sustainability

MDPI

Article

An Empirical Analysis of the Characteristics and Determinants of the China–ASEAN Science and Technology Cooperation Network: Insights from Co-Authored Publications

Fan Wu * and Zhixu Liu

School of Public Policy and Management, Guangxi University, Nanning 530004, China; aubrey@st.gxu.edu.cn
* Correspondence: wufan@gxu.edu.cn

Abstract: Regional science and technology cooperation networks are pivotal for fostering sustainable global innovation. The China–ASEAN science and technology cooperation network integrates regional innovation resources, thereby promoting the sustainable flow of innovation elements and complementing technological strengths among countries, which significantly enhances cooperation efficiency and outcomes. This study employs a Social Network Analysis (SNA) and the Temporal Exponential Random Graph Model (TERGM) to analyze co-authored publications between China and ASEAN countries from 2003 to 2022, constructing a cooperation network that integrates both endogenous network structures and exogenous driving factors. This study explores the distinct mechanisms through which these factors influence the formation of cooperative relationships and highlights the key features and determinants of the network. The findings reveal the following: first, the China–ASEAN science and technology cooperation network has evolved from an initial "star-shaped structure" with China and Singapore as central nodes to a more interconnected network exhibiting "small world" and "high clustering" characteristics. Second, endogenous network structures, including the number of edges, node centrality, and closed triadic structures, significantly shape the network's evolution, with some structures inhibiting the formation of new partnerships, while an increase in shared collaborators promotes new connections. Third, the evolution of the network demonstrates both stability and variability. Fourth, human capital is a key driver of partnership formation, while higher per-capita GDP countries show less inclination to form new partnerships. Fifth, proximity factors have heterogeneous effects: linguistic proximity positively impacts the formation of partnerships, while institutional proximity negatively affects the establishment of new collaborations. Based on these findings, this paper suggests improving international cooperation mechanisms, optimizing resource allocation, and enhancing the development of cross-border scientific talent. These measures aim to enhance the connectivity within the China–ASEAN science and technology cooperation network, effectively improve the utilization efficiency of regional innovation resources and technological capabilities, and promote the sharing and long-term collaboration of innovation resources within the region, thereby advancing sustainable development at both regional and global levels.

Keywords: science and technology cooperation network; China–ASEAN; TERGM; sustainability

check for updates

Citation: Wu, F.; Liu, Z. An Empirical Analysis of the Characteristics and Determinants of the China–ASEAN Science and Technology Cooperation Network: Insights from Co-Authored Publications. *Sustainability* **2024**, *16*, 10149. https://doi.org/10.3390/su162210149

Academic Editor: Mário José Baptista Franco

Received: 21 October 2024
Revised: 14 November 2024
Accepted: 17 November 2024
Published: 20 November 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

In the context of global innovation cooperation, international scientific and technological collaboration serves not only as a means to drive technology and resource integration but also as a crucial pathway to support sustainable development. According to the United Nations, sustainable development is defined as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [1]. The China–ASEAN science and technology cooperation network, as an effective model for scientific collaboration, enhances the sustainability of regional innovation by

reducing resource waste and improving cooperation efficiency. It not only meets current innovation demands but also lays a foundation for future technological advancements through the accumulation of knowledge and technology. Additionally, this network aligns with the Sustainable Development Goals (SDGs) in optimizing innovation resources and fostering partnerships to achieve these global objectives [2]. In this context, regional science and technology cooperation networks play a pivotal role, particularly in facilitating the exchange of technologies, resource sharing, and enhancing innovation capabilities among nations [3]. Among these regional networks, the China–ASEAN science and technology cooperation network has played a crucial role in driving technological innovation and economic growth. Under the impetus of the Belt and Road Initiative (BRI), it has not only accelerated regional economic recovery but has also deepened collaboration in key areas such as the digital economy and green economy, strengthening the resilience and sustainability of the partnership [4,5]. In 2021, China and ASEAN countries elevated their relationship to a comprehensive strategic partnership, with cross-border science and technology cooperation becoming central to diplomatic strategy, thereby tightening technological ties [6]. This cooperation network has fostered mutual development, accelerated regional economic integration, and enhanced the region's standing in global technological innovation, providing a solid foundation for addressing global sustainable development challenges [7].

The China–ASEAN science and technology cooperation network has become a cornerstone for promoting regional sustainable development by addressing economic uncertainties and fostering innovation. This network facilitates the integration of innovation resources, enhances collaboration efficiency, and strengthens the region's capacity to respond to endogenous shocks [4,7]. Notably, it has driven the sustainable use of resources and advanced low-carbon economic development, making significant contributions to the SDGs, particularly in the renewable energy and green technology sectors [3,6]. Cooperation in these areas, including environmental monitoring and green technologies, has enhanced both the sustainability and inclusiveness of regional science and technology collaborations [8]. Additionally, these efforts have strengthened the Regional Comprehensive Economic Partnership (RCEP), narrowing economic disparities and boosting supply chain resilience across the region [4,8]. By continuously improving innovation capacity, the network equips ASEAN and China to better tackle global challenges such as climate change and resource depletion [9]. This study thus provides a timely examination of the role of the China–ASEAN cooperation network in promoting sustainable innovation, offering insights for optimizing regional cooperation mechanisms and advancing long-term sustainability.

2. Literature Review

International science and technology cooperation networks play a vital role in the global innovation system. According to the United Nations Educational, Scientific, and Cultural Organization (UNESCO), international science and technology cooperation refers to the sharing of scientific and technological knowledge between citizens of two or more countries based on agreements [10]. Scholars have extensively debated the influencing factors, research subjects, and scope of international science and technology cooperation networks. In terms of influencing factors, countries, research institutions, and enterprises form complex cooperation networks through collaborations. The interaction between nodes (collaborating entities) and edges (collaborative relationships) in the network reflects the intensity and breadth of cooperation [11]. However, high-frequency collaboration does not always translate into higher-quality scientific outcomes, as the structure of the network and factors such as the economic power, technological capacity, geographic proximity, and linguistic preferences of the partners can influence the quality of cooperation [12,13].

Research on science and technology cooperation networks across different regions has mainly focused on the United States and Europe. These studies have demonstrated the significant advantages of international science and technology cooperation in improving research efficiency and driving innovation, revealing how cross-border cooperation

can optimize resource allocation and facilitate the integration of the European research system [14,15]. In terms of the current state of China–ASEAN science and technology cooperation networks, scholars have found that cooperation between China and Southeast Asia focuses primarily on agriculture, new energy, and new materials [16,17]. Among the Belt and Road Initiative (BRI) countries, ASEAN countries account for the highest proportion of international collaborative papers, close to 48.7%, with China and Singapore leading in the number of co-authored papers [18]. In addition, scholars have identified challenges in the current state of collaboration, and some have summarized vertical cooperation models [19].

From the perspective of research subjects in international science and technology cooperation networks, understanding the subjects involved is key to revealing the structure of cooperation between countries. Co-authored papers, as a critical carrier of international science and technology cooperation networks, allow for the evaluation of a country's role and position in the global cooperation network based on the quantity and quality of the collaborations. For instance, co-authored papers can reveal a nation's influence in the global research collaboration network from the perspective of partner countries and academic disciplines [20], facilitating the global flow of knowledge and technology [21]. In addition, patent cooperation serves as an essential component of international science and technology cooperation networks. Through cross-border patent cooperation, one can uncover the role of countries in technological innovation and the sharing of intellectual property rights [22]. Joint research projects are another vital form of international scientific collaboration. By analyzing jointly funded and executed research projects across countries, one can gain insights into collaboration models related to resource allocation, technology sharing, and the commercialization of research outcomes [15].

Regarding research methods in international science and technology cooperation networks, many scholars have applied bibliometric analysis and Social Network Analysis (SNA) to reveal the internationalization of scientific activities among the studied subjects [23]. Early studies on international cooperation networks predominantly employed static analysis methods to uncover the characteristics of international scientific collaboration [24]. Later, researchers began using dynamic network models to analyze the evolution of international cooperation networks, revealing the patterns of change over time [25]. However, despite the increasing use of dynamic models in studying international science and technology cooperation networks, existing research still faces challenges in addressing the complex endogenous driving factors affecting these networks [26].

Previous research has investigated international science and technology cooperation networks from multiple perspectives, offering valuable theoretical and empirical support for understanding their structures and functions. However, the dynamic evolution of such networks, particularly the complex interaction mechanisms between endogenous driving factors (e.g., network structural attributes) and exogenous determinants (e.g., geographic proximity and institutional proximity), has not been fully elucidated in existing studies. Therefore, this study holds significant academic and practical value in deepening our understanding of how cooperation networks adapt to evolving innovation demands and drive regional sustainable development. The China–ASEAN science and technology cooperation network provides an ideal case for exploring these dynamics. As an integral component of the Belt and Road Initiative (BRI), this network has played an increasingly critical role in advancing regional scientific collaboration and achieving sustainable development goals, such as optimizing innovation resources and fostering partnerships. However, it still faces numerous challenges, including uneven resource allocation, insufficient stability in cooperative relationships, and underutilized cross-national scientific synergies. These issues constrain the network's capacity to optimize regional innovation resource allocation and enhance the integration of cooperation mechanisms.

To address this, this study employs Social Network Analysis (SNA) and the Temporal Exponential Random Graph Model (TERGM) to systematically analyze the structural characteristics and dynamic evolution of the China–ASEAN science and technology cooperation network from 2003 to 2022. It provides empirical evidence for the role of science

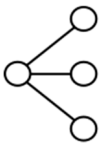
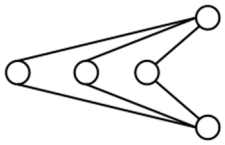
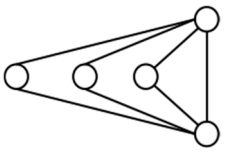
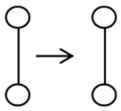
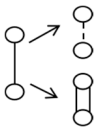
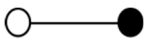
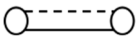
and technology cooperation networks in promoting regional sustainability. On a theoretical level, this research expands the understanding of science and technology cooperation networks by demonstrating the resource allocation mechanisms of transnational collaboration within the sustainable development framework. It enriches the existing literature by exploring the role of these networks in facilitating knowledge flow and enhancing regional competitiveness. On a practical level, by identifying key nodes and efficient resource flow characteristics within the cooperation network, this study offers valuable data for policymakers. It supports the formulation of targeted cooperation incentives and regional innovation policies that enhance economic resilience and inclusive growth through collaboration. The China–ASEAN science and technology cooperation network serves as a compelling model of transnational collaboration. By facilitating the sharing of innovation resources and the flow of knowledge, it has become a critical pathway for achieving sustainable development goals such as optimizing regional innovation resources and fostering target partnerships, thereby further advancing global sustainable development.

This paper presents three key innovations: 1. Methodological optimization and application innovation. While previous studies have employed dynamic network models, this paper introduces the Temporal Exponential Random Graph Model (TERGM) to systematically analyze the dynamic evolution characteristics of the China–ASEAN science and technology cooperation network. The model integrates both exogenous network structures and endogenous driving factors, proposing a multi-dimensional framework for understanding the evolution of cooperation networks. Unlike previous models, this approach not only captures the dynamic changes within the network but also more accurately reveals the temporal evolution patterns and the interaction between endogenous and exogenous factors. 2. Integration of endogenous and exogenous factors. This study innovatively combines endogenous network structures (such as the number of edges and geometrically weighted degree) with endogenous driving factors (such as human capital and geographic proximity) to analyze the different mechanisms that influence the formation of collaborative relationships. Compared to previous studies that focus on single perspectives, this paper provides a more comprehensive framework by exploring the complex interactions between endogenous and exogenous factors, offering new insights for policymakers in the context of regional science and technology cooperation. 3. Practical recommendations for sustainable regional cooperation. Based on the context of the Belt and Road Initiative (BRI), this paper emphasizes the strategic significance of the China–ASEAN science and technology cooperation network in enhancing regional innovation capacity, promoting technological flow, and facilitating knowledge sharing. Furthermore, it offers a new theoretical framework and empirical support for the sustainable development of regional science and technology cooperation.

3. Theoretical Framework and Hypothesis Development

The formation of relationships within the China–ASEAN science and technology cooperation network is influenced by both endogenous and exogenous factors. Endogenous factors primarily include higher-order structural dependencies and temporal dependencies, where higher-order dependencies represent complex, interdependent structures within the network. Temporal dependencies include stability and variability, and the specific meanings and functions of these variables are shown in Table 1. Exogenous factors consist of country-level node attributes and network covariates. By incorporating node attributes and network covariates as explanatory variables into the Temporal Exponential Random Graph Model (TERGM), the model more accurately captures the mechanisms of dynamic network evolution, enabling better predictions and explanations of phenomena and behaviors within the network. Particularly, in the analysis of complex networks, the inclusion of covariates significantly enhances the explanatory and predictive power of the model.

Table 1. Corresponding network structures in Temporal Exponential Random Graph Model (TERGM).

Category	Variable	Diagram	Mechanism	Hypothesis
Endogenous structural variables	edges		Basic effect	H1a
	gwdegree		Expansionary effect	H1b
	gwdsp		Transitivity effect	H1c
	gwesp		Closure effect	H1d
Temporal dependencies	stability		Stability	H2
	variability		Variability	
Node attributes	nodecov		Matthew effect	H3
Network covariates	edgecov		Proximity	H4

3.1. Endogenous Structural Variables

In undirected networks, lower-order structural dependencies refer to the number of edges (edges), while higher-order structural dependencies primarily include the geometrically weighted degree (gwdeg), geometrically weighted dyadic shared partners (gwdsp), and geometrically weighted edgewise shared partners (gwesp). In this study, we incorporate the number of edges, geometrically weighted degree, dyadic shared partners, and edgewise shared partners into the model to analyze the effects of basic, expansionary, transitive, and closure mechanisms on the evolution of the China–ASEAN science and technology cooperation network.

Wagner and colleagues analyzed the growth of global scientific cooperation networks and its impact on the formation of new collaborative relationships. They proposed that as the density of cooperative relationships increases, network cohesion strengthens, and

opportunities for new collaborations become limited [27]. Crane's research indicated that when a cooperation network becomes saturated, the probability of forming new collaborative relationships decreases, and the existing network structure tends to stabilize [28]. Based on this, Hypothesis H1a is proposed to observe the effects of the number of edges on the formation of science and technology cooperation networks.

Freeman's research explored the issue of centrality in networks, pointing out that a high degree of centralization can lead to the monopolization of cooperative resources by a few core nodes, thereby inhibiting the creation of new cooperative opportunities [29]. To explore the effects of the concentration of geometrically weighted degree distribution (gwdeg) on science and technology cooperation networks, Hypothesis H1b is proposed.

Robins and G. et al. pointed out that geometrically weighted edgewise shared partners (gwesp) measure triangular collaborative relationships shared between nodes. As these relationships increase, network cohesion rises, and nodes become more inclined to consolidate existing collaborations rather than form new ones [30]. Research by Authorsd demonstrated that triadic closure is one of the key mechanisms leading to the formation of high-density communities within networks, particularly in complex networks such as scientific cooperation networks. The increase in triadic closure often strengthens network cohesion and reduces the random generation of new connections [31]. Thus, Hypothesis H1c is proposed.

Katz and Martin pointed out that indirect collaborative paths, such as geometrically weighted dyadic shared partners (gwdsp), help provide scientists with more opportunities for collaboration, thereby promoting the formation of new cooperative relationships [32]. Therefore, Hypothesis H1d is proposed.

Hypothesis H1a. *The number of edges (connections) in the network has a significant impact on the formation of new cooperative relationships.*

Hypothesis H1b. *The concentration of geometrically weighted degree (gwdeg) negatively impacts the formation of new collaborative opportunities.*

Hypothesis H1c. *The increase in geometrically weighted edgewise shared partners (gwesp) leads to greater network cohesion, reducing the likelihood of forming new partnerships.*

Hypothesis H1d. *The increase in geometrically weighted dyadic shared partners (gwdsp) positively impacts the formation of new cooperative relationships.*

3.2. Temporal Dependencies

Extending from cross-sectional to longitudinal dimensions and incorporating temporal dependencies for dynamic network analysis is one of the key advantages of the Temporal Exponential Random Graph Model (TERGM). Temporal dependencies encompass both stability and variability. Stability refers to the network's tendency to maintain its overall structure over time, while variability reflects the degree of randomness or unpredictability in the evolution of the network—i.e., whether the relationships between nodes increase or decrease compared to the previous period.

Newman, in his study on scientific collaboration networks, highlighted that such networks exhibit both high stability and complex evolutionary dynamics. Core relationships within the network tend to persist over long periods, while new collaborations continue to emerge in response to innovation demands in scientific fields, contributing to dynamic changes in the network structure. This reveals the coexistence of stability and variability within the network [33]. Additionally, Glänzel and colleagues, through their research on international scientific cooperation, demonstrated the long-term stability of collaboration networks while emphasizing their dynamic evolution, wherein the formation of new collaborations and the dissolution of old ones contribute to high variability [34]. Based on this, we propose Hypothesis H2:

Hypothesis H2. *The China–ASEAN science and technology cooperation network exhibits both stability and variability, meaning that while the network's collaborative relationships remain relatively stable over time, new relationships will emerge, and existing ones may dissolve.*

3.3. Node Attributes

The Matthew effect is a critical concept for explaining the evolution of science and technology cooperation networks. First introduced by Merton, the Matthew effect refers to the phenomenon where "the rich get richer, and the poor get poorer" [35]. Gazni and colleagues explored the global distribution of international scientific cooperation and found imbalances in the network. They discovered that economically stronger countries, often measured by per capita GDP, tend to dominate science cooperation networks. Wealthier countries are able to invest more in scientific research, making them more likely to form new international collaborations, thereby further enhancing their influence within the global scientific network [36]. Guan and others highlighted that countries with high levels of technological outputs tend to occupy central positions in cooperation networks, leading to more innovative outcomes and greater scientific impact [37]. Fontes et al. emphasized that the international mobility of human capital facilitates the formation of long-lasting knowledge networks. Countries with a high level of human capital, especially those with a highly mobile scientific workforce, are more likely to occupy central positions in global scientific cooperation networks. Through these collaborations, such countries can enhance their scientific output and capacity for innovation.

This Matthew effect enables countries with a concentration of human capital to continually benefit from collaborative activities, further reinforcing their advantageous positions [38]. Based on this, we propose Hypothesis H3:

Hypothesis H3. *The China–ASEAN science and technology cooperation network exhibits a Matthew effect, where variables such as per capita GDP (pcap), scientific output (paper), and human capital (hci) positively influence the formation of cooperative relationships in the China–ASEAN science and technology cooperation network.*

3.4. Network Covariates

Multidimensional proximity plays a critical role in the dynamic evolution of cooperation networks by stabilizing partnerships and enhancing innovation outputs [39]. Several studies have examined the relationship between proximity and network evolution in international science and technology cooperation networks. However, due to differences in research objectives, scales, time periods, and methodologies, the conclusions remain inconsistent.

Research suggests that geographic proximity can promote exchanges and knowledge sharing among researchers, particularly in cross-regional cooperation [40]. Geographic proximity has often been regarded as a key factor in facilitating the spread of scientific knowledge [41]. Furthermore, linguistic proximity is crucial for effective communication and knowledge sharing within international cooperation networks, particularly among cross-national research teams [42]. Additionally, institutional proximity has been shown to enhance remote collaboration and improve the quality of scientific output by helping to overcome geographic distance [43]. Drawing on these findings, we propose Hypothesis H4:

Hypothesis H4. *Geographic proximity, institutional proximity, and linguistic proximity positively influence the formation of cooperative relationships in the China–ASEAN science and technology cooperation network.*

4. Research Design

4.1. Research Methods

4.1.1. Social Network Analysis (SNA)

To analyze the structural characteristics of the China–ASEAN science and technology cooperation network, this study applies a Social Network Analysis (SNA). Key indicators such as network size, density, average path length, clustering coefficient, and network centrality are used to display the structural features of the China–ASEAN science and technology cooperation network. Visualizations of the network structure for key years are also presented to observe the overall evolution of the network. SNA analyzes relationships between nodes and edges, using indicators such as network size, density, and centrality to characterize the network [44,45].

4.1.2. Temporal Exponential Random Graph Model (TERGM)

In social network research, the Exponential Random Graph Model (ERGM) is widely used to analyze network structures. However, ERGM is mostly applicable to cross-sectional data and cannot capture the dynamic evolution of networks over time. To address this limitation, Hanneke and colleagues introduced the Temporal Exponential Random Graph Model (TERGM) [46]. This model extends ERGM by incorporating time dependence, allowing for the analysis of multiple time points in the network as an integrated whole, which enables modeling of the dynamic evolution of network relationships. Unlike traditional ERGM, TERGM is applicable to longitudinal data analysis, effectively capturing structural changes over different periods and making the model estimation results more reflective of the formation and dynamic changes of network relationships [47].

Additionally, TERGM allows researchers to simulate and reproduce observed dynamic network structures and conduct hypothesis testing and inferences on potential mechanisms driving network evolution. This statistically grounded framework offers stronger predictive capabilities compared to traditional agent-based dynamic network models [48].

TERGM incorporates time dependence into the ERGM framework by considering network evolution over multiple time points. Its basic form is expressed as follows:

$$P_r\left(Y^t = y^t \middle| Y^{t-1} = y^{t-1}, \theta\right) = \frac{exp\left(\theta^T \cdot g\left(y^t, y^{t-1}\right)\right)}{c\left(\theta, y^{t-1}\right)} \quad (1)$$

where y^t represents the network structure at time t, θ are the model parameters, $g\left(y^t, y^{t-1}\right)$ is a vector of network statistics describing the relationship between the current and previous time points, and $c\left(\theta, y^{t-1}\right)$ is a normalizing constant ensuring that the sum of the probabilities equals 1. This equation demonstrates that the current network structure depends not only on the model parameters and statistics but also on the structure of the previous time point, allowing TERGM to capture time-dependent network changes and relationships.

4.2. Variables and Data Sources

Dependent variable: The dependent variable in this study is the probability of node connections in the China–ASEAN science and technology cooperation network, representing the likelihood of cooperative relationships being formed between countries. The construction of the cooperation network is based on co-authored papers, a widely used measure in existing studies to reflect the internationalization of scientific activities within a specific timeframe [23]. In this study, the time period spans from 2003 to 2022, and the data include co-authored papers between China and 11 ASEAN countries, comprising a total of 394,406 papers. These papers form the basis for constructing the China–ASEAN science and technology cooperation network. The data were sourced from the Web of Science Core Collection. Papers with authors from three or more countries were split into multiple bilateral relationships. For example, a paper co-authored by researchers from China, Singapore, and Thailand would result in bilateral relationships between China and Singapore,

Singapore and Thailand, and China and Thailand. After data cleaning and processing, 20 matrices of co-authored papers were constructed, representing the China–ASEAN science and technology cooperation network from 2003 to 2022.

Explanatory variables: In TERGM, explanatory variables typically include endogenous structural variables, temporal dependencies, node attributes, and network covariates (see Table 2). Endogenous structural variables include geometrically weighted degree, geometrically weighted dyadic shared partners, and geometrically weighted edgewise shared partners. Exogenous factors are captured through node attributes and network covariates.

Table 2. Explanatory variable indicators.

Primary Indicators	Secondary Indicators	Data Sources
Endogenous structural variables	edges gwdegree gwdsp gwesp	Web of Science core collection and network structure
Temporal dependencies	stability variability	
Network covariates	edgecov.geography edgecov.language edgecov.institution	World development indicators CEPII databases World development indicators
Node attributes	nodecov.hci nodecov.paper nodecov.pcap	UNCTADstat Web of Science core collection World development indicators

Node attributes: This study initially considered six indicators, including economic development, communication capacity, network infrastructure, innovation capability, human development index, and human capital index. To ensure data completeness over the 20-year period, variables with missing values were excluded, and three were retained: economic development level (measured by per capita GDP), scientific output (measured by the total number of published papers), and human capital level (measured by the human capital index). Data for per capita GDP (pcap) were sourced from the World Bank's World Development Indicators (WDI), scientific output (paper) from the Web of Science Core Collection, and human capital index (hci) from UNCTAD. The human capital index captures education, skills, health conditions, and overall research expenditure within the population. Gender aspects were reflected in fertility rates, with higher fertility rates lowering human capital scores.

Network Covariates: Geographic proximity was represented by a geographic distance matrix, institutional proximity by the World Bank's governance index, and linguistic proximity by a symmetric matrix sourced from the CEPII database. For institutional proximity, the average difference in governance quality scores (including factors such as political stability, regulatory quality, and rule of law) between countries was used [49]. Linguistic proximity was coded as zero for countries sharing an official language, and one otherwise.

5. Empirical Analysis and Results

5.1. Overall Network Characteristics

This section analyzes the structural characteristics of the China–ASEAN science and technology cooperation network from 2003 to 2022 based on the co-authorship of scientific papers between China and ASEAN countries. The network structure indicators, including network size, number of edges, density, average path length, and clustering coefficient, were calculated for each year (as shown in Figure 1).

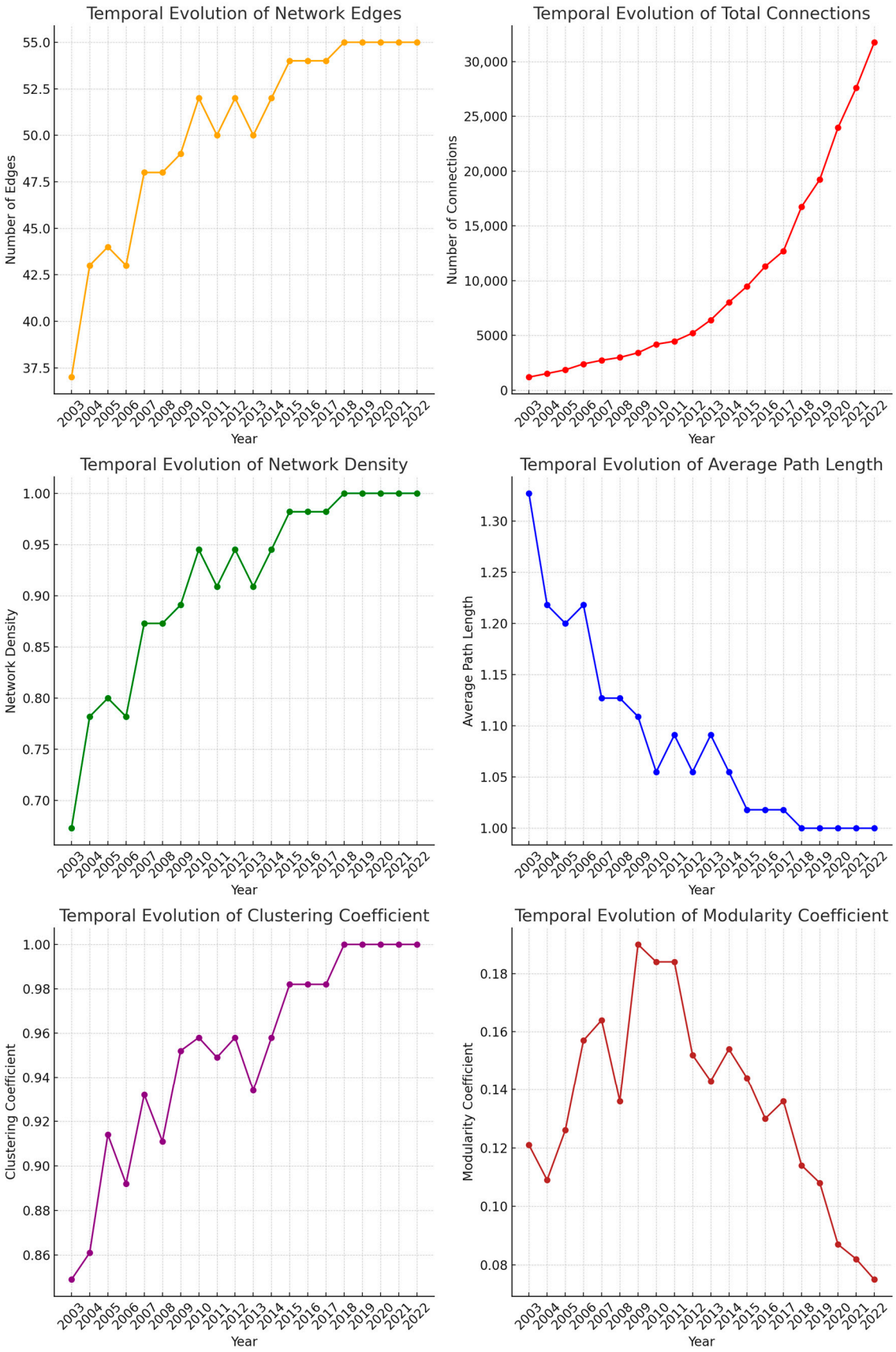


Figure 1. Evolution of structural characteristics in the China–ASEAN science and technology cooperation network.

1. Network scale: Since 2003, all 11 ASEAN countries have been involved in the China–ASEAN science and technology cooperation network.

2. "Number of edges" refers to the actual number of connections between nodes, representing the existing cooperative relationships. In contrast, "connection frequency" indicates the interaction intensity of these cooperative relationships, such as the frequency of co-authored publications. As shown in Figure 1, the number of edges in the network increased from 37 in 2003 to 55 in subsequent years, approaching the maximum possible number of edges for the 11 nodes in a fully connected network (which is 55). This suggests that the China–ASEAN science and technology cooperation network is evolving from being sparse to becoming more fully connected. The connection frequency also shows a steady upward trend, and the growth in the number of connections is much greater than the increase in edges, indicating that cooperation between countries has become more frequent and stable.

3. "Network density" measures the degree of connectivity among nodes in a network, defined as the ratio of the actual number of connections to the theoretically maximum possible connections. Density reflects the overall tightness of the network. Theoretical maximum connections refer to the total number of edges that could exist if every node in the network were directly connected to every other node. From the perspective of network density, the proportion of actual connections to the theoretical maximum connections has steadily increased, rising from 0.673 in 2003 to 1 in 2018 and maintaining a density of 1 through 2022. A density of 1 indicates that all nodes are fully connected with one another, reflecting increasingly close cooperative ties among countries.

4. "Average path length" refers to the mean shortest path between any two nodes in the network, serving as a measure of the network's overall compactness. The "clustering coefficient" quantifies the tendency of nodes in the network to form tightly knit triangular relationships, reflecting the local clustering characteristics of the network. From the perspective of average path length and the clustering coefficient, the China–ASEAN science and technology cooperation network gradually exhibits the characteristics of a "small world" network, with the average path length steadily decreasing, indicating improved connectivity among the 11 countries. The clustering coefficient, represented by the transitivity ratio (the proportion of closed triangles to total triangles), shows a steady increase, reaching 100% by 2022. This demonstrates that the closure effect of triadic relationships in the network is significant.

5. The "modularity coefficient" is an indicator used to measure the grouping structure of nodes within a network. A higher modularity coefficient typically indicates the presence of multiple distinct community structures in the network, whereas a lower coefficient suggests a more uniformly distributed network. From the perspective of the modularity coefficient, the modularity coefficient showed an increasing trend from 2003 to 2007, peaking at 0.190, indicating that the initial development of the China–ASEAN cooperation network was marked by the formation of distinct communities that strengthened intra-community connections. Between 2008 and 2016, the modularity coefficient fluctuated, reflecting variable levels of cooperation among the 11 countries during this period. Since 2017, the modularity coefficient has been steadily decreasing, reaching 0.075 in 2022. This suggests that the boundaries between communities in the network have become blurred, leading to a more uniformly distributed and interconnected network structure. The overall trend indicates that, over the 2003–2022 period, the cooperation network has transitioned from being highly modular to more evenly distributed, reflecting the expansion and balance of cooperation.

In summary, from the perspective of the overall network characteristics, the structure of the China–ASEAN science and technology cooperation network has become increasingly complex, exhibiting prominent "small world" and "high clustering" features, which align closely with the conclusions of previous studies. Although the modularity coefficient has decreased since 2018, indicating that the cooperation network has expanded and become more balanced, this change does not contradict the "small world" and "high clustering"

characteristics of the network. On the contrary, this transformation reflects a shift from community-focused collaboration in the early stages to a more evenly distributed and widespread cooperation pattern. Ultimately, the co-authorship network of China–ASEAN papers not only retains the characteristics of a "small world" network with "high clustering" but also demonstrates the breadth and flexibility of cooperative relationships. To more intuitively display the evolution of the structural characteristics of the China–ASEAN science and technology cooperation network, ArcGIS software was used to visualize the network topology for the years 2003, 2013, and 2022, as shown in Figure 2.

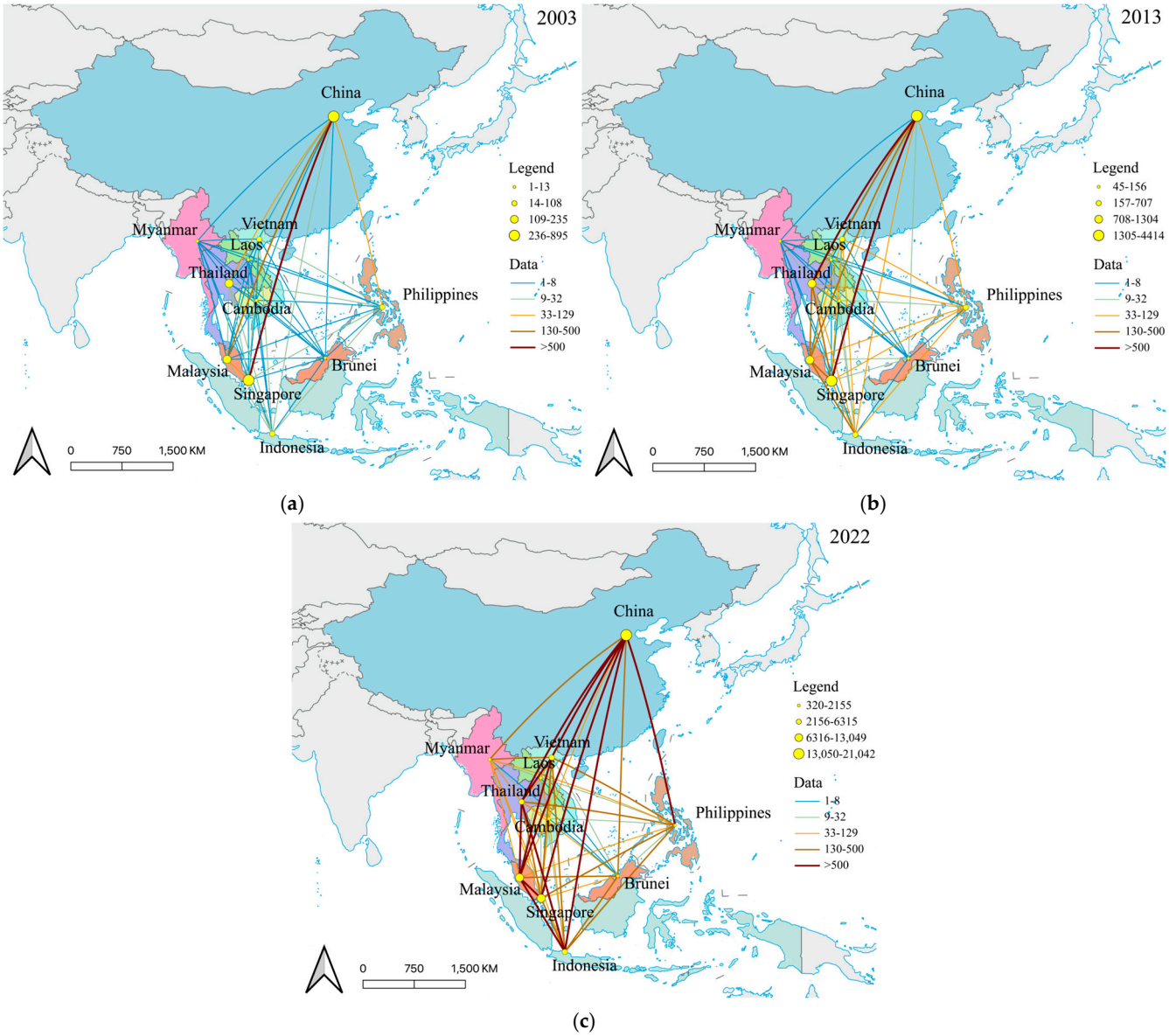


Figure 2. Topology of the China–ASEAN Science and Technology Cooperation Network. (**a**) 2003, (**b**) 2013, (**c**) 2022.

5.2. Overall Network Evolution Trend Analysis

As illustrated in Figure 2, China and Singapore consistently occupy central positions in the network, with their influence extending to more peripheral countries over time. Specifically, the 2003 network was relatively sparse, with China and Singapore as the core nodes forming cooperative relationships with surrounding countries. The network at this stage exhibited a star-shaped structure with few triangular formations, reflecting

the expansionary phase of the cooperation network. By 2013, the number of core nodes increased, and a new pattern emerged, with China and Singapore as central nodes and countries like Malaysia and Thailand—nations with strong scientific capabilities—emerging as secondary cores. By 2022, the network had formed 55 edges, with nodes participating in dynamic evolution, resulting in a more interconnected network structure. Although core nodes began forming closed triangular structures, the cooperation network continued to display characteristics of both "small world" and "high clustering" features, alongside widespread and flexible cooperation patterns.

5.3. Mechanisms of the China–ASEAN Science and Technology Cooperation Network's Evolution

5.3.1. Baseline Empirical Results

To explore the driving factors behind the evolution of the China–ASEAN science and technology cooperation network in greater depth, we used the co-authored paper data from 2003 to 2022 between China and 11 ASEAN countries to construct a binary matrix containing only 0s and 1s. The median value of all node data, 18, was used as the threshold for binarization (i.e., node values greater than or equal to 18 were coded as 1, and those below 18 were coded as 0). The result was a baseline empirical analysis of the longitudinal network data for China–ASEAN science and technology cooperation. We employed the Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMCMLE) method, iterating the system to gather possible parameter values, conducting parameter tests and corrections, until the estimated parameters stabilized. The final empirical results are shown in Table 3.

Table 3. Corresponding network structures in Temporal Exponential Random Graph Model (TERGM).

	Model Variables	Model 1	Model 2	Model 3	Model 4
Endogenous structural variables	edges	−13.42331 ***	−15.05679 ***	−10.75034 ***	−4.91264 ***
		(0.84095)	(1.01421)	(0.99207)	(1.48655)
	gwdeg			−5.34942 ***	−9.99238 ***
				(0.62413)	(2.55893)
	gwesp			−0.96235 ***	−1.79150 ***
				(0.20202)	(0.42770)
	gwdsp			0.02688	0.84665 **
				(0.10529)	(0.31913)
Temporal dependencies	stability				1.79572 ***
					(0.15360)
	variability				−3.58767 ***
					(0.29835)
Network covariates	edgecov.geography		−0.30603	−0.40777	−1.22149
			(0.55823)	(0.62035)	(0.94718)
	edgecov.language		1.69287 ***	2.04455 ***	1.95929 **
			(0.37130)	(0.43634)	(0.67154)
	edgecov.institution		−1.65638 ***	−1.62621 ***	−0.99151 ***
			(0.17847)	(0.20031)	(0.27726)
Node attributes	nodecov.hci	0.19268 ***	0.22963 ***	0.19603 ***	0.13000 ***
		(0.01206)	(0.01465)	(0.01582)	(0.02115)
	nodecov.paper	−0.00000	−0.00000 **	−0.00000	−0.00000
		(0.00000)	(0.00000)	(0.00000)	(0.00000)
	nodecov.pcap	−0.00011 ***	−0.00010 ***	−0.00008 ***	−0.00006 ***
		(0.00001)	(0.00001)	(0.00001)	(0.00001)
	Num. obs.	2200	2200	2200	2090
	AIC	890.33713	753.15323	651.11886	440.11488
	BIC	910.34939	788.17469	732.01439	527.96886
	Log likelihood	−441.16856	−369.57662	−315.55943	−209.05744

Note: Robust standard errors in parentheses; *** $p < 0.001$; ** $p < 0.01$.

Model 1 includes only network edges (edges) and node attribute variables.

Model 2 incorporates network covariates in addition to the variables in Model 1.

Model 3 introduces endogenous structural factors based on Model 2.

Model 4, the comprehensive model, adds time dependence to Model 3 to examine the stability and variability of network evolution.

By continuously fine-tuning the model, we improved both the exogenous and endogenous structures, enabling a deeper exploration of the endogenous and exogenous driving forces behind the evolution of the China–ASEAN science and technology cooperation network. The estimation models were primarily implemented using the "tergm" package in the R programming language. As shown in Table 3, the coefficients for edges in Models 1 through 4 are negative and statistically significant at the 0.1% level. This indicates that the formation and development of the China–ASEAN science and technology cooperation network is not random. Given that the actual observed network density is far lower than that of a random network, it becomes clear that understanding the endogenous and exogenous factors driving the evolution of the China–ASEAN science and technology cooperation network is of critical importance. The following analysis will focus primarily on Model 4, which includes all the variables.

1. Endogenous structural variables: Based on the results of 4the four models, it is evident that the coefficient for edges is negative across all models, particularly in Model 1 and Model 2, where the values are significantly negative (−13.42331 and −15.05679). This confirms that an increase in the number of edges reduces the likelihood of forming new cooperative relationships, supporting Hypothesis H1a. The findings echo earlier network structure analysis, which showed that as time progresses, the number of edges in the network increases, and the density reaches 1, indicating saturation of cooperative relationships. This further supports Hypothesis H1a.

The coefficient for geometrically weighted degree (gwdeg) in Model 4 is significantly negative (−9.99238), indicating that highly centralized countries are less likely to form new cooperative relationships. This validates Hypothesis H1b, which suggests that centralization within the network negatively impacts the formation of new relationships. This reflects the "star country" effect, where central nodes (such as China and Singapore) dominate the network, reducing the need for new partnerships as their existing networks become stable.

On the other hand, the coefficient for geometrically weighted edgewise shared partners (gwesp) in Model 4 is negative (−1.79150) and significant across all models, confirming that an increase in shared partners reduces the formation of new cooperative relationships, supporting Hypothesis H1c. The increasing number of closed triadic structures reinforces this notion, as nodes within the network prefer maintaining existing partnerships rather than exploring new opportunities. This closed triadic effect strengthens the stability of the network but also limits the creation of new relationships. Despite the network's increasing density, the rate at which closed triadic structures form is relatively slow.

The coefficient for geometrically weighted dyadic shared partners (gwdsp) in Model 4 is positive (0.84665) and significant, indicating that the gradual formation of new cooperative relationships through shared partners validates Hypothesis H1d. Shared partners provide indirect connections, enhancing the cooperation potential between nodes and facilitating the expansion of relationships. This expansion supports the earlier observation that the China–ASEAN science and technology cooperation network exhibits a "small world" characteristic, as collaborations expand to other countries through intermediary nodes, making the network more interconnected and cohesive.

2. Stability and variability analysis: In Model 4, the stability coefficient is positive and significant (1.79572), indicating that, over time, the China–ASEAN science and technology cooperation network increasingly stabilizes, with established cooperative relationships being maintained. This finding aligns with the theory of network stability. At the same time, the coefficient for variability (edgecov. variability) is negative (−3.58767), suggesting that despite the overall stability, dynamic characteristics persist within the cooperation network. Innovation-driven factors compel some countries to adjust their partnerships continually,

which enhances the flexibility and adaptability of the network. This indicates that while the cooperation network remains stable in the long term, it retains a considerable degree of dynamism, supporting Hypothesis H2. These results resonate with the modularity coefficient changes observed earlier, illustrating the network's transition from an early-stage community structure to a more balanced development process. This conclusion is also consistent with the findings of Wang et al. [50], who reported that science and technology cooperation between ASEAN countries and China has steadily expanded over the past few decades, particularly through the establishment of multi-level cooperation mechanisms for technology transfer and innovation collaboration.

3. Node attribute analysis: The coefficient for human capital (hci) is positive and significant across all models, confirming that countries with higher human capital levels are more likely to form new partnerships. These countries typically possess advanced technological and innovation resources, which attract other nations to collaborate with them. This finding aligns with the core concept of the Matthew effect, wherein resources and opportunities increasingly concentrate in countries that already have substantial resources. The ASEAN Secretariat [5] has similarly emphasized that the cultivation of scientific talent and the establishment of collaborative centers have greatly promoted science and technology cooperation among ASEAN countries, reinforcing the idea of the Matthew effect. However, the coefficient for scientific output (paper) does not show a significant positive effect in the models, reflecting the complexity of spillover effects from scientific output. This result suggests that countries with higher scientific output may not immediately form more collaborative relationships, but they often play a critical role as knowledge exporters, attracting other countries to connect with them through indirect pathways (e.g., shared partners). This phenomenon may be influenced by other factors, such as institutional environments or geographic proximity.

Notably, the coefficient for per capita GDP (pcap) is negative and significant, which contradicts the initial expectations of Hypothesis H3. This suggests that countries with higher per capita GDP within the China–ASEAN science and technology cooperation network may not actively seek new partnerships. Instead, they are more likely to maintain their existing cooperative networks, perhaps because they already receive sufficient innovation resources and technological spillovers from their established collaborations. This finding aligns with the "star country" effect, where economically advanced countries rely on their established advantages to stabilize their core roles in the network rather than proactively expanding their partnerships. The National Development and Reform Commission (NDRC) [51] has similarly noted that while economic ties between China and ASEAN countries are becoming closer, particularly in countries with higher per capita GDP, these nations may prefer to maintain their existing cooperation networks to access innovation resources. This observation helps explain why wealthier countries within the network may not actively seek out new partners in science and technology cooperation.

Based on the above analysis, Hypothesis H3 is only partially validated. While the significant positive effect of hci supports the existence of the Matthew effect, the negative result for pcap indicates that wealthier countries follow strategies that differ from initial expectations. This finding may reflect the asymmetric nature of the China–ASEAN science and technology cooperation network, where countries with higher human capital take a more active role in forming new partnerships, while wealthier countries rely more on their existing networks. Therefore, while the Matthew effect is validated in certain dimensions, the effect is more complex when economic factors come into play.

4. Network covariates analysis: The coefficient for linguistic proximity (language) is positive and significant across multiple models, especially in Model 4 (1.95929), indicating that countries with linguistic similarities are more likely to form cooperative relationships. Linguistic proximity facilitates international science and technology cooperation by reducing communication barriers and increasing efficiency and trust among collaborating partners. This finding is consistent with previous studies, such as Gu et al. [52], who emphasized that linguistic differences are a critical factor in international cooperation. Countries

that share a common or similar language are more likely to communicate smoothly during collaboration, while countries with language barriers may face challenges related to translation costs, cultural differences, and information misinterpretation. Thus, the positive impact of linguistic proximity in Hypothesis H4 is confirmed. The commonality of language is a key driving force in cross-national cooperation, particularly in science and technology, where complex communication and coordination are required.

Conversely, the coefficient for institutional proximity (institution) is significantly negative, indicating that institutional similarity may, in fact, hinder cooperation in the science and technology network. This finding suggests that institutional environments, while similar, may not necessarily promote cooperation, and in some cases, institutional differences may complicate collaboration. This result contradicts the expectations of Hypothesis H4. In the context of China–ASEAN cooperation, institutional differences may not provide an obvious advantage for collaboration. For geographic proximity (geography), the coefficient is not significant, which may be due to advances in communication and transportation technologies, reducing the importance of geographic distance in science and technology cooperation. Geographic proximity does not have as significant an effect as hypothesized, likely due to improvements in regional transportation infrastructure and technology, which have diminished the traditional impact of geographic distance.

Based on this analysis, Hypothesis H4 is only partially validated. Linguistic proximity positively influences the formation of relationships within the China–ASEAN science and technology cooperation network, while institutional proximity does not have the expected facilitative effect and may even act as a barrier. Similarly, geographic proximity did not have a significant positive effect, likely due to improvements in transportation infrastructure, which have reduced the influence of geographic distance.

By analyzing the results of the Temporal Exponential Random Graph Model (TERGM) alongside conclusions derived from the social network analysis, it can be observed that the China–ASEAN science and technology cooperation network has evolved from an initially sparse and community-based structure to a more balanced and widespread structure. Throughout this process, core nodes (such as China and Singapore) have played a particularly significant role in driving the expansion of the cooperation network. As the network has evolved, linguistic and institutional factors have increasingly become important considerations in cross-national cooperation. Future research could further explore the impact of different policy contexts on institutional dynamics and examine how cross-national coordination mechanisms can enhance the overall connectivity of the network

5.3.2. Robustness Test

To ensure the robustness of the results, two approaches were used: adjusting the longitudinal network data and changing the estimation method. First, the longitudinal network data were adjusted by selecting every two years, resulting in a dataset for 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2019, and 2021, forming the longitudinal network data for the China–ASEAN science and technology cooperation network (results shown in Model 5). Next, a different dataset was selected for the years 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020, and 2022, forming another longitudinal network dataset (results shown in Model 6). Finally, the MCMCMLE method was replaced with the Maximum Pseudo-Likelihood Estimation (MPLE) method [52] (results shown in Model 7). The MPLE method estimates model parameters by maximizing the conditional likelihood function. Its advantage lies in higher computational efficiency compared to the MCMCMLE method, although the precision of the estimation results may be somewhat reduced. The specific estimation results are detailed in Table 4.

Table 4. Robustness test.

	Model Variables	Model 5	Model 6	Model 7
Endogenous structural variables	edges	−4.63064 *	−4.88855 *	−5.02229 *
		−1.9449	−2.33749	[−7.67078; −2.18013]
	gwdeg	−6.35056	−9.50868 *	−7.64632 *
		−3.32896	−4.17716	[−16.40679; −3.94845]
	gwesp	−1.30555 *	−2.18662 **	−1.69012 *
		−0.61058	−0.7479	[−3.15247; −0.87238]
	gwdsp	0.32784	0.7243	0.53533 *
		−0.42801	−0.50943	[0.11734; 1.50457]
Temporal dependencies	stability	1.56084 ***	2.08160 ***	1.76616 *
		−0.20126	−0.32526	[1.51351; 2.12748]
	variability	−3.19067 ***	2.09331 ***	1.76616 *
		(0.41323)	(0.31395)	[1.51351; 2.12748]
Network covariates	edgecov.geography	−1.61558	−2.18249	−1.54376 *
		−1.21812	−1.54116	[−3.18750; −0.38416]
	edgecov.language	1.75879 *	1.93554 *	1.82221 *
		−0.77992	−0.97902	[0.97959; 2.94498]
	edgecov.institution	−0.91376 *	−0.96842 *	−1.06173 *
		−0.36332	−0.4151	[−1.67011; −0.53580]
Node attributes	nodecov.hci	0.11984 ***	0.15106 ***	0.13263 *
		−0.02668	−0.03284	[0.10007; 0.17410]
	nodecov.paper	−0.00000	0.00000	−0.00000
		0.00000	0.00000	[−0.00000; 0.00000]
	nodecov.pcap	−0.00005 **	−0.00007 ***	−0.00006 *
		−0.00002	−0.00002	[−0.00009; −0.00004]
	Num. obs.	990	990	2090
	AIC	256.61231	210.85992	
	BIC	327.96865	282.21626	
	Log likelihood	−117.30615	−94.42996	

Note: Robust standard errors in parentheses; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Models (5) and (6) reflect the robustness tests based on adjusted longitudinal network data, while Model 7 represents the robustness test based on the alternative estimation method. As shown in Table 4, the results from Model 5, Model 6, and Model 7 are consistent with the baseline empirical results: expansiveness (gwdeg) is significantly negative, confirming that countries within the cooperation network tend to avoid establishing new cooperative relationships. Transitivity (gwesp) remains significantly negative, while closure (gwdsp) is significantly positive, further validating that, while there is a tendency for transitivity between nodes, the overall network leans toward forming and developing cooperative relationships through closure mechanisms.

Regarding time dependencies, stability remains significantly positive, while variability remains significantly negative, confirming that the conclusion that the network's evolution exhibits both stability and dynamic development is robust. The results for exogenous factors once again indicate that human capital in the China–ASEAN science and technology cooperation network exhibits the Matthew effect. At the same time, the coefficient for scientific output (papers) does not show a significant positive impact, suggesting that the spillover effects of scientific output are more complex. The coefficient for per capita GDP (pcap) is consistently negative and significant, suggesting that countries with higher per capita GDP tend to rely more on their existing cooperative networks.

Linguistic proximity has a positive impact on the formation of relationships within the China–ASEAN science and technology cooperation network, but institutional proximity does not show the expected facilitative role and may even act as an obstacle to cooperation. Similarly, geographic proximity did not demonstrate a significant positive effect on cooperation within the current network.

5.3.3. Goodness-of-Fit (GOF) Test

To assess the scientific validity and reliability of the constructed China–ASEAN science and technology cooperation network model, this study conducted a Goodness-of-Fit (GOF) test. The convergence of the model was set as a prerequisite, with the simulated network based on the established model used as a reference to compare with the actual observed network. This comparison aimed to determine whether the model could accurately fit the structure of the observed network. Key statistics selected for the test included network degree distribution (degree), dyad-wise shared partner distribution (dyad-wise shared partners), edge-wise shared partner distribution (edge-wise shared partners), geodesic distances, and Receiver Operating Characteristic (ROC) and Precision–Recall (PR) curves. The results are presented in Figure 3. In Figure 3, the black solid line represents the measurement results of the actual observed network, while the gray boxplots with dashed lines represent the measurement results of the simulated network within the 95% confidence interval. When the black solid line is close to the median of the gray boxplot, it indicates that the measurement results of the observed network fall within the 95% confidence interval of the simulated network, signifying a good model fit. By observing the model fit graphs, it can be seen that the TERGM successfully simulated the structural characteristics of the observed network and was able to capture the dynamic evolution mechanism of the China–ASEAN science and technology cooperation network.

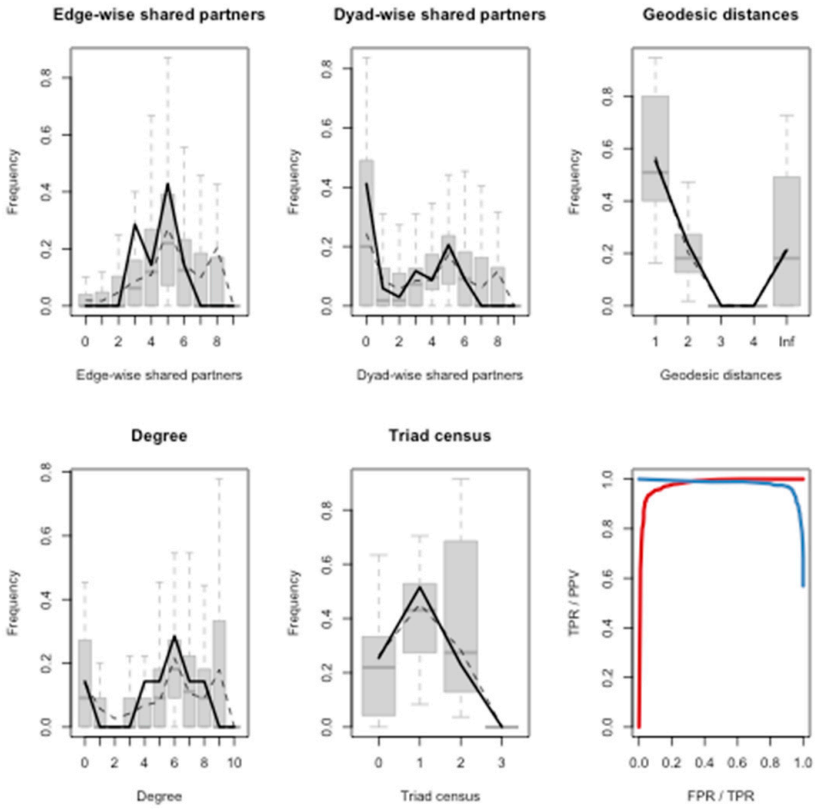


Figure 3. Goodness-of-fit plot. Note: The ROC curve (red line) and PR curve (blue line) are shown in the bottom-right pane.

Additionally, ROC and PR curves were also employed to evaluate the fit of the TERGM model. The larger the area under the ROC and PR curves (AUC), the better the model performance [47]. As shown in Figure 3, the ROC and PR curves approach the top-left and top-right corners, respectively, indicating a good model fit and further confirming the scientific validity and reliability of the network model constructed in this study.

6. Conclusions and Implications

6.1. Conclusion Analysis

This study conducted an in-depth analysis of the science and technology cooperation network between China and ASEAN countries from 2003 to 2022, revealing the evolution characteristics and key influencing factors of this cooperation network under the influence of the Belt and Road Initiative (BRI) and the Regional Comprehensive Economic Partnership (RCEP). Co-authored papers, as an important form of science and technology cooperation, have effectively facilitated the flow and complementarity of innovation resources between China and ASEAN countries, thereby improving the efficiency and outcomes of regional science and technology cooperation and providing a solid foundation for achieving the sustainable development goals (SDGs). The main conclusions are as follows:

1. Network evolution: The China–ASEAN science and technology cooperation network has gradually evolved from an initial "star-shaped structure" to a more interconnected network structure, exhibiting "small world" and "high clustering" characteristics. As the network has evolved, the role of core nodes (such as China and Singapore) has strengthened, leading to increased connectivity and stability within the network. This network structure helps enhance the efficiency of regional cooperation and the ability to resist endogenous shocks while also promoting the flow of innovation elements and the complementarity of technological advantages within the region, driving regional science and technology cooperation toward long-term, inclusive, and sustainable development.
2. Influence of endogenous network structure: The evolution of the network's endogenous structure has a significant impact on the formation of cooperative relationships. This study shows that the number of edges, node centrality, and closed triangular structures (such as the increase in shared partners) either inhibit or promote the formation of new cooperative relationships. Specifically, an increase in the number of edges and higher centrality suppressed new partnerships, while an increase in shared partners promoted new relationships. This indicates that structural dependencies significantly affect the dynamic evolution of the China–ASEAN science and technology cooperation network, enhancing the efficiency of cooperation and ensuring its sustainability over the long term.
3. Stability and variability: The evolution of the science and technology cooperation network exhibits both stability and variability. Existing partnerships show high continuity, and the network structure gradually stabilizes. However, as the demand for science and technology cooperation changes, new partnerships continue to emerge, maintaining the network's dynamic nature. The coexistence of stability and variability within the network reflects the robustness and innovativeness of science and technology cooperation in the China–ASEAN region. These characteristics not only facilitate the effective allocation of innovation resources and deepen cross-national collaboration but also align closely with sustainable development goals such as optimizing innovation resources and fostering partnerships.
4. Node attribute variables: Human capital, per-capita GDP, and scientific output all play critical roles in the formation of the science and technology cooperation network. Countries with higher levels of human capital are more likely to form new cooperative relationships. These countries typically possess higher levels of education, research capabilities, and research personnel, attracting other countries to collaborate with them. This finding aligns with the core concept of the Matthew effect, where resources tend to concentrate in countries that already have more, thus reinforcing their core positions within the network and contributing to the sustained growth of regional innovation capacity. On the other hand, countries with higher per capita GDP tend to maintain existing cooperative networks rather than actively seek new partners, possibly because they already acquire sufficient innovation resources and technological spillovers from their current relationships. Lastly, scientific output did not show a significant positive effect in the models, suggesting that countries with high scientific

output, although often serving as knowledge exporters, may face barriers to forming new partnerships due to factors such as language or institutional proximity.

5. Proximity factors: The proximity variables exhibited heterogeneity in the dynamic evolution of the science and technology cooperation network. Specifically, linguistic proximity had a significant positive effect on the formation of cooperative relationships, facilitating smooth collaboration between countries and reducing communication costs. Conversely, institutional proximity in some cases had a negative effect on the formation of new partnerships, possibly due to the complexities and uncertainties introduced by institutional differences between countries. Geographic proximity had a less significant effect than expected, reflecting the diminishing importance of physical distance in the context of globalization and digitalization. By overcoming barriers to cooperation and optimizing collaboration mechanisms, countries can more effectively coordinate institutional differences, promote the sharing of innovation resources, and foster long-term synergistic development within the region. This aligns with the sustainable development goals of optimizing the allocation of innovation resources and fostering partnerships. Furthermore, it enhances the robustness of regional science and technology cooperation and strengthens the region's capacity to address future environmental challenges.

Through a systematic analysis of the China–ASEAN science and technology cooperation network, this study reveals the dynamic evolution of the network and explores the impact of endogenous and exogenous factors on cooperative relationships. The findings suggest that the expansion and deepening of the science and technology cooperation network not only enhance regional innovation capacity but also provide strategic insights into the future role of China and ASEAN countries in global technological innovation. By optimizing cross-border cooperation mechanisms, promoting the sharing of science and technology resources, and fostering the development of cross-national talent, this cooperation network is expected to enhance regional innovation capacity while ensuring the sustainability of science and technology cooperation, thus supporting the achievement of the global Sustainable Development Goals (SDGs).

6.2. Policy Implications

Based on the findings of this study, the following policy recommendations are proposed to strengthen the linkages within the China–ASEAN science and technology cooperation network, optimize resource allocation, enhance regional innovation capacity, and ensure the sustainability and inclusiveness of science and technology cooperation:

1. Strengthening the role of core nodes and optimizing sustainable resource allocation: Certain countries or regions within China and ASEAN have already become core nodes in the science and technology cooperation network, playing a leading role. However, the concentration of these core nodes may result in unequal resource distributions. Policymakers should establish regional cross-border innovation centers and technology transfer platforms to enable core node countries to share their technological advancements with neighboring nations. For example, these centers could focus on facilitating joint R&D programs, patent sharing, and technology licensing agreements between universities and industries across China and ASEAN. Additionally, governments can provide tax incentives or funding for companies and institutions that participate in these technology transfer initiatives. This approach will help improve regional science and technology innovation capacity, promoting balanced and sustainable development of science and technology resources.
2. Promoting diversity and inclusivity in the cooperation network: This study found that developed countries often maintain existing relationships, limiting the formation of new partnerships and, in turn, stifling the vitality of regional innovation networks. Therefore, to promote diversity in the cooperation network, governments should create specific funding programs that incentivize developed countries to collaborate with less-developed ASEAN nations. These could include joint innovation grants

for projects in areas such as digital technology and AI, along with preferential access to government research contracts for institutions that partner with less-developed regions. Additionally, offering matchmaking events and technology expos that bring together stakeholders from different development levels would help foster new connections. Policy incentives should support long-term cooperation between enterprises and research institutions, promoting diversity and sustained innovation in the science and technology cooperation network.

3. Enhancing cross-national mobility of human capital: Human capital plays a crucial role in the formation and development of cooperative relationships within the science and technology cooperation network. To further enhance the sustainability of the cooperation network and to enhance cross-national mobility of human capital, governments should launch scholarship programs for postgraduate students and young researchers to participate in joint research initiatives. These programs can be supplemented by bilateral exchange agreements between universities, where students and faculty members can spend a semester abroad in partner institutions. Additionally, regional career fairs and research competitions that offer collaboration opportunities between China and ASEAN researchers can further stimulate talent exchange and innovation. Establishing joint research programs, offering scholarships, and providing research funding projects will promote the flow of cross-national scientific talent, improve regional innovation capacity, and ensure the long-term sustainability of the cooperation network.
4. Fostering multilateral cooperation and closed structures: This study showed that closed structures (such as trilateral or multilateral cooperation) significantly enhance the stability of the science and technology cooperation network. Policymakers should establish a multilateral R&D fund specifically aimed at promoting trilateral or multilateral partnerships in sectors such as renewable energy, biotech, and smart manufacturing. This fund could be co-financed by China and ASEAN governments and managed by an independent regional body. In addition, hosting regular collaborative innovation forums where multiple countries present joint research proposals could help solidify partnerships and create long-term cooperative structures. This will help build trust in cooperation, improve the efficiency of resource sharing and information flow, and strengthen the long-term stability and sustainability of the cooperation network.
5. Responding to the dynamic changes in cooperation networks: While the science and technology cooperation network exhibits a certain degree of stability, its dynamic nature cannot be ignored. Policymakers should adjust cooperation policies flexibly and regularly assess the evolution trends of the cooperation network to ensure that they can meet emerging technological challenges. By exploring cooperation in frontier fields such as the digital economy and intelligent manufacturing, the vitality and innovation of the cooperation network can be maintained, ensuring its long-term sustainable development.
6. Reducing institutional barriers: Institutional proximity may sometimes hinder the construction of science and technology cooperation networks. To mitigate this negative impact, governments should work towards creating a unified intellectual property (IP) framework that harmonizes patent laws and enforcement mechanisms across China and ASEAN. This could be achieved by establishing a China–ASEAN intellectual property working group to address cross-border IP disputes and provide standardized procedures for technology licensing and patent applications. Additionally, governments can develop guidelines for research management practices, including data sharing protocols and publication ethics, ensuring smoother collaboration between institutions. By establishing a unified framework agreement for science and technology cooperation, institutional barriers can be reduced, ensuring the smooth progress of cross-national cooperation and promoting the long-term sustainable development of the science and technology cooperation network.

By implementing these policy measures, we can provide theoretical and practical references for regional science and technology cooperation, supporting the sustained development of regional economic integration and contributing to the achievement of global sustainable development goals. The construction and optimization of science and technology cooperation networks is a long-term, dynamic process, and policy formulation and adjustments need to adapt to the changing network. Future research should continue to focus on the dynamic evolution of science and technology cooperation networks and their impact on sustainable development, providing more robust theoretical support for broader regional and global cooperation.

7. Contributions and Limitations

7.1. Research Contributions

This study introduces the Temporal Exponential Random Graph Model (TERGM) to systematically reveal the evolution characteristics and driving mechanisms of the China–ASEAN science and technology cooperation network, addressing the gap in the existing literature regarding the dynamic evolution of regional science and technology cooperation networks. This paper is the first to apply the TERGM model to the study of the evolution of the China–ASEAN science and technology cooperation network. In doing so, it extends existing methodologies for international science and technology cooperation research and provides new tools and insights for empirical studies on similar topics. The research results indicate that human capital and linguistic proximity significantly promote the formation of the China–ASEAN science and technology cooperation network, providing scientific evidence and reference for governments and policymakers when formulating science and technology cooperation policies. Moreover, this study provides empirical support for enhancing regional innovation capacity and achieving the United Nations Sustainable Development Goals (SDGs).

7.2. Research Limitations

The data used in this study mainly come from the Web of Science Core Collection, which may not fully reflect other forms of science and technology cooperation between China and ASEAN countries (such as patent cooperation or technology transfer). This limitation may affect the comprehensive understanding of the science and technology cooperation network. Additionally, although the TERGM model has advantages in capturing the dynamic evolution of networks, its parameter settings are limited to a binary matrix (0 or 1), which may not fully capture the complexity of the entire network. Moreover, the limitations of data availability between China and ASEAN countries may mean that some assumptions in this study do not fully reflect the complexity of the actual network, which could limit the generalizability of this study's conclusions. Future research could expand data sources and the range of exogenous variables, such as by incorporating political and cultural factors, to improve the explanatory power of the model and the generalizability of the study's conclusions.

Author Contributions: Conceptualization, F.W. and Z.L.; methodology, Z.L.; software, Z.L.; validation, Z.L.; formal analysis, Z.L.; resources, F.W. and Z.L.; data curation, Z.L. writing—original draft preparation, F.W. and Z.L.; writing—review and editing, F.W. and Z.L.; visualization, Z.L.; supervision, F.W.; project administration, F.W.; funding acquisition, F.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Fund of China, grant number 23XZZ006; the Guangxi Human Resources and Social Security Department Project, grant number GXRS- 2024-223; and the Guangxi Philosophy and Social Science Planning Project, grant number 20FGL050.

Data Availability Statement: The data in this study were collected from: (1) Web of Science Core Collection https://www.webofscience.com/ (accessed on 15 August 2024); (2) World Development Indicators https://databank.worldbank.org/ (accessed on 15 August 2024); (3) DCEPII Databases https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele.Asp (accessed on 15 August 2024). (4) UNCTADstat https://unctadstat.unctad.org/EN/Index.html (accessed on 15 August 2024).

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

References

1. World Commission on Environment and Development. *Our Common Future*; Oxford University Press: Oxford, UK, 1987. Available online: https://sustainabledevelopment.un.org/content/documents/5987our-common-future.pdf (accessed on 11 October 2024).
2. United Nations. *Transforming Our World: The 2030 Agenda for Sustainable Development*; United Nations: New York, NY, USA, 2015. Available online: https://sdgs.un.org/2030agenda (accessed on 11 October 2024).
3. Ministry of Science and Technology of the People's Republic of China. Minister Wang Zhigang Attends the 11th Forum on China-ASEAN Technology Transfer and Collaborative Innovation and Delivers Keynote Speech. Available online: https://en.most.gov.cn/pressroom/202308/t20230823_187619.htm (accessed on 11 October 2024).
4. China Daily. China and ASEAN Forge Sustainable Development Pathways Through Collaborative Action. Available online: https://www.chinadaily.com.cn/a/202403/26/WS660295bba31082fc043bec5f.html (accessed on 11 October 2024).
5. ASEAN Secretariat. ASEAN Cooperation in Science and Technology. Available online: https://cariasean.org (accessed on 11 October 2024).
6. World Bank. China's Transition to a Low-Carbon Economy and Climate Resilience Needs Shifts in Resources and Technologies. Available online: https://www.worldbank.org/en/news/press-release/2022/10/12/china-s-transition-to-a-low-carbon-economy-and-climate-resilience-needs-shifts-in-resources-and-technologies. (accessed on 11 October 2024).
7. China-ASEAN Joint Statement on Strengthening Common and Sustainable Development. Available online: https://asean.org/asean-china-joint-statement-on-strengthening-common-and-sustainable-development/ (accessed on 11 October 2024).
8. ASEAN-China Center. China and ASEAN Promote Trade and Innovation Cooperation. Available online: http://www.asean-china-center.org/trade/dtmy/2024-07/13738.html (accessed on 11 October 2024).
9. Guangming Daily. China and ASEAN Work Together to Address Climate Change. Available online: https://news.gmw.cn/2022-11/01/content_36128275.htm (accessed on 11 October 2024).
10. United Nations Educational, Scientific and Cultural Organization (UNESCO). International Cooperation in Science and Technology: A Global Perspective. Available online: https://unesdoc.unesco.org/ark/48223/pf00000858980 (accessed on 22 August 2024).
11. Bozeman, B.; Fay, D.; Slade, C.P. Research Collaboration in Universities and Academic Entrepreneurship: The State-of-the-Art. *J. Technol. Transf.* **2013**, *38*, 1–67. [CrossRef]
12. Liu, F.; Chen, X. The Causal Relationship Between GDP and Technology Innovation in China. *Econ. Res.-Ekon. Istraživanja* **2014**, *27*, 39–54. [CrossRef]
13. Gui, Q.; Liu, C.; Du, D. Globalization of Science and International Scientific Collaboration: A Network Perspective. *Geoforum* **2019**, *105*, 60–74. [CrossRef]
14. Bozeman, B.; Corley, E. Scientists' Collaboration Strategies: Implications for Scientific and Technical Human Capital. *Res. Policy* **2004**, *33*, 599–616. [CrossRef]
15. Cunningham, J.A.; Link, A.N. Fostering University-Industry R&D Collaborations in European Union Countries. *Res. Policy* **2015**, *44*, 59–67. [CrossRef]
16. Wang, Y.; Wang, X. The Development Process and Prospects of China-ASEAN Agricultural Cooperation. *Econ. Horiz.* **2018**, *12*, 88–95. [CrossRef]
17. Zhao, F.; Liu, Y. A Study on the Science and Technology Cooperation Between China and ASEAN from the Perspective of Bibliometrics. *World Sci. Res. Dev.* **2020**, *42*, 376–387. [CrossRef]
18. Ding, J.; Yang, L.; Sun, H.; Liu, X.; Huang, X.; Yue, T. Research on the Situation of Scientific Cooperation in the Belt and Road Region and Along the Route Based on Bibliometrics. *Bull. Chin. Acad. Sci.* **2017**, *32*, 626–636. [CrossRef]
19. Xiao, S.; Yan, Y. A Study on the Vertical Model of China-ASEAN (CAFTA) Science and Technology Cooperation. *Sci. Manag. Res.* **2018**, *36*, 108–111. [CrossRef]
20. Zhu, L. A Study of China's Science and Technology Cooperation Trend in the Past Decade from the Perspective of Scientometrics. *J. Inf. Sci.* **2015**, *34*, 116–121.
21. Zhang, L.; Glänzel, W. The Impact of Research Collaboration on Academic Performance: An Empirical Analysis Based on Chinese International Research Collaboration in the Fields of Chemistry and Materials Science. *Scientometrics* **2012**, *91*, 89–104.
22. Li, W.; Zhu, C. The Evolution of China's Role and Status in International Science and Technology Cooperation Networks: An Empirical Study Based on 2000–2015 International Patent Cooperation Data. *Sci. Technol. Manag. Res.* **2019**, *39*, 44–50.
23. Ren, X.; Yang, Y.; Chi, J. A Review of the Current Research and Methodologies of International Science and Technology Innovation Cooperation. *Glob. Sci. Technol. Econ. Outlook* **2019**, *34*, 66–76.

24. Glänzel, W. National Characteristics in International Scientific Co-Authorship Relations. *Scientometrics* **2001**, *51*, 69–115. [CrossRef]
25. Zhang, S.; Wang, L.; Liu, Z.; Wang, X. Evolution of International Trade and Investment Networks. *Physica A* **2016**, *462*, 752–763. [CrossRef]
26. Coccia, M. A Theory of Classification and Evolution of Technologies within a Generalized Darwinism. *Technol. Anal. Strateg. Manag.* **2018**, *30*, 1465–1490. [CrossRef]
27. Wagner, C.S.; Whetsell, T.A.; Leydesdorff, L. The Continuing Growth of Global Cooperation Networks in Research. *PLoS ONE* **2015**, *10*, e0131816. [CrossRef]
28. Crane, D. *Invisible Colleges: Diffusion of Knowledge in Scientific Communities*; University of Chicago Press: Chicago, IL, USA, 1972; p. 213. [CrossRef]
29. Freeman, L.C. Centrality in Social Networks: Conceptual Clarification. *Soc. Netw.* **1979**, *1*, 215–239. [CrossRef]
30. Robins, G.; Pattison, P.; Kalish, Y.; Lusher, D. An Introduction to Exponential Random Graph (p) Models for Social Networks. *Soc. Netw.* **2007**, *29*, 173–191. [CrossRef]
31. Peixoto, T.P. Disentangling Homophily, Community Structure, and Triadic Closure in Networks. *Phys. Rev. X* **2022**, *12*, 011004. [CrossRef]
32. Katz, J.S.; Martin, B.R. What Is Research Collaboration? *Res. Policy* **1997**, *26*, 1–18. [CrossRef]
33. Newman, M.E.J. Coauthorship Networks and Patterns of Scientific Collaboration. *Proc. Natl. Acad. Sci. USA* **2004**, *101*, 5200–5205. [CrossRef] [PubMed]
34. Glänzel, W.; Schubert, A. Domesticity and Internationality in Co-Authorship, References and Citations. *Scientometrics* **2005**, *65*, 323–342. [CrossRef]
35. Merton, R.K. The Matthew Effect in Science: The Reward and Communication Systems of Science are Considered. *Science* **1968**, *159*, 56–63. [CrossRef]
36. Gazni, A.; Sugimoto, C.R.; Didegah, F. Mapping World Scientific Collaboration: Authors, Institutions, and Countries. *J. Am. Soc. Inf. Sci. Technol.* **2012**, *63*, 323–335. [CrossRef]
37. Guan, J.; Zhang, J.; Yan, Y. The Impact of Network Position on Knowledge Creation: A Case of Nanotechnology Innovation. *Scientometrics* **2015**, *105*, 617–632.
38. Fontes, M.; Videira, P.; Calapez, T. The Impact of Long-term Scientific Mobility on the Creation of Persistent Knowledge Networks. *Mobilities* **2013**, *8*, 440–465. [CrossRef]
39. Guan, J.; Zhang, J.; Yan, Y. A Dynamic Perspective on Diversities and Network Change: Partner Entry, Exit and Persistence. *Int. J. Technol. Manag.* **2017**, *74*, 221–242. [CrossRef]
40. Hoekman, J.; Frenken, K.; Oort, F. The Geography of Collaborative Knowledge Production in Europe. *Ann. Reg. Sci.* **2009**, *43*, 721–738. [CrossRef]
41. Katz, J.S. Geographical Proximity and Scientific Collaboration. *Scientometrics* **1994**, *31*, 31–43. [CrossRef]
42. Hwang, K. International Collaboration in Multilayered Center—Periphery in the Globalization of Science and Technology. *Sci. Technol. Hum. Values* **2008**, *33*, 101–133. [CrossRef]
43. Hoekman, J.; Frenken, K.; Tijssen, R.J.W. Research Collaboration at a Distance: Changing Spatial Patterns of Scientific Collaboration within Europe. *Res. Policy* **2010**, *39*, 662–673. [CrossRef]
44. Newman, M.E.J. The Structure and Function of Complex Networks. *SIAM Rev.* **2003**, *45*, 167–256. [CrossRef]
45. Pappi, F.U.; Scott, J. *Social Network Analysis: A Handbook*; University of Chicago Press: Chicago, IL, USA, 1993; p. 128. [CrossRef]
46. Hanneke, S.; Fu, W.; Xing, E.P. Discrete Temporal Models of Social Networks. *Electron. J. Stat.* **2010**, *4*, 585–605. [CrossRef]
47. Leifeld, P.; Cranmer, S.J.; Desmarais, B.A. Temporal Exponential Random Graph Models with btergm: Estimation and Bootstrap Confidence Intervals. *J. Stat. Softw.* **2018**, *83*, 1–36. [CrossRef]
48. Goodreau, S.M.; Kitts, J.A.; Morris, M. Birds of a Feather, or Friend of a Friend? Using Exponential Random Graph Models to Investigate Adolescent Social Networks. *Demography* **2009**, *46*, 103–125. [CrossRef]
49. Li, L.; Guo, L. Institutional Distance and Transnational Cooperative Innovation Performance: The Moderating Role of Cultural Strictness. *Sci. Technol. Prog. Policy* **2021**, *38*, 16–25.
50. Wang, S.; Xue, X.; Zhu, A.; Ge, Y. The Key Driving Forces for Geo-Economic Relationships between China and ASEAN Countries. *Sustainability* **2017**, *9*, 2363. [CrossRef]
51. National Development and Reform Commission (NDRC). Economic Ties with ASEAN Set to Become Even Closer. Available online: https://en.ndrc.gov.cn/news/mediarusources/202112/t20211216_1308200.html (accessed on 19 August 2023).
52. Gu, H.; Yang, W.; Chen, W. The Pattern Evolution and Mechanism of China-ASEAN Cross-Border Regional Innovation Networks. *Sci. Technol. Manag. Res.* **2021**, *41*, 25–32.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.