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Exploring Innovation Ecosystem with Multi-Layered Heterogeneous Networks of Global 5G Communication Technology

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Abstract: This study explores the dynamics of emerging technology innovation ecosystems, viewing them as complex systems comprising social actors and knowledge artifacts engaged in innovation interactions. Employing a multilayer network perspective, we present a Social-Knowledge-Science-Technology (A-K-S-T) framework, examining both homogeneous and heterogeneous interactions among innovators and knowledge elements. Within this framework, we map out the technological landscape, identify ecological niches for specific actors and knowledge elements, and gauge knowledge proximity among innovators, revealing opportunities for collaboration and knowledge innovation. Using 5G technology as an illustrative example, key findings include the potential for innovation development in 5G, the need for enhanced collaboration among organizations in related technological fields, and the complementary nature of scientific and technological knowledge. This research contributes to innovation ecosystem literature, offering insights for management, governance, efficiency, and shared prosperity; meanwhile, it is a valuable reference for decision-makers to shape effective strategies.

Keywords: 5G; innovation ecosystem (IE); social network; knowledge network; ecological niche; knowledge proximity

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1. Introduction

Innovation ecosystems (IE) have gained significant attention in the past decade [1] due to the pivotal role of innovation in implementing sustainability [2–4]. Recognized as a new driver of economic growth and a pathway to sustainable competitive advantage [5,6], scholars have sought to define IE concepts and components through literature reviews and qualitative research [7,8]. However, given diverse research focuses and theoretical foundations, the study of IE frameworks is currently marked by "diversity and contention". The composition and boundaries of IE have yet to be unified and established through quantitative research [9].

The subject of innovation, such as scientists, inventors, companies, research institutions, government departments, and investors, drives and influences the development of innovation through various interactions. Interactions, which encompass collaboration, competition, coopetition, and more, serve as the core driving force for promoting innovation. And the object of innovation, including knowledge, products, and services, represents both the resources and outcomes of innovation. Hence, at the conceptual level, based on quadruple and quintuple helix innovation systems, the innovation ecosystem is complex and heterogeneous [10], comprising actors, activities, and artifacts [7].

Network science serves as a crucial perspective for studying the innovation ecosystem, acting as a driving force for innovation development [11,12]. However, existing research on innovation networks commonly utilizes single-layer or homogeneous networks [13,14], which presents certain limitations in characterizing and describing the complexity and heterogeneity of the innovation ecosystem framework [15,16]. It is necessary to introduce multi-layered and heterogeneous networks for future inquiries into its structure and patterns.

Moreover, the utilization of multi-source heterogeneous data facilitates accurate identification and in-depth exploration of the distribution and proximity of actors and artifacts, interconnected through various activities. This approach establishes a robust data foundation and technical support for uncovering the collaborative mechanisms within the innovation ecosystem [17].

Existing research on innovation ecosystem architecture often focuses on individual components, such as actors or activities, neglecting the integration of all three components [15]. This study fills this gap by introducing a comprehensive and versatile framework for heterogeneous innovation ecosystems. The framework investigates the layout of innovation actors, distribution of innovation artifacts, and path dependence of innovation activities.

It introduces an innovation ecosystem framework that aims to quantitatively study the ecosystem using multi-layered and heterogeneous networks. The framework incorporates social innovators as actors, knowledge elements as artifacts, and collaboration/combination as activities. The framework has the potential to address the following questions:

1. What is the holistic IE framework?
2. Which innovative actors occupy critical niches in the macro–micro social cooperation network?
3. How do knowledge elements in specific niches differ between science and technology sub-ecosystems?
4. What is the knowledge proximity among actors and distribution of knowledge areas?

This study expands the research on innovation ecosystem theory by proposing a novel multi-layered complex network framework to study interactions in innovation. It enriches the understanding of innovation ecosystem theory and provides new insights for managing, governing, and enhancing the efficiency and shared prosperity of the innovation ecosystem, sustaining innovation advantage.

The remainder of the paper is structured as follows: Section 2 offers an overview of the relevant literature. Section 3 introduces the proposed framework and methodology. Section 4 outlines the case, presents data, and applies the framework to the global 5G communication technology industry. Section 5 discusses the findings. Finally, Section 6 concludes with implications.

2. Literature Review

2.1. Innovation Ecosystem and Its Compositions in Network Perspective

The innovation ecosystem concept arises from the integration of "business ecosystems" [18] and value co-creation process [19]. It has become a new research perspective in innovation and innovation management [8,20,21].

Etzkowitz and Leydesdorff (2000) proposed the Triple Helix innovation model consisting of university–industry–government, emphasizing the importance of knowledge generation and innovation in the economy [22,23]. Subsequently, Carayannis and Campbell (2006) added the 'media-based and culture-based public' and 'civil society' as a fourth helix to the Triple Helix model, forming the Quadruple Helix innovation model [24]. This model highlights the need for the sustainable innovation of knowledge in the economy to evolve in conjunction with knowledge society and democracy. Furthermore, considering the importance of the 'natural environments of society', Carayannis, E.G., et al. (2012) proposed the more comprehensive Quintuple Helix innovation model [25,26]. This model emphasizes the crucial role of socio-ecological transformation in driving innovation. Therefore, innovation ecosystems, based on both democracy and ecology, exhibit broader scope, increased complexity, diversity, and heterogeneity.

Researchers defined the composition and boundaries of IE architecture according to different research preferences and goals [9] through literature review and bibliometric studies [27,28]. Based on previous research, Granstrand and Holgersson (2020) [7] proposed the "3A" architecture of innovation ecosystems, including participants, artifacts, and activities. However, quantitative research in this area is limited, with most studies being theoretical. This study proposes a new IE framework from the perspective of quantitative complex networks based on the "3A" architecture.

Innovation actors collaborate to form social networks, while knowledge elements combine to form knowledge networks. Both are innovative interactive networks. Previous social network research has explored cooperative relationships, information flows, and decision-making processes among countries, organizations, and individuals, respectively [29–31]. However, a comprehensive analysis of innovative social networks at these levels is lacking. This study aims to fill this gap by examining innovation social networks at the macro, meso, and micro levels, focusing on countries, organizations/firms, and individuals as innovation actors. Knowledge elements are the preliminary conclusions held by research communities in scientific and technological fields [32]. They encompass facts, theories, methods, and procedures related to specific topics [33,34]. The innovation of emerging technologies relies on combining or recombining these knowledge elements, making them crucial for innovation [34,35]. In fact, existing knowledge network research has divided knowledge elements into scientific knowledge and technical knowledge. Scientific knowledge elements focus on knowledge discovery [36], while technological knowledge elements emphasize ownership and application [37]. Both types of knowledge are important in the innovation ecosystem [32,38] and are interconnected with the relationships between innovation actors. Several studies have examined networks of scientific knowledge elements [39,40], while others have focused on networks of technological knowledge elements [27,41,42]. Previous studies have examined scientific knowledge element networks [39] or technical knowledge element networks [17,43].

Research specifically analyzing and comparing these two types of knowledge meta-networks is still limited. The network characteristics of scientific and technological knowledge need to be integrated and mined. Furthermore, collaborative interactions among innovators [44] and their impact on the potential to combine scientific and technological knowledge are key factors in promoting innovation. Our study focuses on the collaboration between innovation subjects and the combination of knowledge elements.

2.2. Multilayer Heterogeneous Network for Innovation and Data

The social network formed by innovators and the knowledge network composed of knowledge elements have a double embedded relationship [32]. At the same time, they exhibit heterogeneity and decoupling [15]. Previous research has explored the impact of dual embedded relationships in heterogeneous networks on organizational innovation [45], emphasizing that the degree of integration of social networks and the diversity of knowledge networks are two driving factors for organizational-level innovation. Over time, they evolve in a spiral pattern [26]. Thus, the IE construction includes two heterogeneous networks: social network and knowledge network.

Innovation collaborations can be organized and managed at multiple levels of analysis [29] with a multilevel network perspective [46,47]. However, most studies on innovative complex networks focus on single-layer and homogeneous networks, ignoring the underlying characteristics of real complex innovation ecosystems. Combining the above studies and the diversity and heterogeneity of innovation ecosystems, it becomes imperative to utilize multi-layer heterogeneous networks [16,48] to study and understand the IE framework.

Furthermore, utilizing multivariate heterogeneous datasets allows for improved resolution and consideration of multiple characteristics of real innovation ecosystems [49]. Bibliometrics [50] and patent data [27] have been widely used in innovation research to assess and characterize technological innovations. This study integrates different heterogeneous data to improve the validity and credibility of the study [16] and analyzes a novel IE framework for emerging technologies [51].

2.3. Key Attributes of Innovation Ecosystems: Ecosystem Niche and Knowledge Proximity

An innovation ecosystem niche, as a fundamental element of the structuralist approach to ecosystems, refers to the specific position of actors and artifacts within the flow of overall system activity [5]. It is related to strategic resources and direction [52] and has a positive impact on the exploration and utilization of innovation [53]. Assessing the positioning of innovation subjects and products in the ecosystem and distinguishing the focus subjects and internal logic of the innovation ecosystem are of great significance to value creation [36].

Hub nodes and bridging nodes occupy special ecological niches in the ecosystem framework [53]. Hub nodes have a large number of connections and play a critical role in strong connections. Collaboration between Hub nodes drives technological progress, promotes cooperation and standardization, identifies key areas and innovators of the technology ecosystem, and guides and supports technological development and innovation. On the other hand, bridging nodes have the ability to bridge different sub-networks in weak connections, facilitating information transfer and facilitating collaboration between different actors or knowledge areas. Network features, degree [32], and betweenness centrality [54] are used to identify these nodes.

Knowledge proximity, which focuses on the similarity of knowledge structure and technological experience among innovation actors, has received significant attention in recent innovation network research [55,56]. Exploring the proximity of knowledge in the innovation ecosystem is beneficial to the interactive learning, knowledge acquisition and innovation success of innovative subjects.

In summary, this study provides a comprehensive IE framework from a network perspective [57], where actors are classified into macro–meso–micro levels, knowledge elements as artifacts are categorized into scientific knowledge and technological knowledge, and collaboration among actors and combination of knowledge elements are identified as activities [52].

3. Theoretical Framework and Methodology

3.1. Social-Knowledge-Science-Technology(A-K-S-T) Ecosystem Framework

We construct a social-knowledge-science-technology (A-K-S-T) framework that involves four main components: social actor collaboration in the scientific sub-ecosystem, knowledge combination in the scientific sub-ecosystem, social actor collaboration in the technological sub-ecosystem, and knowledge combination in the technological sub-ecosystem, as shown in Figure 1. The corresponding networks are A-S, K-S, A-T, and K-T networks, which are homogeneous networks. A-K-S and A-K-T networks connect innovation participants with knowledge elements to form heterogeneous networks. The network was constructed using multidimensional data and qualitative interviews, with academic paper data for the scientific sub-ecosystem and patent data for the technology sub-ecosystem. This framework aims to encompass the diverse actors and heterogeneous interactions within the innovation ecosystem, facilitating a comprehensive and holistic exploration of its architecture. By adopting a comprehensive and global perspective, our study avoids potential limitations associated with a focus on a single research problem.

3.1.1. A-S Network and A-T Network

A-S and A-T networks describe the collaboration of social participants in the innovation ecosystem, where nodes represent innovation participants and edges represent collaboration on academic papers or patents. The A-S network focuses on basic research cooperation, and the A-T network focuses on feasibility research cooperation. The networks were constructed at different levels, including country-based (C-S and C-T), organization-based (O-S and O-T), and author-based (I-S and I-T) networks, using data from academic articles and patents. When generating edges, the repetition number for a country or organization is set equal to the number of corresponding authors, reflecting the significance of country or organization in innovation collaboration.

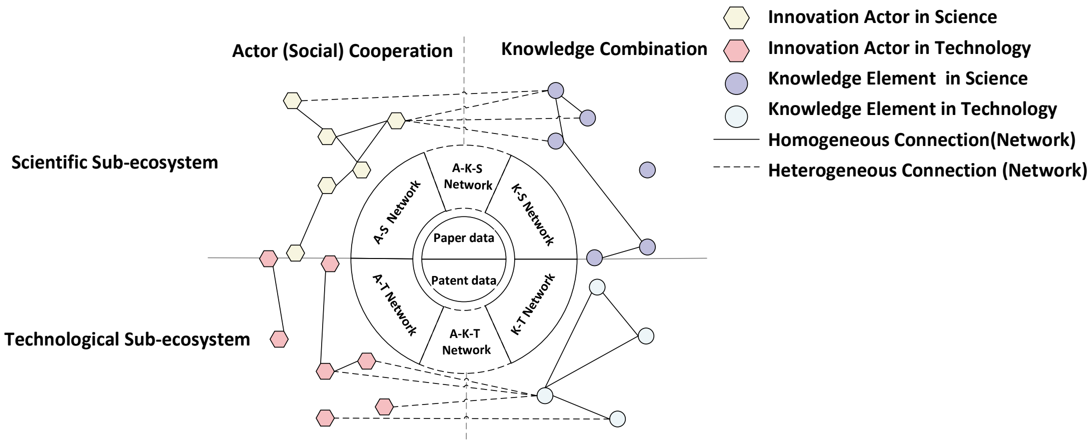

Figure 1. Innovation ecosystem framework.

3.1.2. K-S Network and K-T Network

The K-S and K-T networks emphasize the combination of knowledge elements within the innovation ecosystem, focusing on knowledge discovery and technological experimentation, respectively. In these networks, knowledge elements are represented as nodes, and combinations between knowledge elements in academic papers or patents are represented as edges. Knowledge elements, obtained from academic paper and patent data, such as keywords or IPC (international patent classification) codes, are used to establish K-S network in the scientific sub-ecosystem and K-T network in the technological sub-ecosystem.

3.1.3. A-K-S Network and A-K-T Network

The A-K-S and A-K-T networks emphasize the connections between actors and knowledge elements in scientific and technological innovation. Nodes represent innovators and knowledge elements, while edges link these two types of nodes. An edge is created when an innovator is associated with a knowledge element in a paper or patent. Due to the hierarchical nature of actors, these heterogeneous networks are divided into different levels. A-K-S network includes the C-K-S network (country-based), O-K-S network (organization-based) and I-K-S network (author-based) in the scientific sub-ecosystem, while the A-K-T network comprises the C-K-T network, O-K-T network, and I-K-T network in the technological sub-ecosystem.

3.2. Network Construction

The A-K-S-T framework is represented by a multilayer heterogeneous network, $G = \{G_{A-S}, G_{K-S}, G_{A-T}, G_{K-T}\}$. The first layer, $G_{A-S} = (V_{A-S}, E_{A-S})$, represents the scientific social actor collaboration network; the second layer, $G_{K-S} = (V_{K-S}, E_{K-S})$, represents the scientific knowledge combination network; the third layer, $G_{A-T} = (V_{A-T}, E_{A-T})$, represents the technological social actor collaboration network; and the fourth layer, $G_{K-T} = (V_{K-T}, E_{K-T})$, represents the technological knowledge combination network, as shown in Figure 2 and Table 1.

$$V_{A-S} = \left\{v_{A-S(1)}, v_{A-S(2)}, v_{A-S(3)}, \ldots, v_{A-S(N_{A-S})}\right\},$$

$$V_{K-S} = \left\{v_{K-S(1)}, v_{K-S(2)}, v_{K-S(3)}, \ldots, v_{K-S(N_{K-S})}\right\},$$

$$V_{A-T} = \left\{v_{A-T(1)}, v_{A-T(2)}, v_{A-T(3)}, \ldots, v_{A-T(N_{A-T})}\right\} \text{and}$$

$$V_{K-T} = \left\{v_{K-T(1)}, v_{K-T(2)}, v_{K-T(3)}, \ldots, v_{K-T(N_{K-T})}\right\}$$

represent the sets of nodes in corresponding homogeneous networks, where $N_{A-S} = |V_{A-S}|$, $N_{K-S} = |V_{K-S}|$, $N_{A-T} = |V_{A-T}|$, and $N_{K-T} = |V_{K-T}|$ are the node numbers.

$$E_{A-S} = \left\{ e_{(v_{A-S(i)}, v_{A-S(j)})}, v_{A-S(i)}, v_{A-S(j)} \in V_{A-S} \right\},$$

$$E_{K-S} = \left\{ e_{(v_{K-S(i)}, v_{K-S(j)})}, v_{K-S(i)}, v_{K-S(j)} \in V_{K-S} \right\},$$

$$E_{A-T} = \left\{ e_{(v_{A-T(i)}, v_{A-T(j)})}, v_{A-T(i)}, v_{A-T(j)} \in V_{A-T} \right\} \text{and}$$

$$E_{K-T} = \left\{ e_{(v_{K-T(i)}, v_{K-T(j)})}, v_{K-T(i)}, v_{K-T(j)} \in V_{K-T} \right\}$$

represent the sets of edges within corresponding homogeneous networks, where $M_{A-S} = |E_{A-S}|$, $M_{K-S} = |E_{K-S}|$, $M_{A-T} = |E_{A-T}|$, and $M_{K-T} = |E_{K-T}|$ are the edge numbers.

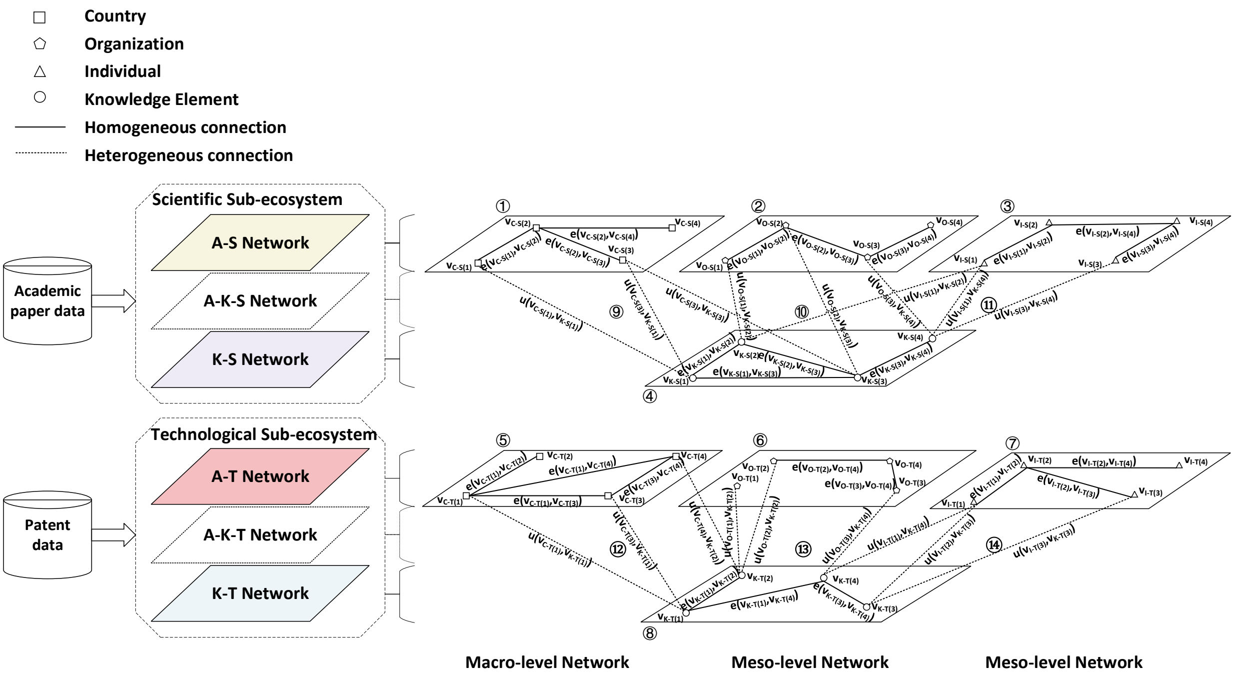

Figure 2. A-K-S-T framework.

Table 1. Network description within A-K-S-T framework.

Layer	G_{Node} / $G_{Network}$	Social Actor Cooperation at Macro–Meso–Micro Level: $V_{Country}$	$V_{Organization}$	$V_{Individual}$	Knowledge Combination: $V_{Knowledgeelement}$	Sample
1st	G_{A-S}	① G_{C-S}	② G_{O-S}	③ G_{I-S}		
2nd	G_{K-S}				④ G_{K-S}	
3rd	G_{A-T}	⑤ G_{C-T}	⑥ G_{O-T}	⑦ G_{I-T}		
4th	G_{K-T}				⑧ G_{K-T}	
1st–2nd	G_{A-K-S}	⑨ G_{C-K-S}	⑩ G_{O-K-S}	⑪ G_{I-K-S}		
3rd–4th	G_{A-K-T}	⑫ G_{C-K-T}	⑬ G_{O-K-T}	⑭ G_{I-K-T}		

Note: A—social actor, K—knowledge element, S—scientific sub-ecosystem, T—technological sub-ecosystem, C—country, O—organization, I—individual; ⬠ represents social actor, ◯ represents knowledge element.

Interlayer links between nodes from different layers (social actor collaboration network layer and knowledge combination network layer in two sub-ecosystems) are converged into the link sets $U_{A-K-S} = \{u_{ij} \subseteq V_{A-S} \times V_{K-S}, i \in V_{A-S}, j \in V_{K-S}\}$ and $U_{A-K-T} = \{u_{mn} \subseteq V_{A-T} \times V_{K-T}, m \in V_{A-T}, n \in V_{K-T}\}$, forming subordinate heterogeneous networks $G_{A-K-S} = (V_{A-S}, V_{K-S}, U_{A-K-S})$ and $G_{A-K-T} = (V_{A-T}, V_{K-T}, U_{A-K-T})$.

Moreover, social actors [58] can be categorized from macro to micro levels, such as nations, organizations, and individuals. Accordingly, the corresponding homogeneous social actor cooperation networks, G_{A-S} and G_{A-T}, are divided into country cooperation networks G_{C-S} and G_{C-T}, organization cooperation networks G_{O-S} and G_{O-T}, and individual cooperation networks G_{I-S} and G_{I-T}. Similarly, the heterogeneous knowledge networks, G_{A-K-S} and G_{A-K-T}, consist of country knowledge networks G_{C-K-S} and G_{C-K-T}, organization knowledge networks G_{O-K-S} and G_{O-K-T}, and individual knowledge networks G_{I-K-S} and G_{I-K-T}.

The A-K-S-T framework consists of four layers, including two sub-ecosystems, for a total of fourteen networks. Among them, there are 8 homogeneous networks and 6 heterogeneous networks, reflecting the collaboration and knowledge combination relationships of various actors at different levels and dimensions. By adopting a complex network perspective, this study enables a quantitative exploration of the innovation ecosystem, thereby complementing the existing qualitative research that may lack comprehensiveness.

3.3. Network Measurement

To fully understand the performance and properties of the entire A-K-S-T framework, network analysis [59] is needed to measure global network characteristics, detect special ecosystem niches of central and bridging nodes, and identify knowledge proximity. This approach enables a multi-faceted exploration of the innovation ecosystem. Table 2 lists the correspondence between innovation characteristics and network measures.

Table 2. Correspondence between innovation feature and network metric.

A-K-S-T Framework	Innovation Feature	Network Metric	Formula	Explanation	Reference
Network characteristics	Innovators' connection distance	Average shortest path and diameter	$L = \frac{2}{N(N-1)} \sum_{G} L_{v_i v_j}$ $D = \max_{G} L_{v_i v_j}$	Shorter distances, closer collaboration. $L_{v_i v_j}$ is shortest path length between nodes v_i and v_j, N is node number. If $L \leq \ln N$, it is a small-world network.	[60,61]
	Community stability	Modularity and community quantity	$Q = \frac{1}{2M} \sum_{v_i, v_j \in G} \left[A_{v_i v_j} - \frac{d_{v_i} d_{v_j}}{2M} \right] \delta\left(C_{v_i}, C_{v_j}\right)$	Stronger community structure, higher value of modularity. M is edge number, A is adjacency matrix. If v_i and v_j belong to same module, $\delta\left(C_{v_i}, C_{v_j}\right) = 1$; otherwise, $\delta\left(C_{v_i}, C_{v_j}\right) = 0$.	[62]
	Cohesion	Clustering coefficient	$C_{v_i} = \frac{2M_{v_i}}{d_{v_i}\left(d_{v_i} - 1\right)}$ $C = \frac{1}{N} \sum_{v_i \in G} C_{v_i}$	C relates the openness and synergies of networks. M_{v_i} is actual edge.	[61,63,64]
	Interaction effectiveness	Global efficiency	$E_{glob}(G) = \frac{\sum_{v_i \neq v_j \in G} \epsilon_{v_i v_j}}{N(N-1)}$	High E_{glob} exhibits high efficiency in global interaction. Efficiency $\epsilon_{v_i v_j} = \frac{1}{L_{v_i v_j}}$, $\forall v_i, v_j \in G$.	[30,65,66]
Special ecosystem niche	Influence of hub node	Degree and degree distribution	$d_{v_i} = \sum_{\forall v_j \in G} x_{v_i v_j}$ $f(x) = \lambda x^{-\alpha}$	d_{v_i} represents the importance and centralization of nodes [67]. Power − law exponent α reveals the cooperative strength of network.	[47,68–70]
	Bridging capability of articulation points	Betweenness centrality	$BC(v_i) = \sum_{v_s, v_t \in G} \frac{\sigma(v_s, v_t \mid v_i)}{\sigma(v_s, v_t)}$	Bridging nodes controls the flow of non-redundant innovation resource or information [54]. $\sigma(v_s, v_t)$ represents the number of shortest paths passing through v_s and v_t, and $\sigma(v_s, v_t \mid v_i)$ is the number of these paths passing through v_i.	[54,60,71,72]
Innovators' knowledge proximity	Knowledge distribution	JS divergence	$JS_{v_i v_j}(p, q) = \frac{1}{2}\left[KL\left(p, \frac{p+q}{2}\right) + KL\left(q, \frac{p+q}{2}\right)\right]$	Dissimilarity of knowledge domains evaluates innovators' knowledge focus distribution $p(v_i)$ and $q(v_j)$ are probability densities of knowledge distributions between two innovators. $KL(\cdot)$ is KL distance.	[54,73–76]
	Knowledge cognitive distance	Euclidean Distance and machine learning.	$dist(v_i, v_j) = \sqrt{\sum_{w=1}^{m} \left(v_{iw} - v_{jw}\right)^2}$	Cognitive distance among innovators in knowledge domains. Dimension m is module number, w is the wth knowledge module, v_i and v_j are two inventors in same knowledge areas.	[55]

Sources: summarized by authors.

3.4. Data

The emergence of 5G telecommunication technology in recent years has sparked a wave of technological revolution, which is an impactful development. Although the novel innovative ecosystem framework holds broad practicality and can be applied to various technological innovation field, this study focused on conducting a case study using representative innovation data related to 5G technology.

We collected heterogeneous data on global 5G communication technologies [77], including 43,357 research papers from the ISI Web of Science Core Collection and 28,478 patents from the Derwent World Patent Index. After filtering and deduplication, we retained 32,732 articles and 22,039 patents. Relevant information, such as identity, time, country, organization, author, and keywords, were extracted. Data were peer-reviewed, uncommon entities were removed, and branches and subsidiaries were consolidated. Unsupervised learning, expert interviews, literature analysis and other methods were used to classify knowledge elements into modules. Network generation and social network analysis were conducted using Python 3.8.8 and Gephi 0.9.2

4. Case Study: Worldwide 5G Telecommunication Ecosystem

4.1. Overview: Worldwide 5G Telecommunication Technology

5G telecommunications [78,79] are crucial to building a new generation of information infrastructure that provides high speed, large capacity, and low latency. It supports enhanced mobile broadband (eMBB), massive machine type communications (mMTC), and ultra-reliable and low-latency communications (uRLLC) as envisioned by the International Telecommunications Union. The continuous optimization and advancement of 5G technology is the basis for the digital transformation of social economy [80–82].

Since the 5G technology vision was proposed in 2012, countries around the world have formulated policies and invested large amounts of money to actively develop 5G technology. 5G technology has become a global emerging technology with a relatively complete life cycle [43,83]. Understanding the personnel distribution of 5G technology and the overall development of technical knowledge means that finding opportunities to achieve technological catch-up and progress are issues of common concern to policymakers and innovation participants. This work applies the A-K-S-T ecosystem framework to study 5G technology IE on a global scale.

Additionally, through unsupervised learning, expert interviews and modularity measurements of G_{K-S} and G_{K-T}, the knowledge elements of 5G technology, are categorized into five modules: wireless communication, network architecture, termination, application scenarios, and security and privacy protection. Figure 3 presents 16 main functions associated with these modules.

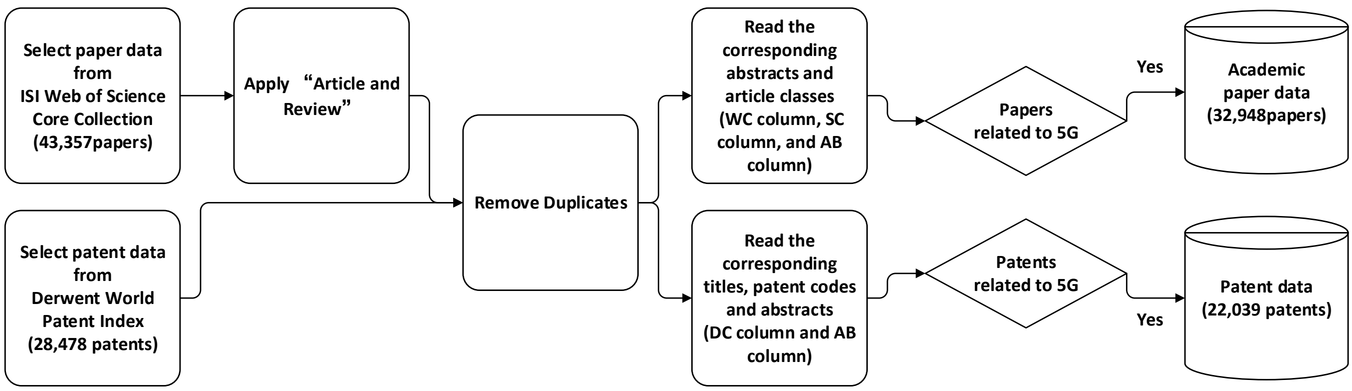

Figure 3. Flowchart of the data processing.

4.2. A-K-S-T Framework of 5G Telecommunication Ecosystem

The 5G technology innovation ecosystem within the A-K-S-T framework is shown in Figure 4, which presents the diverse network structures between different networks. Table 3 summarizes the overall characteristics of the eight homogeneous networks.

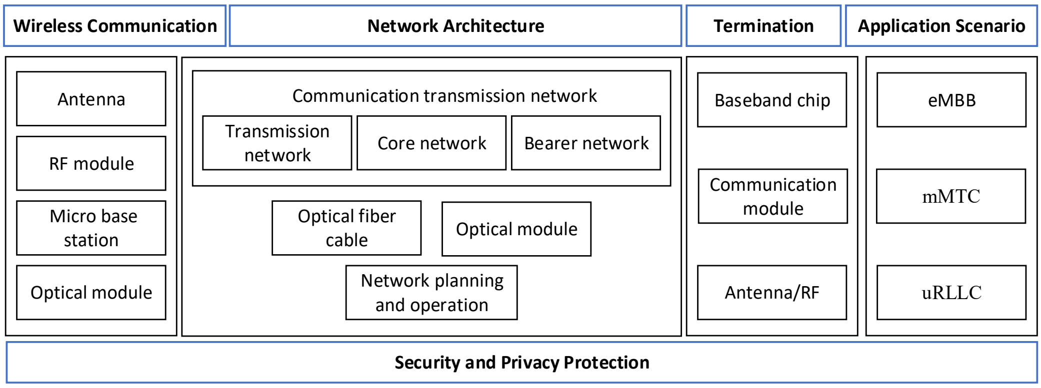

Figure 4. Knowledge modules of 5G technology (Sources: summarized by authors, adapted from expert interviews, machine learning, and Akyildiz et al.(2016) [84]).

Table 3. Statistics of network features of homogeneous networks.

	G	N_G	M_G	D_G	L_G	Q_G	$N_{com}(G)$	C_G	$E_{glob}(G)$	$G_{connected}$
①	G_{C-S}	131	1790	4	1.917	0.113	5	0.776	0.5841	True
②	G_{O-S}	3535	28,061	9	3.257	0.406	50	0.437	0.3133	False
③	G_{I-S}	7758	43,157	15	4.598	0.661	215	0.557	0.2003	False
④	G_{K-S}	5356	145,997	6	2.226	0.313	5	0.436	0.4663	False
⑤	G_{C-T}	37	336	3	1.505	0.080	2	0.899	0.7508	True
⑥	G_{O-T}	334	399	8	2.846	0.933	81	0.691	0.0182	False
⑦	G_{I-T}	3172	74,554	8	2.676	0.350	41	0.509	0.3901	False
⑧	G_{K-T}	2230	60,758	7	2.641	0.454	5	0.515	0.4094	False

Note: G—network, N_G—number of nodes, M_G—number of edges, D_G—diameter of network, L_G—average shortest path, Q_G—modularity, $N_{com}(G)$—number of communities, C_G—clustering coefficient, $E_{glob}(G)$—global efficiency, $G_{connected}$—whether network is connected.

First, numbers of innovators and collaborations increase from macro to micro levels in both sub-ecosystems. In the scientific sub-ecosystem, the numbers of innovators and collaboration follows the sequence: $N_{G_{C-S}} < N_{G_{O-S}} < N_{G_{I-S}} = 131 < 3535 < 7758$ and $M_{G_{C-S}} < M_{G_{O-S}} < M_{G_{I-S}} = 1790 < 28,061 < 43,157$. In technological sub-ecosystem, the sequences are: $N_{G_{C-T}} < N_{G_{O-T}} < N_{G_{I-T}} = 37 < 334 < 3172$ and $M_{G_{C-T}} < M_{G_{O-T}} < M_{G_{I-T}} = 336 < 399 < 74,554$.

It is worth noting that in the scientific sub-ecosystem, organizations account for 45.56% of the total number of individual inventors, and cooperation between organizations accounts for approximately 65.04% of the total cooperation between individuals. In contrast, in the technology sub-ecosystem, organizations account for only about 10.53% of the total number of individual inventors, and cooperation between organizations only accounts for 0.54% of the total cooperation between individuals.

Second, as shown in Table 4, in addition to the number of collaborations at the micro level, scientific ecosystems generally exceed technology ecosystems in terms of participants and collaborations. The most significant differences in collaboration among technological innovations occur at the organizational level. Furthermore, although scientific innovation involves more individuals than technological innovation, there is less collaboration in scientific innovation.

Table 4. Ratio of innovator and collaboration in scientific and technological innovation.

Ratio	National-Level	Organizational-Level	Individual-Level
$N_{G_{A-S}}/N_{G_{A-T}}$	3.54	10.59	2.45
$M_{G_{A-S}}/M_{G_{A-T}}$	5.33	70.43	0.58

Note: $N_{G_{A-S}}/N_{G_{A-T}}$—ratio of scientific innovators to technological innovators. $M_{G_{A-S}}/M_{G_{A-T}}$—ratio of scientific collaborations to technological collaborations.

From the perspective of knowledge elements, both sub-ecosystems present rich and diverse knowledge elements and their combinations. There are approximately twice as many knowledge elements and combinations in G_{K-S} as in G_{K-T}, $N_{G_{K-S}} > N_{G_{K-T}} = 5356 > 2230$ and $M_{G_{K-S}} > M_{G_{K-T}} = 145,997 > 60,758$. In the complete framework, G_{K-S} has the highest number of edges, $M_{G_{K-S}} = 145,997$, which reflects the abundance of scientific knowledge combinations.

G_{I-S} has the highest diameter and average shortest path, with $D_{G_{I-S}} = 15$ and $L_{G_{I-S}} = 4.598$, indicating greater distance among scientific innovators. G_{I-S} also exhibits the longest connection distance compared to other networks in the framework. In contrast, G_{C-T} has the fewest nodes and edges, but it is a connected graph with the smallest diameter of $D_{G_{C-T}} = 3$ and the shortest average shortest path of $L_{G_{C-T}} = 1.5045$. G_{C-T} has the shortest connection distance in entire framework.

G_{C-T} has the lowest modularity value of $Q_{G_{C-T}} = 0.080$ when $N_{com}(G_{C-T}) = 2$, indicating weak community stability. G_{I-S} achieves a high modularity value of $Q_{G_{I-S}} = 0.661$ when $N_{com}(G_{I-S}) = 215$. G_{O-T} has the highest modularity of $Q_{G_{O-T}} = 0.933$ when $N_{com}(G_{O-T}) = 81$, illustrating the most stable communities.

The clustering coefficient of G_{K-S} is the smallest, $C_{G_{K-S}} = 0.436$, indicating relatively lower node cohesion. Conversely, G_{C-T} exhibits the largest clustering coefficient, $C_{G_{C-T}} = 0.899$, signifying higher node cohesion and interconnectedness.

G_{C-T} exhibits the highest global efficiency, $E_{glob}(G_{C-T}) = 0.7508$, reflecting high effective national cooperation in the technological sub-ecosystem. In contrast, G_{O-T} has the lowest global efficiency, $E_{glob}(G_{O-T}) = 0.0182$, indicating less effective organizational cooperation. Only G_{C-S} and G_{C-T} are connected, while the other networks contain isolated nodes or disconnected subgraphs, limiting their connectivity.

4.3. Special Ecosystem Niche in 5G Telecommunication Ecosystem

4.3.1. Hub Nodes in Strong Connections

- Degree and degree distribution

As show in Table 5, in the scientific sub-ecosystem, innovators' collaboration degrees decline from macro to micro levels: $d_{Mean}(G_{C-S}) > d_{Mean}(G_{O-S}) > d_{Mean}(G_{I-S})$. Within the technological sub-ecosystem, organizational-level collaboration is the lowest: $d_{Mean}(G_{C-T}) > d_{Mean}(G_{I-T}) > d_{Mean}(G_{O-T})$. Standard deviation in G_{I-S} is the smallest, indicating relatively similar cooperation levels among individuals in the scientific sub-ecosystem.

Table 5. Descriptive statistics of degrees.

	G	d_{Mean}	d_{Max}	d_{Min}	$d_{Meadian}$	$d_{S.D.}$
①	G_{C-S}	344.02	4614	1	57	724.01
②	G_{O-S}	28.31	1562	1	9	75.4
③	G_{I-S}	25.80	529	1	16	32.42
④	G_{K-S}	99.62	30,005	1	32	505.87
⑤	G_{C-T}	3329.83	19,522	1	649	5613.09
⑥	G_{O-T}	15.60	350	1	5	33.77
⑦	G_{I-T}	95.43	2194	1	40	178.28
⑧	G_{K-T}	194.79	15,988	1	40	655.96

Cooperation degrees and their standard deviations are lower in the scientific sub-ecosystem compared to the technological sub-ecosystem at macro and micro levels: $d_{Mean}(G_{C-S}) < d_{Mean}(G_{C-T})$, $d_{Mean}(G_{I-S}) < d_{Mean}(G_{I-T})$, $d_{S.D.}(G_{C-S}) < d_{S.D.}(G_{C-T})$, and $d_{S.D.}(G_{I-S}) < d_{S.D.}(G_{I-T})$. This suggests that scientific innovation exhibits less pronounced cooperation than technological innovation at the national and individual levels, with minimal variation among countries or individuals.

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Conversely, at the meso level, the degree of cooperation and its standard deviation in the scientific sub-ecosystem surpass those in the technological sub-ecosystem: $d_{Mean}(G_{O-S}) > d_{Mean}(G_{O-T})$ and $d_{S.D.}(G_{O-S}) > d_{S.D.}(G_{O-T})$. This indicates that, within organizational settings, scientific innovation exhibits higher levels of cooperation and dispersion compared to technological innovation.

From the perspective of knowledge elements, scientific innovation features fewer knowledge combinations than technological innovation, $d_{Mean}(G_{K-S}) < d_{Mean}(G_{K-T})$. Moreover, the differences in knowledge combinations within scientific innovation are less pronounced than those within technological innovation, as $d_{S.D.}(G_{k-S}) < d_{S.D.}(G_{K-T})$.

The degree distribution of each network is shown in Figure 5. After fitting the power law [85], the minimum coefficient Alpha value and the distance from the empirical data are summarized in Table 6, which reflects the degree of integration of organizational cooperation, individual cooperation, and knowledge, except for national-level cooperation with larger distance values.

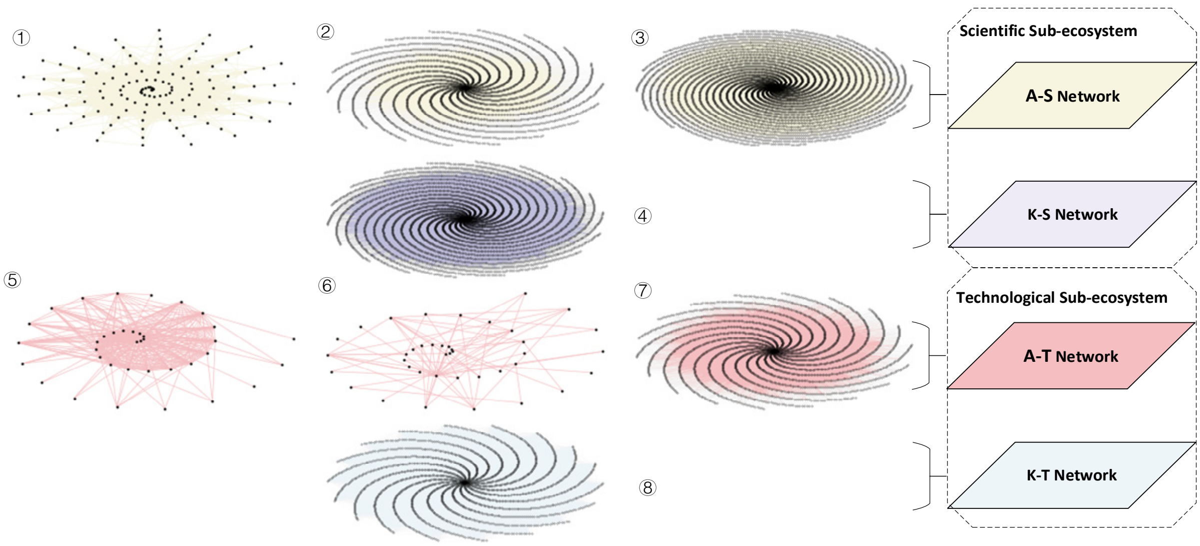


Figure 5. A-K-S-T framework of 5G telecommunication technology.

Table 6. Alpha α of the power law fitting function.

	G_{C-S}	G_{O-S}	G_{I-S}	G_{K-S}	G_{C-T}	G_{O-T}	G_{I-T}	G_{K-T}
α	2.897	2.792	3.753	2.051	9.156	3.271	2.462	3.283
Distance	0.15	0.052	0.051	0.053	0.26	0.096	0.049	0.069

- Hub nodes

Extensive collaboration among central nodes facilitates the exchange of information and resources. Figure 6 shows the comparison and geographical affiliation of the five most influential nodes in each network from macro to micro.

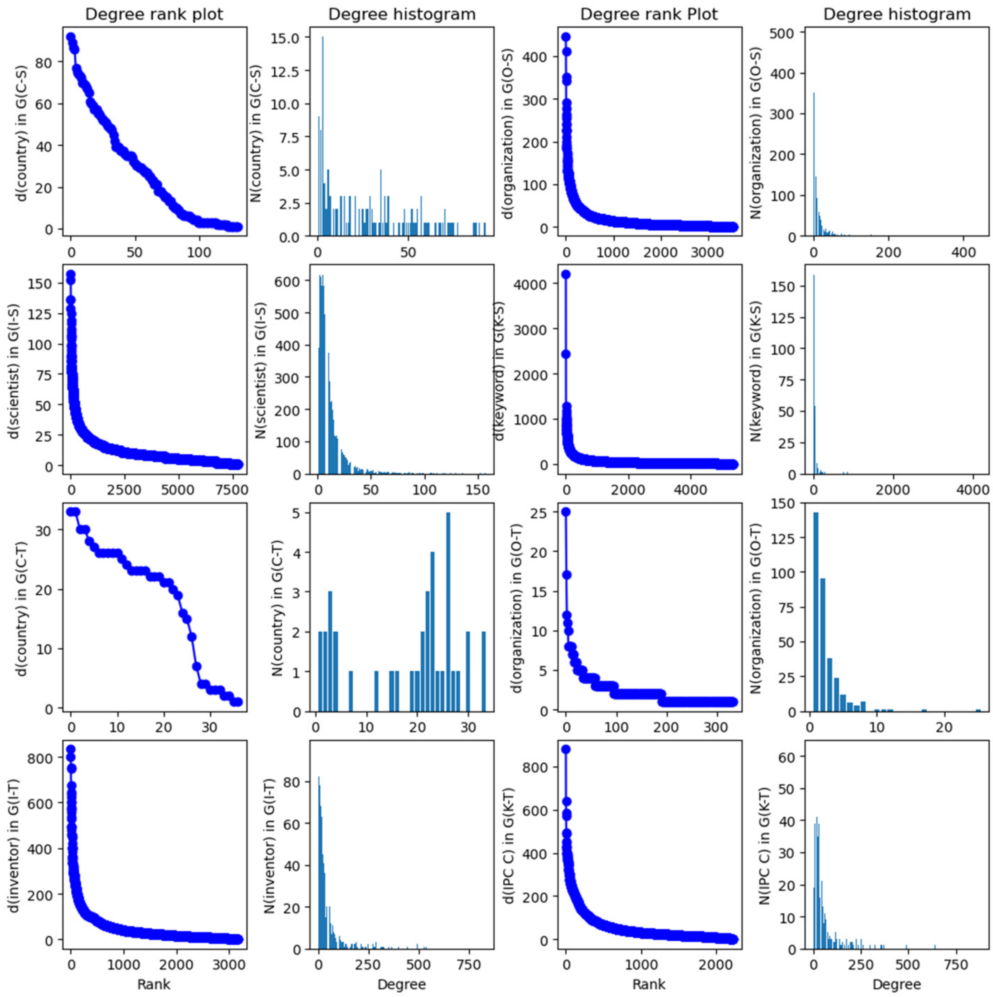


Figure 6. Degree distribution in each network.

China and the United States (US) exhibit remarkable collaboration in both scientific (G_{C-S}) and technological (G_{C-T}) innovation. United Kingdom, France, and Germany hold significant influence in scientific innovation cooperation, while the EP and WO, as country unions, along with China and the US, play crucial roles in technological innovation. These countries contribute to national-level knowledge innovation, exchange, and protection.

In G_{O-S} and G_{O-T}, Huawei and Nokia are influential players in both sub-ecosystems. Ericsson, Beijing University of Posts and Telecommunications (BUPT), and Southeast University focus on scientific cooperation, while Oppo, Samsung, and Sony demonstrate stronger collaboration in the technological sub-ecosystem. Among the top-20 influential organizations, universities and research institutes dominate in scientific innovation (75%), while enterprises dominate in technological innovation (100%). Chinese organizations, both enterprises and universities, have a significant presence in both scientific and technological innovations. European companies from Finland and Sweden excel in scientific innovation, while Samsung from Korea and Sony from Japan hold substantial influence in technological innovation.

In G_{I-S}, influential scientists in 5G telecommunications, such as Zhiguo Ding and H. Vincent Poor, provide references for other researchers. There are multiple scientists named

Yangyang in G_{I-S}, which may be due to shared names or scientists changing workplaces. With comprehensive personal information, this method could accurately identify high-impact inventors in specific technical fields.

In G_{K-S} and G_{K-T}, hub nodes share similarities and differences. Both networks emphasize digital signal transmission (H04L) and wireless communication (H04W). In G_{K-S}, scientists show interest in the Internet of Things, MIMO, and machine learning, while in G_{K-T}, inventors focus on improving communication system frequency characteristics (H04B) through network entry. These similarities and differences highlight the distinct collaboration emphasis and knowledge connections within each sub-ecosystem.

4.3.2. Bridges of Weak Connections: Bridging Nodes

- Betweenness centrality

As show in Table 7, in the scientific sub-ecosystem, average bridging capacity and standard deviation of innovators decrease from macro to micro levels: $BC_{Mean}(G_{C-S}) > BC_{Mean}(G_{O-S}) > BC_{Mean}(G_{I-S})$ and $BC_{S.D.}(G_{C-S}) > BC_{S.D.}(G_{O-S}) > BC_{S.D.}(G_{I-S})$. In technological sub-ecosystems, national innovators have the highest average bridging capacity, followed by individuals, and organizational have the lowest:$BC_{Mean}(G_{C-T}) > BC_{Mean}(G_{I-T}) > BC_{Mean}(G_{O-T})$ and $BC_{S.D.}(G_{C-T}) > BC_{S.D.}(G_{I-T}) > BC_{S.D.}(G_{O-T})$. National actors have the highest average bridging capacity with notable variation, and individuals and organizations have the lowest in scientific and technological innovation, respectively.

Table 7. Descriptive statistics of betweenness centrality.

	G	BC_{Mean}	BC_{Max}	BC_{Min}	$BC_{Meadian}$	$BC_{S.D.}$
①	G_{C-S}	0.007	0.12	0	0.0005	0.018
②	G_{O-S}	0.0006	0.06	0	0.00002	0.003
③	G_{I-S}	0.0004	0.03	0	0.00005	0.001
④	G_{K-S}	0.0002	0.41	0	0.00001	0.006
⑤	G_{C-T}	0.014	0.17	0	0.0010	0.037
⑥	G_{O-T}	0.0002	0.01	0	0	0.001
⑦	G_{I-T}	0.0005	0.04	0	0.00003	0.002
⑧	G_{K-T}	0.0007	0.11	0	0.00008	0.004

At both macro and micro levels, the average bridging capacity and variability of actors in scientific ecosystem are lower compared to technological ecosystem, with $BC_{Mean}(G_{C-S}) < BC_{Mean}(G_{C-T})$, $BC_{Mean}(G_{I-S}) < BC_{Mean}(G_{I-T})$, $BC_{S.D.}(G_{C-S}) < BC_{S.D.}(G_{C-T})$ and $BC_{S.D.}(G_{I-S}) < BC_{S.D.}(G_{I-T})$, but at the micro level, it is the opposite, with $BC_{Mean}(G_{O-S}) > BC_{Mean}(G_{O-T})$ and $BC_{S.D.}(G_{O-S}) > BC_{S.D.}(G_{O-T})$. Additionally, most organizations in the technological sub-ecosystem lack bridging capability, with $BC_{Meadian}(G_{O-T}) = 0$.

For knowledge elements, bridging capability in scientific innovation is lower compared to the technological field, with $BC_{Mean}(G_{K-S}) < BC_{Mean}(G_{K-T})$.

- Bridging nodes

As show in Figure 7, in G_{C-S}, the US and China serve as hub and bridging countries, while Latvia and Kenya connect communities despite not being the prominent hubs. In G_{C-T}, strong bridging capabilities are observed in country alliances (WO and EP), as well as in the US, China, and Switzerland. China and the US play crucial roles in facilitating cross-community collaborations in both scientific and technological sub-ecosystems.

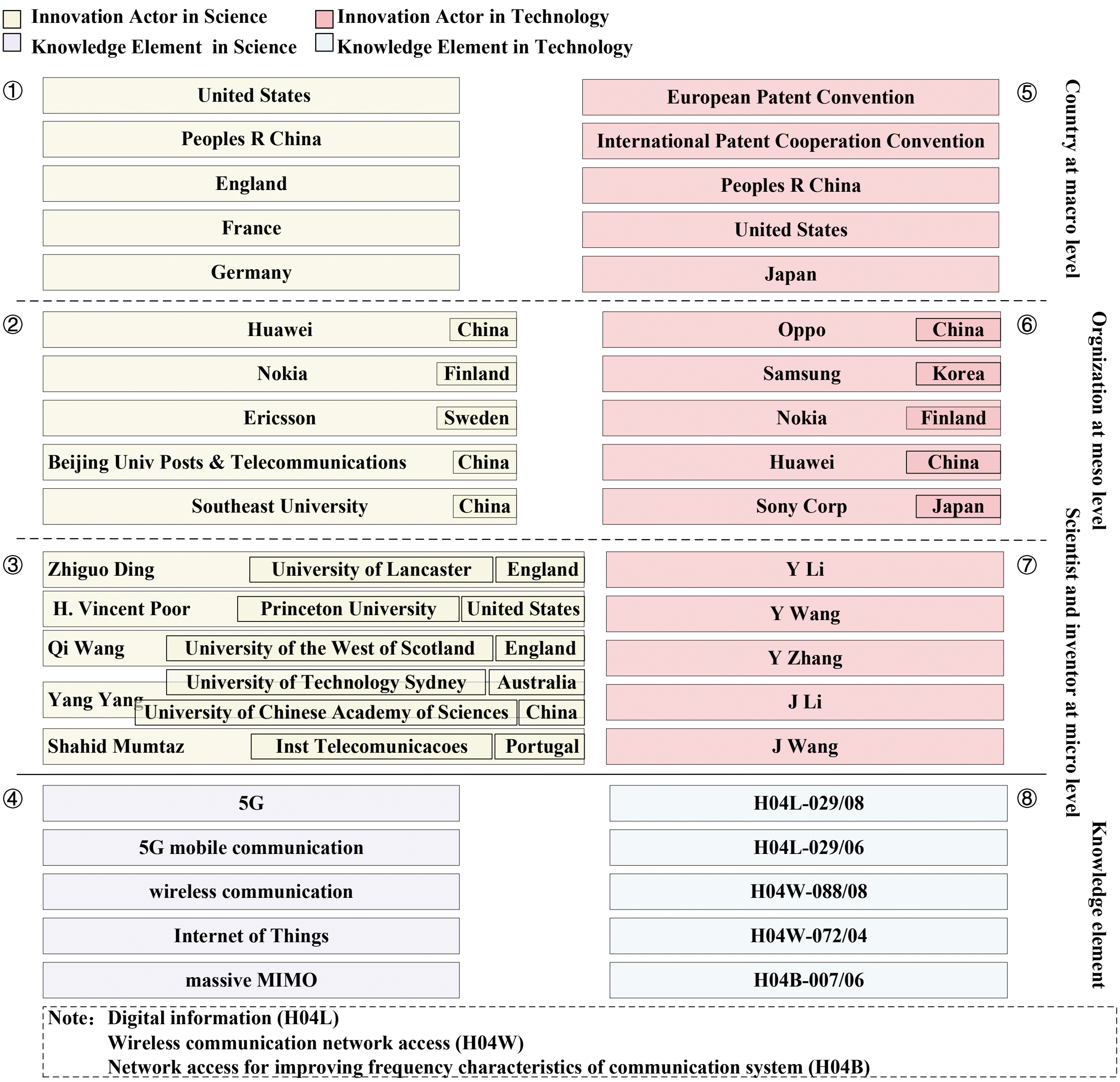


Figure 7. Comparison and geographical affiliation of top-5 influence nodes.

In G_{O-S}, 355 bridging organizations, including Nokia, University of Basque Country, Yonsei University, and Jinan University, are consisted of 69 enterprises and 286 universities and research institutes, playing bridging roles. In G_{O-T}, there are 54 prominent bridging organizations, such as the State Grid Corporation of China, Samsung, Huawei, AT&T, and Purdue Research Foundation, with 46 enterprises and eight universities and research institutes. Enterprises take on bridging role.

In G_{I-S}, there are 382 bridging scientists, including Thar Baker, Ronan Farrell, and others. In G_{I-T}, there are 48 bridging inventors, including inventors like Liu J, Li C, and others.

Table 8 summarizes the number and percentage of bridging nodes. G_{C-S} has a higher proportion of bridging countries compared to G_{C-T} (6.11% vs. 5.41%). G_{O-S} has more bridging organizations compared to G_{O-T} (355 vs. 54), but a lower proportion of them (10.04% vs. 16.17%). There is also a greater willingness among organizations in technological collaborations to undertake a bridging role. Additionally, the number of bridging scientists is nearly eight times higher than bridging inventors (382 vs. 48), and their proportion is also three times greater than bridging inventors (4.92% vs. 1.51%).

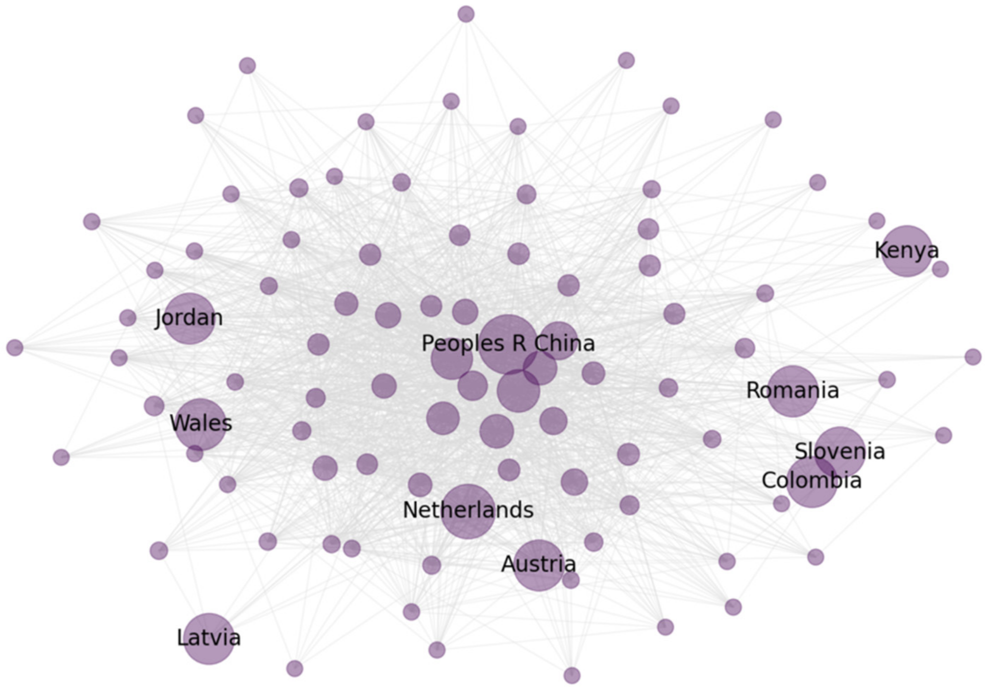
Stronger presence of as bridging roles in scientific innovation cooperation compared to inventors in technological innovation cooperation.

Table 8. No. and percentage of bridging node in networks.

	G	No. of $BC_G(v_i)$	Percentage of $BC_G(v_i)$
①	G_{C-S}	8	6.11%
②	G_{O-S}	355	10.04%
③	G_{I-S}	382	4.92%
④	G_{K-S}	7	0.13%
⑤	G_{C-T}	2	5.41%
⑥	G_{O-T}	54	16.17%
⑦	G_{I-T}	48	1.51%
⑧	G_{K-T}	10	0.45%

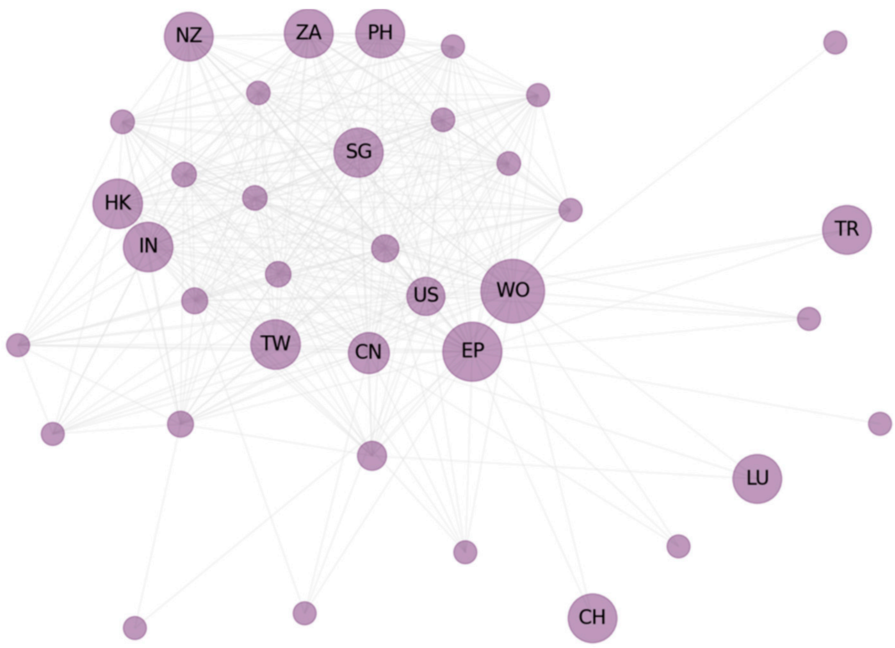
In G_{K-S} and G_{K-T}, number of bridging knowledge elements is small. Only seven keywords and 10 IPC Codes serve as bridging nodes, representing 0.13% and 0.45%, as show in Figure 8.

Furthermore, bridging knowledge elements in scientific innovation focus on scientific issues and extensibility of 5G technology, while in technological innovation, the emphasis is on practical implementation of firmware, equipment, and devices related to 5G technology.



(**a**)

Figure 8. *Cont*.



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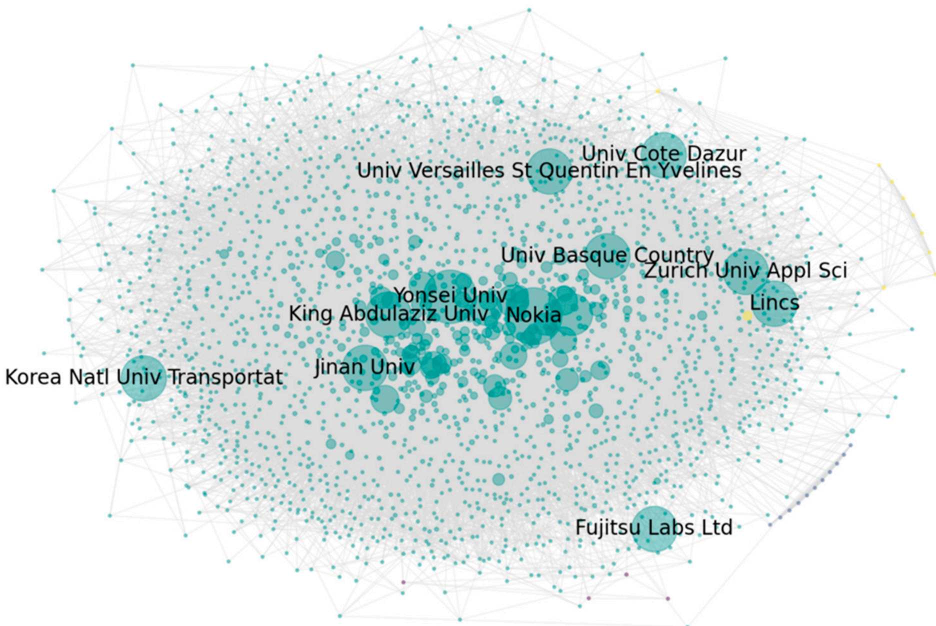

(**c**)

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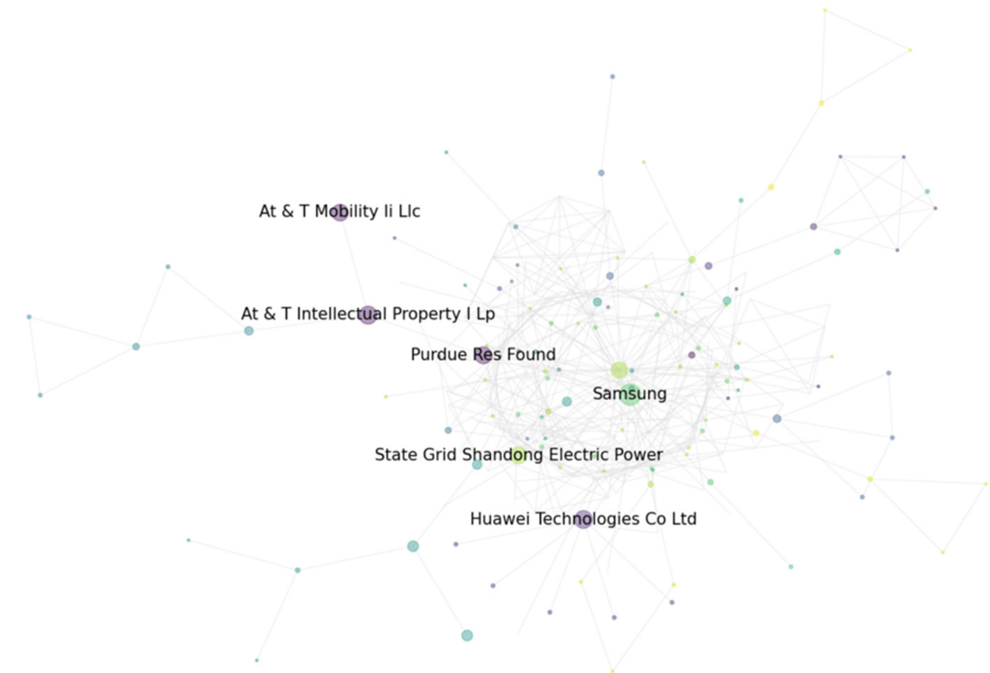

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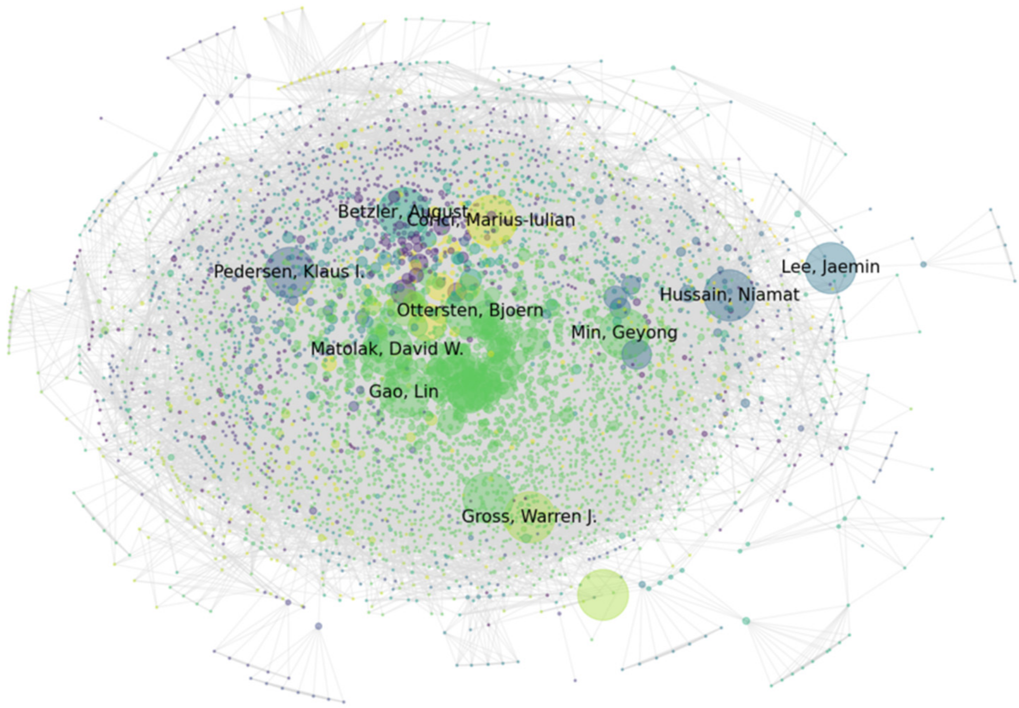
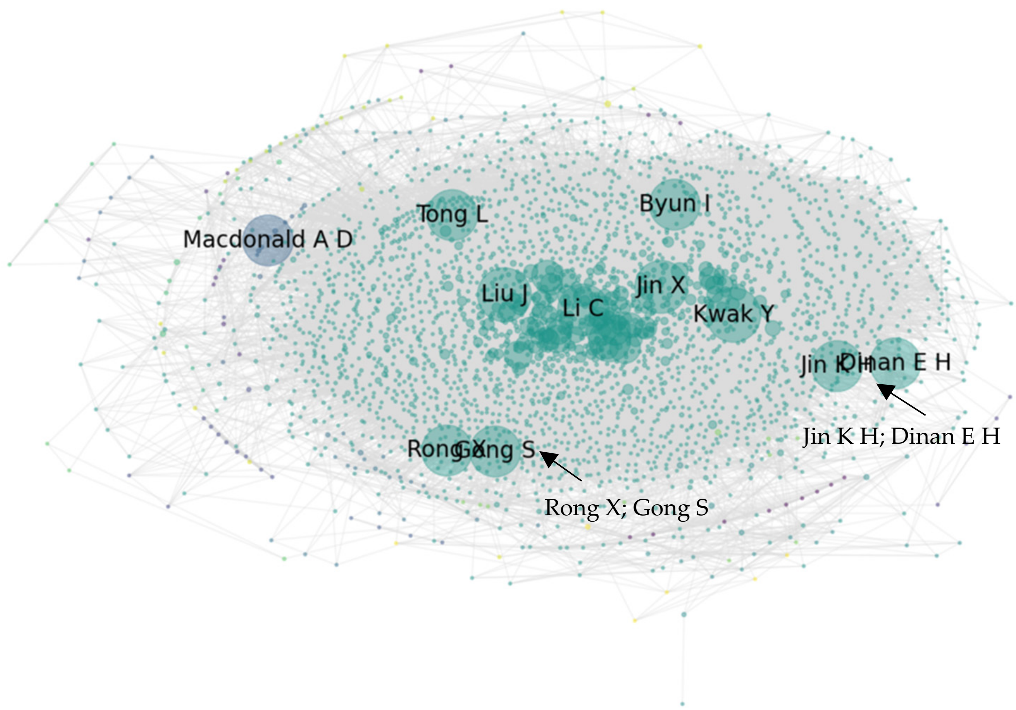


(**e**)

Figure 8. *Cont.*



(**f**)

Figure 8. Distribution of bridging nodes with the top-10 highlighted in social networks (Note: node size—betweenness centrality), (**a**) G_{C-S}; (**b**) G_{C-T}; (**c**) G_{O-S}; (**d**) G_{O-T}; (**e**) G_{I-S}; (**f**) G_{I-T}.

4.4. Knowledge Proximity of Social Actors in 5G Telecommunication Ecosystem

4.4.1. Knowledge Distribution in Innovation Actors

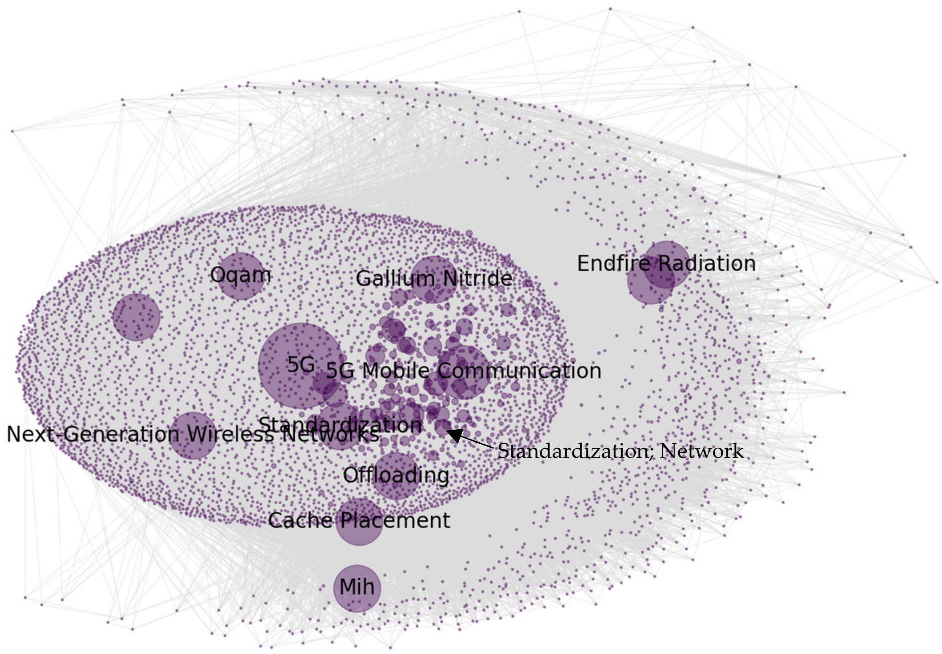
Since the IMT-2020 standard [86] was proposed in 2012, 5G technology has developed rapidly [87,88], and its five knowledge modules have attracted increasing attention. Figure 9 shows the interest of these modules in the 5G ecosystem over time. In terms of scientific knowledge, 2020 is the peak of attention, with network architecture, wireless communications, and terminals receiving the most attention. Application scenarios and security and privacy protection pay relatively little attention. From the perspective of technical knowledge, network architecture received the most attention, reaching its peak in 2018, surpassing other modules, indicating a faster development cycle. Network architecture is developing faster in technological innovation than in scientific innovation and is the module that receives the most attention among the two subsystems.

Figure 10 shows the distribution of five knowledge modules among the top-10 innovators with the highest overall attention in knowledge across six heterogeneous networks. In G_{C-K-S} and G_{C-K-T}, China and the US lead in 5G knowledge attention. In G_{C-K-S}, other countries have similar overall attention but differ in specific knowledge modules. In G_{C-K-T}, countries other than China and the US show significant variation, with a focus on network achievements and less interest in other modules.

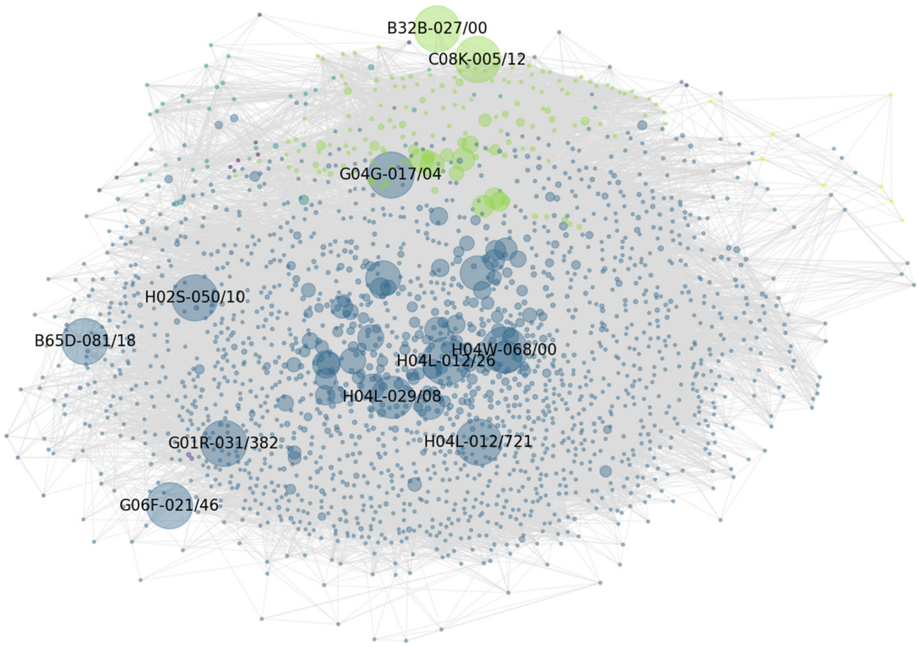
In G_{O-K-S}, BUPT stands out with significant knowledge attention, while other organizations show no clear differences. Tsinghua University pays relatively high attention to application scenarios. In G_{O-K-T}, Samsung leads in overall knowledge attention, and the top-10 organizations focus on network architecture.

In G_{I-K-S}, Ismail Guvenc focuses more on security and privacy protection compared to other scientists. In G_{I-K-T}, inventors have similar knowledge distributions, possibly due to the namesakes.

JS divergence quantifies knowledge domain differences: China-US has 0.0228 in scientific innovation and 0.0719 in technological innovation. Huawei-Nokia has 0.0157 in scientific innovation, while Huawei-Samsung has 0.0119 in technological innovation. The top two scientists have JS divergence of 0.2038, and the top two inventors have 0.0053.



(**a**)



(**b**)

Figure 9. Distribution of top-10 bridging nodes in each knowledge network (Note: node size—betweenness centrality), (**a**) G_{K-S}; (**b**) G_{K-T}.

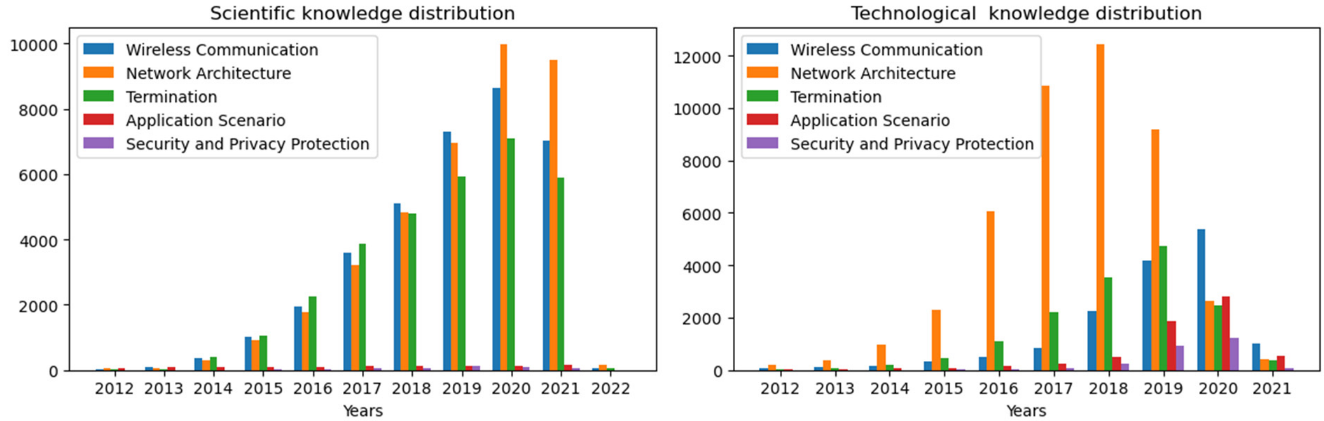


Figure 10. Temporal distribution of five knowledge modules since 2012.

4.4.2. Knowledge Proximity of Innovation Actors

Knowledge proximity reveals research domain similarity and facilitates potential collaboration. Greater knowledge distribution disparity results in lower proximity, as show in Figure 11.

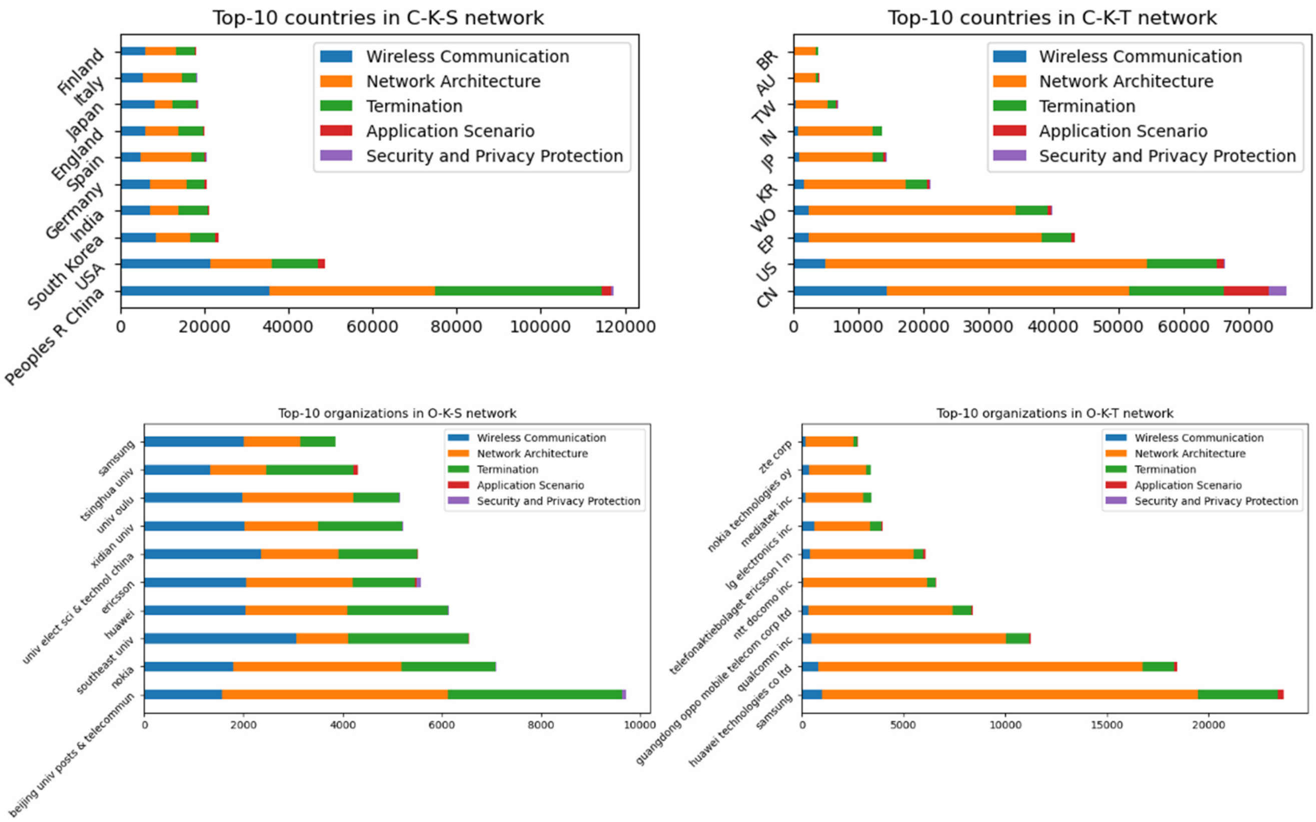


Figure 11. *Cont.*

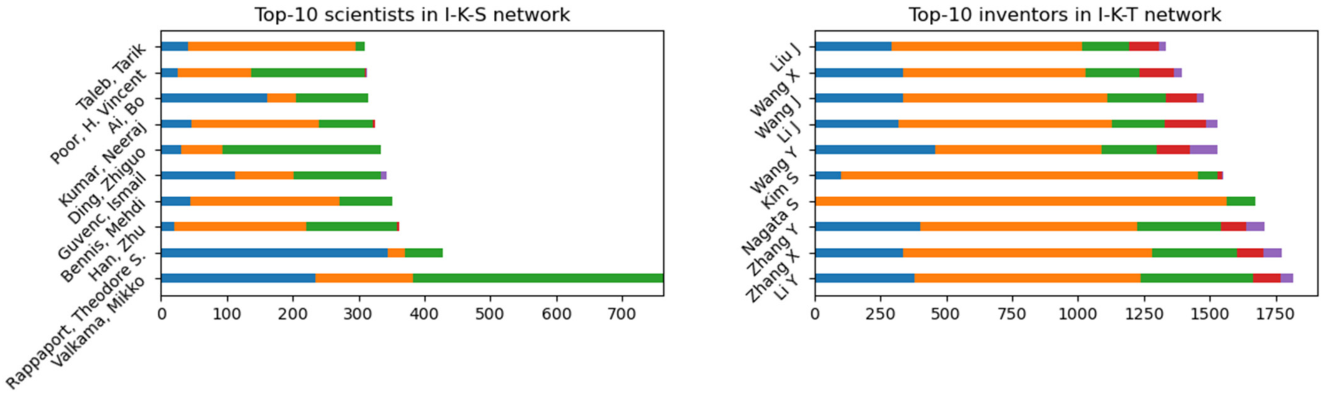


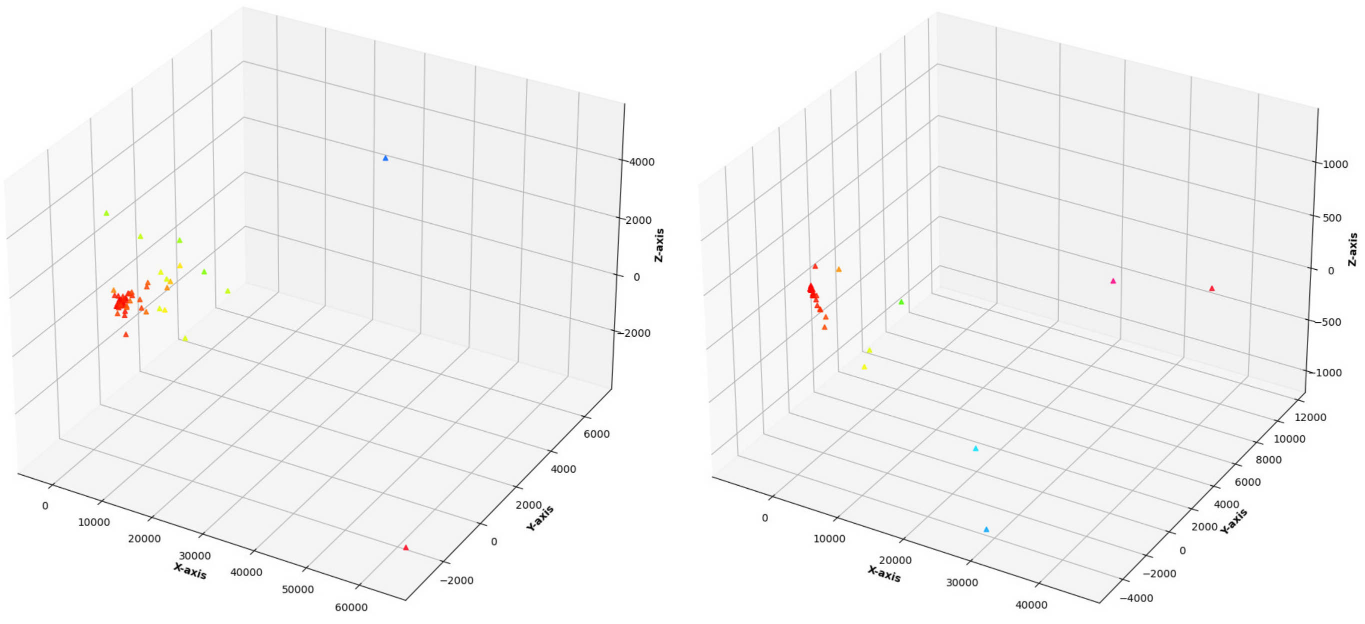
Figure 11. Distribution of knowledge among top-10 innovators.

In G_{C-K-S}, China, Japan, and the US have significant differences in knowledge distribution, indicating low proximity. India and Italy exhibit high proximity, while Greece, Spain, and Sweden also show a high level of proximity. In G_{C-K-T}, China and the US lead with large knowledge distribution distances, resulting in low proximity. India and Japan demonstrate high proximity, while South Korea forms a distinct category. EP and WO show high proximity, and countries like Australia, Brazil, Canada, Hong Kong, Russia, Singapore, and Vietnam exhibit considerable proximity.

In G_{O-K-S}, renowned institutions like BUPT, Ericsson, Huawei, Nokia, Southeast University, Oulu University, and Xidian University show significant proximity. Kyoto University forms a distinct category, while INFN Milano, Jadavpur University, Manipur Institute of Technology, and Ritsumeikan University also exhibit high proximity. In G_{O-K-T}, Huawei and Samsung have relatively low knowledge proximity. Oppo, LG Electronics, Nokia, NTT DoCoMo, Qualcomm, and Ericsson demonstrate similar knowledge distributions and high proximity.

In G_{I-K-S} and G_{I-K-T}, researchers' proximity positions can accurately be identified through more comprehensive and detailed information.

Overall, innovators in scientific knowledge have greater proximity, compared to technological knowledge, as shown in Figure 12.



(**a**) (**b**)

Figure 12. *Cont.*

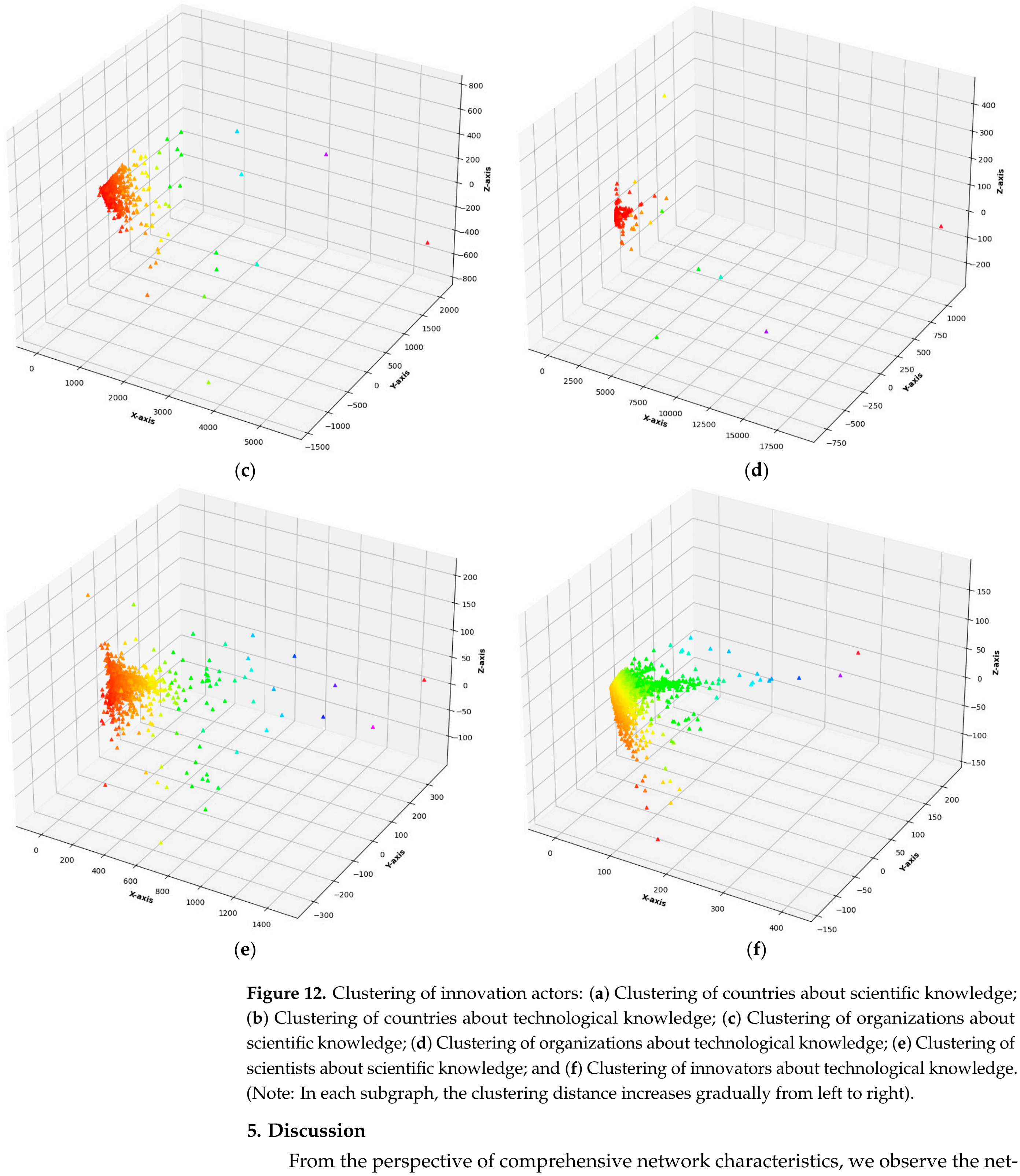


Figure 12. Clustering of innovation actors: (**a**) Clustering of countries about scientific knowledge; (**b**) Clustering of countries about technological knowledge; (**c**) Clustering of organizations about scientific knowledge; (**d**) Clustering of organizations about technological knowledge; (**e**) Clustering of scientists about scientific knowledge; and (**f**) Clustering of innovators about technological knowledge. (Note: In each subgraph, the clustering distance increases gradually from left to right).

5. Discussion

From the perspective of comprehensive network characteristics, we observe the network topology differences of technological innovation in the 5G technology ecosystem and the innovative interaction between innovation subjects and knowledge elements. Compared with technological innovation, scientific innovation involves more countries, organizations, and researchers. There are significant differences in the collaboration networks of scientific and technological innovation organizations. Scientific organizational networks have larger communities with stronger cohesion and interconnectedness, whereas technical networks have smaller communities with weaker cohesion. Compared with technical knowledge, 5G technology has a richer knowledge base and more closely integrated scientific knowledge. In addition to the national level, collaboration at the organizational level and individual level, as well as the combination of scientific and technological knowledge, all show the characteristics of a small world. While 5G presents promising innovations globally, there is a need for greater inter-organizational collaboration related to technological advancements.

For special ecological niches, first, the distribution of hub nodes is not entirely consistent at the national, organizational, and individual levels. China and the United States are pioneers in national-level 5G technology innovation cooperation. China's Huawei and Finland's Nokia occupy the most influential positions at the organizational level. Individual-level hub nodes are influential scientists and inventors who play an important role in scientific and technological progress through their research results and patent contributions. The technical knowledge of 5G mainly focuses on digital signal transmission (H04L) and wireless communication (H04W). Scientific knowledge focuses on breakthroughs in 5G emerging technologies, and technical knowledge focuses on its application and implementation.

The bridging nodes of scientific and technological innovation cooperation are randomly distributed at the national, organizational and individual levels. National bridge nodes cover scientific and technological cooperation between developed and developing countries, and national alliances play an important bridging role in technical cooperation. State-level actors show the highest ability to communicate across communities compared to organizations and individuals. At organizational level, universities and research institutes dominate bridging in both scientific and technological innovation, while enterprises lead in technological bridging. There is a shortage of scientists and inventors to build bridges. Bridging science knowledge focuses on 5G telecommunications technology and scalability, while bridging technical knowledge emphasizes the actual implementation of firmware, devices and components.

From the perspective of knowledge proximity, 5G-related scientific and technological knowledge shows differences in content and time, reflecting the inherent differences and unique needs of innovation. The relationship between scientific and technological knowledge innovation is not a competitive or hierarchical relationship; instead, it is a complementary and mutually reinforcing relationship. Major countries attach great importance to 5G technical knowledge, but there are differences in the degree of knowledge acquisition. Generally speaking, organizations value technical knowledge over scientific knowledge. Knowledge proximity determines the position of researchers in knowledge clusters, indicating their positioning in the innovation ecosystem.

6. Conclusions

First, this study proposes the universally applicable-K-S-T IE framework to study the homogeneous and heterogeneous interactions between innovators and knowledge elements in technological innovation. By analyzing the integration of the A-K-S-T innovation ecosystem, we evaluate its interaction topology and reveal the system structure. In addition, the framework also specifically maps the relationship between innovation subjects and knowledge elements and evaluates their differences in technological innovation. This study enriches the research of innovation ecosystem theory, and this framework is essential for motivating innovators to open up innovation, tap the potential of knowledge innovation, and promote the development of emerging technologies. It provides a foundational reference for innovation managers, guiding strategic decisions, optimizing resource allocation, and advocating for collaborative development.

Secondly, this paper adopts a multi-layer homogeneous and heterogeneous network method to analyze the collaboration and combination of knowledge elements among innovation subjects from the macro, meso, and micro levels. By identifying niches and knowledge proximity, it is possible to gain a comprehensive understanding of the innovation landscape and gain a clear understanding of the situation of the innovation actors themselves. This enables innovators to dynamically adjust innovation strategies and collaboration directions, thereby guiding the sustainable evolution of the innovation ecosystem. Taking global 5G communication technology as an example, it highlights the need to improve organizational collaboration efficiency and further study security and privacy protection. By employing a multi-layered complex network approach to investigate emerging technology innovation ecosystems, and by proposing a new quantifiable multi-layered complex network conceptual framework (the A-K-S-T IE framework) to study the homogeneous and heterogeneous interactions between innovators and knowledge elements in scientific and technological innovation, this study provides theoretical support and empirical references for the expansion of research on innovation ecosystems. It offers new insights for the management, governance, efficiency, and shared prosperity of the innovation ecosystem, sustaining innovation advantage, as well.

This research utilizes data integration and mining techniques to analyze innovation ecosystems. The composition of IE is examined using heterogeneous data sources, such as bibliometric analysis, patent analysis, and expert interviews. Machine learning improves data processing efficiency. These methods provide quantitative analysis of innovation ecosystems and provide valuable references for government and corporate decision-making.

This research has important implications for innovation participants, innovation managers, and policymakers.

1. Strengthening innovation cooperation: Governments and enterprises could encourage enterprises, universities, and individuals to cooperate in emerging technology fields. Complementary advantages promote coordinated development of the innovation ecosystem.
2. Establishing a knowledge sharing platform: Governments and enterprises can create a sharing platform to realize the exchange of knowledge, experience, and best practices, and promote learning and cooperation within the innovation ecosystem.
3. Determining their position in the innovation collaboration network: Innovators could analyze and understand their position in the collaboration network. By identifying leading innovators and key players, strategic partnerships can be formed to leverage each other's strengths and focus on breakthrough innovations.
4. Harnessing knowledge proximity: High knowledge proximity between entities reduces information transfer costs and barriers. Governments and enterprises should actively explore and utilize knowledge proximity to accelerate innovation and obtain better knowledge resources and cooperation opportunities.

This research has some limitations. First, the analysis only considers the timeline of knowledge combination and doesn't take into account the timeline of actor's innovative collaboration. Second, it doesn't consider the external factors such as government policies, market demands, and societal norms, as well as the internal cultural norms and individual characteristics of the actors. Third, it is a single case study, and to enhance the generalizability of the A-K-S-T framework, it can be validated and extended using other techniques or innovation areas. Increasing the number of cases studied can provide a better understanding and broader application of this framework of innovative ecosystem.

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