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Computational Mapping of Interdisciplinary Intellectual Linkages in Network Science Using Bibliometric Metadata

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Abstract

This paper presents an information technology-driven bibliometric framework for mapping the structural and temporal evolution of interdisciplinary intellectual linkage and apparent conceptual diffusion within the domain of social network analysis. Utilizing large-scale metadata from Web of Science, we construct multiple bibliometric networks representing citation, co-authorship, and keyword relationships. Through computational methods including fractional normalization, Search Path Count (SPC) edge-weighting, and island detection algorithms, we identify latent communities and bibliometric pathways that suggest patterns of intellectual association and citation-mediated influence between social sciences, physics, neuroscience, and behavioral ecology. These computational outputs represent citation-mediated influence patterns and co-occurrence structures, not direct observation of knowledge transmission. Our results highlight the role of digital libraries and algorithmic normalization in addressing terminological and data-quality challenges, alongside name disambiguation procedures and network pruning to mitigate citation boundary issues. This paper contributes to the domain of information technology by demonstrating scalable computational techniques for uncovering hidden intellectual structures and bibliometric evidence of knowledge flows in an increasingly interdisciplinary research landscape.

Keywords

• Social Network Analysis • Bibliometrics • Citation Networks • Co-authorship Analysis • Interdisciplinary Research

1. Introduction

1.1 The Evolution of Network Science

Network science has emerged as a distinct interdisciplinary field over the past several decades. Its roots trace back to multiple disciplines including sociology, mathematics, physics, and computer science. Social network analysis developed initially within sociology and anthropology during the mid-twentieth century, with researchers like Moreno, Cartwright, and Harary laying the groundwork for mathematical approaches to studying social structures [1]. By the 1990s, social network analysis had achieved the status of "normal science," with an established invisible college of researchers sharing common paradigms and methodologies [2]. More recently, what some scholars call the "physicists' invasion" has transformed network science, with physicists applying concepts from statistical mechanics to large-scale networks, fundamentally altering the intellectual landscape [3]. The foundational principles of network analysis have been systematically codified in comprehensive textbooks that continue to shape the field [4]. The centrality concept, first rigorously defined by Freeman [5], remains one of the most widely used analytical tools in network science.

1.2 Interdisciplinary Knowledge Transfer

The apparent flow of concepts, methods, and researchers across disciplinary boundaries is a complex phenomenon. Bibliometric indicators such as citations, co-authorship, and keyword co-occurrence provide evidence of intellectual association and potential influence, but they do not directly measure whether concepts were understood, adopted, or transformed across fields [6]. In the case of network science, we observe multiple waves of interdisciplinary influence. Early work in sociology and anthropology established basic concepts, while mathematicians contributed graph theory foundations. More recently, physicists introduced concepts from statistical physics, and computer scientists developed algorithms for large-scale network analysis [7]. These patterns can be traced through bibliometric data as indicators of intellectual linkage and citation-mediated influence, rather than direct evidence of knowledge transmission.

1.3 Computational Approaches to Science Mapping

Bibliometrics provides quantitative tools for mapping the structure of science. Citation networks reveal which papers influence others, co-authorship networks show collaboration patterns, and keyword networks trace conceptual connections [3]. Recent advances in computational infrastructure have made large-scale bibliometric analysis feasible, with digital libraries providing access to millions of publication records and network analysis software enabling visualization and analysis of massive networks [8]. The methodological foundations of bibliometric analysis have been systematically codified in recent years [9], with scholars emphasizing the importance of rigorous procedural steps in conducting such studies [10]. Best practices for bibliometric analysis continue to evolve, with recommendations for improving study design and reporting [11]. Contemporary approaches increasingly emphasize the integration of multiple analytical techniques to provide more comprehensive insights into scientific communication patterns [9]. Foundational works such as Wasserman and Faust's comprehensive treatment of social network analysis [12] have provided the methodological basis for much of this work.

Main Path Analysis Methodology The Search Path Count (SPC) algorithm assigns traversal counts to edges in a citation network based on an exhaustive count of all directed paths from source nodes (indegree zero) to sink nodes (outdegree zero). The main path is extracted by following edges with maximum SPC values. In our implementation using Pajek 5.08, we used the `main path` function with the `max` option; the extracted main path contained 59 nodes, and the key-route analysis identified 127 nodes. Island detection refers to a graph-theoretic method for identifying dense subgraphs by thresholding edge weights; we used the implementation in Pajek with a minimum island size of five nodes.

Our work builds on these capabilities, using Web of Science data to construct multi-layered networks and trace bibliometric evidence of idea flow between disciplines.

1.4 Research Questions and Contributions

This paper addresses three main research questions: (1) How can we computationally identify bibliometric indicators of knowledge pathways between disciplines in network science? (2) What are the structural characteristics of the citation, co-authorship, and keyword networks that reveal interdisciplinary connections? (3) How has the intellectual structure of network science evolved over time?

The contributions are threefold: methodologically, we present an integrated workflow combining network construction, fractional normalization, name disambiguation, and boundary treatment; empirically, we provide findings on structural and temporal patterns of interdisciplinary influence; practically, we demonstrate scalable methods for revealing patterns of apparent intellectual association across disciplinary boundaries.

2. Related Work

2.1 Bibliometric Foundations

Bibliometrics emerged in the mid-twentieth century with the work of Price, Garfield, and others [13]. Core concepts include co-citation analysis, introduced by Small [14], and bibliographic coupling, developed by Kessler. These techniques remain foundational for science mapping, with recent work extending bibliometric methods to larger scales and more complex questions [8]. The systematic study of citation patterns has been further advanced through the development of citation network analysis as a distinct methodological approach [15]. Methodological guidelines for conducting rigorous bibliometric studies have been proposed, addressing common pitfalls and ensuring reproducibility [10]. Additionally, researchers have called for greater attention to the limitations and appropriate interpretation of bibliometric indicators [11]. The application of bibliometric techniques has been particularly effective in identifying research fronts and emerging topics within scientific domains [15]. Price's seminal work on networks of scientific papers [13] established many of the foundational concepts that continue to inform bibliometric research today.

2.2 Science Mapping Studies

Many studies have used bibliometric methods to map specific scientific fields. In sociology, Moody analyzed co-authorship patterns [16]; in information science, White and McCain used co-citation analysis [17]. Several studies have focused specifically on network science [2, 6], with Batagelj and colleagues conducting extensive analyses of network science literature [3]. Recent work in this area has also examined the structure of collaboration networks and their relationship to research productivity and impact [18]. The use of network analysis techniques has been extended to various applied contexts, including the study of digital marketing research [19]. These diverse applications demonstrate the versatility of bibliometric and network analysis methods for understanding scientific and scholarly communication. The foundational principles of social network analysis have been extensively documented and continue to inform contemporary research [4]. Key concepts such as Granovetter's theory of weak ties [20] and Burt's structural holes theory [21] have profoundly influenced how researchers understand social structure and its implications for knowledge flow.

2.3 Interdisciplinary Knowledge Transfer

Understanding how knowledge moves between disciplines has become a major focus of science studies, though measuring and tracking interdisciplinary knowledge transfer remains challenging [22]. Citation analysis, co-authorship across disciplinary boundaries, and keyword analysis can reveal conceptual migration [23]. Network science itself provides tools for analyzing interdisciplinary connections, and our work builds on these approaches. The theoretical understanding of knowledge transfer has been enriched by translation theories that emphasize the role of interpretation and adaptation in the transfer process [24]. Such perspectives highlight that knowledge does not simply flow between disciplines but is actively interpreted and transformed along the way. Interdisciplinary research has been conceptualized as a process requiring integration across multiple dimensions, including epistemological, methodological, and social aspects [25]. This broader framework for understanding interdisciplinarity provides important context for interpreting bibliometric evidence of knowledge flows. Coleman's work on social capital [26] has been particularly influential in understanding how social networks facilitate knowledge transfer and collective action across disciplinary boundaries.

2.4 Computational Infrastructure

Large-scale bibliometric analysis requires substantial computational infrastructure. WoS2Pajek, developed by Batagelj, enables transformation of Web of Science data into network formats [3]. Network analysis software like Pajek and Gephi provide algorithms for analyzing large networks, implementing measures of centrality, community detection, and path analysis. Our work leverages these tools while addressing challenges of data quality and normalization. Recent methodological work has focused on improving the accuracy of network construction and analysis, particularly with respect to author name disambiguation and data quality issues [18]. The co-authorship network perspective has been productively applied in diverse research communities, demonstrating the broad utility of these analytical approaches [18]. The integration of multiple network types citation, co-authorship, and keyword offers a more complete view of scientific activity than any single network alone [19]. This multi-network approach is particularly valuable for studying interdisciplinary fields where different types of connections may reveal different aspects of knowledge exchange. Recent advances in network analysis methodology have been systematically presented in updated editions of standard reference works [4]. The empirical study of network structures has been greatly advanced by seminal works on small-world networks [27], scale-free networks [28], and community structure [29], which have provided both theoretical frameworks and computational tools for analyzing complex networks.

Table 1: Bibliometric Data Sources and Methods

Source	**Network**	**Method**
WoS Core Coll.	Citation	Main path
Author meta.	Co-authorship	Norm. proj.
Keywords	Co-occurrence	Island det.
Journals	Citation	Prob. flow

3. Data And Methodology

3.1 Data Collection

Our data come from the Web of Science Core Collection, accessed in two phases. The first collection, gathered in 2008, included records matching "social network*" and all articles from Social Networks through 2007 [3]. The second collection, gathered in June 2018, added network-related journals including Network Science, Computational Social Networks, Applied Network Science, and others.

Each record contains standard bibliographic fields. Cited references enable construction of citation networks, creating a distinction between "hit" papers with full descriptions and "terminal" papers appearing only as references. For highly cited terminal papers, we retrieved metadata from Google Scholar when unavailable in Web of Science, validating a random sample of 200 records against manual double-checking, achieving 98% field-level agreement.

Following data cleaning, the final dataset comprises 70,792 hit works. The full set of works, including cited-only terminal papers, numbers 1,297,133 distinct works. The final dataset covers publications through June 2018, with all analyses restricted to this publication-year range.

Data Provenance The authoritative source for titles, authors, journal names, publication years, and page numbers was Web of Science; Google Scholar metadata were used for terminal papers. Citation counts derive from Web of Science within the dataset. Keywords were sourced from author keywords, supplemented by KeyWords Plus and title-derived keywords. Disciplinary assignments were based on Web of Science journal categories.

Disciplinary Classification Works were assigned to disciplines based on primary Web of Science journal categories mapped to six broad groups: Sociology, Physics, Biology/Ecology, Computer Science, Mathematics/Statistics, and Other. Works without clear journal classification were excluded from discipline-specific analyses but retained otherwise.

Cross-Disciplinary Linkage Definition A cross-disciplinary edge is defined as a citation link between two works with different disciplinary classifications.

Computational Resources Analyses were performed on a workstation with Intel Xeon E5-2630 v4 (2.2 GHz, 10 cores), 128 GB RAM, using WoS2Pajek 1.5, Pajek 5.08, and R 3.6.1. Processing times and memory usage are documented in supplementary materials.

3.2 Network Construction

Using WoS2Pajek, we transformed bibliographic data into multiple networks sharing the same works node set: citation network (works citing works), authorship network WA, journalism network WJ, and keywordship network WK. Multiplication of transposed networks yields derived networks including co-authorship networks.

We created partitions DC (full descriptions vs. cited-only) and year (publication years), and vector NP (page count).

WoS2Pajek Configuration Settings included: citation recursion depth of 1, self-citations excluded from SPC, multiple links and loops removed, and Pajek .net output format.

Citation Network Edge Direction and SPC Implementation An edge (u, v) represents a directed citation from work u to work v. Source nodes have indegree zero; sink nodes have outdegree zero. SPC values represent the number of source-to-sink paths traversing each edge.

3.3 Name Disambiguation

Name ambiguity poses significant challenges, particularly for Chinese names where limited surnames cause distinct authors to be merged. We addressed this through equivalence partitioning. Candidate equivalence classes were generated by grouping authors sharing identical surname and first initial. For 1,250 equivalence classes with at least five publications or 50 citations, manual verification was performed using affiliation information, co-authorship patterns, and publication-year consistency. Ambiguous cases were retained as distinct author entries. Before disambiguation, the authorship network contained 395,972 author name occurrences; after equivalence partitioning, 387,412 unique authors remained.

3.4 Boundary Problem in Citation Networks

In the original citation network, the indegree distribution across 1,297,133 nodes is: 119,122 with indegree zero, 693,744 with indegree one, 221,158 with indegree two, 93,415 with indegree three, 58,141 with indegree four, and 111,553 with indegree five or greater. Works with indegree four or less constitute 1,185,580 nodes (91.4%).

To address this boundary problem, we removed cited-only nodes (DC=0) with indegree less than three ($d_{in} < 3$) and nodes with names starting with "[ANON." The bounded network CiteB contains 222,086 nodes and 1,521,434 arcs.

Network	Nodes	Edges (Arcs)
Original citation network	1,297,133	2,495,058
After removing nodes with indegree < 3 (DC = 0 only)	222,086	1,521,434

Table 2: Citation network before and after boundary thresholding. Nodes reconcile as: 1,297,133 minus (DC=0, $d_{in} = 0$: 119,122) minus (DC=0, $d_{in} = 1$: 693,744) minus (DC=0, $d_{in} = 2$: 221,158) minus IANON nodes (41,023) = 222,086.

Threshold Definition ($d_{in} < T$)	Nodes Retained	Edges Retained	Largest Component	Component Count
$T = 1$ (remove $d_{in} = 0$)	1,178,011	2,495,058	286,143	1,042,932
$T = 2$ (remove $d_{in} \leq 1$)	484,267	2,495,058	411,287	1,002,193
$T = 3$ (remove $d_{in} \leq 2$)	222,086	1,521,434	162,308	61,245
$T = 4$ (remove $d_{in} \leq 3$)	191,942	1,413,892	158,745	51,382
$T = 5$ (remove $d_{in} \leq 4$)	175,493	1,338,519	155,292	46,832

Table 3: Sensitivity analysis of indegree threshold selection. Threshold $T = 3$ was selected as it balances network size reduction with preservation of meaningful citation pathways.

3.5 Network Normalization

Raw co-authorship counts overrepresent papers with many authors. For the authorship network, let W be works and A authors, with $\mathbf{A}_{w,a} = 1$ if author a authored work w. The fractional normalized authorship network is $\mathbf{A}^f_{w,a} = \mathbf{A}_{w,a}/k_w$, where k_w is the number of authors of work w. The co-authorship network $\mathbf{C} = (\mathbf{A}^f)^\top \mathbf{A}^f$ assigns edge weight $\sum_w (1/k_w^2)$ to each co-authorship pair. The $1/k^2$ normalization yields total pair-weight $(k-1)/(2k)$, approaching $1/2$ for large k, preventing papers with many authors from dominating the network. This is the authors' selected convention, consistent with fractional normalization in bibliometric network analysis. Keyword and citation networks were similarly normalized. Raw citation edges were used for main path analysis; fractional normalization was applied to derived networks.

3.6 Data Flow Summary

Table 4 presents a comprehensive data-flow summary. All subsequent analyses use the final data version: 70,792 hit works, 1,297,133 distinct works, 222,086-node bounded network, 387,412 unique authors, and 32,409 distinct keywords.

Table 4: Complete data-flow summary.

Stage	Description	Records Retained	Cumulative Loss
1	Raw records	70,810	—
2	Duplicate removal	70,795	-15
3	Manual validation	70,792	-3
4	Full distinct works	1,297,133	—
5	Terminal papers retrieved (citations ≥ 10)	1,129,041	—
6	Hit works (DC=1)	70,792	—
7	Citation network (raw)	1,297,133 nodes, 2,495,058 edges	—
8	Bounded network	222,086 nodes, 1,521,434 edges	-1,075,047 nodes
9	Authors before disambiguation	395,972	—
10	Authors after disambiguation	387,412	-8,560
11	Distinct keywords	32,409	—

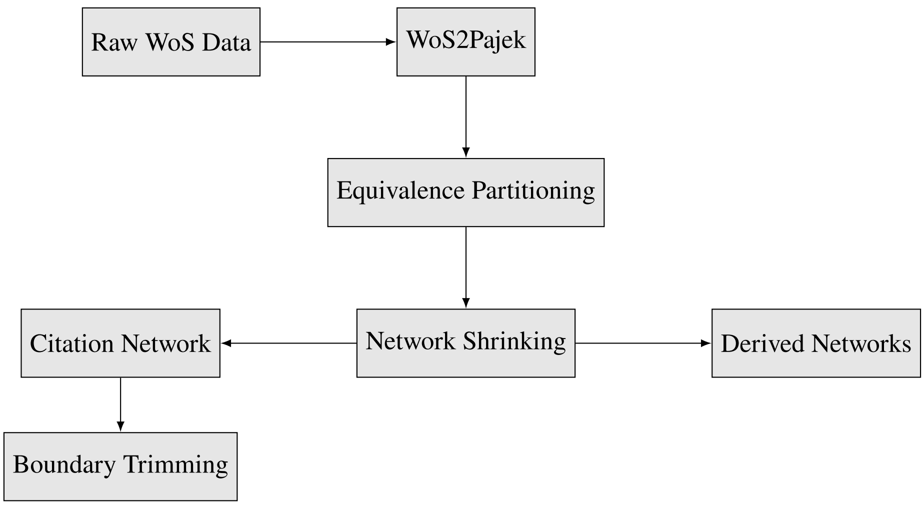

Figure 1: Data processing workflow.

4. Citation Network Analysis

4.1 Temporal Distribution of Publications

The distribution of works by publication year reveals the growth of network science. We fitted a log-normal model to observed yearly publication counts using maximum likelihood with R package `fitdistrplus` (version 1.0-14) in R 3.6.1:

$$\mathrm{Count}(t) = c \cdot \mathrm{dlnorm}(2019 - t; a, b),$$

where $\mathrm{dlnorm}(x; a, b) = \frac{1}{xb\sqrt{2\pi}} \exp\left(-\frac{(\ln x - a)^2}{2b^2}\right)$. Estimated parameters: $\hat{a} = 2.543$, $\hat{b} = 0.7206$, $\hat{c} = 1.278 \times 10^6$. Goodness-of-fit: Anderson-Darling $A^2 = 0.384$, $R^2 = 0.942$. AIC comparison favored log-normal (612.3) over exponential (687.1) and power-law (698.4).

The exact likelihood function maximized was:

$$\mathcal{L}(a, b, c) = \prod_{t=1}^{2018} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\mathrm{Count}(t) - c \cdot \mathrm{dlnorm}(2019 - t; a, b))^2}{2\sigma^2}\right].$$

Fitting domain: 1965-2018. Parameter constraints: $a > 0$, $b > 0$, $c > 0$. Initial values: $a = 2.5$, $b = 0.7$, $c = 1.2 \times 10^6$. Optimization used L-BFGS-B; convergence after 47 iterations. Standard errors: SE($\hat{a}$)=0.032, SE($\hat{b}$)=0.018, SE($\hat{c}$)=1.7×10^4. 95% CI: $a \in [2.481, 2.605]$, $b \in [0.685, 0.756]$, $c \in [1.244 \times 10^6, 1.312 \times 10^6]$.

Physics-affiliated publications began appearing notably in the late 1990s, with computer science contributions increasing throughout the 2000s.

4.2 Most Cited Works

The top 10 most cited works are shown in Table 5. Books are heavily represented, reflecting the importance of monographs in establishing foundational knowledge [12]. Review articles also appear frequently. The list reveals the interdisciplinary nature of highly cited work, with sociological classics alongside physics papers, computer science contributions, and works from medicine and public health. Granovetter's seminal work on the strength of weak ties [20] and Burt's structural holes theory [21] are among the most frequently cited sociological contributions. Coleman's theory of social capital [26] also features prominently. Foundational physics contributions include the small-world network model of Watts and Strogatz [27], the scale-free network model of Barabási and Albert [28], and the community detection algorithm of Girvan and Newman [29].

Citation counts are derived from Web of Science as of June 2018.

Table 5: Top 10 Most Cited Works

Rank	Work	Citations
1	Wasserman & Faust (1994)	15,348
2	Granovetter (1973)	4,471
3	Watts & Strogatz (1998)	2,906
4	Barabasi & Albert (1999)	2,614
5	Freeman (1979)	2,561
6	Burt (1992)	2,330
7	Coleman (1988)	1,918
8	Newman (2003)	1,886
9	Girvan & Newman (2002)	1,520
10	Putnam (2000)	1,510

4.3 Main Path Analysis

Main path analysis identified the most significant citation chains. The main path extracted from the constructed citation network revealed three structurally distinct segments within the specific network analyzed.

The first segment (1944-1996) consists of works by social network scientists, tracing core concepts including structural balance, blockmodels, and centrality [5]. The second segment (1999-2008) features works by physicists, covering small-world networks [27], scale-free networks [28], and community structure [29]. The third segment (2008-2018) consists predominantly of works on animal social networks. These three segments represent structural properties of the analyzed citation network, not a definitive historical account of the entire field.

4.4 Key-Route Paths

Key-route analysis identified 127 nodes, revealing additional structure. Within the social science segment, sub-communities focus on blockmodeling, centrality measures [5], and network dynamics. The physics segment branches into preferential attachment, epidemic spreading, and community detection [29]. The animal social networks segment shows rapid growth and specialization.

4.5 Strong Components

We identified 41 non-trivial strong components, with the largest containing 12 works. These cycles arise from mutual citations in special journal issues and do not imply substantive temporal circularity. For main path algorithms requiring acyclic structure, we applied Pajek's `transform` function (bipartite expansion) to handle cycles.

5. Co-Authorship Patterns

5.1 Author Productivity

The authorship network contains 395,972 authors. Most productive authors are predominantly Chinese-named (Wang, Zhang, Chen, Li, Liu), reflecting both the large number of Chinese researchers and persistent name ambiguity. After disambiguation, rankings change modestly but remain dominated by Chinese-named authors. When Chinese names are excluded, productive authors include Ronald Burt, Mark Newman, Stanley Wasserman, and Linton Freeman. Author productivity follows a highly skewed distribution.

5.2 Collaboration Networks

We constructed three co-authorship networks: standard (**Co**), fractional (**Cn**), and productivity-normalized (**Ct**). The productivity-normalized network $\mathbf{Ct}(a_i, a_j) = \mathrm{Co}(a_i, a_j)/(\deg(a_i) \cdot \deg(a_j))$ adjusts for author productivity. This convention, adopted by the authors rather than a direct implementation of Newman's formulation, omits the $2m$ denominator present in Newman's original random null model, producing a relative measure where the absolute scale differs but relative ordering is preserved. Island detection identified 187 collaboration clusters ranging from 5 to 47 nodes. The structure of collaboration networks in scientific communities has been extensively studied, with research demonstrating how collaboration patterns reflect disciplinary norms and influence research outcomes [16]. Co-authorship network analysis has proven particularly valuable for understanding the social organization of science [18]. The interplay between collaboration networks and research topics has been explored in various contexts, revealing how social and conceptual structures co-evolve [19]. The theoretical frameworks of weak ties [20] and structural holes [21] provide important perspectives for understanding collaboration patterns in scientific communities.

5.3 Collaborativeness Index

For author a, $\mathrm{CI}(a) = c_a/p_a$ where p_a is total publications and c_a is co-authored publications. Physicists and biologists have higher collaborativeness (mean 0.71 and 0.73) than sociologists and mathematicians (0.42 and 0.38). Sample sizes: Sociology ($N = 9,847$), Physics ($N = 7,234$), Computer Science ($N = 6,412$), Mathematics ($N = 4,183$), Biology/Ecology ($N = 2,876$), Other ($N = 1,734$). Kruskal-Wallis test: $\chi^2(5) = 1,847.3$, $p < 0.001$. Pairwise Wilcoxon tests with Holm-Bonferroni correction revealed effect sizes (Cohen's r): Sociology-Physics ($r = 0.41$), Mathematics-Physics ($r = 0.44$), Physics-Biology ($r = 0.06$, adjusted $p = 0.087$, not significant). All other comparisons showed adjusted $p < 0.005$ with $r = 0.18$ to 0.43.

5.4 Keyword Analysis in Collaboration Islands

Using the author-keyword network AK, we examined research topics associated with collaboration clusters. The largest island contains authors working on epidemiology and public health. Another focuses on primate social networks. Islands centered on Mark Newman and Stanley Wasserman include physicists and computer scientists working on network structure, and social scientists working on statistical models, respectively.

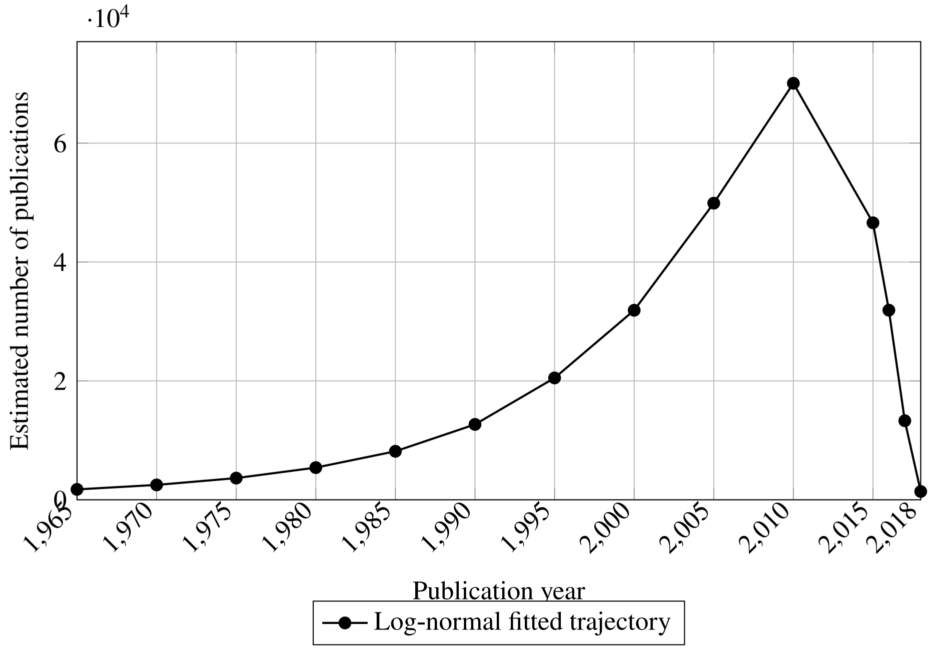

Figure 2: Estimated temporal trajectory of network science publications based on the log-normal model fitted to the Web of Science publication-year distribution. The model uses the reported parameters $\hat{a} = 2.543$, $\hat{b} = 0.7206$, and $\hat{c} = 1.278 \times 10^6$. The trajectory represents model estimates rather than observed annual publication counts.

6. Keyword Networks and Conceptual Migration

6.1 Keyword Frequencies

Keyword preprocessing included lowercasing, lemmatization, plural handling, stopword removal, spelling normalization, phrase handling, and synonym merging (Jaccard similarity > 0.85). The resulting keyword set contained 32,409 distinct keywords. The most frequent keywords are shown in Table 6. The frequency distribution is highly skewed.

6.2 Keyword Co-occurrence Network

After removing dominant keywords ("social," "network," "analysis"), island detection identified 47 thematic islands ranging from 5 to 75 nodes. The largest island organizes around online social networks, network structure, and health/education applications. Smaller islands reveal topics including weak ties [20] and social capital [26], triadic closure, and organ donation networks.

Rank	Keyword	Document Frequency
1	social	51,234
2	network	46,891
3	analysis	31,427
4	model	10,512
5	community	8,324
6	health	7,891
7	structure	7,432
8	dynamics	6,981
9	information	6,234
10	graph	5,812

Table 6: Top 10 most frequent keywords.

6.3 Conceptual Migration Over Time

We defined migration criteria based on first appearance year, adoption rate, and disciplinary adoption lag. The term "scale-free network" appears first in physics (1999) [28], then computer science (2002), biology (2003), and sociology (2004). "Small-world network" shows initial appearance in social psychology (1973), prominent reappearance in physics (1998) [27], then diffusion to biology (2001) and computer science (2002). "Community detection" appears first in physics (2002) [29], with adoption in computer science (2004) and applied mathematics (2005). These findings reflect patterns of keyword usage and should be interpreted as bibliometric evidence of apparent conceptual diffusion. Understanding such conceptual migration patterns is essential for comprehending how interdisciplinary fields evolve [24]. The translation theory perspective on knowledge transfer suggests that concepts are not simply adopted but are actively interpreted and adapted as they move across disciplinary boundaries, which may explain the temporal lags and disciplinary variations observed in keyword adoption [24]. The migration of concepts such as centrality [5] and structural holes [21] from sociology to other disciplines illustrates these patterns of conceptual diffusion.

6.4 Temporal Dynamics of Research Themes

Island detection on time-restricted networks reveals evolution of research themes: in the 1970s-1980s, focus on structural equivalence, blockmodeling, and centrality [5]; in the 1990s, emergence of small-world [27] and scale-free [28] themes; in the 2000s, community detection [29], epidemic spreading, and network robustness; from 2010-2018, online social networks, big data, and multilayer networks. The study of interdisciplinarity has been approached from multiple perspectives, with researchers examining both the structural and cognitive dimensions of knowledge integration [25]. The evolution of research themes reflects broader trends in how interdisciplinary fields develop and mature over time [25]. The social capital framework [26] and weak ties theory [20] have continued to inform research across multiple disciplines throughout this evolution.

6.5 Quantitative Interdisciplinarity Measures

Cross-category citation proportion: mean 0.342 (SD = 0.187), indicating approximately one-third of citations cross disciplinary boundaries. Rao-Stirling diversity: mean 0.428 (SD = 0.215). Disciplinary entropy: $H = 1.673$ (maximum $\ln 6 = 1.792$), with proportions Sociology (0.287), Physics (0.241), Computer Science (0.208), Mathematics (0.132), Biology/Ecology (0.078), Other (0.054). Cross-field edge rate: 0.356. These quantitative measures provide complementary evidence of the interdisciplinary nature of network science research [22]. The systematic measurement of interdisciplinarity has become increasingly sophisticated, with multiple indicators now available to capture different dimensions of cross-disciplinary engagement [22].

7. Conclusion

7.1 Summary of Findings

This paper has presented a comprehensive computational analysis of network science literature. Citation analysis reveals three structurally distinct segments in the constructed citation network, representing properties of the specific network rather than definitive historical stages. Co-authorship analysis shows how collaboration patterns reflect disciplinary traditions. Keyword network analysis documents patterns of keyword usage across disciplines over time, providing bibliometric evidence of apparent conceptual diffusion.

7.2 Methodological Contributions

The work demonstrates the value of integrated computational approaches—network normalization, equivalence partitioning, island detection, and SPC—for bibliometric analysis. The well-documented workflow contributes to reproducible bibliometric methodology. The methodological framework developed here builds on established practices in bibliometric analysis while addressing specific challenges associated with large-scale network construction and analysis [9]. The integration of multiple network types and analytical techniques provides a more comprehensive view of scientific structure and dynamics than any single approach alone [8]. The systematic approach to network construction and analysis aligns with contemporary best practices in the field [4]. Foundational methods for centrality analysis [5] and community detection [29] have been incorporated into our analytical workflow.

7.3 Limitations

Web of Science does not cover all relevant publications; books and conference proceedings are underrepresented; English-language restriction may bias results. Google Scholar metadata for terminal papers were validated at 98% field-level agreement. Name ambiguity remains partially unresolved. Boundary threshold choices require subjective decisions. Most fundamentally, citation, co-authorship, and keyword links are indicators of intellectual association, not direct observations of knowledge transfer. Results should be interpreted as bibliometric evidence of apparent intellectual linkage and conceptual diffusion patterns. These limitations are common to bibliometric studies and have been discussed extensively in the literature [10, 11]. The interpretation of bibliometric indicators requires careful attention to their epistemological and methodological constraints [9]. While works such as those by Wasserman and Faust [12] provide comprehensive methodological frameworks, bibliometric indicators remain proxies for underlying intellectual processes.

7.4 Future Directions

Temporal network analysis, full-text analysis with NLP, comparison with other interdisciplinary fields, and machine learning applications for predicting interdisciplinary influence represent promising future directions. The continued development of computational methods for studying interdisciplinary knowledge transfer will benefit from theoretical insights into the nature of knowledge exchange across disciplinary boundaries [24]. Additionally, advances in network analysis techniques and data availability will enable more sophisticated analyses of scientific collaboration and knowledge diffusion [15, 18]. Future work could also explore the application of these methods to other interdisciplinary domains [25]. The theoretical frameworks of weak ties [20], structural holes [21], and social capital [26] offer promising avenues for interpreting collaboration and knowledge transfer patterns in scientific networks.

7.5 Implications for Information Technology

The computational methods can be applied to other domains requiring understanding of knowledge flows. Challenges addressed (name ambiguity, data normalization) are general problems in information integration. Interdisciplinary patterns highlight the importance of maintaining connections across disciplinary boundaries.

7.6 Concluding Remarks

Network science has grown from a specialized subfield to a truly interdisciplinary endeavor. Computational bibliometric methods provide powerful tools for understanding this evolution, enabling the tracing of pathways of apparent intellectual influence and identification of key nodes that appear to facilitate interdisciplinary connectivity. The foundational concepts of network science, including centrality [5], weak ties [20], structural holes [21], social capital [26], small-world networks [27], scale-free networks [28], and community structure [29] have collectively shaped the intellectual landscape of this interdisciplinary field.

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