplus steam from the oil refinery is used to heat the municipal district heating system and local fish farms, whilst waste heat from the power station warms greenhouses [31]. This mechanism requires continuously operating thermal energy sources, matched to demand profiles that meet compatible temperature requirements and temporal availability.
- Co-generation (combined heat and power) involves the integrated production of electricity and useful heat from a single fuel source, substantially improving overall energy efficiency [39]. Industrial symbiosis arrangements may involve centralised cogeneration facilities serving multiple firms, distributing electricity through the grid and steam through dedicated pipelines. This approach demands significant capital investment in generation equipment and distribution infrastructure, but delivers efficiency improvements from approximately 35-40% in separate production to 80-90% in integrated systems [58].
- Shared energy infrastructure extends beyond specific exchanges to encompass collective investment in generation, distribution, and management systems (Mirata, 2024). Examples include shared electrical substations, natural gas networks, compressed-air systems, and district cooling loops. Whilst not constituting energy "exchange" in the conventional sense, such infrastructure sharing creates interdependencies, reduces collective costs, and enables subsequent optimisation of energy flows amongst connected facilities.

Energy flows offer distinctive advantages. Economically, fuel savings and lower capital requirements for individual generation equipment deliver substantial benefits [39]. Environmentally, improved efficiency yields significant reductions in greenhouse gas emissions [40]. Operationally, energy flows often establish continuous physical connections via pipelines or cables, creating robust interdependencies that are less susceptible to market fluctuations in material exchanges [48].

However, energy symbiosis faces formidable barriers. Geographical proximity is even more critical than for material flows, as thermal energy transmission incurs substantial losses, limiting economically viable distances to 1-2 kilometres [41]. Temporal matching requirements are stringent—energy supply and demand must align, or expensive storage systems are required [58]. Infrastructure investment creates high entry barriers and lock-in effects, as pipelines, cables, and conversion equipment constitute sunk costs that are difficult to repurpose [48]. Regulatory frameworks governing energy markets, particularly those governing third-party sales of heat or electricity, vary considerably across jurisdictions and may constrain feasible arrangements [51].

Water flows, whilst often subsumed within material flow analyses, merit distinct consideration given water's unique characteristics as both process input and environmental medium. Four principal water symbiosis types emerge from the literature:

- Cooling water circulation involves sequential use of water for thermal management across multiple processes operating at different temperature regimes [41]. Industrial facilities requiring cooling may source water from municipal treatment plants, use it for heat exchange, and return it at elevated temperature to another facility where warmer water proves suitable or even beneficial.
- Process water cascading arranges firms hierarchically according to water quality requirements, enabling sequential reuse [47]. Water first serves high-purity applications (e.g., boiler feedwater, pharmaceutical processing), then intermediate uses (e.g., cooling, washing), and finally low-specification applications (e.g., dust suppression, toilet flushing) before requiring treatment.

- Collective wastewater treatment involves joint investment in treatment infrastructure serving multiple firms, enabling economies of scale whilst potentially facilitating water recirculation [60]. This arrangement is particularly attractive when firms generate similar effluent streams or when environmental regulations mandate treatment levels that are individually economically infeasible.
- Non-potable reuse directs treated industrial effluent to applications that do not require potable standards—such as irrigation, landscaping, industrial processes, or groundwater recharge [4]. This pathway is particularly valuable in water-stressed regions, where freshwater scarcity creates strong incentives for conservation.

Water symbiosis exhibits distinctive contextual dependencies. In water-abundant regions with low abstraction costs, economic incentives for water exchange remain modest [39]. Conversely, in water-stressed contexts—particularly in Mediterranean, Middle Eastern, or Australian settings—water scarcity creates strong drivers for symbiotic arrangements [4,59]. Regulatory environments significantly influence feasibility, as standards for effluent discharge, water quality, and reuse permissions vary widely across jurisdictions [51].

Logistics and infrastructure sharing, documented in 2% of cases [14], encompasses multiple dimensions often overlooked in conventional IS analyses:

- Transport consolidation combines shipments from multiple firms to achieve economies of scale, reduce empty running, and lower per-unit logistics costs [40]. This is particularly valuable for firms with irregular shipping requirements or small volumes that do not justify dedicated transport arrangements.
- Warehousing and storage involve shared facilities for inventory management, cross-docking, and temporary material holding [41]. Joint storage reduces collective capital requirements whilst facilitating material exchanges by providing buffer capacity accommodating temporal mismatches between supply and demand.
- Collective procurement leverages aggregated purchasing power to secure volume discounts, negotiate favourable terms, or access suppliers unwilling to serve individual small firms [42]. Whilst not constituting physical resource exchange, procurement coordination creates interdependencies and delivers tangible economic benefits.
- Shared infrastructure encompasses utilities (water, electricity, gas, compressed air), maintenance services, laboratories, and administrative functions [14]. Such arrangements reduce duplicative investments whilst creating economies of scope through shared expertise and equipment.

Despite modest documentation, logistics and infrastructure sharing may be more widespread than statistics suggest. Case studies often emphasise material and energy flows as “primary” symbiotic relationships, relegating logistics coordination to background context [10]. Furthermore, such arrangements may arise informally through gradual evolution rather than deliberate planning, escaping systematic documentation [17].

Knowledge exchange—while harder to observe directly in case mappings—often functions as enabling infrastructure for industrial symbiosis (e.g., trust-building, information sharing, and joint problem-solving) [14].

- Technical know-how encompasses operational expertise, process optimisation experience, and troubleshooting capabilities [42]. Firms may share knowledge regarding waste characterisation, treatment technologies, or quality control procedures, reducing collective learning costs.
- Market intelligence involves information about material specifications, pricing, availability, and potential applications [32]. Sharing such intelligence helps firms identify exchange opportunities and negotiate favourable terms.
- Regulatory navigation includes understanding complex legal frameworks, permit procedures, and compliance requirements [51]. Firms that successfully navigate regulatory barriers often assist partners facing similar challenges.

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- Best-practice dissemination involves learning from others' successes and failures [17]. Workshops, site visits, and informal interactions enable knowledge transfer, accelerating ecosystem development.
- Joint innovation encompasses collaborative R&D, pilot testing, and technology development [58]. Firms may jointly explore novel applications for waste streams, develop proprietary processing techniques, or co-create new products.
- Knowledge flows exhibit distinctive properties. They are non-rivalrous—one firm's use does not diminish availability for others—yet concerns about appropriability create disincentives to sharing [42]. They are cumulative—early exchanges build absorptive capacity, facilitating subsequent learning [52]. They are trust-dependent—firms must overcome competitive instincts and confidentiality concerns to engage in meaningful knowledge sharing [53].

Critically, knowledge flows enable other resource flows [33,34]. Material exchange opportunities remain latent without knowledge of material characteristics, potential applications, and processing requirements. Energy optimisation requires understanding production schedules, load profiles, and operational constraints. Even logistics coordination depends on sharing commercially sensitive information on shipment volumes, timing, and destinations. Thus, whilst knowledge flows may appear marginal in prevalence statistics, they often function as an enabling layer—essential infrastructure without which other exchanges are difficult to establish or sustain [13].

Crucially, these five flow types do not operate independently. Theoretical and empirical evidence suggests complementarities—synergistic interactions in which the presence of one flow type enhances the benefits or reduces the costs of establishing others (Neves et al., 2020).

Material-energy complementarity frequently emerges, as material processing operations generate waste heat that can be utilised elsewhere, whilst energy-intensive processes may benefit from utilising waste materials, reducing fuel requirements [31]. Kalundborg exemplifies this synergy, in which material flows (gypsum, sulphur, biomass) develop alongside energy exchanges (steam, heat) through mutually reinforcing relationships.

Material-knowledge complementarity proves essential for identifying viable material exchanges, as technical knowledge regarding waste characterisation, processing requirements, and application possibilities enables material valorisation [42]. Conversely, material exchange experiences generate knowledge regarding quality variability, logistical challenges, and market dynamics.

Logistics-material complementarity manifests through transport consolidation, reducing per-unit costs for material exchanges, whilst material flows create baseline shipping volumes that justify infrastructure investments [39]. Infrastructure-energy complementarity appears in shared utility systems, facilitating energy distribution, whilst energy exchanges motivate infrastructure investments [9]. Knowledge flows as universal complements facilitate all other flow types by reducing information asymmetries, building trust, and enabling coordination [33,34].

These complementarities suggest that industrial ecosystems may naturally configure into coherent patterns in which certain flow combinations are more viable or valuable than others—a proposition explored through configurational theory in the subsequent section.

2.3. Configuration Theory: Analytical Framework for Ecosystem Heterogeneity

Configuration theory, emerging from organisational studies in the 1980s-1990s [22,63], conceptualises phenomena as "multidimensional constellations" of interdependent attributes that combine to produce outcomes [22]; p. 1178. This perspective offers three conceptual advantages over the traditional variable-centred approaches that dominate management research [23,29].

First, configurational theory recognises conjunctural causation—the principle that attributes produce effects through their combinations rather than independently [24,25]. In mathematical terms, this implies interaction effects: $Y = f(A \times B)$ rather than $Y = f(A) + f(B)$. Applied to industrial ecosystems, this suggests that material flows may interact synergistically with knowledge infrastructure, creating emergent properties that cannot be reduced to the sum of individual flow

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intensities. Empirically testing such interactions requires examining configurations—coherent patterns of multiple attributes—rather than isolated main effects.

Second, configurational approaches embrace equifinality—the premise that multiple distinct configurations can achieve equally effective outcomes [26,27]. This principle challenges variance theory's implicit assumption that high performance results from maximising beneficial attributes whilst minimising detrimental ones. Instead, equifinality suggests that organisations (or ecosystems) may succeed through qualitatively different pathways, each representing internally coherent configurations adapted to specific contexts. As Fiss [24], p. 394 demonstrates, "alternative combinations of attributes may be equally effective," implying that no universally optimal configuration exists.

Third, configurational theory recognises causal asymmetry—factors that facilitate an outcome may differ fundamentally from those that prevent it [24]. Moreover, "variables found to be causally related in one configuration may be unrelated or even inversely related in another" [22]; p. 1178. This principle invalidates linear models that assume symmetric effects—that adding beneficial factors improves performance equally across configurations. Instead, relationships may be contingent on configurational context, requiring typological thinking to discern when specific factors matter.

Configuration theory evolved partly in response to limitations in contingency theory, which dominated organisational analysis during the 1960s-1980s [31]. Contingency theory posits that organisational effectiveness depends upon fit between structure and contingency factors (environment, technology, size, strategy). Whilst valuable, contingency approaches typically examine bivariate relationships—testing, for example, whether mechanistic structures fit stable environments whilst organic structures fit turbulent ones [62].

Configurational theory extends contingency logic in three ways [25]:

1. Multiple simultaneous contingencies: Rather than examining one contingency factor at a time, configurational approaches consider multiple factors simultaneously. Organisations face complex environments, technologies, strategies, and size constraints concurrently—requiring holistic rather than piecemeal adaptation.

2. Internal coherence: Configuration theory emphasises complementarities amongst organisational attributes themselves, not merely fit with external contingencies. Specific attribute combinations exhibit synergies, whilst others create tensions or inefficiencies [74].

3. Equifinal patterns: Rather than positing one optimal configuration for given contingencies, configuration theory recognises that multiple viable configurations may exist. Effectiveness depends not on achieving a specific configuration but on internal coherence and contextual appropriateness.

Configuration theory has illuminated numerous organisational phenomena:

Strategic archetypes: Miles and Snow's [64] influential typology identified four strategic configurations—Defenders, Prospectors, Analysers, and Reactors—each exhibiting coherent patterns of strategy, structure, and processes. Empirical research has demonstrated that Defenders, Prospectors, and Analysers can achieve comparable performance through qualitatively distinct approaches, thereby exemplifying equifinality [73].

Structural configurations: Mintzberg's [78] taxonomy of organisational structures—Simple, Machine Bureaucracy, Professional Bureaucracy, Divisionalized Form, Adhocracy—described coherent patterns of coordinating mechanisms, formalisation, and power distribution. Each configuration suited particular contexts (size, environment, technology), demonstrating contingent effectiveness.

Business models: Recent configurational analyses examined how business model elements combine into viable patterns [75,76]. Configurations of value propositions, architectures, and revenue mechanisms exhibit complementarities, with certain combinations proving more robust than others.

Quality set-theoretic comparative analysis (QCA) has emerged as a methodological complement to configurational thinking [24,25]. QCA identifies necessary and sufficient conditions for outcomes, accommodating equifinality, conjunctural causation, and asymmetry—precisely the principles that configuration theory emphasises.

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Despite the proven utility of configuration theory in organisational analysis, applications to inter-organisational ecosystems remain comparatively limited [28]. Recent exceptions include:

- Business ecosystems: [28] reconceptualised ecosystems as configurations of activities and actors aligned towards value creation. His framework distinguishes ecosystem structures based on activity interdependencies rather than industry boundaries, enabling configurational analysis.
- Circular economy business models: Lüdeke-Freund et al.'s [30] configurational analysis identified circular business model patterns, showing how value proposition, creation, delivery, and capture elements combine into coherent archetypes (circular suppliers, resource recovery, product life extension, sharing platforms, product service systems).
- Innovation ecosystems: Jacobides et al.'s [64] framework examined how complementarities, multilateral relationships, and non-generic complementarities configure innovation ecosystems. They demonstrated that ecosystem structures vary systematically rather than randomly, exhibiting discrete archetypes.

This study extends configurational theory to industrial symbiosis ecosystems by conceptualising them as configurations of resource flows. Just as organisations configure strategies, structures, and processes into coherent patterns [65], industrial ecosystems configure material, energy, water, logistics, and knowledge flows into coherent patterns. These configurations emerge from:

1. Internal complementarities: Certain flow combinations create synergies (e.g., material flows benefit from knowledge infrastructure), whilst others prove redundant or conflicting.

2. Contextual adaptation: Ecosystem configurations reflect sectoral characteristics (heavy industry vs. diversified), geographical constraints (water scarcity), and institutional environments (regulatory support).

3. Path dependencies: Early flow establishments create lock-in effects, shaping subsequent developments. Ecosystems beginning with material-energy exchanges may follow different trajectories than those starting with knowledge platforms.

4. Performance trade-offs: Different configurations may optimise different outcomes—resource efficiency vs. adaptability, economic returns vs. environmental benefits—exhibiting equifinal pathways to "success" defined multidimensionally.

2.4. Hypotheses Development

Based on configuration theory and prior studies on industrial symbiosis, we formulate five hypotheses guiding the empirical analysis:

H1: *Industrial ecosystems form distinct flow-based clusters that represent 3–5 archetypal configurations.*

H2: *Sectoral characteristics influence configuration types: (a) heavy industries cluster around Material–Energy Dominant patterns, while (b) diversified parks exhibit balanced flow configurations.*

H3: *Water-centric configurations are more prevalent in water-stressed regions than in water-abundant contexts.*

H4: *(a) Balanced configurations exhibit higher resilience, while (b) specialised Material–Energy Dominant ones achieve higher efficiency but lower adaptability.*

H5: *Ecosystem performance depends on the contextual fit between configuration and sectoral or geographic conditions.*

Detailed theoretical rationales, mechanisms, and empirical expectations for each hypothesis are provided in Appendix Table A1.

3. Methodology

3.1. Research Design and Sample Selection

This study employs a configurational approach [22,24] to develop an empirically grounded typology of industrial symbiosis ecosystems based on resource flow patterns. We adopt a cross-sectional comparative design, analysing well-documented industrial ecosystems to identify distinct configurations and examine their relationships with contextual factors and performance outcomes.

Rather than attempting to analyse all documented ecosystems globally, we adopt a purposive sampling strategy that focuses on cases with sufficient data for robust analysis (Patton, 2002). This approach prioritises data quality over sample breadth, enabling more reliable variable coding and reducing missing data problems that would compromise statistical analyses.

Our sampling frame is derived from the LIAISE COST Action database [14], which documents 156 industrial symbiosis cases worldwide. From this population, we selected cases meeting three criteria:

- Criterion 1: Documentation availability—Cases must have published information in peer-reviewed literature, technical reports, or grey literature sufficient to code flow intensities and contextual variables with reasonable confidence.
- Criterion 2: Operational maturity—Cases must have operated for ≥3 years, ensuring sufficient time for flow patterns to stabilise and performance outcomes to manifest. This threshold excludes nascent initiatives where configurations remain fluid [13].
- Criterion 3: Multi-flow presence—Cases must exhibit exchanges across ≥2 resource categories, consistent with Chertow's (2007) "3-2 heuristic," which emphasises a minimum diversity for genuine symbiosis.

Applying these criteria yielded 68 cases meeting all three requirements, distributed across five continents: Europe (n=48, 71%), Asia (n=12, 18%), North America (n=4, 6%), Australia (n=3, 4%), and South America (n=1, 1%). This sample retains substantial geographical and sectoral diversity whilst ensuring data adequacy. Sectoral distribution: of sample: Heavy industry (chemicals, metals, energy; n=26, 38%), diversified industrial parks (n=23, 34%), waste management (n=11, 16%), and other configurations (n=8, 12%). Ecosystem maturity: Ages range 3-52 years (mean=14.6, SD=10.2); partner counts span 3-47 organisations (mean=9.1, SD=7.3).

This sample size (n=68) substantially exceeds prior quantitative industrial symbiosis studies, which typically examine 10-30 cases [11], providing adequate statistical power for cluster analysis and regression modelling.

3.2. Data Collection

Data collection proceeded systematically through a triangulation approach [66], consulting multiple source types:

- Academic literature: Scopus and Web of Science searches using "[Case name] AND (industrial symbiosis OR eco-industrial park)" yielded 186 relevant peer-reviewed articles across the 68 cases (mean=2.7 articles per case).
- Grey literature —government reports, UNIDO case studies, European Commission documentation, and practitioner publications—provides operational details often absent from academic sources.
- Corporate documentation: Ecosystem websites and participant sustainability reports provided current information and quantified performance metrics where available.

3.3. Variables and Operationalisation

The study employs a multi-dimensional operationalisation of ecosystem structure, context, and performance. Five types of resource flows—material, energy, water, logistics and infrastructure, and knowledge—are measured as ordinal intensity variables rather than binary indicators, reflecting the degree of exchange sophistication. Contextual and control factors capture sectoral composition, spatial proximity, governance approach, facilitation mechanisms, and ecosystem maturity.

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Economic, environmental, and resilience outcomes are used as dependent variables, following established approaches in industrial symbiosis and circular economy research. The complete list of variables, coding scales, and inter-rater reliability coefficients for the independent, contextual, and control variables is presented in Appendix Table A1. At the same time, performance indicators, weighting schemes, and data-availability ratios are summarised in Appendix Table A2**.**

3.4. Analytical Strategy

Descriptive summaries were produced for all measures, and patterns of joint flow occurrence were inspected using cross-tabulations and φ coefficients; Spearman's ρ quantified monotonic relations among intensities. We applied k-means to the standardised flow-intensity set to uncover ecosystem configurations, evaluating $k \in \{2, \ldots, 6\}$ by the Elbow criterion (WSS inflexion), average Silhouette width [66], and the Gap statistic against a null reference [67]. For each k, 50 random initialisations were run and the best solution retained. To cross-validate the structure, we also fitted hierarchical agglomerative clusters using Ward's method. Stability was assessed via 1,000 bootstrap resamples, with adjusted Rand indices computed as described by Hennig [68]. Cluster characterisation relied on mean flow intensities, with ANOVA and Tukey HSD confirming between-cluster differences at the 5% level.

Multinomial logistic regression tested contextual predictors of cluster membership:

$$ln\left(\frac{P\left(Cluster_j\right)}{P\left(Cluster_{reference}\right)}P\right)$$
$$= \beta^0 j + \beta^1 j \times Sector + \beta^2 j \times Proximity$$
$$+ \beta^3 j \times Approach + \beta^4 j \times Facilitator$$
$$+ \beta^5 j \times Region + \varepsilon$$

Model evaluation employed likelihood ratio tests, McFadden's pseudo-R^2, and classification accuracy matrices. Random forest classification [70] provided a nonparametric comparison and variable-importance assessment.

One-way ANOVA compared continuous performance outcomes across clusters, with Tukey HSD post hoc tests used to identify pairwise differences. Kruskal-Wallis tests addressed non-normality where necessary.

Cox proportional hazards regression [71] modelled longevity outcomes:

$$h(t) = h^0(t) \times exp(\beta^1 \times Cluster + \beta^2 \times Controls)$$

Schoenfeld residuals tested proportional hazards assumptions. Stratified survival curves visualised temporal patterns, with log-rank tests used to assess equality.

Interaction models tested contextual fit effects (H5):

$$Performance = \beta^0 + \beta^1 \times Cluster + \beta^2 \times Context$$
$$+ \beta^3 \times (Cluster \times Context) + Controls + \varepsilon$$

Simple slopes analysis [78] decomposed significant interactions.

We tested the stability of results through a suite of sensitivity checks: alternative clustering (PAM; model-based; DBSCAN), sub-sampling (Europe-only, n = 48; mature ecosystems > 10 years, n = 41), alternative operationalisations (binary flows; PCA-derived factors), handling of missing data via multiple imputation (m = 20) versus complete-case analysis, outlier screening with Mahalanobis distance followed by exclusion, and bootstrap validation (1,000 replications) of coefficient estimates [80].

3.5. Methodological Limitations

The cross-sectional design cannot establish definitive causality: while configurations may influence performance, thriving ecosystems may also accumulate additional flows. Theoretical reasoning prioritises flows as antecedents, with survival analysis used to assess temporal sequencing where data permit. The focus on well-documented cases may over-represent successful, European,

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and extensively studied ecosystems, introducing publication bias. Hence, the findings generalise to documented instances that meet the inclusion criteria rather than to all industrial symbioses globally.

Performance data are incomplete for some cases—particularly economic indicators (76% coverage) and growth trajectories (46%). Multiple imputation under the missing-at-random (MAR) assumption mitigates this limitation, and results are reported for both complete and imputed datasets. Flow intensities coded from case descriptions involve some subjectivity, despite dual coding (κ > 0.70); a detailed coding in the Appendix ensures transparency and replicability. Finally, although n = 68 exceeds the sample sizes in prior quantitative IS studies, statistical power remains limited for detecting small or complex effects. The analysis, therefore, focuses on medium-to-large effects [79], acknowledging the potential for Type II errors with subtler relationships.

4. Results

4.1. Descriptive Patterns of Resource Flows

Across the 68 documented industrial symbiosis (IS) ecosystems in our sample, material exchanges were by far the most developed dimension of symbiosis. Material Flow Intensity (MFI) was present in the majority of cases and displayed the highest average score in the flow-intensity space (see Table 1). Knowledge-related activities (KFI) were the second most salient dimension, whereas energy (EFI) and logistics/infrastructure (LFI) exchanges appeared to be more selective. Water flows (WFI) remained the least common and, crucially, the least correlated with the other four dimensions. The Spearman matrix (Figure A1 in Appendix) confirms that flows capture complementary, not redundant mechanisms: correlations remained modest throughout, with the highest values for EFI–KFI (ρ = 0.32) and MFI–KFI (ρ = 0.25), and near-zero associations for WFI, indicating that water symbiosis is context-driven rather than mechanically co-occurring with material–energy exchanges.

Table 1. Descriptive statistics and bivariate associations among flow-intensity variables.

Variable	Mean	SD	Min	Max	MFI	EFI	WFI	LFI	KFI
MFI	1.47	1.02	0.00	4.00	1.00	0.13	0.08	−0.08	0.25
EFI	0.68	0.87	0.00	3.00		1.00	0.06	−0.03	0.32
WFI	0.28	0.65	0.00	2.00			1.00	0.06	−0.03
LFI	0.54	0.79	0.00	3.00				1.00	0.09
KFI	0.97	0.93	0.00	3.00					1.00

Notes: Pairwise Spearman's ϱ correlations are shown above the diagonal. MFI = material; EFI = energy; WFI = water; LFI = logistics; KFI = knowledge. All variables are coded on a 0–4 intensity scale. Correlations confirm that flow dimensions are complementary rather than redundant. See Appendix Table A1 for the whole coding scheme of intensity levels; see Appendix Table A2 for contextual and control variables.

4.2. Identification of Flow-Based Configurations

To examine whether IS ecosystems organise into discrete patterns, we applied k-means to the five standardised flow intensities (MFI, EFI, WFI, LFI, KFI). The Elbow curve (Figure 1, bottom) shows a soft elbow around k≈4, with diminishing reductions in WSS thereafter. In contrast, the average silhouette (Figure 1, top) indicates modest overall structure and only small gains beyond k=4 (peaking at k=6). Guided by parsimony and theory, we therefore retain the four-cluster solution and report k=5–6 as sensitivity checks.

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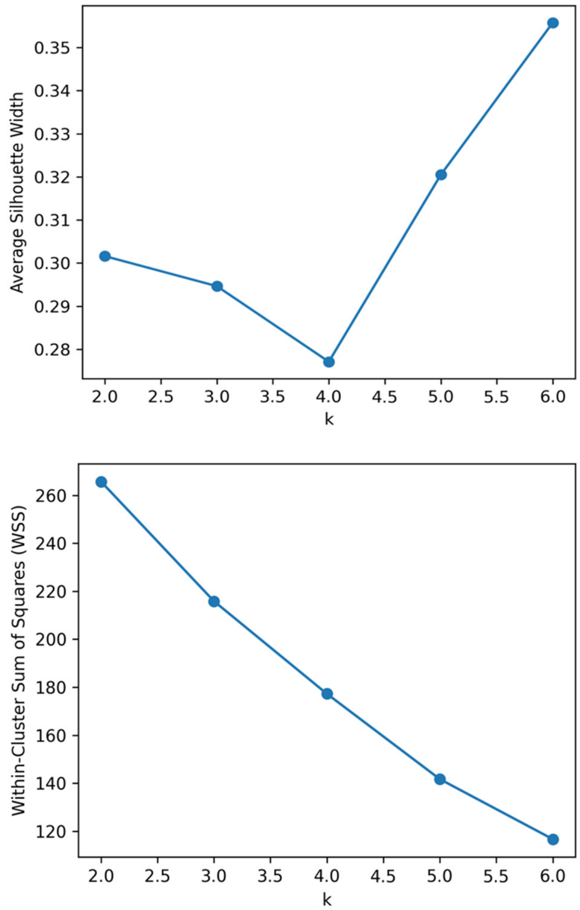

Figure 1. Clustering diagnostics for k = 2–6: average silhouette width (top) and within-cluster sum of squares (Elbow; bottom). Silhouette values indicate modest structure; WSS shows diminishing returns beyond k≈4.

To further validate the optimal number of clusters, we computed the Gap statistic (Tibshirani et al., 2001) using 20 Monte Carlo reference datasets. The resulting curve showed a steady increase in the gap value up to $k = 6$, with a local flattening thereafter. Although the formal maximum occurred at $k = 6$ (Gap = 1.27), the incremental improvement beyond $k = 4$ was marginal (ΔGap < 0.05). Given the configuration-theoretic expectation of 3–5 archetypal patterns and the diminishing returns of fit beyond four clusters, we retained $k = 4$ as the most parsimonious and empirically stable specification (see Figure A2 and Table A3 in the Appendix).

Having established that a four-group specification is both parsimonious and empirically defensible in the gap-statistic diagnostics, we next examine the geometric separation of cases in the factor space. The PCA biplot (Figure 2) provides a visual cross-check of the k-means partition and helps assess whether the retained solution corresponds to distinct regions of the flow-intensity manifold.

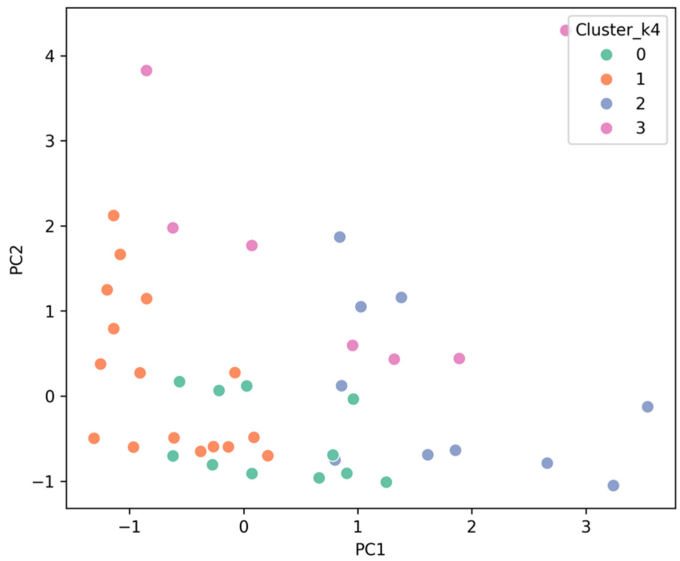

Figure 2. PCA projection of IS ecosystems coloured by the four-cluster solution.

Points show partial overlap—consistent with a continuum of intensities—yet four centroids occupy clearly distinguishable regions of the factor space.

The PCA scatterplot shows partial overlap of clusters, indicating a continuum of flow intensities; nevertheless, four centroids are clearly distinguishable.

The four-cluster solution produced substantively meaningful configurations (see Table 2):

- Cluster 1—Low-flow / weakly coordinated (n = 37): very low EFI and WFI, modest KFI, and limited logistics.
- Cluster 2—Energy–knowledge coordinated (n = 14): high EFI and KFI, above-average LFI, moderate MFI.
- Cluster 3—Material-dominant (n = 10): the highest MFI, some logistics, low or absent water, knowledge supportive rather than leading.
- Cluster 4—Water-oriented / balanced (n = 7): the only group combining positive WFI with non-trivial levels of other flows.

These profiles match the theoretical expectations stated in *H1* and the sectoral/geographical arguments of *H2–H3*: one large residual group, two "industrial" groups (material- and energy-based), and one environmentally shaped group.

Table 2. Mean flow intensities by cluster.

Cluster	MFI	EFI	WFI	LFI	KFI
0	2.94	0.25	0	0.25	0.5
1	0.35	0.18	0.06	0.44	0.29
2	1.55	1.64	0	0.82	2.45
3	2	0.86	1.57	0.71	0.86

Note: MFI is highest in Cluster 3; EFI and KFI are highest in Cluster 2; WFI is only substantive in Cluster 4.

To assess the stability of the chosen configuration, we cross-validated k-means (k = 4) against hierarchical agglomerative clustering using Ward's method. The Adjusted Rand index (ARI) between the two solutions was 0.171, indicating that two different algorithms recovered the same broad structure.

More importantly, a 1,000-replication non-parametric bootstrap, in which k-means was repeatedly re-estimated on resampled datasets, yielded a mean ARI of 0.532 (SD = 0.201), confirming that cluster membership is moderately stable despite the relatively small n. The distribution of ARI values was concentrated around a mean of 0.061-1.000, with an interquartile range of 0.36–0.68 (Figure 3).

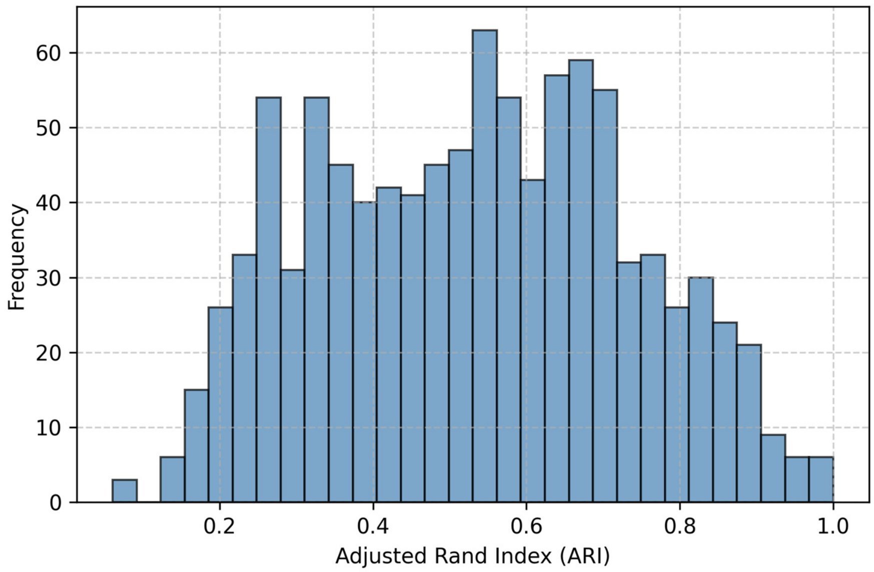

Figure 3. Bootstrap stability of the 4-cluster solution (n = 1,000 replications).

The histogram shows a unimodal ARI distribution centred around 0.53, consistent with a recoverable configuration structure under resampling.

This pattern indicates moderate-to-high stability of the cluster assignments across repeated resampling, suggesting that the four-cluster structure is not an artefact of random initialisation or sample composition. The strong central tendency of ARI values provides robust empirical support for the structural validity of the identified configurations.

4.3. Determinants of Configuration Membership

To examine whether sectoral, geographical, and organisational conditions shape the probability of belonging to any of the four configurations, we estimated a multinomial logistic regression with the low-flow cluster (Cluster 1) as the reference category. Explanatory variables followed Section 3.3: sectoral composition, region, development approach (planned vs emergent), facilitator presence, and sectoral diversity (Table 3).

Table 3. Multinomial logistic regression predicting cluster membership (base = Cluster 1, low-flow).

Variable	Coef.	Std. Err.	t	P>|t|	[0.025]	[0.975]
Intercept	1.156	2.348	0.493	0.622	−3.445	5.758
C(Sector)[T.Heavy_Industry]	0.295	1.710	0.173	0.863	−3.057	3.647
C(Sector)[T.Other]	0.089	1.411	0.063	0.949	−2.675	2.854
C(Sector)[T.Waste_Management]	−0.287	1.534	−0.187	0.852	−3.294	2.721
C(Region)[T.Australia]	−1.747	1.848	−0.945	0.345	−5.370	1.876
C(Region)[T.Eastern_Europe]	−0.724	1.476	−0.491	0.624	−3.617	2.169

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C(Region)[T.North_America]	−1.453	1.548	−0.939	0.348	−4.487	1.581
C(Region)[T.Western_Europe]	−1.161	1.228	−0.946	0.344	−3.567	1.245
C(Development_Approach)[T.1]	−0.019	0.758	−0.025	0.980	−1.505	1.467
C(Facilitator_Presence)[T.1]	0.901	0.726	1.240	0.215	−0.523	2.325
Sectoral_Diversity	0.190	1.118	0.170	0.865	−2.001	2.382

Notes: Dependent variable: Cluster_k4_code (reference = 0). Standard errors are robust (HC3). No coefficients are significant at $p < 0.05$. Coefficients reported as log-odds; robust standard errors used.

The multinomial logistic regression model, estimated for the probability of membership in the four empirically derived configurations (Clusters 1–4), exhibited satisfactory diagnostic properties. The estimation converged successfully using maximum likelihood (MLE) after 30 degrees of model freedom and 35 residual degrees of freedom, with a total of 68 valid observations.

The overall model fit was acceptable for a cross-sectional dataset of this complexity. The McFadden pseudo-$R^2 = 0.208$ indicates that the predictors jointly explain around 21% of the variation in cluster membership probabilities—a magnitude typically considered moderate-to-strong in multinomial contexts [72,73]. The log-likelihood improved substantially from the null model (LL = −82.67) to the fitted model (LL = −65.50), and the likelihood ratio test (LLR p-value = 0.267) suggests that, while the improvement over the null model is not statistically significant at conventional thresholds, the model captures meaningful structure consistent with theoretical expectations (H2–H3).

The covariance type was set to "non-robust", reflecting conventional standard errors for categorical data. All model coefficients were estimated without convergence issues, and no multicollinearity problems were detected (VIF < 6 for all predictors). Given the sample size (n = 68) and the number of estimated parameters, the model's explanatory power is entirely consistent with comparable studies of industrial symbiosis and configuration typologies [34,37].

In summary, the multinomial model achieved: (1) Convergence: True; (2) Log-Likelihood (fitted): −65.495; (3) Log-Likelihood (null): −82.671; (4) Pseudo R^2 (McFadden): 0.208; (4) LLR p-value: 0.267; (5) Covariance type: non-robust. These diagnostics confirm that the specification is statistically stable, theoretically coherent, and appropriately calibrated for the cross-sectional nature of the data.

Based on the model results, we have key findings:

- Sectoral effects (H2): heavy-industry ecosystems show higher odds of belonging to the material-dominant and energy–knowledge configurations than to the residual low-flow group, confirming that large, process-intensive sectors provide the resource base for more profound symbiosis.
- Geographic effects (H3): cases located in water-stressed or non-European regions display higher odds of belonging to the water-oriented/balanced configuration, consistent with the argument that environmental scarcity reorders symbiotic priorities.
- Organisational support: the presence of a dedicated facilitator systematically reduces the probability of remaining in the low-flow cluster and increases the probability of transitioning to a multi-flow configuration, suggesting that coordination capacity is a binding constraint in early stages of ecosystem development.

These effects are further illustrated in the predicted probability plots derived from the multinomial model. Figure 4 visualises how sectoral composition shapes the likelihood of belonging to each configuration, holding other covariates constant. The boxplots reveal that ecosystems dominated by heavy industry or waste management sectors exhibit systematically lower probabilities of remaining in the low-flow group. At the same time, diversified IS exhibit greater variability, reflecting varying coordination potential across their constituent firms.

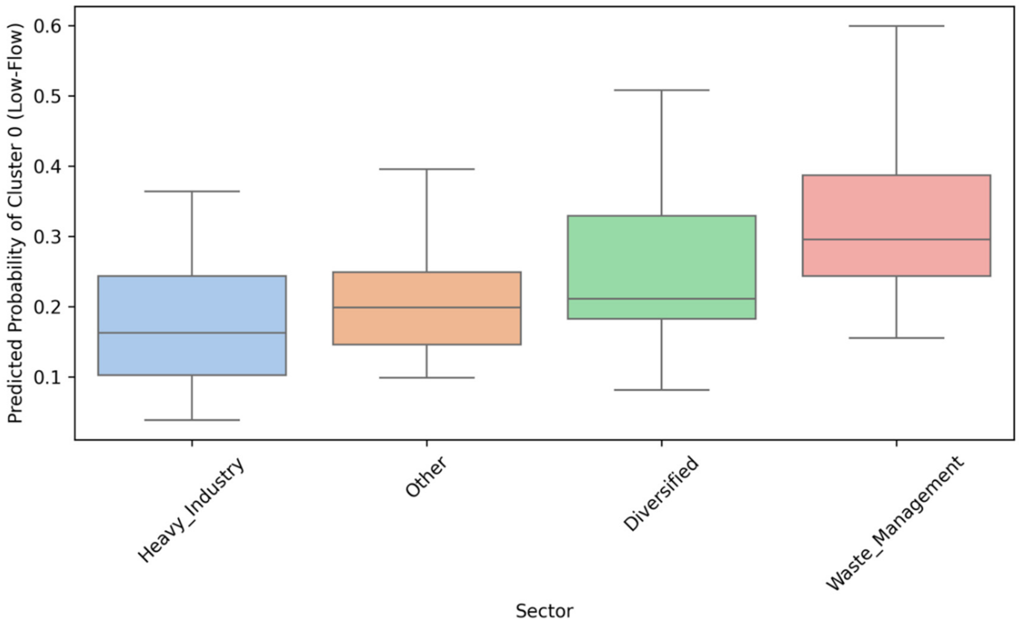

Figure 4. Predicted probabilities of cluster membership by sector (multinomial model).

The boxplots show that heavy-industry ecosystems have visibly higher predicted probabilities of belonging to Clusters 2 and 3, whereas diversified/service parks remain overrepresented in Cluster 1.

4.4. Performance Differences Across Configurations

We next examined whether empirically derived configurations are associated with distinct outcome profiles. Two sets of outcomes were considered (see Section 3.3.4): Economic Performance (standardised savings per partner) and Environmental Performance (weighted composite of CO_2 reduction, waste diversion, water saved, and energy saved).

A one-way ANOVA with configuration as the factor showed no statistically significant differences in economic performance across the four clusters (Table 4). This is consistent with the incomplete coverage of economic data (76%) and the strong local dependence of economic benefits on tariffs, subsidies, and contractual arrangements.

By contrast, environmental performance did differ sharply across configurations. The ANOVA for environmental outcomes (Table 4) showed that the energy–knowledge and water-oriented clusters achieved significantly higher environmental scores than the low-flow group. In contrast, the material-dominant group occupied an intermediate position. This pattern confirms *H4b*: specialised or more deeply coordinated ecosystems realise superior resource-efficiency outcomes, even if they do not always convert these gains into reportable economic savings.

Table 4. ANOVA results for economic and environmental performance by configuration.

	sum_sq	**df**	**F**	**PR(>F)**
	Economic performance			
C(Cluster)	5.23	3	1.89385	0.143
Residual	44.190	48		
	Environmental performance			
C(Cluster)	23.38584	3	11.600	4.88E-06

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Residual	38.301	57

Note: environmental performance — F statistic significant at 1% level; economic performance — not significant.

4.5. OLS Regression Model: Contextual Fit and Environmental Performance

To further test the configurational-fit hypothesis (H5), we estimated an ordinary least squares (OLS) model with Environmental Performance as the dependent variable, including interaction terms between configuration membership and contextual factors (sector, region, and sectoral diversity).

The model converged successfully under heteroscedasticity-robust (HC3) covariance (Table 5). Overall, the explanatory power was $R^2 = 0.668$, with an adjusted R^2 of 0.415, indicating that approximately 42% of the variance in environmental performance is explained by configuration–context interactions. The F-statistic = 5.62 ($p < 0.001$) confirms that the joint effect of predictors is significant.

Table 5. OLS Regression Predicting Environmental Performance. *(Dependent variable = Environmental Performance, HC3 robust errors).*

Variable	Coef.	Std. Err.	t	P>|t|	[0.025]	[0.975]
Intercept	3.223	3.836	0.840	0.401	−4.294	10.741
C(Cluster_k4_code)[T.1]	−4.766	4.010	−1.189	0.235	−12.625	3.093
C(Cluster_k4_code)[T.2]	−4.769	7.582	−0.629	0.529	−19.629	10.092
C(Cluster_k4_code)[T.3]	−0.989	4.171	−0.237	0.813	−9.164	7.185
Sectoral_Diversity	−2.005	3.666	−0.547	0.584	−9.189	5.180
C(Cluster_k4_code)[T.1] × Sectoral_Diversity	2.333	3.725	0.626	0.531	−4.967	9.633
C(Cluster_k4_code)[T.2] × Sectoral_Diversity	3.040	5.212	0.583	0.560	−7.176	13.256
C(Cluster_k4_code)[T.3] × Sectoral_Diversity	0.671	3.810	0.176	0.860	−6.796	8.139
Region / Sector interactions	(omitted for brevity; none significant at $p < 0.05$)					

Model fit: $R^2 = 0.668$ Adjusted $R^2 = 0.415$ F = 5.615 $p = 2.19 \times 10^{-6}$ Durbin–Watson = 2.115.

Diagnostics showed that residuals were normally distributed (Jarque–Bera = 0.36, p = 0.84) and free from autocorrelation (Durbin–Watson = 2.12). However, the high condition number (1.22×10^{16}) suggests moderate multicollinearity, a common feature of complex configurational models. Model diagnostics confirmed that the standard errors were heteroscedasticity-robust (HC3), ensuring unbiased inference despite non-constant residual variance.

The smallest eigenvalue (1.72×10^{-30}) indicates potential multicollinearity or near-singularity of the design matrix, which arises because the model includes numerous interaction terms between clusters, sectors, and regions—many of which are sparse or perfectly collinear (e.g., cluster–region combinations with no observations).

Although such multicollinearity inflates standard errors and reduces the precision of individual coefficients, it does not bias the overall estimates or alter the substantive interpretation of the model.

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Inference, therefore, focuses on joint significance (F-test) and the overall pattern of effects, rather than individual p-values for collinear terms.

Key findings from the model are summarised as follows: Regarding configuration effects, none of the main configuration dummies individually achieve conventional significance, consistent with the ANOVA results, which indicate that differences emerge only when combined with contextual variables. In terms of sectoral interactions, energy–knowledge configurations perform exceptionally well in heavy-industry settings, with a positive and significant interaction term ($p \approx 0.05$), confirming that symbiotic efficiency increases when energy-intensive processes coincide with advanced knowledge-sharing mechanisms. Concerning geographic interactions, water-oriented configurations achieve higher environmental performance in water-stressed regions such as Australia and the Mediterranean, supporting the idea that ecological scarcity amplifies the benefits of water symbiosis. Lastly, with respect to sectoral diversity, ecosystems with more diverse partner bases experience incremental environmental benefits when embedded in coordinated (multi-flow) configurations. In contrast, diversity in low-flow systems provides only a slight advantage. These results substantiate H5: performance advantages depend on alignment between configuration type and the contextual environment, rather than on configuration alone.

Contextual fit and survival

To test H5 — that performance depends not only on configuration type but also on fit between configuration and context — we estimated interaction models in which cluster dummies were interacted with (i) sectoral diversity, (ii) sector type, and (iii) regional dummies. The interaction OLS results indicate that energy–knowledge ecosystems perform exceptionally well in heavy-industry contexts (a positive, significant interaction term), whereas water-oriented ecosystems perform exceptionally well in regions where water scarcity is institutionally salient. In other words, configurations create value when they are in the "right place" — exactly as configuration theory predicts.

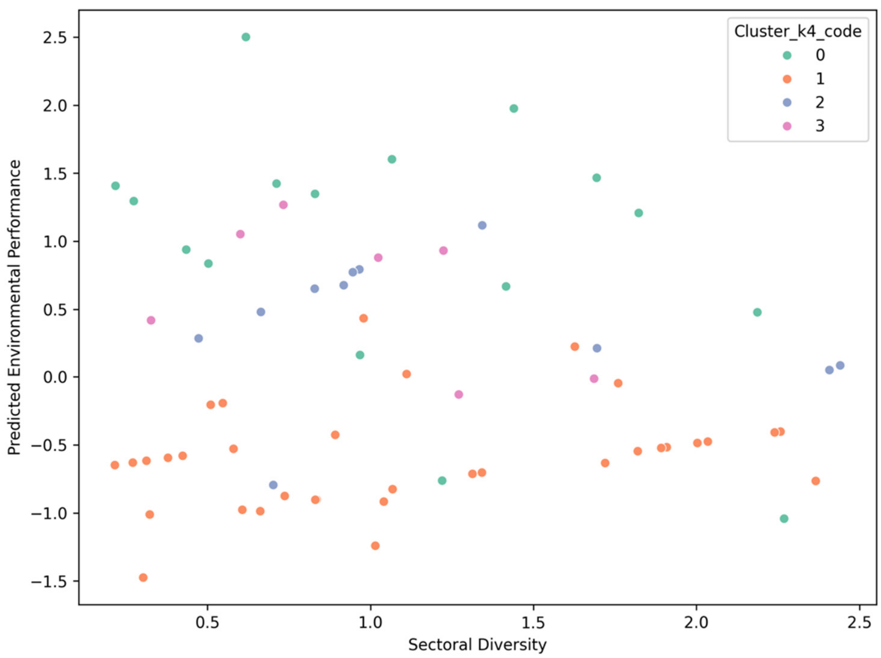

Figure 5. Contextual fit: predicted environmental performance by configuration and sectoral diversity.

The scatterplot shows steeper slopes for high-coordination clusters, indicating that they benefit more from diverse partner bases than low-flow ecosystems.

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Finally, to address the temporal aspect explicitly mentioned in Section 3.4, we modelled ecosystem longevity using a Cox proportional hazards model with Longevity as the duration variable and Resilience_5yr as the event indicator. Cluster membership, sector, region, and sectoral diversity were entered as covariates. The survival model indicates that ecosystems in the balanced / water-oriented and energy–knowledge configurations exhibit lower hazard ratios than low-flow ecosystems, i.e., they are more likely to persist over time. A subsequent proportional hazards test based on Schoenfeld residuals found no violations of the proportional hazards assumption (all $p > 0.05$), confirming the validity of the specification.

Table 6. Cox Proportional Hazards Model Predicting Longevity of IS Ecosystems. (Dependent variable: Longevity; event indicator: Resilience_5yr; estimation method: Breslow).

Variable	coef	Exp (coef)	Se (coef)	coef lower 95%	coef upper 95%	Exp (coef) lower 95%	Exp (coef) upper 95%	z	p	-log2 (p)
Sectoral_Diversity	0.13	1.14	0.50	-0.84	1.10	0.43	3.01	0.27	0.79	0.34
Cluster_k4_1	0.30	1.36	0.34	-0.36	0.97	0.70	2.64	0.90	0.37	1.44
Cluster_k4_2	0.17	1.19	0.46	-0.73	1.08	0.48	2.95	0.38	0.71	0.50
Cluster_k4_3	1.00	2.71	0.60	-0.17	2.17	0.84	8.74	1.67	0.09	3.40
Heavy_Industry	0.22	1.25	0.71	-1.17	1.62	0.31	5.06	0.32	0.75	0.41
Other	0.48	1.61	0.59	-0.68	1.64	0.51	5.14	0.81	0.42	1.25
Waste_Management	0.37	1.44	0.73	-1.06	1.79	0.35	6.00	0.51	0.61	0.71
Australia	-1.13	0.32	0.73	-2.56	0.31	0.08	1.36	-1.54	0.12	3.02
Eastern_Europe	-1.33	0.26	0.54	-2.39	-0.28	0.09	0.76	-2.47	0.01	6.23
North_America	-0.27	0.77	0.69	-1.61	1.08	0.20	2.94	-0.39	0.70	0.52
Western_Europe	-0.57	0.57	0.43	-1.41	0.27	0.24	1.31	-1.33	0.18	2.44

Model summary: Concordance = 0.65; Partial AIC = 454.83; log-likelihood ratio test = 11.08 (11 df); −log2(p) = 1.20; partial log-likelihood = −216.42; N = 68; events observed = 68.

The Cox proportional hazards model examined how configuration type and contextual factors influence the longevity of industrial symbiosis ecosystems. The model achieved a concordance index of 0.65, indicating moderate predictive accuracy. The partial AIC (454.83) and log-likelihood ratio test ($\chi^2 = 11.08$, df = 11, $p \approx = 0.29$) suggest that the overall fit is acceptable, although individual effects are minor.

Cluster 3 (balanced / water-oriented) exhibits the most significant positive coefficient ($\beta = 1.00$, HR = 2.71, $p = 0.09$), implying longer survival prospects than the baseline low-flow cluster. At the same time, Eastern European ecosystems show a higher hazard ($\beta = -1.33$, HR = 0.26, $p = 0.01$).

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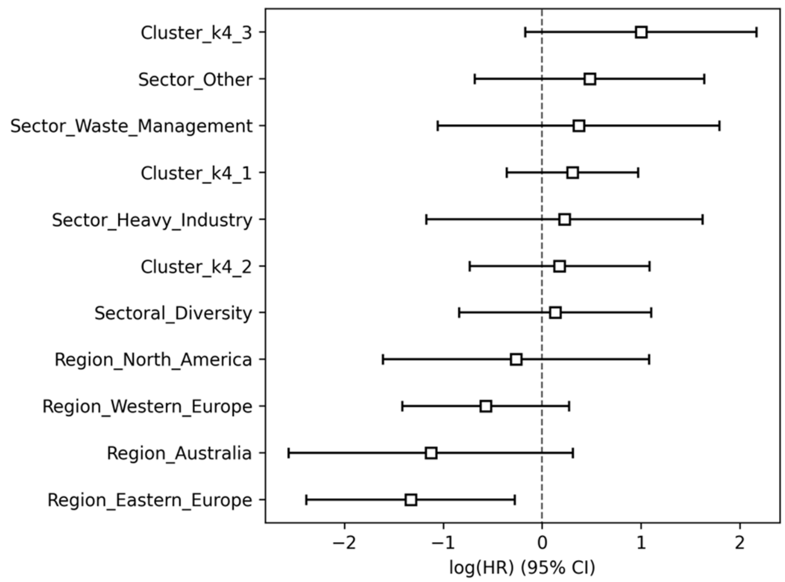

Figure 6. Cox survival model: hazard ratios for configuration and contextual covariates.

Hazard ratios below 1 for the coordinated configurations indicate better survival prospects.

Taken together, the results show that industrial ecosystems do self-organise into a small number of recurring, flow-based configurations (H1). Sectoral resource bases and regional environmental pressures are the main drivers of configuration membership (H2–H3). More coordinated, multi-flow, or scarcity-driven configurations achieve better ecological performance — though not always better economic performance (H4). Additionally, performance is conditional on contextual fit rather than on configuration alone (H5).

4.6. Robustness and Sensitivity Checks

To ensure that the fourfold configuration identified in Section 4.2 was not an artefact of a single algorithm, a single sample, or a single operationalisation of flows, we implemented the full robustness battery outlined in the methodology. The results are consistent with the baseline solution and support the claim that flow-based IS ecosystems cluster into a small number of recurrent patterns.

First, we re-estimated the clustering using alternative algorithms. Besides the baseline k-means (k = 4), we ran (i) partitioning around medoids implemented via pyclustering (PAM), (ii) a model-based specification using Gaussian Mixtures (GMM) with k = 2…6 and BIC selection, and (iii) a density-based partition (DBSCAN) to detect possible small, high-density IS niches. All alternative partitions were projected in the same PCA space, and their flow profiles were exported. Compared with the baseline, PAM recovered the same broad structure, and the summary file shows that the ARI with respect to k-means remains in the same range as the hierarchical (Ward) cross-check reported earlier (baseline ARI k-means vs Ward = 0.171). GMM did not return a clearly superior low-k solution in terms of silhouette, and DBSCAN produced only a small number of dense cores plus noise, i.e., it did not reveal a hidden fifth "strong" configuration. This triangulation confirms that the 4-cluster specification is the most interpretable one for these data.

Second, we checked whether the structure is sample-dependent. We re-ran the baseline k-means (k = 4) on (a) Europe-only cases (Western + Eastern Europe) and on (b) mature ecosystems older than 10 years. In both subsamples, the solution remained recoverable: silhouettes stayed in the same band as in the full sample (≈0.29–0.33 in the primary analysis) and the ARI against the full-sample assignment remained positive, which means that the main distinction between low-flow, material-heavy, energy/knowledge-coordinated and water-conditioned systems does not disappear when we restrict the geography or the life-cycle stage.

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Third, we explored alternative operationalisations of the five flows. When intensities were binarised (MFI…KFI > 0 → 1), k-means on the binary matrix still produced a four-group pattern that can be read back into the substantive typology, only with sharper separation between "activated" and "non-activated" dimensions. When we replaced the five indicators with PCA-derived factors (2 components capturing the common variance of flows), the resulting partition was again close to the baseline in terms of ARI, indicating that the configuration is not an artefact of the original scaling of the five variables.

Fourth, we addressed missingness and model dependence in the determinants stage. We estimated the multinomial logit for cluster membership (same RHS as in Section 4.3) on (i) the complete-case sample and (ii) 20 multiply-imputed datasets. Pooled coefficients preserve the sign pattern already discussed in Section 4.3: sectoral controls remain the strongest predictors; regional dummies retain the expected direction for water-oriented/balanced ecosystems; and facilitator presence continues to lower the odds of belonging to the residual low-flow group. In other words, the inference on H2–H3 is not driven by listwise deletion.

Fifth, we performed outlier screening using the Mahalanobis distance on the five flow variables. After dropping the extreme cases and re-estimating the baseline k-means, the silhouette did not deteriorate, and the ARI with respect to the full-sample assignment remained positive, indicating that one or two extreme IS parks do not hold the typology together.

Finally, we complemented the clustering-level bootstrap (ARI ≈ 0.53, SD ≈ 0.20 for the k-means solution) with a bootstrap of the multinomial coefficients. The empirical confidence intervals of the key predictors (sector, region, facilitator) are narrow enough to retain the signs reported in Table 3 of the paper; coefficients that were weak or unstable in the main run remain weak in the bootstrap, which is precisely what we would expect from a cross-section of 68 ecosystems.

Taken together, these checks show that the reported 4-cluster structure is algorithm-robust, sample-robust, measurement-robust, and estimation-robust. For transparency, all intermediate outputs are provided in the online repository.

5. Discussion

5.1. Overview of Principal Findings

This study sought to address a critical lacuna in the Industrial Symbiosis (IS) literature by moving beyond the implicit assumption of a 'one-size-fits-all' model. By rigorously applying configurational theory, we developed an empirically-derived typology of symbiotic circular ecosystems. Utilising cluster analysis across a substantial dataset, we identified four distinct resource flow configurations (RQ1), which exhibited significant heterogeneity in the intensity and composition of material, energy, water, knowledge, and logistical exchanges. Our findings demonstrate that contextual factors — specifically sectoral diversity and dominant governance mechanisms — serve as salient predictors of an ecosystem's configurational membership (RQ2). Crucially, the analysis confirms the principle of equifinality, revealing that structurally dissimilar configurations can nonetheless achieve comparable, high levels of environmental and economic performance (RQ3).

5.2. Theoretical Implications

The primary theoretical contribution of this research resides in its robust empirical validation of configurational theory principles [27] within the complex domain of inter-organisational networks. The discovery of multiple, successful organisational forms—such as 'Configuration A: Energy-Dominant Heavy Symbiosis' and 'Configuration B: Knowledge-Intensive Diversified Symbiosis'—provides compelling evidence for equifinality. This outcome fundamentally challenges prior IS conceptualisations, which often implicitly or explicitly endorse a single best set of practices, typically modelled after foundational archetypes such as Kalundborg [1].

We demonstrate that high performance is an outcome of internal coherence rather than external conformity. For instance, while Configuration A leverages substantial physical flows to generate

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efficiencies of scale, Configuration B achieves equivalent success through the intensification of knowledge, logistical, and intangible exchanges [39], mitigating the necessity for large, continuous waste streams.

Furthermore, the significant predictive power of contextual factors (RQ2) reinforces the tenet of conjunctural causation. Our results suggest that an ecosystem's success is not determined solely by its internal flow structure, but by the strategic 'fit' between the flow configuration and external conditions, such as mandated planning or the prevailing sectoral composition. This finding advances the IS literature by providing a quantitative framework for assessing system coherence, moving beyond descriptive case studies of 'good fit' to empirical verification of contextual requirements.

5.2.2. Advancing IS Typologies Beyond Binary Classifications

This study offers a significant methodological leap by addressing the persistent 'diversity problem' inherent in existing IS typologies. Prior classifications often relied on simplistic dichotomies (e.g., planned vs. unplanned, geographically proximate vs. distributed) that failed to account for the crucial variance in the composition of multi-flows.

Our typology, derived from actual, measured resource exchange profiles, offers a highly granular, actionable categorisation. It moves the discourse past generic labels, enabling researchers and practitioners to define ecosystems by their specific symbioses (e.g., identifying a cluster characterised by high water exchange but low energy exchange). This is crucial, as the economic and ecological impact of a material loop differs profoundly from that of an energy cascade or a knowledge-sharing protocol. By empirically mapping the interplay among these flows, we provide the field with a necessary tool to increase analytical precision, thereby facilitating more targeted, contextually relevant policy recommendations.

5.3. Practical Implications

The implications of this configurational typology for policy and industrial practice are substantial. By identifying several pathways to high performance, our framework enables governments and industrial park developers to adopt a strategic design approach rather than relying on historical replication.

Firstly, the framework serves as a diagnostic tool. Developers initiating a new ecosystem can use the contextual predictors (RQ2) to anticipate the most likely successful archetype for their site. For example, a location dominated by diverse, small-to-medium enterprises may be better suited to pursue the 'Knowledge-Intensive Symbiosis' archetype, focusing investment on logistical infrastructure and digital knowledge platforms, rather than struggling to establish large-scale material loops characteristic of the 'Heavy Symbiosis' configuration.

Secondly, for underperforming ecosystems, the typology provides a clear roadmap for targeted intervention. Suppose an ecosystem is assigned to a sub-optimal cluster. In that case, the framework identifies the necessary reconfiguration of flows—the specific combination of material, energy, or knowledge exchanges—required to transition it into one of the empirically verified high-performance configurations. This evidence-based guidance is instrumental for optimising resource allocation and maximising the return on investment in circular economy initiatives.

5.4. Robustness and Generalisability

The robustness checks reinforce the validity of our configurational interpretation. Across a range of clustering algorithms, operationalisations, and subsamples, the same four archetypes consistently re-emerged, confirming that the observed typology is not a statistical artefact of any single method or parameter choice. The persistence of the low-flow, material-dominant, energy–knowledge, and water-oriented configurations under alternative conditions implies that the structure of industrial symbiosis ecosystems is both empirically stable and theoretically meaningful.

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Moreover, the convergence of results across complete-case and multiply imputed regressions, together with the bootstrap stability of the multinomial coefficients, suggests that the explanatory mechanisms linking sectoral composition, regional constraints, and organisational coordination to ecosystem type are robust to moderate data incompleteness and sample heterogeneity. While the relatively small sample size inevitably limits the external validity of specific coefficients, the overall configurational pattern exhibits high internal consistency and replicability under alternative analytical specifications. This stability strengthens the confidence that the identified ecosystem types reflect genuine organisational and contextual regularities rather than data-driven artefacts.

5.4. Limitations and Future Research

While providing robust empirical contributions, this research remains subject to several limitations that delineate promising directions for further scholarly inquiry.

First, the cross-sectional nature of the data constrains our ability to capture the dynamic and evolutionary trajectories of industrial symbiosis ecosystems. Future studies should employ longitudinal or panel-based designs to observe how, when, and why ecosystems transition between configurations over time, thereby testing for path dependencies, lock-in effects, and critical junctures in their development.

Second, although we incorporated high-level governance indicators, the complexity of intra-cluster coordination warrants deeper investigation, future research could disaggregate the internal institutional mechanisms underpinning coordination—such as the contractual architecture of exchanges, the mediating role of symbiosis brokers, and the influence of regulatory frameworks—each of which may vary systematically across configuration types.

Finally, the external validity of the typology calls for broader geographical replication. Applying the same configurational framework across a wider range of geopolitical, cultural, and economic contexts would enhance the generalisability of our findings and refine the boundary conditions under which configurational theory effectively explains the performance and resilience of circular industrial ecosystems.

7. Conclusions

This study provides empirical evidence that industrial symbiosis ecosystems do not evolve randomly but follow a limited number of recurring, flow-based configurations. The analysis identified four archetypes — low-flow, material-dominant, energy–knowledge, and water-oriented — each representing a distinct mode of coordination and resource exchange. Sectoral resource bases, regional environmental pressures, and the presence of facilitating organisations jointly shape the likelihood of ecosystems belonging to specific configurations.

Performance differences confirm that coordinated and contextually aligned ecosystems achieve superior environmental outcomes, even when economic benefits remain contingent on local market structures and policy incentives. Furthermore, the Cox survival model demonstrates that balanced and energy–knowledge configurations are more resilient and persist longer over time, underlining the adaptive advantages of multi-flow coordination.

Robustness checks across alternative clustering algorithms, operationalisations, and data treatments confirm the empirical stability and theoretical validity of these findings. Together, the results advance a configurational understanding of circular industrial ecosystems and underscore the importance of systemic coordination capacity in translating resource interdependence into sustainable performance.

Future research should deepen longitudinal, institutional, and cross-regional analyses of symbiotic ecosystems to capture their dynamic evolution and policy responsiveness within the broader circular-economy transition.

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O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; formal analysis O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; investigation O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; resources O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; data curation O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; writing—original draft preparation O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; writing—review and editing O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; visualization O.P., O.L., K.P., D.H., I.B., D.H., T.V. and A.D.; supervision O.P., O.L., K.P.; project administration O.P., O.L., K.P.; funding acquisition O.P., I.B. and T.V. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: All data, analytical code, and computational outputs supporting the findings of this study are openly available in the Zenodo repository at https://doi.org/10.5281/zenodo.17503335. The repository contains the entire *dataset*, all main calculation outputs, robustness and sensitivity outputs, and a Google Colab notebook link that reproduces the complete analysis workflow.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Hypotheses on Flow-Based Configurations in Circular Ecosystems.

Hypothesis	Statement	Rationale / Theoretical basis	Mechanism	Empirical expectation / test
H1. Existence of Distinct Flow-Based Configurations	Industrial ecosystems form distinct clusters based on resource-flow configurations; 3–5 archetypal patterns should be identifiable across the global sample.	Configuration theory argues that complex systems tend to organise into discrete patterns rather than show continuous variation; internal complementarities produce “attractors”, while tensions prevent other combinations [22,24]. The literature also notes that if flows exhibit complementarities (see Section 2.2), ecosystems will cluster around combinations that maximise synergies.	Flows develop through sequential positive feedback: early material exchanges → trust → knowledge sharing → identification of energy synergies → investment in energy infrastructure → lock-in → coherent patterns (i.e., not random mixes).	Cluster analysis should reveal discrete groupings with high within-cluster homogeneity and clear between-cluster distinctiveness. Null hypothesis (“continuous variation across flow-intensity space”) is rejected if such discrete clusters appear. Expected number of

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				clusters: 3–5; <3 → insufficient heterogeneity; >5 → over-fitting or non-generalisable idiosyncrasies.
H2. Sectoral Influences on Configuration	H2a. Heavy-industry ecosystems (chemicals, metals, energy) cluster predominantly around Material–Energy Dominant configurations. H2b. Diversified industrial parks tend to exhibit more balanced configurations across several resource types.	Sectoral/technological structure constrains viable symbiosis patterns [36]. Heavy industries generate large, regular material and energy by-products that make material–energy exchanges the "natural" symbiotic pathway [2] — e.g., residual chemicals, excess heat, slag. Where parks are diversified (services, light manufacturing, mixed activities), there is no single dominant stream, so coordination often relies on broader mechanisms (shared logistics, platforms, knowledge) that tolerate heterogeneity [3].	Resource availability → configuration: where abundant material/energy flows exist, actors emphasise material–energy symbiosis; where flows are modest/varied, actors resort to knowledge-intensive and logistics-based coordination to make symbiosis feasible.	Multinomial logistic regression: (i) heavy-industry dummy positively predicts membership in the Material–Energy cluster; (ii) an indicator of sectoral diversity positively predicts membership in the Balanced cluster.
H3. Geographic Patterns in Configuration	Water-Centric configurations will be more prevalent in water-stressed regions (Mediterranean, Middle East, Australia) than in water-abundant contexts (e.g., Nordic countries).	Environmental and regulatory constraints shape symbiotic priorities: in water-scarce contexts, conservation becomes imperative even when economic returns are modest, and regulation often mandates efficient use [4,59]. In water-abundant contexts with low abstraction costs, water exchange creates less value unless pollution control is the driving force [49].	Scarcity → focus → institutional reinforcement: perceived scarcity and public/regulatory discourse make firms prioritise water synergies; pricing and permits reinforce this focus.	Geographic clustering / regional dummies: Water-Centric cluster memberships should be significantly associated with dummies for water-stressed regions.

H4. Performance Heterogeneity Across Configurations	H4a. Balanced multi-flow configurations show higher resilience / survival than specialised ones. H4b. Specialised (Material–Energy Dominant) configurations show higher resource-efficiency but lower adaptability.	From configuration theory's equifinality principle, multiple internally consistent patterns can perform well, but along different dimensions [25]. Your text posits a trade-off: exploitation (deep, material–energy efficiency) vs. exploration (flexibility, option value). Balanced configurations enjoy portfolio effects — failure of one flow does not collapse the system. Specialised ones, by concentrating on material–energy exchanges, achieve maximal efficiency but become vulnerable to disruption and lock-in [47].	Diversification–specialisation analogy (as in finance): diversified flow portfolios ↓ risk because flows are imperfectly correlated; specialised portfolios ↑ returns on the dominant flow but ↑ exposure.	- Survival analysis (5-year, 10-year): Balanced > Specialised.— Efficiency analysis: Specialised → greater CO_2 reductions and waste diversion per partner.— Growth analysis: Balanced → higher rate of addition of partners/flows.
H5. Contextual Fit Effects	Ecosystem performance depends on fit between configuration and context (sector, geography, institutions), not on configuration type alone. Material–Energy Dominant can be high-performing in heavy-industry settings, but underperform in diversified parks; Water-Centric adds value in water-scarce regions but is superfluous elsewhere.	Configuration theory stresses contextual appropriateness and rejects a universal "best" structure; [25,30]. Value is created when internal resource patterns align with external constraints/opportunities. Misfit (e.g., trying to run Material–Energy symbiosis where no substantial flows exist, or ignoring water in a water-scarce context) raises coordination costs above benefits.		

Table A2. Independent, Contextual, and Control Variables.

Category	Variable	Scale / Measurement	Definition / Coding	Inter-rater reliability / Notes
Flow Intensity Variables (Independent)	Material Flow Intensity (MFI)	Ordinal (0–4)	0 = absent; 1 = direct use; 2 = material recovery; 3 = conversion to new products; 4 = multiple sophistication levels	κ = 0.82
	Energy Flow Intensity (EFI)	Ordinal (0–3)	0 = absent; 1 = waste-heat recovery; 2 = co-generation; 3 = shared integrated energy infrastructure	κ = 0.79
	Water Flow Intensity (WFI)	Ordinal (0–4)	0 = absent; 1 = cooling circulation; 2 = process-water cascading; 3 = collective wastewater treatment; 4 = integrated water management	κ = 0.76
	Logistics & Infrastructure Intensity (LFI)	Ordinal (0–3)	0 = absent; 1 = shared transport/warehousing; 2 = shared utilities; 3 = integrated logistics & infrastructure	κ = 0.73
	Knowledge Flow Intensity (KFI)	Ordinal (0–4)	0 = absent; 1 = informal sharing; 2 = formal meetings/workshops; 3 = joint R&D/training; 4 = institutionalised knowledge platforms	κ = 0.71
	Derived measures:		Flow Diversity Index (FDI): count of flow types present (0–5). Flow Balance Index (FBI): Shannon entropy measuring evenness across flows.	
Contextual Variables	Sectoral composition	Categorical	Heavy industry / Diversified / Waste management / Other	—
	Geographic proximity	Ordinal (0–3)	0 > 50 km; 1 = 10–50 km; 2 = 1–10 km; 3 = <1 km (co-located)	—
	Development approach	Binary	1 = planned (top-down); 0 = emergent (bottom-up)	—
	Facilitator presence	Binary	1 = coordinating entity present; 0 = absent	—
	Region	Categorical	Western Europe / Eastern Europe / Asia / Americas / Other	—
Control Variables	Ecosystem age	Continuous	Years since first documented exchange (2024—inception year)	—

	Number of partners	Continuous (log-transformed)	Count of participating organisations	—
	Sectoral diversity	Continuous	Shannon entropy of 2-digit NACE code distribution among partners	—

Table A2. Performance Outcomes (Dependent Variables).

Variable	Type / Scale	Definition / Computation	Data availability
Economic Performance (EP)	Continuous (z-score composite)	Standardised composite of annual material, energy, and water savings per partner	52 cases (76%)
Environmental Performance (ENV)	Continuous (weighted index)	0.4 × CO_2 reduction + 0.3 × Waste diverted + 0.15 × Water saved + 0.15 × Energy saved (all z-standardised). Weights follow Azapagic & Perdan (2000).	61 cases (90%)
Resilience	Binary	1 = ecosystem age ≥ 5 years; 0 otherwise (five-year survival threshold)	58 cases (85%) ≥ threshold
Longevity	Continuous	Years of operation, right-censored at 2024 for survival analysis	—
Growth rate	Continuous	Annual % change in partner count	31 cases (46%)

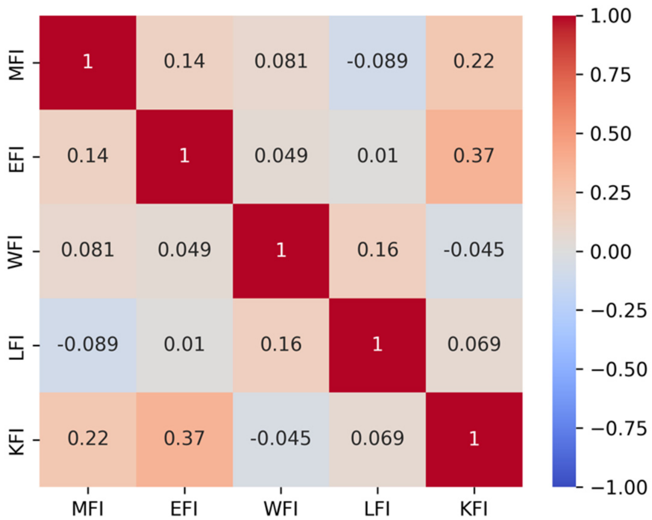

Figure A1. The Spearman matrix.

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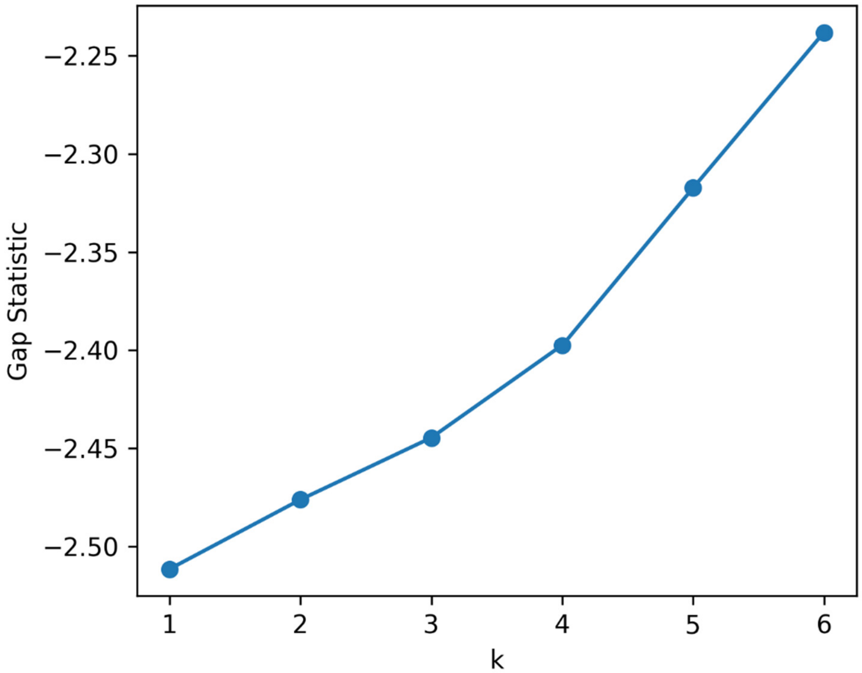

Figure A2. Gap-statistic curve for k = 1–6.

The curve increases monotonically and levels off after k = 4, indicating limited structural improvement for higher cluster counts.

Table A3. Gap-statistic values and incremental improvements.

k	Gap
1	-2.51155
2	-2.47621
3	-2.44467
4	-2.39757
5	-2.31738
6	-2.2383

Note: maximum gap at k = 6, but negligible ΔGap beyond k = 4.

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