Mapping Complexity Science in Policy: ...

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Abstract

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1 Introduction

Contemporary public policy faces challenges of unparalleled complexity: adapting to climate change demands coordination across multiple scales and sectors; health crises expose vulnerabilities within interconnected systems; economic inequality arises from feedback loops between markets and institutions; and digital transformation is redefining the very nature of governance. When policymakers apply conventional approaches to complex adaptive systems—treating symptoms rather than systemic structures, optimizing individual components rather than whole-system dynamics, or imposing rigid top-down control on self-organizing processes—the results often include policy resistance, unintended consequences, and the exacerbation of the very problems interventions sought to solve.

Over the past two decades, complexity science has evolved from a primarily theoretical field into a practical framework for understanding and managing real-world systems. Complexity science offers both conceptual lenses and technical methods to study public policy problems and to inform policy cycles. For instance, behavioral insights teams apply complexity concepts about bounded rationality and emergent social norms to "nudge" behavior change[Dosi et al., 2021]; Organizations employ adaptive co-management frameworks in pursuit of sustainable resource use and social-ecological resilience [Plummer and Armitage, 2007]; Environmental governance increasingly embraces adaptive and polycentric approaches informed by complex systems thinking [Staub and Tirmizi, 2025], and more. The field has achieved cultural diffusion through worldwide communities composed of members from multiple disciplines. It has been driven by intellectual curiosity and an openness to engage with new problems, fostering a shared recognition of the importance of interdisciplinarity and even embracing "the vagueness" of the term [Hébert-Dufresne et al., 2024].

Although public policy problems increasingly display hallmarks of complex systems—such as heterogeneous agents, dense interdependencies, and strong feedback loops, there remain gaps in the literature on how complexity science has influenced public policy at large. Most policies adopt complexity methods pragmatically—"systems mapping seems useful for stakeholder engagement," "agent-based models help visualize scenarios"—without explicit reference to underlying theoretical foundations. This gap between practice and theory is consequential. Without understanding why complexity methods work, practitioners cannot distinguish effective applications from superficial ones, cannot adapt tools appropriately to context, and cannot articulate their value to skeptical policymakers. Several

We draw from Simon initial concept of bounded rationality in policymaking to argue for methodological approaches and tools of complexity science in policy.

This project addresses the following central question: *How are complexity science methods being applied in public policy and how are complexity concepts being understood* *in this field?* Complementary sub-questions include:

- What specific complexity methods (system dynamics, agent-based modeling, network analysis, participatory systems mapping) are integrated into policy?
- In which form is complexity being interpreted in policy? Is it through policy strategies, proposals, drafts, projects?

This research builds directly on the Complexity Global School's emphasis on moving from metaphorical uses of "complexity" toward analytically rigorous applications in public policy. The CGS curriculum provided the methodological foundation for this empirical investigation, particularly through modules on network science, systems mapping, and adaptive governance.

The remainder of this paper proceeds as follows. Section 2 presents the literature review. Section 3 describes the methodological approach. Section 4 presents preliminary findings. Section 5 discusses challenges and unexpected discoveries. Section 6 outlines potential future directions. Section 7 concludes with implications for practice and research.

2 Theory

2.1 Policy as Design: Adaptive Problem-Solving under Bounded Rationality

In this section, we introduce Herbert´s Simon concept of bounded rationality in the context of policy-decision making, and the role of complexity science at the operational layer of policy design.

Policy design faces an enduring challenge: decision-makers must act under cognitive and informational limits. Herbert Simon's concept of bounded rationality overturned the assumption that policymakers can achieve full rationality as posited in classical economics. Instead, Simon demonstrated that attention, memory, and computational capacity constrain what agents can know and process [Simon, 1947, 1955, 1996a]. Because of these limits, actors satisfice rather than optimize, they search for solutions that are "good enough" to meet aspiration levels rather than maximizing utility [Simon, 1957].

This idea reoriented the study of decision-making toward the actual processes through which choices are made. As Jones [2002, p. 269] observed, "bounded rationality insists that processes matter, that successful science must properly link the process of making individual decisions to organizational processes responsible for collective choices." Policy outcomes, therefore, depend less on idealized rational calculation and more on the procedural architectures —heuristics, routines, and institutional rules—that shape how decisions unfold [March and Simon, 1958, Newell and Simon, 1972]. In his later work, Simon extended bounded rationality into a broader philosophy of design. In *The Sciences of* *the Artificial* [Simon, 1996b], he argued that designed systems, including policies, should be understood not through universal laws but through their fitness to purpose within specific environments. Policymaking thus becomes an iterative process of constructing artifacts that perform well in their context rather than deriving optimal solutions from abstract principles.

Simon described design as “devising courses of action aimed at changing existing situations into preferred ones” [Simon, 1996b, p. 111]. This “design stance” reframes policy-making as crafting under constraint: given limited information and uncertainty, policymakers must proceed through experimentation, feedback, and progressive refinement. Decision-making under bounded rationality thus becomes a process of adaptive problem-solving —learning by doing in complex and evolving environments.

Building on Simon’s insights, Barzelay [2019] developed a design-oriented vision for public management. In *Public Management as a Design-Oriented Professional Discipline*, he argues that public management should unite multiple conceptions of professional practice around an expansive notion of design. Drawing on Simon’s ideas, Barzelay defines the field as requiring “thoughtful and skillful use of purposive theories of public organizations, along with reverse-engineered design-precedents, in problem-solving for public programs and organizations” [Barzelay, 2019, p. 23].

Rather than prescribing fixed solutions, Barzelay’s framework is generative: it equips practitioners with conceptual tools to create context-appropriate interventions. Its knowledge base includes three key elements:Design precedents: Reverse-engineered cases that illustrate successful problem-solving in specific contexts; Purposive theories: Frameworks that link mechanisms to intended outcomes;Professional judgment: The practical wisdom to know which precedents and theories apply to which problems.

Moreover, Geyer and Rihani [2010] explore this further and introduce the concept of policy entrepreneurship. They explore the connection between policy, complexity and policy entrepreneurship. Their work presents adaptive capacity as a framework to determine how applying a complex adaptive systems (CAS) perspective can enhance deploying some policy entrepreneurial characteristics. They underline several properties as particularly important for policy studies and their relation to complexity: the presence of negative and positive feedback loops; strange attractors, which present recurring patterns of behavior that can be disrupted by brief periods of change; sensitivity to initial conditions of path dependence and the emergence of system-level patterns from interactions among local elements [Geyer and Rihani, 2010]. This approach resonates with Simon’s emphasis on procedural rationality —knowing how to approach problems rather than seeking universal optima [?].

2.2 Complexity Science at the Operational Layer

Complexity science provides the computational and participatory tools that operationalize Simonian design principles in real-world policy contexts. Its methods translate the abstract logic of design into practical, data-driven modeling techniques.

First, complexity methods make visible the feedback loops, nonlinearities, and emergent properties that Simon recognized but could not formally model. System dynamics represents the "accumulation processes and feedback structures" that generate counterintuitive policy outcomes [Forrester, 1961, Sterman, 2000]. Classic works such as Meadows et al. [1972] show how feedback delays can lead to overshoot and collapse—dynamics missed in equilibrium frameworks. Likewise, agent-based modeling reveals how macro-level patterns emerge from micro-level interactions, explaining why aggregate interventions often fail [Epstein, 1999]. For instance, in their study [Goldstick and Jay, 2022] showed that ABMs leverage major advantages in community violence research in their capacity to study the natural evolution of a process governed by the actions of autonomous agents and how it changes based on counterfactual conditions, such as policy changes (e.g alcohol licensing policies). Other use cases can be seen in public health and epidemic control [Morshed et al., 2019].

Second, complexity tools enable iterative design cycles. Rather than requiring full information before action, they allow policymakers to test ideas through simulation, observe system reactions, and refine their assumptions [Miller and Page, 2007]. For example, before introducing the congestion tax in Stockholm, policymakers used system dynamics and traffic simulations to test different fee structures and assess public response and traffic flow impacts. This model was refined iteratively with real-world traffic data and during trial before the implementation [Eliasson, 2008]. Other applications include system dynamics learning to resource allocation in different decision scenarios, as the case of Weeks et al. [2022] who used systems thinking to understand HIV continuum in the Ryan White CARE Act, which provides federal resources supporting low income people living with HIV/AIDS to help the Regional Ryan White Planning Councils responsible for prioritizing these resources.

Third, participatory complexity methods bring bounded rationality into the collective domain. Techniques such as participatory system dynamics and group model building help articulate and integrate diverse stakeholder perspectives [Vennix, 1996, Sterman, 2000]. This addresses Simon's insight that decision-making in organizations depends on the coordination of distributed, partial knowledge [March and Simon, 1958]. By making mental models explicit and shared, these participatory processes strengthen implementation and foster mutual understanding. Barbrook-Johnson and Penn [2021] present a method called participatory systems mapping (PSM) which involves stakeholders collaboratively creating a causal map of a system to capture variables, feedback loops and interconnections in complex policy environments. They present two real-case world studies in the UK on enery policy, combining network analysis with subjective information from stakeholders and showing that PSM is particularly appropiate when there is stakeholder diversity, when complexity and feedback are significant, when new questions or evaluation scopes need to emerge, and when existing models (logic models, theories of change) are too linear or narrow.

The trajectory from bounded rationality to design-based governance and finally to complexity-informed design represents a coherent intellectual lineage. Simon's recognition of cognitive limits prompted a shift from optimization to procedural intelligence; Barzelay institutionalized this shift as a design discipline in public management; and complexity science now provides the computational and participatory infrastructure to enact it in practice.

Together, they advance a vision of policy-making as adaptive design under constraint: an iterative, feedback-driven, and context-sensitive process of sense-making and intervention in complex systems. Rather than abandoning rationality, this evolution redefines what it means to act rationally under uncertainty—transforming policy design into a science of learning within complexity.

3 Methodology

This section presents our methodology for tracking the impact of complexity science and its methods on public policy. First, we describe the data construction process and present descriptive insights. Second, we analyze these metrics and outline our analytical approach for subsequent sections.

3.1 Core Corpus Construction

To construct a representative corpus of complexity science literature, we employed a multi-stage filtering approach informed by network analysis. We began with a seed corpus comprising all publications authored by researchers affiliated with three prominent complexity science institutions: the Santa Fe Institute, the Vermont Complex Systems Center, and the Complexity Science Hub Vienna. These publications and their metadata were retrieved from the OpenAlex database.

From this seed corpus, we extracted all cited references, yielding an initial candidate set of approximately 10,000 publications. We applied an initial citation threshold, retaining only works cited at least three times by the seed corpus to ensure a baseline level of relevance to complexity science research.

To systematically reduce this set while preserving the field's intellectual structure, we constructed a bibliographic coupling network in which nodes represent publications and edge weights reflect co-citation frequency—specifically, how often two papers were cited together by works in the seed corpus. We then applied two network-based filtering criteria. First, we retained only the M strongest connections for each node (where M represents the maximum number of edges per node), which reduces network density while preserving the most important relationships and removing isolated nodes. Second, we applied k-core decomposition, a standard graph-theoretic technique that recursively removes nodes with fewer than k connections until all remaining nodes have at least k neighbors, thereby extracting the densely interconnected core of the network (see section A.1 for more details.).[2]

3.2 Descriptive Statistics of the Co-Citation Network

The resulting co-citation network comprises 5,252 publications connected by 80,045 edges, with an overall network density of 0.0058 (Figure A.2). The network exhibits full connectivity, primarily as a result of the process followed to obtain the "gold standard" core of complexity science, though it still shows a low density, characteristic of citation networks where authors cite selectively.

The degree distribution reveals substantial heterogeneity, with an average degree of 30.34 but a maximum of 626, suggesting the presence of highly influential hub publications that serve as common references across multiple research streams (Figure A.3).[3] The minimum degree of 3 reflects our k-core filtering criterion. Edge weights, representing co-citation frequency normalized by the bibliographic coupling measure, average 0.36 with a maximum of 1.0, indicating that while most publication pairs share only a modest proportion of common citations, some exhibit nearly identical citation patterns, signaling tightly coupled research subdomains or methodological clusters.

3.3 Policy Impact Measurement

To analyze the policy and public engagement impact of the complexity science core corpus, we integrated bibliometric data from two complementary sources. OpenAlex provided comprehensive academic metadata including citation counts, author affiliations, institutional networks, journal information, referenced works, and SDG (Sustainable Development Goals) classifications. Altmetric supplemented this with alternative impact

[2] The parameters M and k were not predetermined but rather selected iteratively through community detection analysis. Specifically, we tested various parameter combinations and evaluated their ability to preserve both the field's major thematic communities (identified through modularity-based clustering) and a set of highly influential "gold standard" papers (identified through network centrality measures). This procedure yielded a refined core corpus of approximately 5,000 publications that capture the essential literature of complexity science while maintaining computational tractability for bibliometric analysis.

[3] The node with the highest degree is *Emergence of Scaling in Random Networks*[Barabási and Albert, 1999] followed by *Collective Dynamics of 'Small-World' Networks*[Watts and Strogatz, 1998] and *Statistical Mechanics of Complex Networks*[Albert and Barabási, 2002], all highly influential papers in the field of complexity science.

indicators, including policy document mentions, mainstream media coverage (news outlets, blogs, videos, podcasts), social media engagement (Twitter, Facebook, Reddit), and additional scholarly metrics (Mendeley readership, peer reviews, Wikipedia mentions). Altmetric data were retrieved via API using DOIs from the 5,252 deduplicated OpenAlex records as query parameters. This yielded 3,652 matched records (69.53% coverage), with the match rate determined by DOI availability in the Altmetric database.[4]

The merged dataset enables comparative analysis of academic versus policy impact, identification of papers with disproportionate policy influence relative to academic citations, and examination of how complexity science research propagates through different dissemination channels.

3.4 Limitations

4 Results

The merged OpenAlex-Altmetric dataset (N=3,652) reveals substantial heterogeneity in both academic and alternative impact indicators for complexity science publications. The "Golden Standard" literature in complexity science shows strong coverage with a median of 372 and 315 academic citations in both OpenAlex and Altmetric metrics and mean citations of 1,620 and 1,292, which reflects the well-studied power law in academic citations documented in the literature [Redner, 1998], with high variability (SD>4,500). Among alternative metrics, Mendeley readership shows the highest penetration (98.7% of papers, mean=728), followed by mentions in Twitter/X (64.3%, mean=63.4), Wikipedia (45.6%, mean=3.6), mainstream media (30.7%, mean=7.9), patent (23.3%, mean=8.7), Facebook (17.4%, mean=0.8), Bluesky (8.0%, mean=0.3), and Reddit (5.0%, mean=0.2). **Policy impact remains concentrated, with only 32.8% of papers mentioned in policy documents (mean=4.6)** (See Table A.1).

All indicators exhibit substantial right-skewness, with means consistently exceeding medians. This pattern suggests that impact—whether academic or societal—concentrates heavily in a small subset of highly influential papers, consistent with the well-documented Matthew effect in scholarly communication [Teixeira da Silva, 2021].

4.1 Divergent Pathways of Scholarly and Policy Impact

There exists a divergence between academic influence and policy/media engagement. Papers achieving the highest academic citations are predominantly focused on methodologi-

[4]Both datasets underwent internal deduplication using normalized DOIs (removing URL prefixes, standardizing format). For the small subset of papers where API retrieval succeeded but records lacked DOIs or contained duplicates in the Altmetric data, title-year matching with aggressive text normalization (lowercasing, punctuation removal, whitespace standardization) was applied as a fallback. Post-merge validation confirmed no duplicate entries in the final dataset.

cal and research tools, with 7 out of 10 top papers focused on bioinformatics and molecular biology, while three of the top ten papers focused on theoretical approaches to behavior, communication, and management. In contrast, the top policy-cited papers center on economics and behavioral decision-making, particularly Prospect Theory, agency theory, and financial economics. Only one paper, Jensen and Meckling [1976]'s foundational work on the theory of ownership structure of the firm, appears in both the academic and policy top-10 lists. This paper's dual prominence reflects its integration of rigorous economic modeling—synthesizing the theory of agency, the theory of property rights, and the theory of finance—with directly actionable implications for corporate governance and regulatory design through mathematical formalization of principal-agent relationships. (See Figure A.4)

Interestingly, mainstream media coverage demonstrates near-complete temporal clustering, with all top-10 media papers published in 2020 addressing COVID-19 transmission dynamics and epidemiological modeling, papers that have far fewer academic citations despite their immediate societal relevance. This underscores that academic impact, policy influence, and public attention tend to operate as uncorrelated dimensions of scholarly impact.

4.2 Key Topics of Policy-Relevant Complexity Science

Figure 1 presents the network of primary fields for papers in the analyzed corpus, where node size represents the number of papers within each field and edge width indicates the relative co-occurrence of two fields in the same paper. Green nodes denote fields where the share of academic citations exceeds the share of policy citations. The network reveals that Biochemistry, Genetics, and Physics & Astronomy are the most represented fields in the corpus with greater academic importance, followed by Economics, Social Sciences, and Environmental Sciences that have a higher citation share in the policy domain. The high connectivity of the network underscores the multidisciplinary nature of the Complexity Science "Golden Standard."

Figures Figure A.6 and Figure A.5 display keyword co-occurrence networks for the whole corpus and policy-cited papers respectively, with node size indicating frequency, edge width representing co-occurrence strength, and colors identifying communities detected through modularity maximization using the Louvain algorithm[5]. In the policy network, several distinct communities emerge: biology-related papers frequently co-occur with ecology, ecosystems, and genetics; computer science papers occupy a central position and co-occur with statistical physics and network analysis; economics and business papers cluster with sociology and mathematics; while psychology and anthropology form a less common community. In contrast, the academic network reveals three main communities:

[5]Which partitions the network to maximize the density of edges within communities compared to edges between communities

a central biology cluster related to ecology, evolution, genetics, and virology; a computer science community associated with methods such as statistical physics and mathematics; and a socioeconomic network encompassing economics, business, psychology, and cognitive sciences.

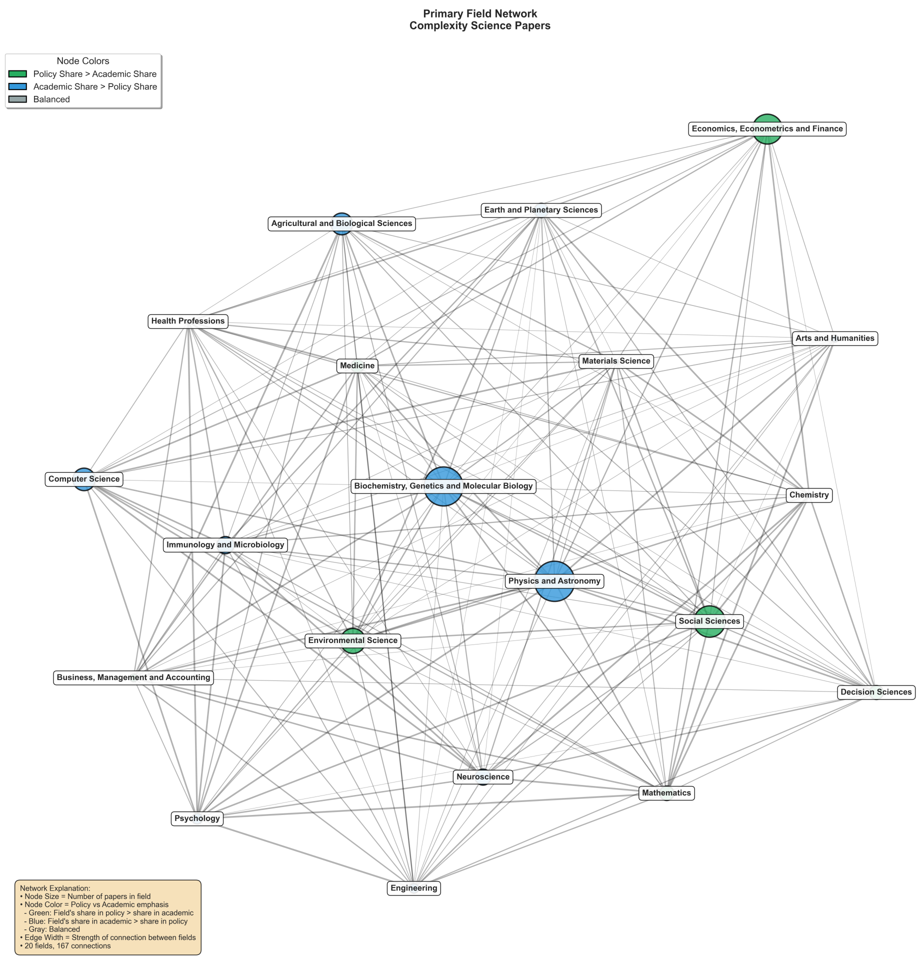

Figure 1: Primary Field Network in Complexity Science

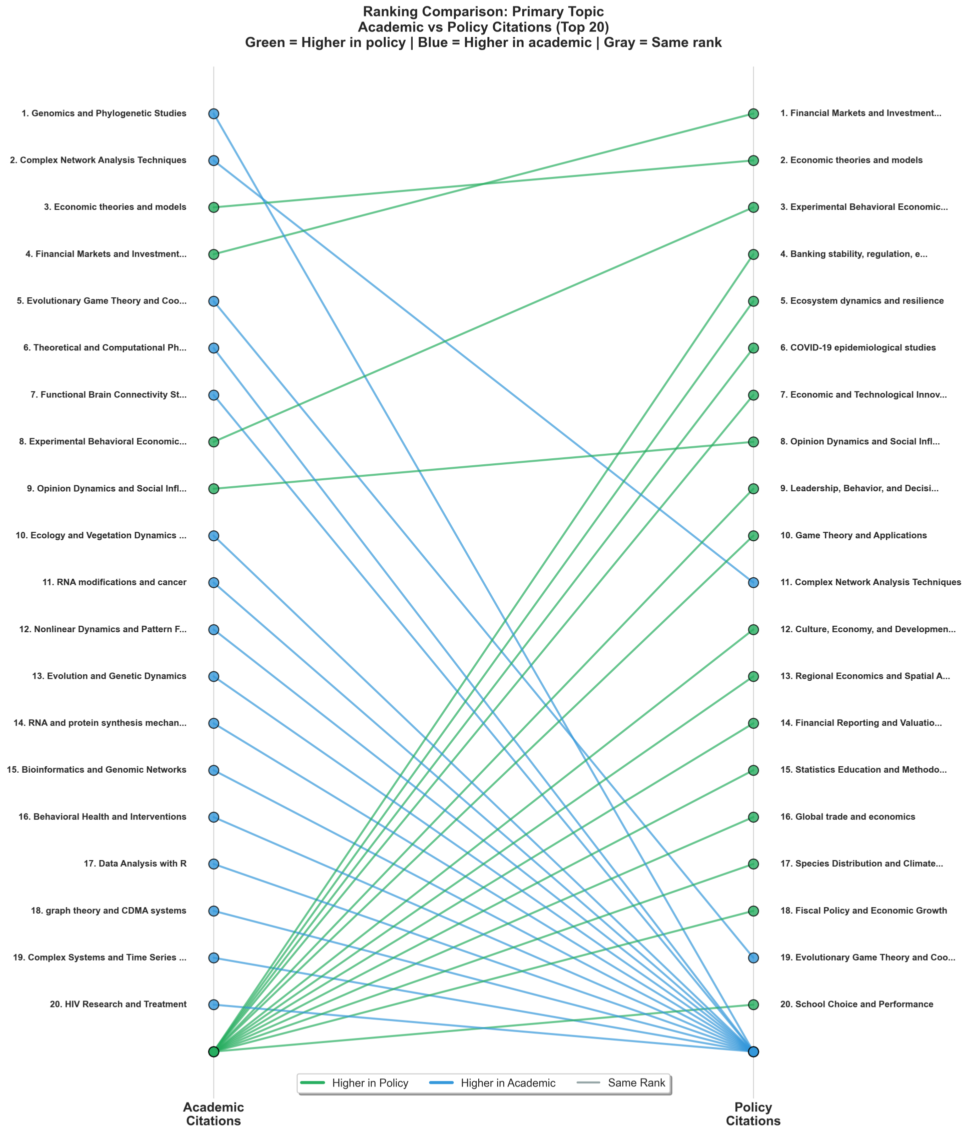

Figure 2: Primary Topic Rank Comparison

4.3 Patterns Identified

[This section would discuss emerging typologies: academic vs. government-led labs, shared complexity methods, network structures]

5 Reflections and Challenges

5.1 What Worked and What Didn't

[Methodological reflections on the research process]

5.2 Unexpected Findings and Absences

[Discussion of surprising patterns or notable gaps in the data]

5.3 Complexity in Practice

[Reflections on how complexity manifests in real policy settings: adaptive iteration, stakeholder diversity, constraints]

5.4 Connections to CGS Learnings

[Explicit links to CGS curriculum and how it informed the analysis]

6 Potential Next Steps

6.1 Future Research Directions

Potential extensions include:

- Expanding regional coverage and depth of case studies
- Conducting rigorous network analysis with quantitative metrics (centrality, modularity)
- Developing an open-access “Complexity Labs Atlas”
- Longitudinal analysis of lab evolution and impact

6.2 Implications for Policy Practice

[Discussion of practical implications for lab practitioners and policymakers]

6.3 Academic Research and CGS Network Collaboration

[Opportunities for continued research within the CGS community]

7 Conclusion

[Summary of key findings, theoretical contributions, and practical implications]

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A Appendix

A.1 Parameter Tuning

To systematically evaluate the impact of network filtering parameters on corpus quality, we tested all combinations of m (maximum edges per node, ranging from 4 to 11) and k (k-core threshold, ranging from 2 to 5). For each parameter combination, we measured three key metrics: the resulting number of nodes (network size), modularity (quality of community structure, ranging from 0 to 1), and gold standard coverage (fraction of highly influential papers retained, ranging from 0 to 1). Figure A.1 presents heatmaps visualizing how these metrics vary across the parameter space. Lower values of m and higher values of k produce smaller, more selective networks, while the inverse produces larger networks. The systematic exploration of this parameter space informed the selection of filtering thresholds that balanced network size, preservation of thematic structure, and retention of influential publications as reported in Section 3.

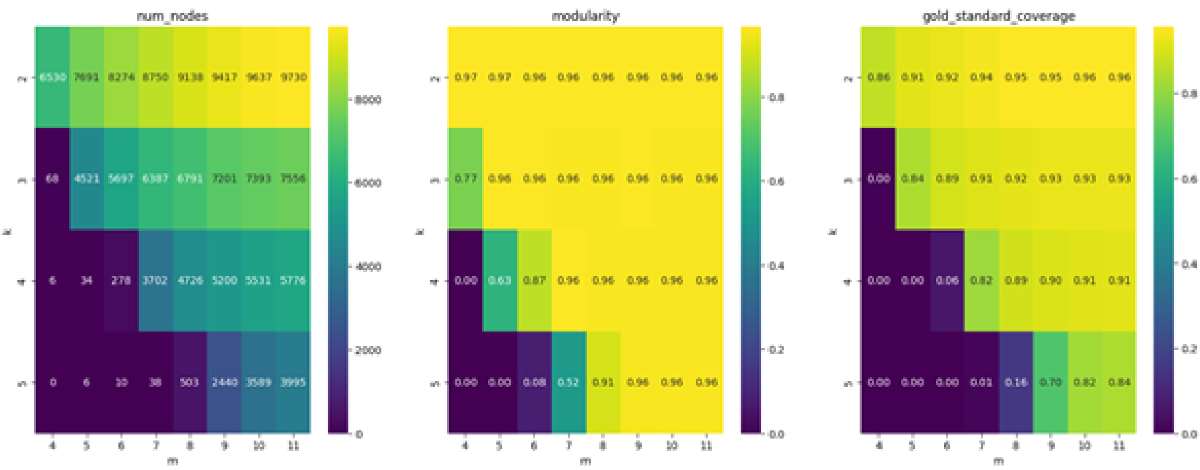

Figure A.1: Parameter tuning analysis for network filtering.
Heatmaps show the effect of varying m (maximum edges per node) and k (k-core threshold) on three key metrics: number of nodes (left), modularity (center), and gold standard coverage (right). Darker colors indicate lower values, while brighter colors indicate higher values for each respective metric.

A.2 Co-Citation Network

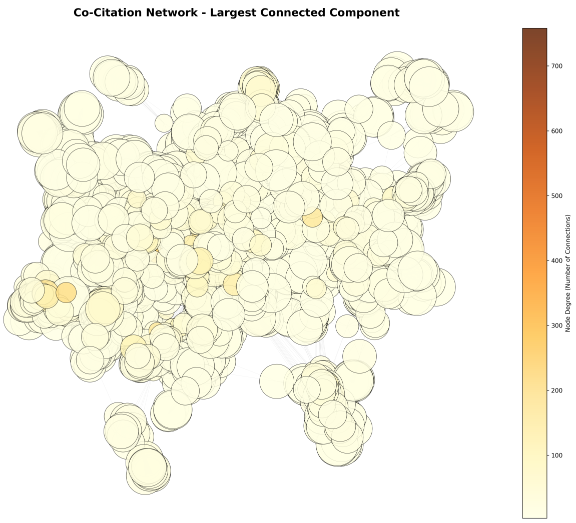

Figure A.2: Co-citation network visualization of the complexity science core corpus. Node size represents the average weight between the node and all its neighbors; node color represents node degree.

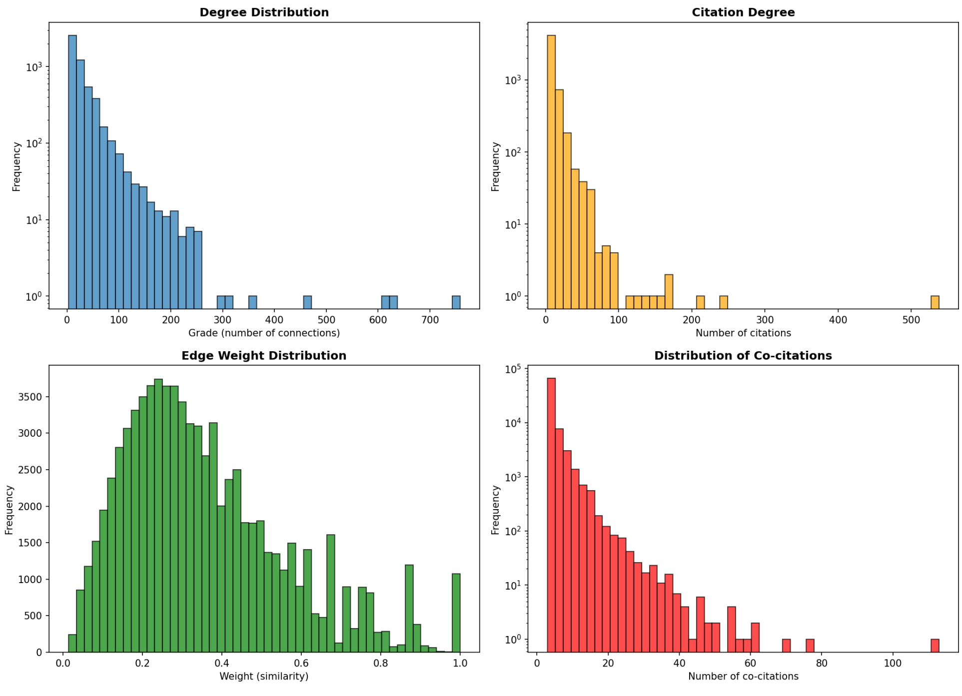

Figure A.3: Distributional properties of the co-citation network: (a) degree distribution, (b) citation degree distribution, (c) edge weight distribution, and (d) distribution of co-citations. Interestingly, the heavy-tailed degree distribution appears to show scale-free properties, characteristic of scientific citation networks.

A.3 Policy and Media Impact

Table A.1: Descriptive Statistics of Impact Indicators from Merged OpenAlex-Altmetric Dataset

Category	Indicator	n>0	%>0	Mean	Median	SD	Q25	Q75	Q90	Q95	Total
Academic	Citations (OA)	3,651	100.00	1,620	372	5,470	137	1,053	3,044	5,635	5,915,566
Academic	Citations (Alt)	3,625	99.29	1,292	315	4,553	117	857	2,472	4,441	4,716,715
Academic	Peer Reviews	25	0.68	0.02	0	0.9	0	0	0	0	87
Policy	Policy Mentions	1,199	32.84	4.6	0	21.7	0	1	7	18	16,625
Media	Mainstream Media	1,120	30.68	7.9	0	82.3	0	1	7	21	28,752
Media	Blogs	1,394	38.18	2.3	0	8.9	0	2	5	9	8,245
Media	Videos	216	5.92	0.2	0	1.3	0	0	0	1	567
Media	Podcasts	211	5.78	0.1	0	0.9	0	0	0	1	443
Social	Twitter/X	2,349	64.34	63.4	2	777.2	0	10	41	96	231,314
Social	Facebook	636	17.42	0.8	0	5.7	0	0	1	3	2,846
Social	Reddit	182	4.98	0.2	0	1.3	0	0	0	0	570
Social	Bluesky	291	7.97	0.3	0	2.1	0	0	0	1	940
Readers	Mendeley	3,602	98.66	728	222	2,581	76	580	1,448	2,566	2,656,582
Other	Wikipedia	1,665	45.60	3.6	0	21.9	0	3	8	15	13,036
Other	Q&A Sites	529	14.49	0.4	0	2.0	0	0	1	2	1,360
Other	Patents	849	23.25	8.7	0	141.1	0	0	6	19	31,794
Other	Guidelines	50	1.37	0.04	0	0.7	0	0	0	0	144

Note: N = 3,652 complexity science publications from merged dataset. OA = OpenAlex; Alt = Altmetric; SD = Standard Deviation; Q25/Q75/Q90/Q95 = respective percentiles. Academic citations show near-universal coverage (99-100%), while alternative metrics vary substantially in prevalence.

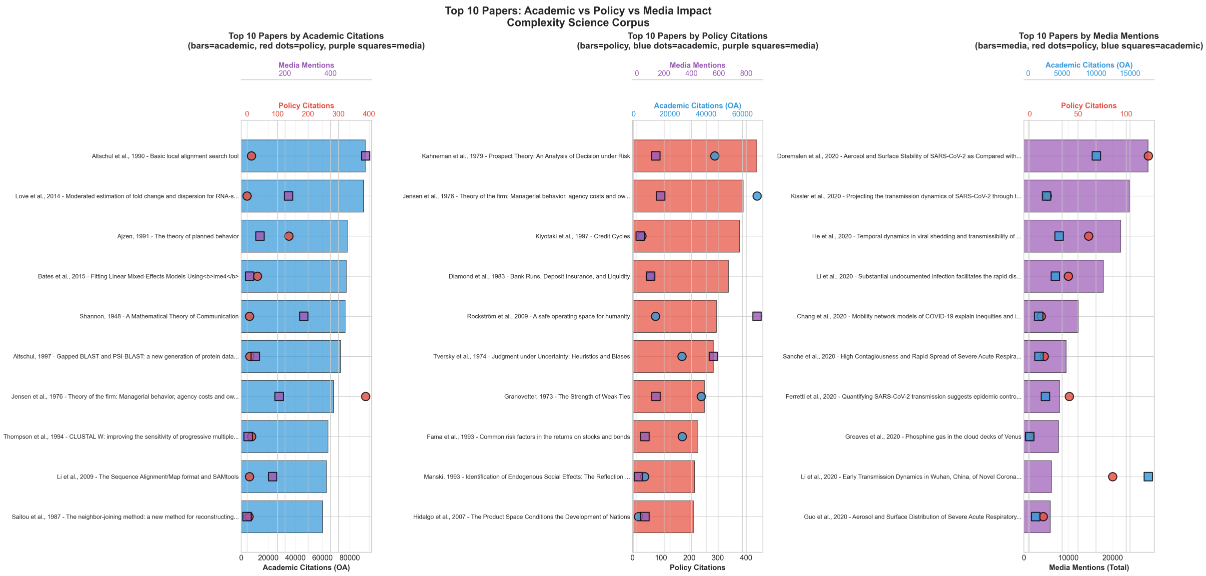

Figure A.4: Top 10 Papers in Academic, Policy and Media Citations.

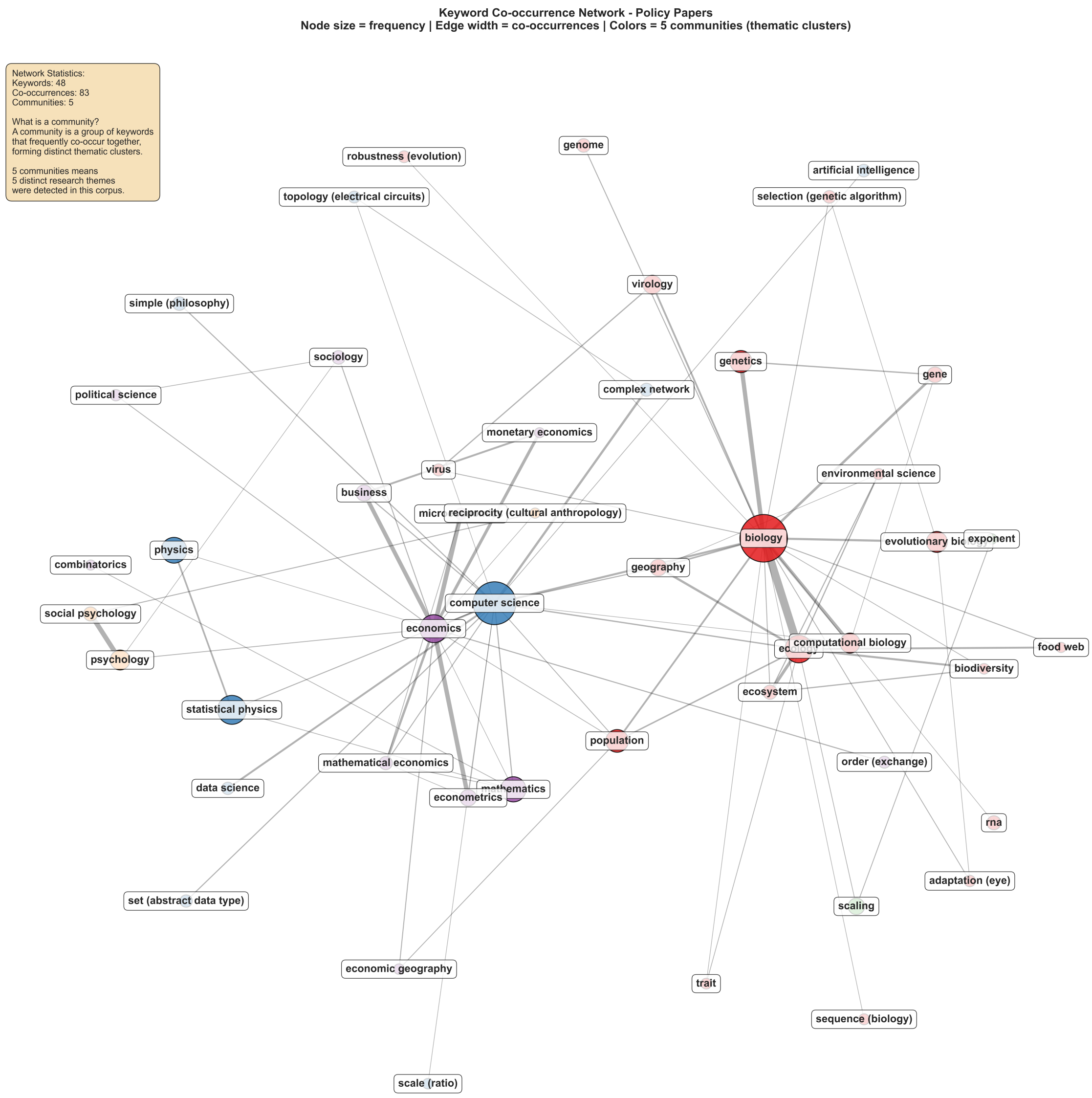

Figure A.5: Keyword co-occurrence in the Policy cited Complexity Science.

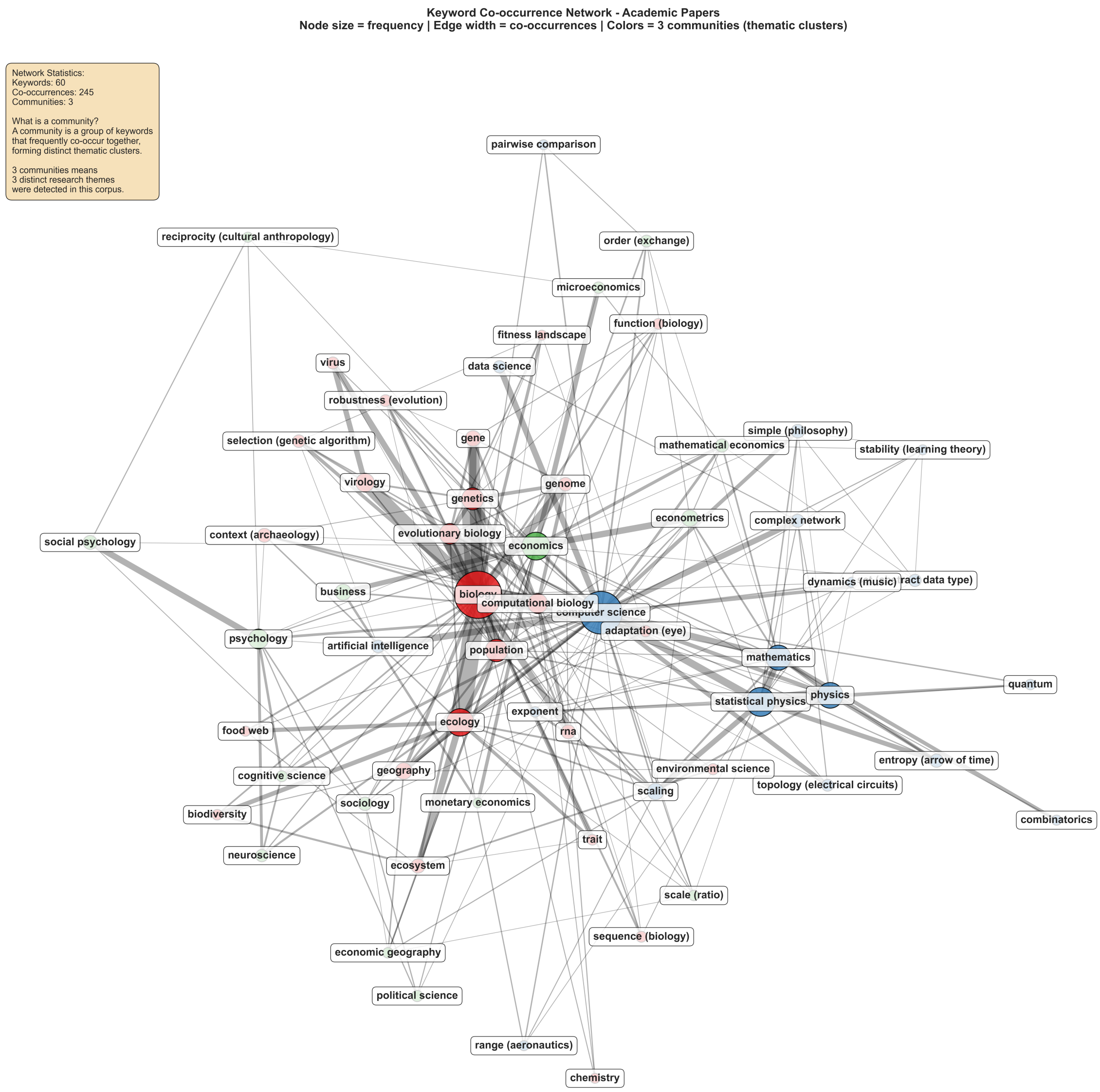

Figure A.6: Keyword co-occurrence in the Complexity Science Corpus.