Structure of Global Innovation Systems and Knowledge Diffusion Patterns: Network Analysis

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Abstract

Digital transformation has fundamentally reshaped innovation dynamics in many parts of the global economy, and knowledge diffusion is no longer spatially bounded, as in large-scale innovation data collection, the density of collaborative ties and cross-border knowledge exchanges are increasing across institutional and technological domains. Due to structural changes in the daily organization of innovation activities, knowledge production has been reshaped by the expansion of digital infrastructures and the proliferation of networked research collaborations and innovation platforms. In this study, we aim to contribute to the understanding of global innovation systems by examining how patterns of knowledge diffusion are structured using network analysis in transnational innovation networks. This paper aims to identify structural configurations and relational mechanisms in innovation networks and how these contribute to theoretical understandings of knowledge diffusion. In this paper, we analyze the process of knowledge creation and diffusion as a networked system, using specific examples from our dataset of global innovation actors in order to examine their relational structures and positional roles of knowledge-producing entities. A sample of innovation network data from multiple sectors of global innovation systems took part in the empirical analysis, drawing from bibliometric indicators and the analysis of over large-scale relational linkages. We empirically found that we cannot assume uniformly that centrality or connectivity are either a prerequisite for innovation performance; a driver for diffusion of technological knowledge; a mechanism for individual learning; a mechanism for collective learning; and a determinant for accumulation of innovation capabilities. The findings indicate that actors adopt different strategies of using network positions in their learning: exploratory engagement or exploitative specialization. We argue for a more nuanced interpretation of innovation networks that acknowledges both its structural heterogeneity in shaping understandings of knowledge flows and providing policymakers with insights on organizations' patterns of using digital infrastructures in other sectors and more complex configurations in the global system. The implications of this study could inform a policy framework in innovation governance on how actors can use their network resources for knowledge accumulation and coordination toward systemic innovation and that networks can function differently in alternative institutional contexts.

Keywords: Global innovation systems; Knowledge diffusion; Innovation networks; Network analysis; Digital infrastructures; Learning strategies; Innovation governance

1. Introduction

Innovation networks are often the primary locus of knowledge creation and diffusion and, therefore, conducting them in distributed settings has been considered that collaboration and connectivity shape the different ways in which ideas are generated and recombined in the context of what innovation systems represent [8] [14]. Recent studies have challenged this assumption: rather than focusing on the scale and spatial concentration of collaboration, these studies emphasize the structural heterogeneity of networks and have indicated the need for more nuanced interpretations of the global innovation system [2-3] [13].

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This network analytical methodology initially emerged from social-network analysis in a relational perspective yet later evolved working from a systems approach grounded in the theory of innovation systems [1] [12] [15]. Therefore, an important shift for innovation studies has occurred due to the increasing use of digital infrastructures in research toward network-based thinking and finally systems-level interpretation.

This shift in the analytical use of networks has given rise to two unresolved issues such as conceptual ambiguity, methodological inconsistency, and interpretative overgeneralization. In addition, the mechanisms governing knowledge diffusion through collaborative networks are subject to multiple contextual contingencies, including institutional environments and technological regimes. Consequently, it is decreasing the explanatory power of prevailing network models and causing potential misallocation of policy interventions related to their implementation. These limitations not only affect the governance of innovation systems but also can cause gross inefficiencies in innovation coordination [5-6].

The innovation network approach is widely used to model knowledge flows where actors that are linked through relational ties represent each node. These relations are commonly measured by bibliometric indicators combined with the integration of structural network metrics. The co-invention model, which according to [2] has extended the analytical scope of the literature, provides a more detailed framework for the analysis and interpretation of collaboration patterns and introduces a representation of the network for data interpretation during empirical assessment. A shared methodological feature in the network literature is a comparative approach [11], combining structural and positional measures that are capable of making visible and interpreting their own relational patterns [9].

In line with earlier critiques on network studies [7] [10] consider density and centrality on the one hand, and diversity and brokerage on the other as mutually dependent and reinforcing one another rather than as two separate dimensions: after more than two decades of network research, there is still surprisingly little systematic evidence available, especially regarding the use of network measures in different contexts and with heterogeneous effects in innovation systems. In a similar vein, empirical evidence on actors' learning through networks remains limited, as highlighted by [4], where existing contributions provide only partial insights and require further clarification regarding positional dynamics and strategic uses of networks [14].

We argue that the process of organizing and conducting innovation activities requires greater analytical clarity that recognizes and differentiates the different ways in which actors are actively embedded in the structure of innovation networks [13]. Recent contributions emphasize this limitation by showing that rather than focusing on scale and density properties of networks, attention should be directed toward relational mechanisms of interaction, stressing the need for more configurational and contextual interpretations than aggregate indicators alone may suggest.

In this study, we aim to contribute to the understanding of global innovation systems by examining how patterns of knowledge diffusion, collaboration, and learning are structurally organized within transnational networks of innovation actors using digital infrastructures in their interactions. Accordingly, the objective of this research is to identify network experiences and structural mechanisms operating within global innovation systems. While network analysis allows us to engage systematically with large-scale empirical material, the implications of our findings extend beyond the immediate empirical setting and are relevant across different institutional contexts of innovation governance and coordination. This study provides further insight by unpacking actors' strategic use of network positions and offering implications for the governance of innovation systems.

In the following sections, we describe how a large-scale innovation network is constructed using network analysis as a methodological approach to examine relational understandings of knowledge diffusion and learning and to develop a structural-positional framework for analysis [11]. The methods combine bibliometric indicators and network metrics implemented through Gephi with the analysis of structural patterns in global innovation data. To advance the analysis, we adopt a network perspective commonly applied to the study of innovation systems [1], as this approach is particularly suitable for capturing the complexity of innovation processes and their multidimensional effects on knowledge creation and diffusion.

2. Methods

Data were collected through a large-scale bibliometric data collection in transnational innovation systems, and the empirical context is typically global in scope to capture cross-border collaboration dynamics [2-3]. Patent records were systematically retrieved from multiple international patent databases to capture innovation activities as reflected in co-invention relationships in all major technological domains.

Our empirical sample included innovation actors of a global population that we identified and, once we constructed the network, subsequently examined among their patterns of collaboration within a particular innovation system [8] [14]. A purposive sampling strategy was used in selecting the actors to ensure the

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required diversity of positions among the actors' experiences of collaboration and learning derived from our large-scale dataset [13].

In all, we created several innovation networks and actor-level datasets, of which thousands were from the global system. For this analysis, a substantial number of innovation actors were included in the final network construction [11]. This dataset was sufficient to represent the complexity of the network regarding the diversity of the actors being connected, and relations were based on the observed collaboration ties.

We believe that this sample size, especially of global innovation actors, is not an exhaustive census, but a representative sample of all major innovation actors of the global system. We followed three main criteria to ensure representativeness among the actors. First, each selected actor had some experience of using digital infrastructures in his or her innovation activities for at least several years to ensure the actors' in-depth understanding in the particular innovation context.

All patents and co-invention records that met the inclusion criteria were retained, while records with incomplete metadata, such as missing application or inventor information, were excluded. Actors were selected from different countries, and multiple sectors of innovation, including high-tech and medium-tech activities, were included in the analysis.

These criteria enabled the collection of information on a wide range of innovation activities, including collaborative patterns of knowledge creation, learning, and diffusion of knowledge through digital infrastructures, as well as network positions and relevance for innovation system governance. Each selected actor had experience using digital infrastructures in innovation activities for at least several years, ensuring in-depth understanding, diversity of strategies across actors, and consistency in standard bibliometric indicators and collaboration measures such as connectivity and centrality.

To operationalize the network-based analysis, we created a structural–positional framework that outlined the analytical dimensions and relationships through a network analytical model [1]. The network was constructed using bibliometric databases that recorded collaboration ties among innovation actors through co-invention events. This approach provided a consistent analytical basis aligned with prior research on innovation systems and enabled systematic analysis through integrated network metrics.

Network construction followed a stepwise procedure in which each innovation actor was treated as a node and linked to collaborating actors. When collaboration between a particular actor and others was observed within a defined time window of five years and exceeded a minimum threshold, the algorithm, generating reciprocal ties, created a relational link. Several analytical procedures and thresholds were adapted at different stages to control for non-representative elements of the empirical network structure. As both relational network data and contextual attributes underlying collaboration were collected, the network was recalibrated where necessary.

Network indicators were used to evaluate the performance of the innovation networks during analysis and visualization stages [9]. Multiple centrality metrics were applied to ensure robustness and validity of the results. To evaluate outcomes related to knowledge diffusion, relational patterns identified by the model were examined to show how innovation actors connect and interact within the network [3] [13]. Network configurations were identified by examining the distribution of structural metrics and positional attributes.

Given the diversity of approaches to network analysis, consistent terminology was adopted throughout the analytical framework. Follow-up interpretations were applied only when network structures did not clearly indicate relational patterns of knowledge diffusion. During analysis, ambiguities were addressed using clarifying procedures to support interpretation of network structures.

Actors were classified using criteria including centrality, density, brokerage, and diversity in one-mode networks. This framework provided six analytical dimensions for examining relational structures and enabled comparison of exploratory and exploitative roles across major actor groups. Relational patterns were identified using network metrics such as degree and betweenness, alongside theoretical constructs from innovation systems literature, including structural heterogeneity, learning strategies, positional roles, collaboration intensity, and governance relevance within the system.

An iterative analytical process was employed, involving careful examination of network outputs and refinement of classifications on an actor-by-actor basis. Network structures were analyzed using standard network metrics including degree, betweenness, and closeness. Visualization and layout algorithms were implemented using Gephi (version 0.10), with force-directed and modularity-based representations guiding interpretation.

A systematic analytical approach was followed to construct networks, collect indicators, and analyze patterns to derive final empirical insights. Analytical procedures were adapted to accommodate the scale of the data, and visualization parameters were calibrated to optimize layout clarity prior to interpretative analysis. The

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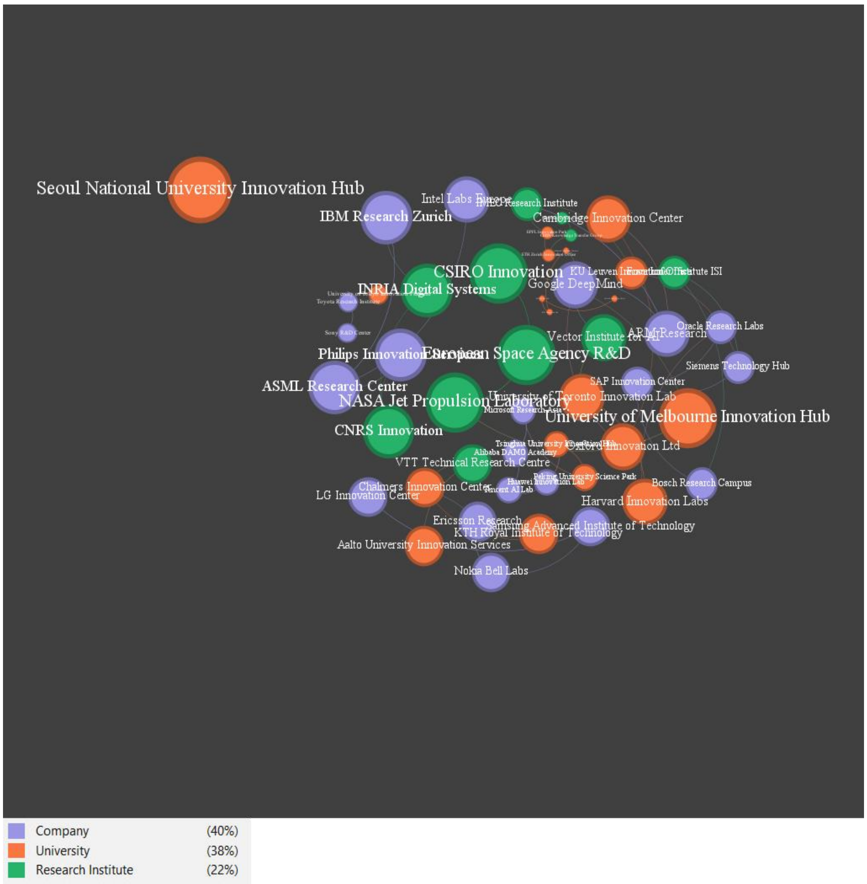
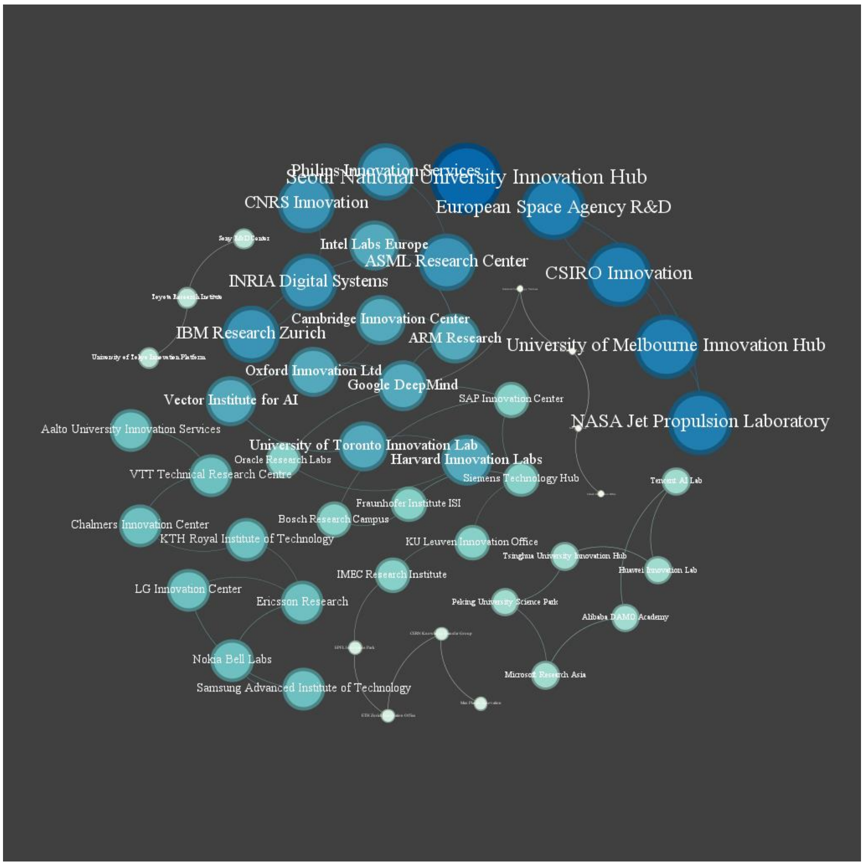
flexibility and transparency of this approach enabled the analysis to capture heterogeneity in network structures, learning strategies, and positional roles, consistent with prior research [13].





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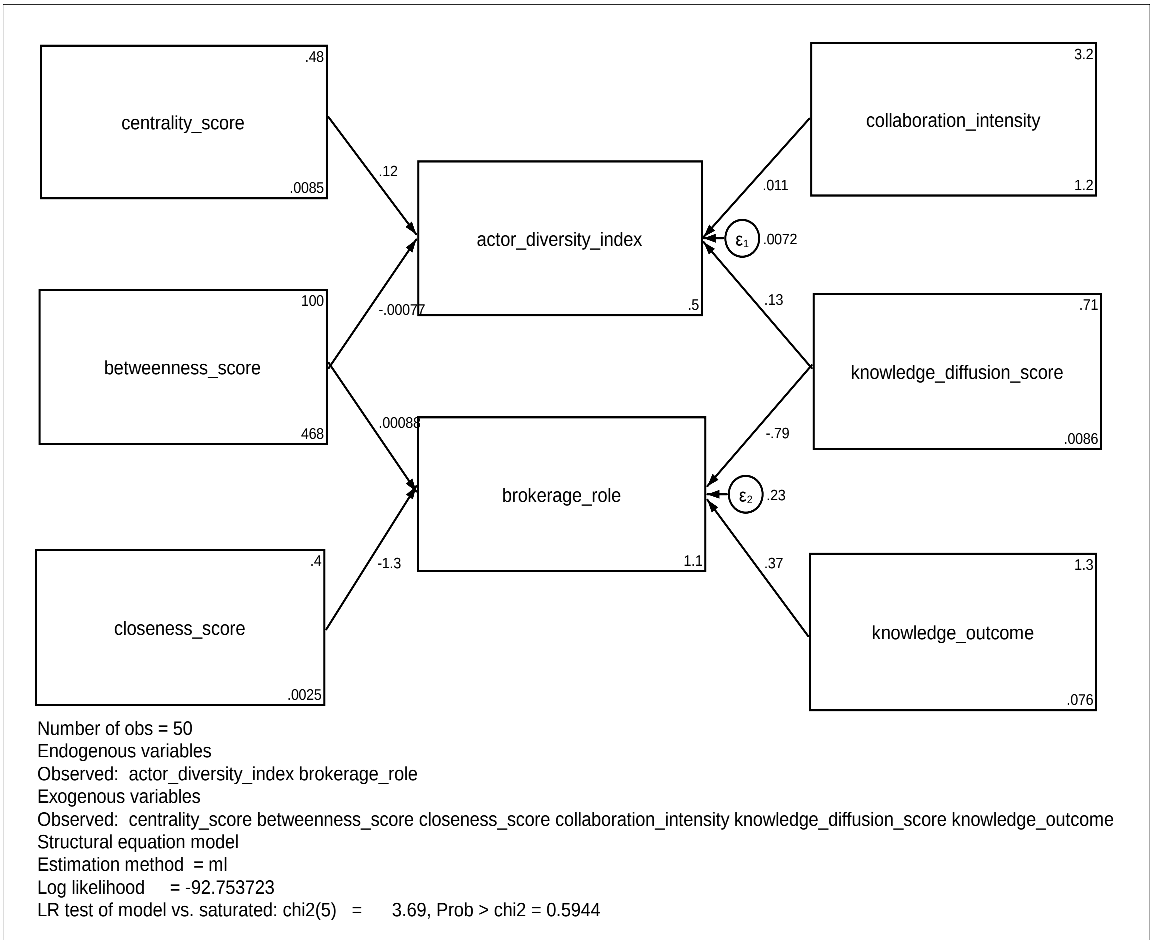

Table 1: Regression Results for Structural Determinants of Actor Diversity and Brokerage Role in Innovation Networks

		OIM				
	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
Structural						
actor_diversity_index						
centrality_score	0.122	0.130	0.940	0.349	-0.134	0.378
betweenness_score	-0.001	0.001	-1.290	0.198	-0.002	0.000
collaboration_intensity	0.011	0.011	1.020	0.309	-0.010	0.033
knowledge_diffusion_score	0.132	0.135	0.980	0.327	-0.132	0.396
_cons	0.497	0.121	4.110	0.000	0.260	0.735
brokerage_role						
betweenness_score	0.001	0.003	0.260	0.797	-0.006	0.008
closeness_score	-1.319	1.394	-0.950	0.344	-4.051	1.412
knowledge_diffusion_score	-0.789	0.771	-1.020	0.306	-2.300	0.722
knowledge_outcome	0.371	0.254	1.460	0.143	-0.126	0.869
_cons	1.056	0.824	1.280	0.200	-0.560	2.672
var(e.actor_diversity_index)	0.007	0.001	0.005	0.011		
var(e.brokerage_role)	0.228	0.046	0.154	0.338		

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3. Results

Table 1 summarizes the regression estimates against the structural characteristics of innovation networks at the actor level and highlights three core patterns that affected actor diversity and brokerage role, heterogeneous learning strategies, and the differentiated use of network positions.

The overall results are consistent in showing limited direct effects of centrality and connectivity as dominant drivers. In particular, the explanatory power of the centrality score and the betweenness score on the structural configuration of the innovation network remains weak.

Several of the assumptions that emerged from our theoretical framework were not supported with statistically significant evidence, indicating that a central position should have been influential in diffusion is not a universally valid assumption. By the end of the estimation procedure, there was no systematic evidence supporting the primacy of network centrality for explaining knowledge diffusion and brokerage outcomes.

Variation in the distribution of network positions revealed actors that appear to have no stable positional advantage, such as a peripheral actor acting as a broker or a highly central actor with limited brokerage relevance. These patterns are commonly observed when actors substitute structural reach for strategic coordination by reallocating their relational resources.

For example, when a central actor relies on dense local collaboration ties, peripheral actors can bypass these ties through global network connections, thereby reducing access constraints that matter for both exploratory and exploitative learning.

To evaluate statistical relevance, one-sample z-tests were applied using estimated coefficients of the structural indicators to assess whether effects differed from zero. A comparison between coefficient magnitudes and standard errors indicates that the model yields limited explanatory gains. Variables associated with large standard errors imply that changes in these indicators do not significantly alter predicted outcomes.

These findings suggest that expected alignment between network indicators and learning outcomes does not consistently materialize in empirical settings. Learning strategies that rely exclusively on positional advantage remain constrained by the contextual configuration of collaboration structures and institutional conditions shaping coordination and diffusion processes.

Differences in structural conditions generating exploration–exploitation trade-offs indicate weak alignment between assumed learning capacities and observed collaboration dynamics. Knowledge accumulated during collaborative phases may instead be recombined or reallocated at later strategic stages rather than directly diffused through immediate network positions.

In this context, brokerage functions as a contingent mechanism rather than a stable structural advantage. Exploratory engagement is associated with increased diversity, whereas exploitative specialization reflects the cumulative use of prior collaboration experience to consolidate roles within specific network segments and technological domains.

Some observations deviate from the dominant patterns. In certain configurations, highly connected actors collaborating with diverse partners simultaneously exhibit characteristics of both central and peripheral positions, relying on others' structural access to coordinate knowledge flows. A third configuration diverges from the first two in both learning orientation and brokerage relevance.

Additional inconsistencies emerge where collaboration intensity does not yield statistically significant effects, despite qualitative indications of coordination pressure and selective participation in collaborative activities. These observations underscore the limits of aggregate network indicators in capturing situational dynamics of coordination, commitment, and exclusion within innovation networks.

4. Discussion

A number of empirical patterns emerged from our network analysis, which we grouped into two distinct learning configurations differentiated by actors' strategic use of their network positions was observed. Overall, the analytical framework was effective in supporting interpretation of demonstrating that: network centrality and connectivity alone are insufficient explanatory mechanisms (see Table 1).

Despite longstanding assumptions that highly connected actors enhance their innovation outcomes, some results indicate how centrality and brokerage they were for the ability to diffuse knowledge in our empirical setting. Our regression results indicate that structural indicators of network position show limited effects on learning outcomes in different collaborative configurations.

The implications of this finding further support the recent network literature, with the roles of diversity, brokerage, coordination, and selective collaboration being the most salient patterns in our dataset. Actors were

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evaluated through their distribution of network ties and their centrality scores and found that the "reach of the network", which was increased from local clusters to global connections over time (five-year window).

This pattern was identified through the comparison of network metrics, where actors for global collaboration gave them an additional capacity to use in learning with diverse partners and their technological domains. This configuration also functions as a "bridging mechanism" to reconcile the trade-off between exploration and exploitation.

These results suggest that learning through network diversity results in less dependence on central positions, as this is one of the very first empirical demonstrations to systematically examine learning strategies following a networked innovation process. The outcome of this analysis could be used to reinterpret these assumptions, and reframe in knowledge flow dynamics.

This, from the innovation systems perspective, highlights interactions between structure and agency and their learning orientation and coordination mechanisms that resulted in heterogeneous outcomes, of knowledge accumulation by exploration–exploitation (diversity > centrality). This increase in actors' average diversity challenges the dominant assumption: central network positions for knowledge diffusion does not affect the learning capacity, for their strategic outcomes.

Our results clearly align with our theoretical expectations; heterogeneity and strategic positioning of the network structure as a mechanism in our analysis. The results show the statistical pattern that centrality decreases the explanatory power, and provides a rationale for continuing with structural diversity and brokerage in innovation networks and other similar contexts.

The model has implications for learning, coordination, and governance in large-scale higher innovation systems, with z-values ("$p < 0.05$"). These results demonstrate that the strategic awareness of actors how they can use their network resources for knowledge coordination. The outcome of this study could support a policy framework in informing innovation governance, increases through adaptive coordination mechanisms.

Initially we thought this only applied locally, such as within a subset of innovation actors about collaboration intensity to our earlier assumptions about centrality and scale-based advantages for learning and knowledge diffusion in our analytical framework. Similarly, a review of evidence in the literature indicates that in the past network centrality for innovation has become less determinative for learning outcomes [3].

For example, [14] provides support for using collaborative ties, but has since been largely context-dependent for diffusion outcomes. While the assumption might have held for a whole generation of the network approach as a means of improving coordination and ensuring access with resources, the current evidence indicated that only some of the actors develop a much deeper understanding of using network positions in strategic learning in global systems.

However, although the results of this study confirm the general importance of networks, this analysis also demonstrates clearly that context the necessary conditions vary for learning outcomes. A limitation of this study is that we know the actors in this one sample may have characteristics that may be different from other contexts not observed in a national system or regional system in one without digital infrastructures and global linkages.

Although our dataset did not contain sufficient observations to fully represent considered to belong to the last generation categories of actors when their thresholds were not being met. Actors were clear about their experience of collaboration with the network and were consistent in their, most of the learning and coordination strategies on diversity, brokerage, selectivity, adaptation, and positioning in general, with centrality, density, and scale less emphasized or not at all strategically prioritized.

This again reminds us that we cannot simply classify actors as either central or peripheral that some forms of network position (e.g. the brokerage role) were not guaranteed to be effective for learning. The findings were also explicit about the need and that we need to understand the strategies of people with different positions to coordinate in certain contexts within larger systemic understandings of what innovation networks and knowledge diffusion entail.

5. Conclusion

We conclude that, rather than searching for the structural dominance and universal explanatory power of centrality measures and connectivity indicators, otherwise, a good policy heuristic for all innovation systems will not be achieved and the capacity for the governance framework to offer effective coordination mechanisms will be limited. This implies how innovation governance needs to adapt while digital infrastructures are being expanded, policy actors should reconsider how network structures work differently in global innovation systems and how they might be leveraged in both the coordination of existing innovation activities and in the development of new configurations of collaboration and learning.

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In addition, such a "structural–positional perspective" might be valuable for innovation policymakers as well, since actors might become more aware of the effects of their use of network positions and relational resources. Therefore, further research from a comparative perspective in moving to using network configurations in policy analysis is required to clarify both learning processes and make the strategic implications of their network positioning explicit [13]. Since this study has shown that effects of network centrality and connectivity might be context-dependent for learning outcomes, future research might also examine the dynamic effects of network positioning in different institutional settings.

There may be two possible reasons for explaining these: first, the purpose of this study was to identify structurally different strategies of using network positions for knowledge diffusion, such as exploration, exploration–exploitation, or specialization. Future studies should consider the interaction, sequencing, and temporal evolution of network structures in other analytical approaches such as longitudinal network analysis and comparative case studies in a broader range of other innovation systems, such as firms' innovation strategies and organizational work, regional clusters, or sectoral systems. However, future research might focus more explicitly on the role of institutional environments and the method of configurational analysis to examine how learning strategies of actors (firms) are shaped or constrained in innovation systems on different levels of analysis, such as regional, national, or global.

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Id	Label	Type	country	sector	Category	Modularity Class	Inferred Class	Eccentricity	Closeness Centrality	Harmonic Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
1	MIT Innovation Lab	University	USA	High-Tech	Research	0	0	14	0.158824	0.258274	50	0.306838
10	Peking University Science Park	University	China	Science	Research	3	3	3	0.555556	0.666667	2	0.226845
11	Samsung Advanced Institute of Technology	Company	South Korea	Electronics	Industry	5	1	6	0.318182	0.492857	0.5	0.310806
12	LG Innovation Center	Company	South Korea	Electronics	Industry	5	1	5	0.388889	0.540476	2.5	0.346335
13	Toyota Research Institute	Company	Japan	Automotive	Industry	2	4	1	1	1	1	0.075487
14	Sony R&D Center	Company	Japan	Electronics	Industry	2	4	2	0.666667	0.75	0	0.053269
15	Siemens Technology Hub	Company	Germany	Industrial Tech	Industry	4	0	11	0.16875	0.292875	135.5	0.606856
16	Bosch Research Campus	Company	Germany	Engineering	Industry	4	0	11	0.156977	0.24724	9.5	0.439512

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17	IBM Research Zurich	Company	Switzerland	ICT	Industry	7	0	16	0.137056	0.246525	24	0.362197
18	Google DeepMind	Company	UK	AI	Industry	6	0	12	0.210938	0.360348	221.5	1
19	Microsoft Research Asia	Company	China	ICT	Industry	3	3	3	0.555556	0.666667	2	0.226845
2	Stanford Technology Ventures	University	USA	High-Tech	Research	0	0	13	0.182432	0.293753	72	0.528791
20	Huawei Innovation Lab	Company	China	Telecom	Industry	3	3	3	0.555556	0.666667	2	0.226845
21	ETH Zurich Innovation Office	University	Switzerland	Engineering	Research	1	0	15	0.114407	0.215549	50	0.198289
22	EPFL Innovation Park	University	Switzerland	Engineering	Research	1	0	14	0.126168	0.230567	72	0.233519
23	KTH Royal Institute of Technology	University	Sweden	Engineering	Research	5	1	3	0.5	0.595238	12	0.321757
24	Chalmers Innovation Center	University	Sweden	Industrial Tech	Research	5	1	4	0.4375	0.559524	10	0.235469

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25	Aalto University Innovation Services	University	Finland	Design & Tech	Research	5	1	6	0.269231	0.378571	0	0.087057
26	VTT Technical Research Centre	Research Institute	Finland	Applied Science	Research	5	1	5	0.35	0.504762	6	0.164534
27	CSIRO Innovation	Research Institute	Australia	Science	Research	8	2	2	0.75	0.833333	0.5	0.226845
28	University of Melbourne Innovation Hub	University	Australia	Engineering	Research	8	2	2	0.75	0.833333	0.5	0.226845
29	University of Toronto Innovation Lab	University	Canada	AI	Research	6	0	10	0.207692	0.289433	180	0.35929
3	Fraunhofer Institute ISI	Research Institute	Germany	Industrial Tech	Research	4	0	12	0.146739	0.241979	3.5	0.439157
30	Vector Institute for AI	Research Institute	Canada	AI	Research	6	0	11	0.210938	0.308144	182	0.545068
31	Nokia Bell Labs	Company	Finland	Telecom	Industry	5	1	5	0.388889	0.540476	2.5	0.346335

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32	Ericsson Research	Company	Sweden	Telecom	Industry	5	1	4	0.5	0.654762	12.5	0.459218
33	Intel Labs Europe	Company	Ireland	Semiconductors	Industry	6	0	14	0.173077	0.293988	110	0.557521
34	ARM Research	Company	UK	Semiconductors	Industry	6	0	13	0.192857	0.329555	135.5	0.837922
35	Philips Innovation Services	Company	Netherlands	Health Tech	Industry	7	0	16	0.137056	0.246525	24	0.362197
36	ASML Research Center	Company	Netherlands	Semiconductors	Industry	7	0	15	0.155172	0.291563	93	0.542027
37	IMEC Research Institute	Research Institute	Belgium	Nanoelectronics	Research	4	0	13	0.139175	0.244575	92	0.282236
38	KU Leuven Innovation Office	University	Belgium	Engineering	Research	4	0	12	0.153409	0.26138	110	0.385503
39	CERN Knowledge Transfer Group	Research Institute	Switzerland	Physics	Research	1	0	16	0.103846	0.195483	26	0.151467
4	Max Planck Innovation	Research Institute	Germany	Science	Research	1	0	17	0.094406	0.157578	0	0.083397

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40	European Space Agency R&D	Research Institute	EU	Aerospace	Research	8	2	2	0.75	0.833333	0.5	0.226845
41	NASA Jet Propulsion Laboratory	Research Institute	USA	Aerospace	Research	8	2	2	0.75	0.833333	0.5	0.226845
42	Caltech Innovation Office	University	USA	Science	Research	0	0	16	0.122727	0.182224	0	0.092546
43	MIT Media Lab	University	USA	Digital Innovation	Research	0	0	15	0.139175	0.227101	26	0.186195
44	Harvard Innovation Labs	University	USA	Multidisciplinary	Research	6	0	9	0.201493	0.281761	176	0.321902
45	Alibaba DAMO Academy	Company	China	AI	Industry	3	3	3	0.555556	0.666667	2	0.226845
46	Tencent AI Lab	Company	China	AI	Industry	3	3	3	0.555556	0.666667	2	0.226845
47	SAP Innovation Center	Company	Germany	Enterprise Software	Industry	4	0	10	0.182432	0.299559	165.5	0.608925
48	Oracle Research Labs	Company	USA	Enterprise Software	Industry	4	0	9	0.192857	0.282128	170	0.396209

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49	University of Tokyo Innovation Platform	University	Japan	Engineering	Research	2	4	2	0.666667	0.75	0	0.053269
5	Cambridge Innovation Center	University	UK	High-Tech	Research	6	0	14	0.164634	0.265593	3.5	0.566976
50	Seoul National University Innovation Hub	University	South Korea	Engineering	Research	9	5	0	0	0	0	0
6	Oxford Innovation Ltd	University	UK	Biotech	Research	6	0	13	0.177632	0.279555	9.5	0.613778
7	CNRS Innovation	Research Institute	France	Science	Research	7	0	17	0.122727	0.223189	1	0.291316
8	INRIA Digital Systems	Research Institute	France	ICT	Research	7	0	17	0.122727	0.223189	1	0.291316
9	Tsinghua University Innovation Hub	University	China	Engineering	Research	3	3	3	0.555556	0.666667	2	0.226845

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