Research on the influencing factors of the evolution of Industry-University-Research collaborative innovation network in Wenzhou

-- based on exponential random graph model

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Abstract

At present, Wenzhou is in urgent need of transforming and upgrading traditional industries and developing strategic emerging industries. The key lies in whether scientific and technological innovation can make a breakthrough. Therefore, it is particularly important to improve the collaborative innovation capability of Industry-University-Research (IUR).In this paper, we use the data of jointly applied patents to build a cooperative innovation network of IUR in Wenzhou from 2001 to 2018. Using the exponential random graph model (ERGM), we make quantitative analysis of the factors that affect the evolution of the collaborative innovation network from three aspects: network node attribute characteristics, network structures, and multidimensional proximity networks. Among the influencing factors of network structure, the geometrically weighted degree representing expansibility, the geometrically weighted edgewise shared partner representing closeness positively affect the network evolution, and the geometrically weighted dyadwise shared partner representing transitivity negatively affect the network evolution; In multidimensional proximity networks, technical proximity positively promotes the generation of cooperative relationships, but institutional proximity has a reverse inhibitory effect, and geographic proximity does not play a role; The last is attribute characteristic variable. The innovation strength, cooperation breadth and cooperation depth of the organization have no influence on the network evolution.

Keywords

ERGM, Wenzhou, collaborative innovation, network, factor.

1. Introduction

Whether Wenzhou, which mainly focuses on traditional industries such as electrical, footwear, clothing, automotive parts, and pumps and valves, can smoothly complete the transformation of old and new driving forces in the city, promote the construction of emerging leading industries such as digital economy, intelligent equipment, and life and health, and build itself into a globally competitive advanced manufacturing base, depends on whether technological innovation can gain advantages[1].

Currently, collaborative innovation between organizations has become one of the main ways to improve innovation capabilities in order to reduce various risks such as time, funding, technology, and market brought about by increasingly fierce competition in technological innovation. Patents are an important manifestation of knowledge and technology, and an important indicator for evaluating innovation level and innovation competitiveness. Enterprises, universities, and research institutes are the main entities of collaborative innovation, and the patents jointly applied for by the three are one of the empirical research indicators of IUR cooperation. Due to the increasing complexity of cooperation between technology innovation organizations, a vast network has been formed. The theory of complex networks can apply methods and tools such as statistics and computer networks to analyze not only the structural characteristics of networks, but also the formation mechanism and evolution laws of network structures and networks. It has become a research hotspot in the current industry university research collaborative innovation network.

2. Current research status at home and abroad

The collective dynamics of small world networks published by Duncan J. Watts et al. in 1998 and the emergence of scaling in random networks published by Albert-L á szl ó Barab á si et al. in 1999 marked the rapid development of complex network theory and application research. Up to now, the research results of complex network theory on collaborative innovation between industry, academia and research are mainly reflected in: at various stages of network evolution, UCINET, PAJEK and other methods have been used to visualize the network graph display, analyzing the overall network evolution from characteristic parameters such as network size, network density, average distance, and aggregation coefficient; We have studied the evolution of individual networks, i.e. the evolution of centrality at the node level, based on characteristic parameters such as degree centrality, intermediary centrality, proximity centrality, and structural holes. For example, in 2021, Yan Juanjuan et al. explored the pharmaceutical manufacturing industry, and in 2022, He Niang explored the evolution of the industry university research network in China's intelligent connected vehicle industry using the above ideas [2-3]; Some also combine proximity theories such as knowledge, technology, organization, institutions, and geography to analyze the external effects of networks and individual innovation capabilities, and use QAP multiple regression analysis to model and analyze the evolutionary impact of networks. For example, Milan et al. explored the evolution of cooperation models and influencing factors of emerging international elderly care technologies in 2021[4].

However, these traditional analysis methods are based on the premise that network relationships are independent of each other and cannot analyze endogenous network structure effects. The Exponential Random Graph Model (ERGM) is based on stochastic statistical theory and can integrate node attribute variables, network structure variables, and multidimensional proximity network effects. By comparing the simulation model conclusions with the real network measurement results, statistical inference results can be obtained. Therefore, the exponential random graph model has inherent compatibility with the problem studied in this paper: if the model is suitable and considers innovative organizational structures as nodes and cooperative relationships as network edges, then the problem of the influencing factors of collaborative innovation network evolution can be transformed into a network modeling problem; Can meet the quantitative analysis needs of influencing factors; Can analyze the impact effects of network structure and solve the problem of network edge self-correlation.From the literature search, there are relatively few articles that use exponential random graph models to study the evolution and dynamics of industry university research collaborative innovation networks. The setting and measurement of ERGM model node

ISSN: 1813-4890

attribute variables, network structure variables, and multidimensional proximity network effect variables; Further research can be conducted on the evaluation of the model and the interpretation of parameters; The collaborative innovation networks in different industries and regions have their own characteristics, and the effects of various factors are also different. Conducting empirical research using exponential random graph models has high practical research value.

Therefore, based on the authorized invention data jointly applied by enterprises, universities, and research institutes in Wenzhou, this article constructs a collaborative innovation network from 2000 to 2018. The exponential random graph model (ERGM) is used to explore the influencing factors of the evolution of the Wenzhou industry university research collaborative innovation network, analyze the node attribute innovation ability, cooperation breadth, and cooperation depth of the network; Sparsity, transitivity, and closure within the network structure; The multidimensional complex factors such as external technological proximity, geographical proximity, and institutional proximity play a role in the diffusion and transmission of innovation resources, and relevant suggestions are provided to promote relevant institutions to leverage their respective capabilities, integrate complementary resources, accelerate technology promotion and industrialization, and provide theoretical support and decision-making references.

3. Research Design

The network nodes of the Wenzhou Industry University Research Collaborative Innovation Network (hereinafter referred to as the Collaborative Innovation Network) are limited to three types of organizations: enterprises, universities, and research institutes, excluding government and individuals. If a granted patent has n application organizations, it is considered that these n organizations have a cooperative relationship with each other, and the corresponding n nodes in the collaborative innovation network have connections with each other.

In the theory of relationship formation, the formation of cooperative relationships in collaborative innovation networks can be attributed to three types of influencing factors: the node attribute characteristics and network structure of the network, and the proximity network [5]. The network node attribute characteristics in this article mainly refer to the innovation strength of the applying organization, as well as the breadth and depth of cooperation and innovation with other organizations. The network structure selected a star shaped structure representing cooperative relationships for scalability, a mediating 2-path for transitivity, and a triangular structure for closure. Exogenous effects consider geographical proximity, technological proximity, and organizational proximity.

3.1. Research Hypothesis and Related Variable Design

3.1.1. Network Node Attributes

In the collaborative innovation network, some nodes enhance their cooperation and innovation advantages by continuously accumulating innovative resources such as information, knowledge, technology, and channels, thereby attracting more innovative resources and partners, ultimately forming a strong Matthew effect[6]. This article evaluates the impact of node attributes on the effectiveness of collaborative innovation networks from three perspectives: node innovation strength(denote by IS), collaborative innovation breadth(BC), and collaborative innovation depth(DC). The following hypotheses are proposed:

$H1_a$: The collaborative innovation network exhibits the Matthew effect, and the organizational innovation strength advantage will significantly affect the network evolution.

$H1_b$: The collaborative innovation network exhibits the Matthew effect, and the deep advantage of collaborative innovation will significantly affect the evolution of the network

$H1_c$: The collaborative innovation network exhibits the Matthew effect, and the depth advantage of collaborative innovation will significantly affect network evolution.

3.1.2. Network Structure

In recent years, many scholars have believed that network structure has a significant impact on network evolution. For example, in the process of transmitting cooperative relationships, newly entered nodes will prioritize connecting to nodes that already have relationships, and nodes with core status are more likely to establish connections with multiple other nodes, which will tend to generate expandable star structures; In the transmission of cooperative relationships, 'my friend's friend also treats me as a friend' tends to generate a structure of intermediary 2 paths; In relationship transmission, the triangular structure is not only beneficial for generating stable and closed cooperative relationships, but the existence of redundant paths can also improve the efficiency of exchanging innovative resources between organizations [7]. When modeling, high-order model geometrically weighted degree distribution (GWD) is chosen to represent expansiveness, geometrically weighted dyadwise shared partner (GWDSP) measures mediation, and geometrically weighted edgewise shared partner (GWESP) represents closure [8]. Propose the following hypothesis:

$H2_a$: Collaborative innovation networks exhibit scalability, and the network structure GWD significantly affects the transmission of cooperative relationships.

$H2_b$: Collaborative innovation networks are intermediary, and the network structure GWDSP significantly affects the transmission of cooperative relationships.

$H2_c$: The collaborative innovation network is closed, and the network structure GWESP significantly affects the transmission of cooperative relationships.

3.1.3. Exogenous Effect

The impact of multidimensional proximity on innovation networks began in the 1990s, and up to now, different scholars have explored the influence of geographic proximity, technological proximity, organizational proximity, and other factors on the formation and evolution of innovation networks.

Among them, geographical proximity(denote by GP) refers to the ability of innovative organizations to reduce the cost of knowledge exchange, factor exchange, and increase the probability of cooperation within the same geographical area. It is the primary factor affecting the network, but excessive geographical proximity can inhibit the absorption of external knowledge and technology[9]. This article stipulates that organizations within a straight-line distance of 400 kilometers are considered as the same geographical area.

The analysis of technological proximity(TP) mainly focuses on the overlap of elements such as knowledge and technological reserves. The closer the technologies are, the more opportunities for mutual learning and communication, which will positively promote the evolution of the network. If the technology is too close, it will reduce the heterogeneity of knowledge and technology, and decrease the possibility of cooperation [10]. This article takes the cosine of the angle between the technical spatial coordinate systems of organizations. The closer the value is to 1, the closer the technical fields of A and B are.

Institutional proximity(IP) refers to innovative organizations having similar cultural attributes, institutional constraints, etc. Organizations of the same type will enhance the trust between innovative organizations and reduce cooperation uncertainty [11]. However, excessive organizational proximity can lead to a lack of flexible interaction between elements and generate excessive knowledge and technology spillovers, which is not conducive to the formation of cooperation [12]. If two organizations belong to the same prefecture level city, it is considered that their institutional constraints, cultural attributes, and other characteristics are the same.

The following hypotheses are proposed:

$H3_a$: Collaborative innovation networks exhibit co matching effects, and geographical proximity significantly affects the evolution of collaborative innovation networks.

$H3_b$: Collaborative innovation networks exhibit co matching effects, and technological proximity significantly affects the evolution of collaborative innovation networks.

$H3_c$: Collaborative innovation networks exhibit a matching effect, and organizational proximity significantly affects the evolution of collaborative innovation networks.

3.2. Research Method

The generalized form of ERGM expresses the probability of an actual network y being observed in a random network set Y, and the value of this probability depends on various network configurations, namely various variables, such as IS、 BC and DC in the node attribute variables in this article, and GWD、GWDSP、GWESP in the network structure variables,and TP、GP、IP in multidimensional proximity effects. The generalized formula is as follows:

$$g(Y = y \mid X) = \frac{exp\{\theta^T g(y, X)\}}{k(\theta, y)} \tag{1}$$

Among them, Y is a random set of binary relationships in the network, and y is a specific implementation of the relationship, which is the observed network. X is a covariate vector. θ is a coefficient corresponding to various network configurations, and its magnitude reflects the effect of network configuration on network formation. G(y,X) is a vector composed of the network configuration statistics included in the model. If a configuration is observed k times in network y, then g(y)=k. NF(θ, y) is a normalization factor used to ensure that the sum of probabilities of all possible network samples occurring is 1.

3.3. Research Data

The data comes from the patent search website of the China National Intellectual Property Administration. First, 459 authorized patents with addresses in Wenzhou from 1985 to 2018 that participated in joint applications were searched. Then, the data of individuals and government agencies were removed from the data of joint applicants for the above patents, and 295 joint applicants were obtained. As the network node of collaborative innovation network data, a 295 * 295 matrix was constructed for analysis; Finally, a list of 295 joint applicants was used to retrieve their respective patent numbers from 1985 to 2018, with a total of 189954 patents, serving as the innovation capability indicator for joint applicants, i.e. network nodes.

4. Empirical Analysis

4.1. ERGM Modeling

This article uses the Rstatnet package in R language and establishes an ERGM by gradually adding variables.

Model 1 only includes edge attribute variables and can be used as a baseline model. Its formula can be expressed as:

$Pr(Y=y) = (1/k) exp (\theta_1 Edges)$

Model 2 has added node attribute variables on the basis of Model 1, namely innovation capability, cooperation breadth, and cooperation depth. The formula can be expressed as:

$Pr(Y=y) = (1/k) exp (\theta_1 Edges + \theta 2 Nodecov(IS) + \theta_3 Nodecov(BC) + \theta_4 Nodecov(DC))$

Model 3 has added network structure variables, namely GWD, GWDSP, and GWESP, on the basis of Model 2. The formula can be expressed as:

$Pr(Y=y) = (1/k) \exp (\theta_1 Edges + \theta_2 Nodecov(IS) + \theta 3 Nodecov(BC) + \theta_4 Nodecov(DC)+ \theta_5 GWD + \theta_6 GWDSP + \theta_7 GWESP)$

Model 4 adds proximity network variables on the basis of Model 3, namely technical proximity network, geographical proximity network, and institutional proximity network. The formula can be expressed as:

$Pr(Y=y) = (1/k) \exp (\theta_1 Edges + \theta_2 Nodecov(IS) + \theta_3 Nodecov(BC) + \theta_4 Nodecov(DC) + \theta_5 GWD + \theta_6 GWDSP + \theta_7 GWESP + \theta_8 Edgecov(Net.TP) + \theta_9 Edgecov(Net.GP) + \theta_{10} Edgecov(Net.IP)$

In the ERGM model, maximum likelihood estimation (MLE) was used for parameter estimation in models 1 and 2, while Markov chain Monte Carlo maximum likelihood estimation (MCMC MLE) was used for models 3 and 4 due to the addition of network structure variables.

After multiple model optimizations and iterative calculations, Table 1 shows the collaborative innovation network model and its parameter estimates.

Table 1 Collaborative Innovation Network Model and Its Parameter Estimation

	Model 1	Model 2	Model 3	Model 4
EDGES	-4.32 *** (0.04)	-4.91 *** (0.06)	-6.21***(0.00)	-7.28***(0.01)
IS		0.00 *** (0.00)	0.00 *** (0.00)	0.00 *** (0.00)
DC		-0.00 ***(0.00)	-0.00 *(0.00)	-0.00(0.00)
BC		0.00 ***(0.00)	0.00 ***(0.00)	0.00 ***(0.00)
GWDEG			2.77 ***(0.01)	4.18 ***(0.02)
GWDSP			-0.10 ***(0.01)	-0.05 ***(0.01)
GWESP			2.28***(0.00)	1.99 ***(0.00)
TP				3.89 ***(0.01)
GP				-0.00 ***(0.00)
IP				-0.17 ***(0.01)
AIC	6064.06	5301.81	4514.58	3620.73
BIC	6072.73	5336.52	4575.33	3707.50
Log Likelihood	-3031.03	-2646.90	-2250.29	-1800.36

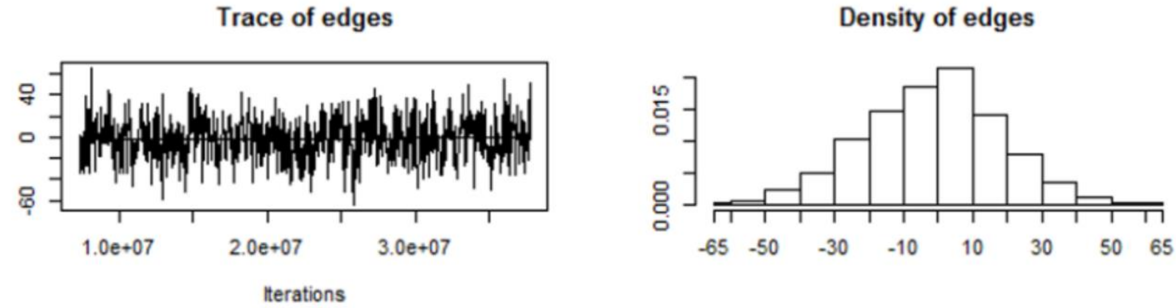
Note:*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

4.1.1. Model Selection

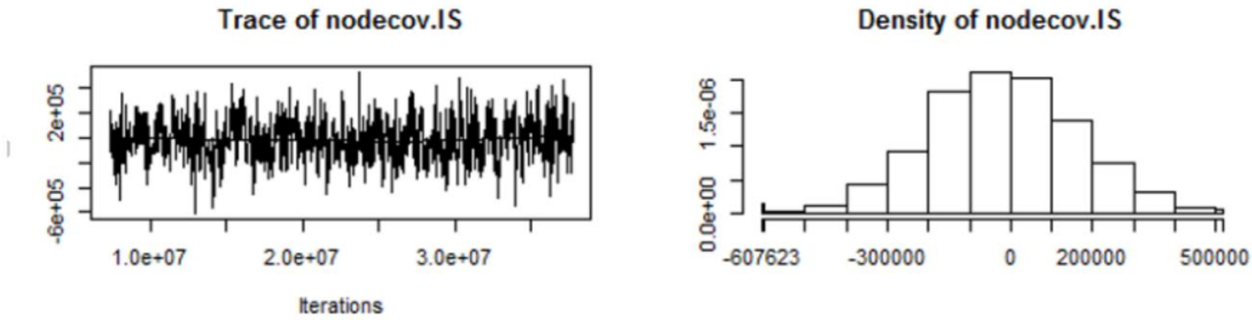
From the model selection indicators AIC and BIC in Table 1, it can be seen that according to Model 1, Model 2, Model 3, and Model 4, AIC and BIC show a significant decreasing trend as the variables gradually increase. It can be concluded that network node attribute variables, structural variables, and exogenous effect variables all promote the formation of collaborative innovation networks; Model 4 has the smallest AIC and BIC, and the highest goodness of fit, making it the best model among the four models.

ISSN: 1813-4890

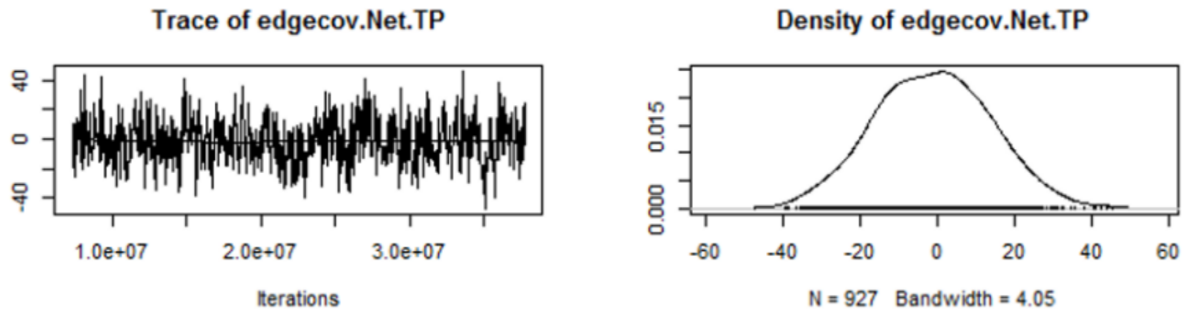
4.1.2. Model Diagnosis



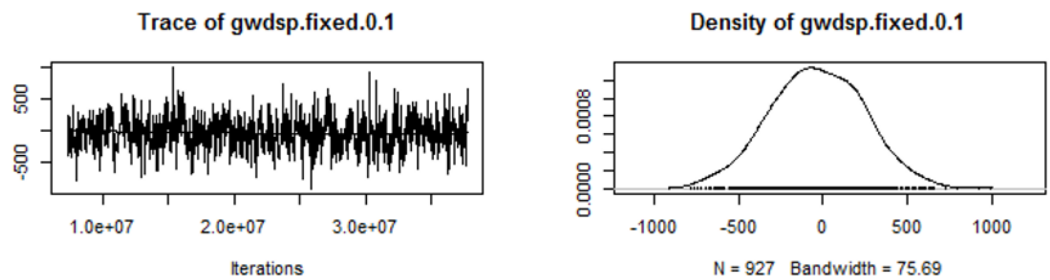
(a) Diagnostic Graphics of edges



(b) Diagnostic Graphics of IS



(c) Diagnostic Graphics of TP



(d) Diagnostic Graphics of GWDSP

Fig.1 MCMC Diagnosis of Model 4 (Partial)

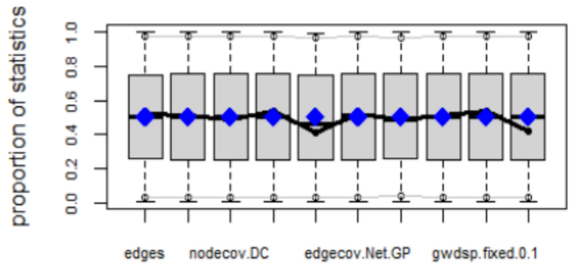
Model diagnosis can assist in determining whether parameter estimation algorithms converge. Due to space constraints, we will now extract one each from the node attribute variable, multidimensional proximity network variable, and network structure variable, which are IS、DC、TP and GWDSP have diagnostic graphs as shown in fig 1. The graphs on the left of fig 1 show the time series of three variables using MCMC chains to illustrate their changes, while the graphs on the right of fig 1 display the corresponding distribution of MCMC chains. If the model

ISSN: 1813-4890

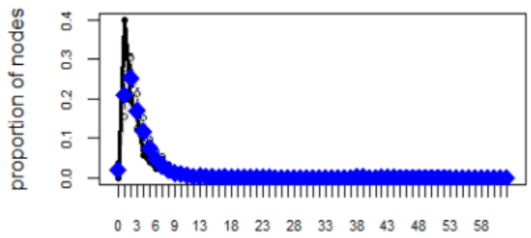
can converge, the graph of each variable in the model will appear as a random variation centered around the observed values of the corresponding variables in the observation network, represented by 0 here. From fig 1, it can be seen that the charts of the three variables basically follow a normal distribution around 0. Therefore, the results of the model diagnosis indicate that Model 4 is a stable model.

4.2. Goodness-of-fit Test

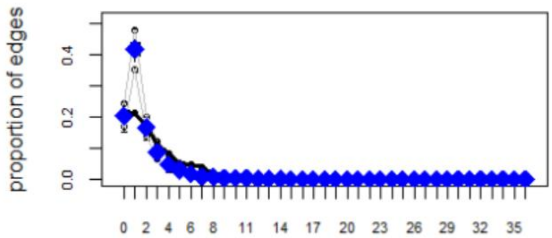
Model 4 is the optimal model among the four models, and it is determined to be a stable and convergent model in parameter estimation. However, at what level can Model 4 reflect the structural characteristics of the actual observed network, a goodness of fit test is still needed. The results of the goodness of fit test are shown in fig 2. The black line in fig 2 represents the observation results of the actual collaborative innovation network; The gray lines and box plots represent the measurement results of the simulation network at a 95% confidence interval. When the black line falls between the gray lines (overlapping with the median is optimal), it indicates that the simulation network can represent the structural characteristics of the real collaborative innovation network. The analysis results of fig 2 show that although the geometric weighting degree and geometric weighting shared edges of the simulation network differ from those of the real network in some individual values, it can basically fit the 10 structural features of the real network as a whole. Therefore, Model 4 basically depicts the real collaborative innovation network, and its coefficient analysis has practical reference value.



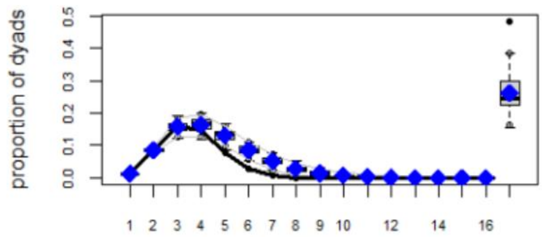
(a)Model Statistics



(b)Degree



(c)GWDESP



(d)Minimum Geodesic Distance

Fig.2 The goodness of fit of Model 4

4.3. Result Analysis

From the data of the collaborative innovation network model and parameter estimation values in Table 1, the edge coefficient is -7.28, which passed the hypothesis test with a significance level of 0.001, indicating that the edge coefficient plays a role in network evolution. For every additional edge added to the network, the probability of the newly added collaborative relationship exp (-7.28) is 0.0007, which is much smaller than 1. This suggests that every additional collaboration between organizations actually reduces the probability of new edge formation in the network by 99.93% compared to random, indicating that the actual observed network has sparse effect characteristics

In the hypothesis testing of network node attribute variables, although the innovation strength IS coefficient and cooperation breadth BC coefficient pass the significance test, their values are

0, which means that for every additional patent added by one organization, the probability of establishing cooperation with another organization exp (0.00)=1. The probability of forming new edges in the network is not different from that of random. The DC coefficient of cooperation depth did not pass the significance level test, directly indicating that the number of cooperative patents between various organizations in the network organization will not promote the formation of new cooperative relationships.

In the hypothesis test of network structure variables, the GWD coefficient of 4.18 passed the significance test, indicating that for every star shaped structure appearing in the network, the probability of new edge formation in the network increases by 6437% compared to random (exp (4.18)=65.37-1), and the star shaped structure representing network scalability has a significant impact on network evolution. The coefficient of GWESP is 1.99, indicating that if two organizations A and B have a common node C, the probability of A and B forming a collaborative relationship increases by 632% compared to the probability of two randomly connected points (exp (1.99)=7.32-1), and the network also tends to generate a 2-path structure representing mediation. The coefficient of GWDSP is -0.05 and significant, indicating that every appearance of a closed triangle structure represents a 5% decrease in the probability of adding new edges to the network compared to the original (exp (-0.05)=0.95-1), which will suppress the formation of new cooperative relationships, but the impact is not significant.

In the hypothesis test of exogenous effect variables, the coefficient of TP is 3.89 and significant, indicating that organizations with the same knowledge and technology fields have a 4791% higher probability of forming a cooperative relationship than two random organizations (exp (3.89)=48.91-1). The coefficient of GP is negative and significant, but because the coefficient is approximately 0, it indicates that geographic proximity has no effect on the probability of forming cooperative relationships between organizations. The coefficient of IP is -0.17 and significant, indicating that the probability of organizations with the same policies forming cooperative relationships in the same prefecture level city is 16% lower than that of randomly two organizations (exp (-0.17)=84%). This also reflects that the Wenzhou innovation organizations are more inclined to form cooperative relationships with organizations from different cities.

5. Conclusion and Recommendation

This article uses an exponential random graph model and the RStatnet package in R language to analyze the influencing factors of the evolution of the collaborative innovation network in Wenzhou from 2000 to 2018 from three aspects: network node attribute characteristics, network structure, and multidimensional proximity network. The following conclusions and inspirations are obtained.

(1) The endogenous network structure has a significant impact on the evolution of the collaborative innovation network. The most influential is the star shaped structure representing expansion, which demonstrates the dominant role of core enterprises in cooperation with other organizations and can actively promote the formation of cooperative relationships; Secondly, the triangular structure representing closure is conducive to forming stable and efficient cooperative relationships, as well as facilitating the formation of new cooperative relationships; The 2-path structure, which represents transitivity, prioritizes cooperation through intermediate nodes and suppresses the formation of new cooperative relationships.

(2) Multidimensional proximity factors also have a significant impact on the evolution of the collaborative innovation network. It is easier to form cooperative relationships in the same technical field. In order to acquire more technology and knowledge, this network tends to collaborate between different cities. Geographical proximity has not exerted its influence.

(3) The network node factor has not played a role in the evolution of the collaborative innovation network. Whether it is the innovation capability factors of the organization or the breadth and depth of cooperation, they have not significantly affected the formation of new cooperative relationships. This indicates that the organization of the network did not specifically consider its innovation capabilities, collaboration experience, and collaboration history when selecting new partners.

The research suggests that governments and relevant organizations should build more convenient, stable, and efficient platforms for cooperation and exchange, with a focus on lowering the threshold for cross disciplinary technology diffusion and promoting the integration and innovation of multidisciplinary technology fields; In addition to further promoting collaborative innovation among different cities, it is also necessary to actively encourage and support cooperation within the same city and geographical region. At the same time, it is necessary to actively promote technological cooperation with leading enterprises and technology leaders, and strive to further expand and strengthen local industries; Promote local organizations to actively build star shaped network cooperation structures in cooperation, encourage central nodes to strive for more resources, actively construct triangular structures, and form efficient and stable cooperative relationships.

Acknowledgements

The article was supported by the Project of "Research on the Evolution Characteristics and Influencing Factors of Wenzhou Industry-University-Collaborative Innovation Network Based on Exponential Random Graph Model" (Project Number: R20220087) ,one basic research project of Wenzhou Science and Technology Bureau in 2022, and the Project of "Analysis of the Evolutionary Characteristics of Customs Technology Cooperation Innovation Network from the Perspective of Patents" (Project Number: LCSRP20230001) , one research project of Lhasa Customs in 2023.

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