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Research on the evolutionary dynamics of interdisciplinary collaboration from the perspective of co–authorship

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ABSTRACT
Despite the growing interest in exploring the interdisciplinary collaboration patterns and the factors in relation to team assembly in the first place, the dynamics of interdisciplinary collaboration with time varying is hardly known. Based on the longitudinally co-authorship network perspective, the paper investigates the evolutionary dynamics of interdisciplinary collaboration using separable temporal exponential-family random graph model (STERGM). The results from STERGM show that structural properties, properties of researcher and link properties affect the evolution of interdisciplinary co-authorship network to varying degrees. Network transitivity and preferential attachment play a decisive role in formation of links and hamper dissolution of ties in the network. The number of collaborators of interdisciplinary researchers plays an active role in the formation of partnerships and hamper dissolution of partnerships in the initial stage; specialization of team members inhibits the establishment of collaborative relationship in the initial stage and promotes the dissolution of connections in the later stage of project; the large difference in specialization value between members is not conducive to the formation of relations in the initial stage, but conducive to the maintenance of collaborative relations after links establishment. The same discipline background is conducive to the formation of relations but not conducive to the maintenance of collaborative relationships in interdisciplinary co-author network.

KEYWORDS
Interdisciplinary collaboration; Co-authorship network; Separable temporal exponential random graph model (STERGM)

1 Introduction

In the era of big science, major academic breakthroughs always are interdisciplinary. Interdisciplinarity and scientific collaboration have become two major trends in scientific research. Collaboration among researchers from different disciplines is both normatively encouraged and extensively studied. How to promote interdisciplinary collaboration effectively is imperative. As a consequence, much research has been done and the conclusions are very enlight-

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ening on this topic.

An under-examined issue within this literature is what factors motivate researchers from different disciplines to be partners. Dynamics analysis in interdisciplinary collaboration research often uses case study or cross-sectional methods that infer, but do not test, how driving force might have occurred over time. This article aims to use this as an entry point to expand research on the issue.

Research team is a natural whole formed in long-term collaboration, its complex evolution process is often hidden in the historical records of academic activities, such as co-authored papers, collaborative research projects, etc. These public literature resources have a good record of the researcher's collaboration historical trajectory, which provides a good perspective of time observation for this paper.

The purpose of this study is to longitudinally examine formation and dissolution of links in the collaboration network and to consider the influence of characteristics of interdisciplinary researchers and features of networks of interdisciplinary collaboration. In view of this, this paper is about to explore the factors that affect the establishment and maintenance of interdisciplinary collaboration relationships with separable temporal exponential random graph model (STERGM) from perspective of co-authorship, thereby revealing the evolutionary dynamics of interdisciplinary teams, with a view to providing reference for interdisciplinary funding and cultivation of interdisciplinary talents.

2 Related Work

In the literature of interdisciplinary collaboration, scholars mainly focus on the exploration of the factors that promote interdisciplinary collaboration at the first place. Relevant studies have shown that demographic characteristics, academic characteristics, similarities between researchers, common collaborative experience, and disciplinary properties are all important driving forces for the formation of interdisciplinary teamwork relationships.

Dai et al. (2014) revealed that there were mobility characteristics in interdisciplinary team collaboration, and the mobility of collaboration was affected by the principles of preferential attachment and reciprocity. The study from Lungeanu's team found that individuals' likelihood of collaboration on proposals submitted to interdisciplinary initiatives was higher among those with longer tenure, lower institutional tier, lower H-index, and with higher levels of prior co-authorship and citation relationships, and individuals' likelihood of collaboration on successful proposals is higher among those with lower institutional tier, lower H-index, (female) gender, higher levels of prior co-authorship, but with lower levels of prior citation relationship (Lungeanu et al., 2014). Government or company work experience have proved to be positively correlated with interdisciplinary research participation(van Rijnsoever & Hessels, 2011). And academic reputation and seniority of researchers, previous collaborators, and collaborators of collaborators are regarded as factors affecting the initial formation of interdisciplinary teams (Lungeanu et al., 2015).

The literature on collaborator recommendation algorithm also provides us with a lot of enlightenment. Araki et al. (2017) proposed an interdisciplinary collaborator recommendation algorithm based on researcher content similarity and academic network based on the data of funded projects, indicating that the similarity of research content has positive significance for the formation of interdisciplinary collaboration. Moreover, there is similarities in research experience and research content by analyzing collaboration in the field of artificial intelligence education (Feng & Kirkley, 2020). The effectiveness of the method of Cho and Yu(2018) predicting interdisciplinary collaboration links proves the existing collaboration experience and common research interest are the driving forces for interdisciplinary collaboration. Cummings and Kiesler (2008) thought that common research experience could reduce communication barriers in cooperation, skip the team adaptation period, and improve the efficiency of interdisciplinary collaboration.

Interdisciplinary collaboration is more likely to occur in specific subfields of certain disciplines. Qiu and Yu (2013) found that the most scholars published papers in the field of library and information were from computer software and computer applications, news media and other fields. Mirc and Rouzies et al. (2017) stated that interdisciplinary collaboration in the field of corporate mergers and acquisitions existed more among a small number of active researchers in the field of organizational behavior and human resource management.

In summary, scholars have analyzed the dynamics of interdisciplinary collaboration from multiple perspectives, which has promoted our understanding of the motivation forming interdisciplinary collaboration. However, current research mainly focuses on the influence of scholars' attributes on the formation of interdisciplinary collaboration. A dearth of research considers the influence of network structure on interdisciplinary collaboration. At the same time, the existing research mainly focuses on the mechanism of the interdisciplinary team formation at the initial stage, without considering the influence of time factor on the development of the interdisciplinary team, and lacks the evolutionary dynamic analysis of its subsequent development stage. The evolution of the network is manifested in the formation and dissolution of edges. In other words, existing research mainly focuses on the factors that affect the formation of edges in the network, and ignores the investigation of the factors that lead to the dissolution of edges.

Therefore, this paper pays attention to the dynamics of the development of interdisciplinary research teams, and comprehensively considers the influence of network structure factors, researcher attributes, and link attributes on the establishment and maintenance of interdisciplinary collaboration relationships, and then reveals the dynamic mechanism of interdisciplinary team evolution.

3 Methodology

3.1 Method

Since "The structure of scientific collaboration networks" published by Newman (2001), a landmark work on the measurement of scientific collaboration network structure in 2001, the related methods and theories of complex networks have gradually been used in the field of library and information science. The social network analysis was applied in the paper.

Exponential Random Graph Model (Exponential Random Graph Model) is in common usage in network analysis. The model is based on related mathematics and simulation inference theory. ERGM simulates thousands of random networks with the same number of nodes and edges as the observed network, and then compares the observed network to the mean value of thousands of simulated random networks, so as to identify the difference between the observed network and randomly generated networks with same size. Finally, it generates the maximum likelihood estimation result, and then infers the generation mechanism of the observed network. This process is analogous to the multiple regression model and reveals whether the specific parameters representing the hypothesized pattern of relationships in the observed network is more or less likely to occur compared to thousands of randomly simulated networks.

Separable Temporal Exponential Random Graph Model is developed on the basis of ERGM (Krivitsky & Handcock, 2014). It observes the network in the form of panel data, similar to the static network as a "slice", which introduces exponential random graph model to the sequential network. The main feature of STERGM is that the model considers that the network at time t+1 is conditioned on the network at time t, and its assumption is that the formation within the time step has nothing to do with the dissolution, but the two is Markov correlation between the time steps, which means that the factors that affect the formation of edges are different from the factors of dissolution, so STERGM requires two formulas, and STERGM does not need to make independence assumptions like traditional models. (The schematic diagram is shown in Figure 1).

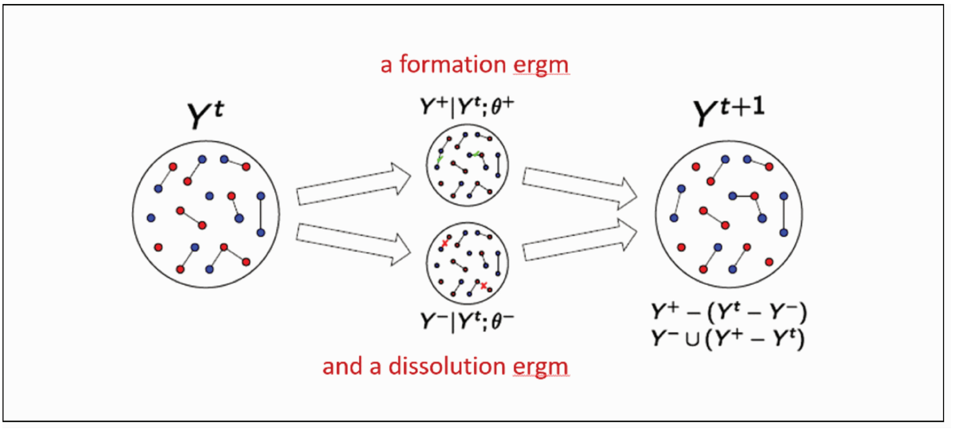


Figure 1 Illustration of STERGM model (Note The picture comes from https://statnet.org/Workshops/tergm_tutorial.html).

3.2 Data source and data processing

The paper selected teams funded by the INSPIRE program established by the National Science Foundation as sample. The INSPIRE (Integrated NSF Support Promoting Interdisciplinary Research and Education) program was established to solve some of the most complex and urgent scientific problems at the intersection of traditional disciplines. The INSPIRE program has a strict review mechanism, including invited submission of proposals and multi-faculty joint review, which makes sure that the awarded research proposals and teams are interdisciplinary in the theoretical and practical sense. Therefore, proposals awarded by INSPIRE provide a pretty appropriate context to examine dynamic evolution mechanism of interdisciplinary collaboration. In order to retain a sufficient time window to investigate the evolution of the interdisciplinary team, this study selected the interdisciplinary team that received the continuing grant of the INSPIRE funding program in 2012 as the research sample. The data acquisition steps are as follows.

Firstly, the paper searched for INSPIRE-awarded proposals information (including the grant number (AwardNumber) and the principal investigator (PI and CO_PI) information) through the NSF website (https://www.nsf.gov/awardsearch/), and then searched on the Web of the Science Core Collection database using grant numbers to obtain information of funding outputs, and further collected the academic track information of interdisciplinary team members through the hyperlink addresses of the authors in the results pages.

As of December 2020, we retrieved 10 INSPIRE-awarded proposals which received continuous funding in 2012. And the papers funded by every awarded proposal were retrieved from Web of Science. The number of funded papers, the number of subjects of Web of Science of the papers and the main composition of researcher's subject background of every awarded proposal was shown in Table 1.

After obtaining the data, the igraph package of Python programming language was used to build co-authorship networks of interdisciplinary teams for follow-up analysis. For each article of the funding papers, the co-authorship information can be obtained through the AF field. Based on the idea of permutation and combination, the coauthors of an article were generated into author collaboration pairs. The collaboration pair information was imported into the igraph instantiation object in the form of list type, then, the construction of the collaboration network of interdisciplinary teams was completed, in which each author was a node, each author was represented by a unique number and each collaboration pair was an edge.

According to the publication year information (PY field) in bibliographic records, a 9-year (2012-2020) time series network information was formed at an interval of 1 year. There was no mature and widely recognized theory of team stage division in the academic community, so the interdisciplinary co-authorship network was divided into three phases with three years as a phase: 2012-2014, 2015-2017, and 2018-2020 in the paper. The basic statistics of co-authorship networks is shown in Table 3 of the section 5.2.

Table 1 The details of research data

Award Number	Title of Project	Number of members[a]	Number of funded papers[b]	Number of disciplines[c]	Main composition of researcher´s subject background (top5 in frequency)[d]
1069104	Interacting with the Brain: Mechanisms, Optimization, and Innovation	178	66	29	Neurosciences; Engineering, Biomedical; Engineering, Electrical & Electronic; Radiology, Nuclear Medicine & Medical Imaging; Clinical Neurology····
1144676	Research and Education in Nanotoxicology at West Virginia University	199	54	42	Toxicology; Chemistry, Multidisciplinary; Biochemistry & Molecular Biology; Cell Biology; Chemistry, Analytical
1144752	Novel ecosystems, rapid change, and no –analog conditions: the future of biodiversity conservation in human –dominated landscapes	130	51	30	Ecology; Environmental Sciences; Geosciences,Multidisciplinary; Veterinary Sciences
1144807	Interdisciplinary Quantitative Biology Program	235	43	43	Microbiology; Biochemistry & Molecular Biology; Ecology、Multidisciplinary Sciences; Biochemical Research Methods
1230543	An Ecologically –Driven Strategy for Ensuring Sustainability of Anthropogenically and Climatically Impacted Lakes	120	38	10	Environmental Sciences; Marine & Freshwater Biology; Microbiology; Ecology; Oceanography

Award Number	Title of Project	Number of members[a]	Number of funded papers[b]	Number of disciplines[c]	Main composition of researcher´s subject background (top5 in frequency)[d]
1233054	Optogenetic Control of the Human Heart–Turning Light into Force	94	34	21	Engineering, Biomedical; Mechanics; Cardiac & Cardiovascular Systems; Surgery´; Radiology, Nuclear Medicine & Medical Imaging
1241032	INSPIRE: Photonic Quantum Heat Engines Including: Lasers without Inversion, Photo –Carnot Engines, Quantum PV Cells and Quantum Coherence Effects in Photosynthesis	116	48	18	Optics; Physics, Multidisciplinary ;Chemistry,Physical; Physics, Applied; Engineering, electrical&electronic
1241332	INSPIRE: Molecular Underpinnings of Bacterial Decision–Making	72	21	17	Multidisciplinary Sciences; Chemistry, Physical; Biophysics; Biochemistry & Molecular Biology; Chemistry, Multidisciplinary
1247945	INSPIRE: Concentrated Dispersions of Equilibrium Protein Nanoclusters that Reversibly Dissociate into Active Monomers	55	20	14	Chemistry; Multidisciplinary; Chemistry, Physical; Optics; Chemistry, Organic; Oncology
1248109	CREATIV: Towards Ubiquitous Adoption of Wireless Sensor Networks in Experimental Biology Research.	61	23	15	Telecommunications; Engineering, Electrical & Electronic; Mathematics; Applied; Cell Biology; Multidisciplinary Sciences

Note: a. Each author of funded papers is an interdisciplinary member. The number of members is calculated by the number of unique authors of funded papers of each projects. b is the number of papers which is funded by an INSPIRE-awarded project. c refers to the number of Web of Science subjects of papers funded by an INSPIRE-awarded project. d shows the five disciplines with the top 5frequency of researcher backgrounds in each funded interdisciplinary team. In the study, a researcher's subject background refers to the subject classification that the literature involves the most in all documents which a researcher published in Web of Science Core Collection.

4 Theoretical background and hypotheses

Existing studies have shown that the link-establishment factors in the network can be divided into three categories: social influence, exogenous effect and homophily (He & Liu, 2017). Social influence refers to individuals changing their behaviors in order tso be consistent with the behaviors of the majority in the community. Homophily refers to the tendency of individuals to establish connections with individuals with similar attributes to themselves, and exogenous effect refers to community attributes and networks factors that are not related to the structure itself, such as the contextual factors faced by an online social network and a network based on company mergers and acquisitions are different. Homophily changes the structure of the network, social influences change the attributes of nodes, and link stability is affected by factors such as topological structure, node attributes, and link attributes (Wan et al., 2009). Topological structure refers to the properties of a network, node attributes refer to nodes' properties such as the age and gender of network individuals, and link attributes refer to the characteristics of the relationship between two nodes that are linked, homophily is one of link attributes. Therefore, this article divides the factors that affect the evolution of interdisciplinary collaboration networks into three categories: structural factors, researcher attributes, and link attributes (that is, relationship attributes).

4.1 Structural factors

Transitivity, brokerage, and preferential attachment are the most prominent endogenous structural dependencies in the network. Transitivity reflects the principle of closure, that is, the theory that a friend's friend is a friend (Wang et al., 2012); brokerage refers to actors on either side of the structural hole become a bridge between the other two unconnected groups or nodes; preferential attachment, also called the Matthew effect (Barabάsi et al., 2002), means that the more connected a node is, the more likely it is to receive new links.

The paper assumes that those rules still work in interdisciplinary co-authoring network. Interdisciplinary collaboration emphasizes the gathering of researchers with different disciplinary backgrounds, however, there have been boundaries between different disciplines and research fields for a long time. Therefore, the probability of a researcher hold the position of structural hole is higher in the coauthoring network, the more likely he/she is to establish interdisciplinary collaboration with others. The central node in the co-authoring network has good social capital and has a network governance function in the interdisciplinary co-authoring network (Liu et al., 2020). After the formation of the interdisciplinary network, the nodes with high degrees hope to maintain the stability of the existing collaboration relationship to ensure that members trust each other, and avoid the dissolution of the current relationship that will lead to the premature aging of the network and affect the performance of interdisciplinary collaboration. In a word, the paper assumes that transitivity, brokerage, and preferential attachment positively influence relationship formation and suppress the relationship dissolution in the process of interdisciplinary collaboration network evolving.

The proponents of STERGMs believe that the current network status is affected by the previous network structure, and the position of nodes in the network in the previous network has an important influence on the formation of their relationship (Hanneke & Xing, 2010). STERGMs corresponds to the setting of Geometrically weighted edgewise shared partners (GWESP), geometrically weighted dyadwise shared partners (GWDSP), and geometrically weighted degree distribution (GWD) to measure the influence of the three special structures on the evolution of the network. The parameter--Edges is similar to the constant term in the general model. GWESP represents the triangular network structure and mainly measures the influence of network transitivity. GWDSP captures the tendency of a certain node to become a bridge connecting the other two unconnected nodes. GWD stands for star network structure and measures the influence of preferential attachment on the network.

Based on above all, the following hypotheses are proposed in the process of interdisciplinary co-authoring network evolving:

H1a: the higher GWESP value the more likely to form network ties.

H1b: the higher GWESP value the less likely to dissolve network ties.

H2a: the higher GWDSP value the more likely to form network ties.

H2b: the higher GWDSP value the less likely to dissolve network ties.

H3a: the higher GWD value the more likely to form network ties.

H3b: the higher GWD value the less likely to dissolve network ties.

As we discussed above all, the mechanism of structural factors we propose is shown in the Figure2, where t1 represents the first time period and t2 represents the subsequent time period and solid lines depict the pattern of connection in the first time period. Dashed lines represent the tie which is hypothesized to form in the subsequent time period.

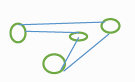
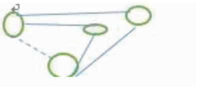
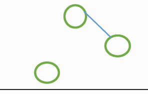
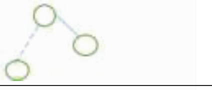
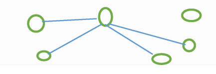
Parameter–Structure	t1	t2
EDGES	similar to the constant term in the general model	
GWESP–Closure		
GWDSP–Brokerage		
GWD–Preferential attachment		

Figure 2 Illustration of the mechanism of structural factors

4.2 Researcher attributes

Interdisciplinary research requires collaboration among researchers with disparate areas of specialization and the incorporation of specialized expertise, concepts, and diverse methodological and theoretical approaches. Interdisciplinary collaboration emphasizes that experts with different knowledge form an interdisciplinary team (Academies, 2004). Different from traditional teams, members of interdisciplinary teams are experts in different fields and are trained to use diverse tools and concepts (Lungeanu et al., 2015). It takes a long time to form knowledge in a field, the knowledge of highly specialized individuals is irreplaceable, and it may be less likely to dissolve relationships in the evolution of interdisciplinary networks. Hence, in the process of interdisciplinary co-authoring network evolving we propose that:

H4a: the more specialized a researcher is, the more likely he/she is to establish network ties.

H4b: the more specialized a researcher is, the less likely he/she is to dissolve network ties.

"Great achievements in knowledge are produced by older innovators today than they were a century ago."(Jones, 2010). The researchers with good human capital and social capital are regarded as having a positive effect on the scientific collaboration (Liénard et al., 2018) . Therefore, researchers who have a good academic reputation, academic research seniority, and many collaborators are seen as more likely to establish extensive partnerships. Nevertheless, the uncertainties and risks of interdisciplinary research often make it difficult to obtain support (Bromham et al., 2016), and researchers with good academic reputation and seniority often have more research resources (Lungeanu et al., 2014) , which makes it is easy for researchers to establish ties in interdisciplinary collaboration network, so we suppose that:

H5a: academic reputation supports relationship formation.

H5b: academic reputation suppresses relationship dissolution.

H6a: the more senior a researcher is, the more likely he/she is to establish partnership with others.

H6b: the more senior a researcher is, the less likely he/she is to end partnership with others.

H7a: the more collaborators the more likely a researcher will establish partnership with others.

H7b: the more collaborators the less likely a researcher will end partnership with others.

4.3 Link attributes

Assortative networks are common, and researchers with the same research interests and cognitive similarities are often more likely to make connections (Duan & Feng, 2019). Cognitive similarity refers to the degree of cognitive similarity between scientific research collaborators in terms of knowledge structure, technical level, understanding perspective, and experience background. Cognitive similarity is a prerequisite for effective communication between scientific research collaborators and determines the researcher's ability to absorb knowledge (You, 2017). The effect of cognitive proximity between researchers is not one-way linear, but in an inverted U shape (Mao et al., 2016). On the one hand, the cognitive proximity between researchers is high, which is conducive to the faster establishment of partnerships between researchers, and promoting innovation through exchanging ideas. However, cognitive similarity is not always beneficial to the innovation performance of collaboration. With the increase of cognitive similarity, the diversity of knowledge between collaborative teams will decrease, hindering knowledge innovation and forming a cognitive lock-in effect (Fernández et al., 2016). Therefore, with the evolution of the interdisciplinary co-authoring network, if the cognition between the two researchers overlaps to a large extent, then the collaboration between the two will not be able to solve the interdisciplinary problems in the research, and the two have to dissolve the collaborative relationship and look for new collaborators, that is the evolution process of the interdisciplinary collaboration network from the assortative to the disassortative (Hu & Wang, 2009).

It is undeniable that there is path dependence between researchers. When two scholars have a long history of collaboration, they will be more inclined to collaborate. Common research experience can reduce communication barriers in collaboration, skip the team adaptation period, and improve the efficiency of interdisciplinary collaboration (Gómez-Zará et al., 2019).

The interdisciplinary team is established to solve difficult problems which can't be solved in a single subject area and its purpose of existence is to gather individuals with different knowledge backgrounds and integrate interdisciplinary knowledge to solve complex issues. As we know, the establishment of a collaboration network has special contextual needs and the similarity of subject background knowledge may be not conducive to solving interdisciplinary research problems. Hence in the process of interdisciplinary co-authoring network evolving the paper assumes that:

H8a: the higher the cognitive similarity between two researchers, the more likely they are to establish ties.

H8b: the higher the cognitive similarity between two researchers, the more likely they are to dissolve ties.

H9a: the higher the historical collaboration frequency between two researchers, the more likely it is to establish ties.

H9b: the higher the historical collaboration frequency between two researchers, the less likely it is to dissolve ties.

H10a: two researchers with the same disciplinary background are less likely to establish ties;

H10b: two researchers with the same disciplinary background are more likely to dissolve ties.

4.4 Definition of parameters

Researcher's subject background: the subject classification that the literature involves the most in all documents which a researcher from interdisciplinary team published in Web of Science Core Collection. (Note: Compared with Incites, the Web of Science subject classification is more fine-grained, so the calculation about subject classification in the study is based on the subject classification of Web of Science, the same below).

Number of collaborators: The number of unique co-authors reflected in the bibliographic records of each interdisciplinary team member.

Specialization: Porter proposed the index in 2007 to measure the interdisciplinary tendency of a researcher (Porter et al., 2007). The index mainly considers the distribution of researcher's papers by discipline:

$$Sp = \frac{\sum sc_i^2}{(\sum sc_i)^2}$$

In the formula, SCi represents the subject classification. The smaller the Sp, the more interdisciplinary the researcher is.

Academic reputation: Since Hirsch put forward the h index, this index has been widely recognized by scholars because it focuses on both quality and quantity characteristics, and is often widely used to measure the academic reputation of researchers (Hirsch, 2005). To be specific, the h index of a researcher can be calculated based on the number of documents published by the researcher and the frequency of citations.

Academic seniority: The career age of the researcher, as a representative of academic seniority (Qi et al., 2017), can be calculated based on the difference between the earliest publication year of the researcher's document and the most recent publication year.

Cognitive proximity: Bibliographic coupling is usually used to measure cognitive similarity (Rafols & Meyer, 2010), but because there are few references in our research data, the coupling number of references' subject classification is used as an alternative measure. This paper draws on the calculation principle of Jaccard similarity to calculate the cognitive similarity of two researchers:

$$con_{pro} = \frac{Coupling\ number\ of\ citing\ subjects\ at\ nodes\ i\ and\ j}{Number\ of\ citing\ subjects\ at\ node\ i + Number\ of\ citing\ subjects\ at\ node\ j}$$

The larger the value the more proximate the recognition is and the higher the similarity of knowledge between two researchers.

Frequency of historical collaboration: The cumulative frequency of collaboration is calculated between two researchers in different periods based on the co-authors of the documents published by the researchers.

5 Empirical Analysis

5.1 Model construction: A 3–year interval approach

STERGMs were run for three 3-year intervals (2012-2014, 2015-2017, and 2018-2020), which had two advantages. First, STERGM assumes that all researchers in the network are observed in each wave of analysis. Second, examining the 3-year intervals allows us to determine which specific factors influenced partnerships formation and dissolution in particular periods and whether those factors persisted over time. Models were constructed using a forward-selection approach (O'Brien et al., 2019): entered one at a time, parameters were retained when models converged and removed when they caused degeneracy.

The STERGMs was implemented with tergm package in R language. Based on the above research hypothesis and the modeling principle of the STERGM, this article divides the parameter items of tergm into three categories: the structure items mainly consider the influence of the network structure on the network evolution, the researcher-attribute items mainly consider the influence of the node attributes on the network evolution, and the homogeneous items mainly consider the link attribute factor, that is, the influence of the similarity of the attributes between nodes on the evolution of the network. The following Table 2 shows the symbols and variables of different parameter items, as well as the description of the model meaning.

Table 2 tergm parameters explain table

Type	Parameters name	Description
Structure terms	edge Gwesp (Geometrically Weighted Edgewise Shared Partners), Gwdeg(Geometrically Weighted Degree Distribution), Gwdsp (Geometrically Weighted Dyadwise Shared Partners)	Explore the influence of special network structures such as star and triangle structures on network evolution
Researcher–attribute terms	nodecov (x), x is the name of the node attribute, including the number of collaborators (num_collaborator), specialization (Sp), academic reputation (h index) and academic seniority (c_age)	Explore the influence of different attributes of researchers on the evolution of the network.
Homophily terms	absdiff(x), x is the name of the node attribute, including the number of collaborators, specialization, academic reputation and academic seniority. nodematch (x), x is a categorical variable, including subject background (su) dyadcov (x), x is the value of the edge attribute, entered in a matrix, and the variables include cognitive proximity (con_prox) and frequency of historical collaboration (fc)	Explore the impact of researcher–attribute differences on network evolution. Explore the influence of homogeneity of discipline on the evolution of the network. Explore the impact of the similarity of researcher´s cognition and joint collaboration experience on the evolution of the network.

Take the Phase1 (2012-2014) network as an example, enter the parameters of the stergm function in the tergm package as follows:

m1 = stergm (ph1_net, formation = ~edges +gwesp (0,fixed= T) +gwdegree (0,fixed=T)+ gwdsp (0,fixed=T) + nodecov ("num_collaborator") + nodecov ("sp") + nodecov ("hindex") + nodecov ("c_age") + absdiff ("sp") + absdiff ("hindex") + absdiff ("c_age") + dyadcov (con_prox_matrix) + dyadcov (fc_matrix) + nodematch ("su") ,

dissolution = ~edges + gwesp (0,fixed= T) + gwdegree (0,fixed=T) + gwdsp(0,fixed=T) +

nodecov ("num_collaborator") + nodecov ("sp") + nodecov ("hindex") + nodecov ("c_age") + absdiff ("sp") + absdiff ("hindex") + absdiff ("c_age") + dyadcov (con_prox_matrix) + dyadcov (fc_matrix) + nodematch ("su"), estimate = "CMLE", times = c(1:3))

In the formula, "ph1_net" is the time series network data at phase1 composed of networks in 2012, 2013 and 2014, "formation" represents the functional relationship that affects the formation of the network edge, "dissolution" represents the functional relationship that affects the dissolution of the network edge, and "CMLE" represents the maximum likelihood estimation method, "times" represents the time period, "(1:3)" means to run tergm for all three interval networks.

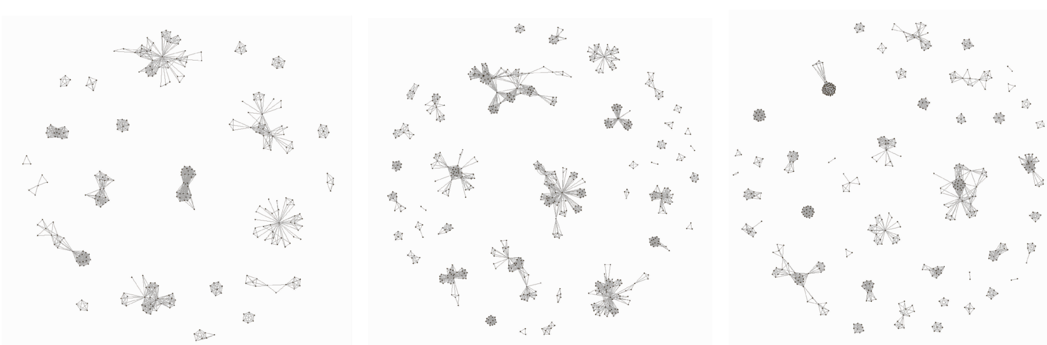
5.2 Results

5.2.1 Analysis of time series characteristics of interdisciplinary team co-authoring network.

Based on the funding papers of the team who received INSPIRE continuous funding, an interdisciplinary team collaboration network has been formed. Through the analysis of the characteristics of the co-authoring network in different time periods from Table 3 and Figures 3, we could know the development trend of interdisciplinary team. The trend of nodes changed revealed that members was increasing at first place and then decreasing, the network density first decreased firstly and then increased, the trend of edges changed indicated that the collaborative relationship between members continued to increase, the number of network components continued to increase, which indicated that interdisciplinary teams continued to differentiate into small teams in the evolutionary process.

Table 3 Statistical table of network characteristics at each phase

Phase	Nodes	Edges	Components	Density
Phase1(2012–2014)	337	1419	22	0.025
Phase2(2015–2017)	659	3077	38	0.014
Phase3(2018–2020)	522	3657	43	0.027

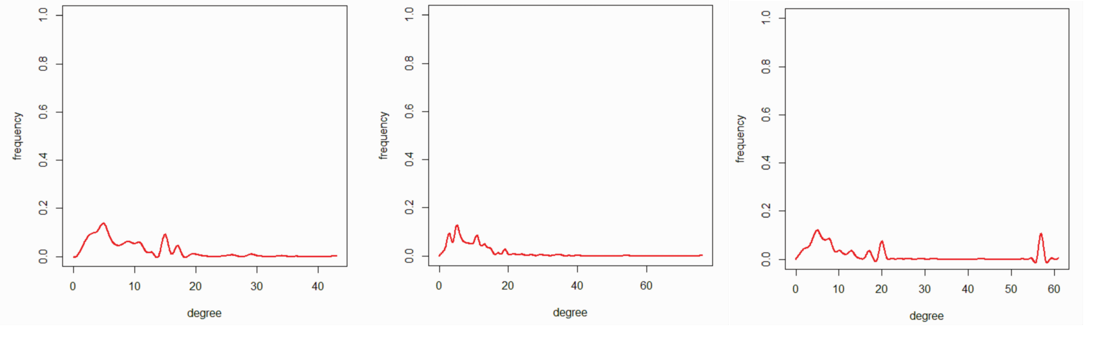


(a)2012-2014 (b)2015-2017 (c)2018-2020

Figure 3 Evolution of Interdisciplinary team co-authored network(2012-2020)

According to Table 3 and Figure 3, Phase1 could be regarded as the initial formation stage of the interdisciplinary team co-authoring network; Phase2 was the stage of development and prosperity, where more nodes were added to the network, and the links in the network further increased; Phase3 was the dissolution and expansion phase. On the one hand, the funded project was about to expire, and the collaborative relationship formed based on the funded project was gradually dissolved. On the other hand, many small research groups have been formed based on the funded project, they further carried out research based on common research interests and mature team communication and collaboration system, even after the funded project has expired.

Figure 4 showed the distribution of degree of networks in different phases. Three diagrams of degree distribution in the three-phase network were the same shape as the classic power law distribution. It means that interdisciplinary team collaboration network has the characteristics of a scale-free network: the network degree distribution does not change with time, and it always obeys the power law distribution.



(a) 2012-2014 (b) 2015-2017 (c) 2018-2020

Figure 4 Evolution of degree distribution in interdisciplinary team co-authored network

This paper further statistically compared the number of added, retained, and disappeared links at different stages, as well as the types of new links, to explore the development trend of interdisciplinary teams. The results were shown in Table 4.

Table 4 Comparison table of added and retained links

Time	Total links	The added			The disappeared	The retained
		N–O[a]	N–N[b]	O–O[c]		
Phase1	1419	1419				
Phase2	3077	1714	947	240	1100	319
Phase3	3657	1022	2366	49	2651	426
All						53

Note: a. "N-O"represents the added link consisting of co-authorship formed between the newly joined researchers and the original members in the previous phase. b. "N-N" refers to the added link consisting of co-authoring relationship formed between new researchers at this phase. c."O-O" represents the added link consisting of new co-authorship formed between original team members in the previous phase.

It could be seen from Table 4 that among all the links in Phase 2, the number of links formed in phase1 retained was about 10%, and the number of newly-added links between the newly joined researchers and the old members in the previous phase accounted for 55.7%, while the new links formed between new researchers at this phase accounted for

30.8% , and the"O-O"links in the Phase1 accounted for 7.8% . It could be seen that interdisciplinary collaborative network was not stable from the initial formation to the development phase of the interdisciplinary team. The driving power of the expansion of the network is mainly derived from the initial interdisciplinary team members to expand the partnerships from the outside.

From the perspective of the changes in the links from Phase2 to Phase3: About 86% of the partnerships formed in Phase2 had disappeared. Among the new relationships formed in Phase 3, "N-N" links accounted for 73.2%. It could be inferred that the force driving the development of the interdisciplinary co-author network at this phase was the new team members. Compared with the period from Phase1 to Phase2, the number of retained relationships increased, and the number of new relationships also further increased during the period from Phase2 to Phase3. The network was still not stable, the collaborative relationships formed based on the original team members at previous phase decreased, indicating that the co-authoring network of interdisciplinary team was open and inclusive.

It is generally considered that growth and preferential attachment are two evolutionary mechanisms of scale-free networks. On the one hand, the scale-free network is open and expands by constantly adding new nodes and the new nodes form new ties with the existing nodes in the network. On the other hand, nodes with more connections among existing nodes can often get more new links. Through the above comparison of the degree distribution of the network and analysis of different type of links, it could be seen that the evolutionary mechanism of interdisciplinary collaboration network was similar to the scale-free network.

5.2.2 Dynamic analysis of interdisciplinary collaboration evolution.

The paper used the STERGM to analyze the evolutionary dynamics of interdisciplinary collaboration and the estimated results of STERGMs were shown in Table 5.

The estimation results showed that different type of variables and the same variable had different effects on the evolution of the interdisciplinary team co-authoring network at different phases.

The estimation results of the structure item showed that the geometrically weighted edge sharing partners had a significant role in promoting the formation of interdisciplinary partnerships at different stages, indicating that the network transitivity could work in a closure structure at different stages, and the H1a was supported validly. However, the influence of geometrically weighted edge sharing partners on the dissolution of edges in different phases of the network is different. In Phase2, gwesp had an adverse effect on the dissolution of edges in the network, H1b was supported, but which significantly promoted the dissolution of the edge of the network in Phase3. This might be due to the fact that in the later stage of the project, more collaborative relations began to dissolve, making the transitivity no longer significant in the later stage of the network.

The gwdsp parameter estimate was significant but negative in the formation function in three phases, which indicated that geometrically weighted dyadwise sharing partners played a reverse role in the formation of edges in the network in the three stages and H2a was rejected. It might be due to the interdisciplinary team co-authoring network formed based on the project was so small that the nodes in the structural hole were regarded as isolated nodes, and it was difficult to have a positive effect on the formation of edges as in a large network. However, it had a significant negative effect on the dissolution of edges in Phase1

Table 5 STERGM results

	Phase1		Phase2		Phase3	
Variables	**Formation**	**Dissolution**	**Formation**	**Dissolution**	**Formation**	**Dissolution**
Structure terms						
edge	–5.284***	0.254***	–6.555***	1.392***	–6.484***	–1.845**
gwesp	3.337***	NA	3.803***	–2.661***	4.001***	0.466***
gwdsp	–0.276***	–1.069***	–0.201***	–0.370***	–0.360***	NA
gwdeg	2.036***	–3.081***	–1.121***	–0.430***	NA	–2.251
Node terms						
Number of collaborators	0.001***	–0.0001	0.009**	–0.0004	–0.0003	–0.0007*
Specialization	–0.691***	–2.394	0.384	–2.684***	–0.905	3.248***
Academic	0.006	0.012	–0.010*	0.0007	0.0087	–0.0008
Academic	–0.012	0.010	–0.001	0.005	–0.0007	0.008
Homophily terms						
Homogeneity of specialization	–0.073	4.619***	–0.983***	3.388***	–1.093	–3.605***
Homogeneity of academic reputation	–0.006	–0.008	0.002	0.0106	0.012	0.022
Homogeneity of academic seniority	0.009	0.0119	0.004	–0.004	–0.0006	–0.010
Cognitive proximity	–0.367	1.664***	NA	NA	NA	NA
Frequency of historical collaboration	0.553	13.327	NA	NA	NA	NA
Homogeneity of discipline	1.609***	1.847***	1.388***	0.148	1.623***	0.693**
AIC	1767	105.1	4206	702.4	2010	307.7
BIC	1875	145.8	4323	761.5	2112	359.2

Note.NA indicates parameters were removed with forward-selection approach.
*p < .05. **p < .01. ***p < .001

and Phase2 in the interdisciplinary team co-authored network, which shown that once the nodes in the structural hole were connected, the formed relationship was not easy to dissolve.

The gwdeg parameter estimate was significant and positive in the formation function at Phase1, which supported that the geometrically weighted degree distribution had a positive effect on the formation of links at Phase1, and it significantly negatively affected the formation of edges in Phase2 inferred from the gwdeg parameter estimate. H3a was partially supported, indicating that the interdisciplinary team collaboration network followed the preferential attachment at the initial phase of formation and the nodes with more connections in the network was easier to expand the collaborative relationship.

At Phase 2, the gwdeg parameter estimate was significant but negative in the formation function, indicating preferential attachment had a significant negative effect on the formation of the network for other reason we didn't figure out in the paper. From Phase1 to Phase2, the gwdeg parameter estimate was significant but negative in the dissolution function, which meant that GWD had an inverse effect on the network dissolution at different phases and H3b was partially supported.

From the estimation results of the node items, it could be seen that the number of collaborators significantly promoted the formation of relationships in the network in Phase1 and Phase2, and H7a was supported, but at Phase3 it was not significant and the sign is negative, which might be due to the network was in the final stage of the project at Phase3. Moreover, the number of collaborators negatively affected the dissolution of links in the network, although it was not statistically significant, it also partially supported H7b.

In Phases1 and Phases3, the specialization had a negative impact on the formation of edges in the interdisciplinary team co-authoring network, which indicated that researchers who mainly focused on a subject area were not easy to establish connections at initial stage in the interdisciplinary collaboration network. On the contrary, researchers with a wide range of fields were more likely to establish ties in an interdisciplinary co-authoring network, and H4a could not be effectively supported. Moreover, specialization in Phase2 and Phase3 had a negative effect on the dissolution of edges in the interdisciplinary team co-authorship network, although it was not statistically significant. It could be speculated that it was difficult for highly specialized researchers to establish new collaborative relationships and dissolve existing partnerships in the interdisciplinary team co-authoring network. This might be explained that highly specialized researchers who had been cultivating in a field for many years and had a more comprehensive grasp of domain knowledge were indispensable for an interdisciplinary research team, therefore, the relationship was not easy to dissolve, H4b was partially supported.

The effect of academic reputation and academic seniority on the evolution of the interdisciplinary co-authoring network was generally not significant, which indicated that the mechanism of academic reputation and academic seniority in the network was more complicated. Hypotheses H5 and H6 were difficult to be supported.

In the estimation result of the homogeneity items, the estimation coefficient of specialization was significantly positive in the process of network dissolution at Phase1 and Phase2, which shown that the difference in specialization between researchers negatively influenced the maintenance of interdisciplinary collaborative relationships. There was a big difference in the knowledge stock and depth of the two researchers, which would make it difficult for both partners to conduct good knowledge exchanges, which was disadvantageous to promote research.

The difference in academic reputation and academic seniority between nodes had no significant effect on the interdisciplinary teamwork network from parameters estimate. Due to the use of the forward-selection approach to screen variable in the model, the cognitive proximity and the frequency of historical collaboration were only retained by the model in Phase 1, in which cognitive proximity had a negative effect on the formation of the network in the initial stage but was not significant and had a positive effect on the dissolution of the edge of the network. This could be speculated that the solution of interdisciplinary research issue required knowledge in different fields to work together, and this in turn depended on the gathering of scholars with different knowledge backgrounds for collision of ideas, so researchers who were too similar in cognition might find that knowledge was highly overlapped and difficult to solve the research problem, thus dissolving the collaborative relationship. Research hypothesis H8a was difficult to obtain support, and H8b hypothesis was supported partially.

It could be seen from parameter estimate that the frequency of joint historical collaboration had no significant effect on the evolution of the interdisciplinary team co-authoring network, and the research hypotheses H9a and H9b were not supported.

Homogeneity of discipline played an active role in promoting the formation of links in interdisciplinary team collaboration networks at different stages. It did not support the H10a, but at the same time the collaboration between researchers with the same disciplinary background was easier to dissolve, H10b was supported, which indicated that the researchers with the same disciplinary background were easy to establish collaborative relations in the interdisciplinary collaboration network, but it was not conducive to the maintenance of collaborative relations.

6 Conclusion

The evolution of the interdisciplinary collaboration network is the result of a variety of factors, its dynamics also changes with the development of time (Ba et al., 2022). Based on the perspective of co-authorship, this paper comprehensively considers multi-level factors, decomposes the network evolution process into the formation and dissolution of edges, uses separable temporal exponential random graph model (STERGM) to construct the evolution model of the co-authoring network, and explores the evolutionary dynamics of interdisciplinary teams.

Empirical research has shown that structural factors, scholar attributes, and link attributes had influence on the network evolution in the evolution of interdisciplinary collaborative networks to some extent. The influence of structural factors on the evolution of interdisciplinary collaboration networks is much the same at different stages, indicating that the influence of special network structure laws on the evolution of interdisciplinary collaboration networks is not affected by time. Network transitivity and preferential attachment play a positive role in the formation of relations in the network and hinder the dissolution of edges in the network. Researcher in the brokerage position is difficult to establish new connections but are good at maintaining existing contacts. There are differences in the influence of scholar attributes on the network in different time periods. Most of variables about scholar attributes have the same effect on the network in the early and mid-term. In the later period, affected by the objective conditions of the end of the project, the impact of some variables on the network have changed. The number of collaborators has a positive effect on the formation of the interdisciplinary team collaboration network in the early formation and development period, and has an inhibitory effect on the dissolution of the edge. In the periods of team expansion and dissolution, the effect of number of collaborators on the formation of edges in the network is not obvious. Specialization inhibits the formation of edges in the initial stage of the interdisciplinary collaboration network, and inhibits the dissolution of the network in the development stage, and promotes the dissolution of the network in the later phase. Among the homophily variables, the similar disciplinary background has a significant effect on the network evolution. In the initial stage and the development period, a large difference in specialization between researchers is not conducive to the formation of the edge of the network, and is conducive to the maintenance of relationships. In the interdisciplinary collaboration network, homogeneity of disciplinary background is conducive to the formation of collaborative links but not conducive to the maintenance of relations.

From a practical perspective, the research conclusions have implications for scientific research administrator and researcher. When building an interdisciplinary team, the researcher's specialization and number of collaborators can be used as indicators to provide decision-making support for the selection of scientific research team members. Researchers can expand their academic relationship network through online academic social platforms such as Sciencenet, ResearchGate, so as to enhance the transmission of knowledge and information in the network, and increase the probability of establishing interdisciplinary partnerships. In order to maintain the reasonable stability of the interdisciplinary team collaboration, administrators concerned can start with the structural factors of the collaboration network and the homogeneity factors among researchers. Furthermore, the interdisciplinary team should establish a mechanism to promote the gradual embedding of field experts in the research work of the team, such as holding regular workshops.

This paper has limitations on the research samples and research methods. For the research samples, the conclusion is only based on collaboration formed by interdisciplinary projects instead of all kinds of interdisciplinary collaboration samples such as laboratory collaboration. For the research methods, quantitative methods such as network analysis and bibliometric are used in the study but qualitative methods are absent. Future research on the dynamics of interdisciplinary collaboration evolution can be improved by expanding the research samples and using qualitative research methods.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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