Structural Analysis of E-Sports Industrial Association Network Based on Complex Network Theory

Haibin Wang[1*], Hong Huo[1], Dongdong Zhang[1]

Abstract
A clear regional imbalance exists in the e-sports industry in terms of the industry's contribution to the overall development of the economy. Available research suggests that this imbalance is a result of regional supporting policies, social culture integration and differences among countries. Therefore, to rationalize the overall structural planning for e-sports industrial association network (IAN), this paper probes into the structure of e-sports IAN based on the complex network theory. Firstly, the key factors affecting the development of the e-sports industry are identified, and an evaluation index system (EIS) is established. Secondly, e-sports IAN is analyzed from two angles, namely, the entire network and enterprise node, based on complex network theory. This study uses an experimental design for gathering data from the respondents. Finally, the clustering structure of e-sports IAN is studied based on modularity, and the network is divided into clusters. The results verify the effectiveness of complex network theory in the structural analysis of e-sports IAN. The economic ties between regional e-sports enterprises enhance slightly in the six years. Compared with the density of the national e-sports industrial network, the region has a certain advantage in e-sports industrial development in 2014. The findings of the present study fill the gaps mentioned in the paper and significantly benenfit practioners and stakeholders as well as help in identifying the salient industries and key areas in e-sports IAN.
Keywords: complex network, e-sports, industrial association network (IAN), structural analysis, China

Introduction

E-sports refers to the sports, culture, and entertainment sectors of the tertiary industry. It covers a wide range of emerging industries, such as science, culture, sports, and media (Li, Wang, & Li, 2021). In 2003, e-sports were recognized as the 99th type of sports in China. Since then, the market size of the relevant industries has grown continuously. Currently, the e-sports industry is dominated by game development and competition broadcasting. The industrial structure is expected to develop towards daily life contents, three-dimensional (3D) scenarios, standard rules and regulations, and professional players (Perrin, Ziarelli, & Dupuis, 2020). However, the structural imbalance of the regional e-sports industry emanates from the differences between countries/regions in terms of the level of economic development, the integration of social culture, and the supporting policies (Ishii, Okano, & Nishikawa, 2021). E-sports industrial association network (IAN) is a complex system. The industry embraces a series of behaviours, ranging from game research and development (R&D), competition planning and implementation, to live broadcast of games (Verma & Bharadwaj, 2017). Therefore, to ensure that the E-Sports IAN's overall structural plan is reasonable, this paper analyzes its network structure. To rationalize the overall structural planning for e-sports IAN, this paper choses to thoroughly analyze the structure of the network.

The domestic and foreign studies on industrial structure primarily focus on updating and optimizing single quantitative evaluation algorithms, e.g., input-output analysis, based on the data of independent enterprises or city samples (Bhatia & Sood, 2017; Ditizio, 2016; Wang, Zhao, & Wiedmann, 2019).The complex direct/indirect association between enterprises in each industry are largely overlooked. To solve the problem, this paper treats the e-sports industry as a massive, directed network of the associations between relevant enterprises, and explores the structure of e-sports IAN based on the complex network theory. Therefore, the basic purpose of this paper is to analyze the factors that affect the development of e-sports along with setting up a system that can be used for evaluation purposes. The present study also analyzes the IAN from the overall level and the enterprise nodes, based on the complex network theory. Additionally, this study analyzes the clustering structure of e-sports based on IAN modularity and through the realization of clustering the IAN.

[1] School of management, Harbin University of Commerce, Harbin 150028, China
*Corresponding author: wanghaibin1980@126.com

Literature Review

Cognition

In the complex design of networks, three words are of great importance. These three words are termed as statistical physics, computer science and cognition. The network analysis method is mainly developed in the environment of sociology. To analyze different complex models, the network analysis is used in the past on several occasions and there are a number of examples as well (Lozano, Calzada-Infante, Adenso-Díaz, & García, 2019). As we all know that internet is a combination of networks of domains and routers. Whereas World Wide Web is the combination of networks of many different websites. On the other hand, a network of people is known as the organization. The network of many different national economies is called the global economy which is the network of several different markets. Moving more towards the examples of networks, the metabolic pathways and food webs are also examples of network models (Sullivan & Manning, 2019).

It is also important to note that a number of different diseases spread because of social networks including computer viruses which are spread mostly through the internet. On the other hand, different networks are also used to distribute the energy in the infrastructure as well as in living organisms. It is also important to understand the role of these networks in cognition. Most of the time, the complex models are suitable for the phenomena of cognition. As we all know the brain is a complex network of neurons. Therefore, it represents one of the key challenges in system science (Dong, Hou, Zhang, & Zhang, 2020).

One of the most important factors which need to be studied under the networks is the study of language. Researchers in past studies envision a program of research related to the field of research. In this program, three different levels are discussed to describe the information processing system. These three levels are named as implementation level, algorithm level and computational level. The computational level is defined as the mental representation in which a system is described. The second level known as the algorithm level which includes the cognitive process and is the level at which system methods are described (Jarecki, Tan, & Jenny, 2020). In the end, the implementation system is known as the neural system that describes the means of the system. The organization needs to take stock of all of the levels and must be given equal consideration. It is key to formuating a comprehensive theory. It is also needed to understand the mechanism by which a certain goal can be achieved. Thus, complex network theory is understood as the toolbox that can provide important insights regarding modular structure, organization and topology (Turnbull et al., 2018).

Researchers indicate that complex network theory can be used as a feasible tool to analyze optimization of the structure which is needed. It is important to mention that it should also be relevant to the allocation of resources with complex attributes (Xing, Shi, Song, Zhao, & Li, 2019). The evolution of structure at the microscale level has some features of the industry. These features are important regarding a certain industry under proposed pertinent and strategic planning to improve the unreasonable structure of the industry (Sugino, Ruzzene, & Erturk, 2021). Based on complex network theory, scholars have established a network model regarding the supply industry of green agricultural products. The network is divided into a number of modules and structure division is obtained through regional modularity at maximum level (Stoffel, Gulakala, Bamer, & Markert, 2020). On the other hand, scholars also employ the quartile method to convert the traditional network of the industry into a graph that is weightless undirected. Whereas, it is also used to compute the weight of vectors having the importance of nodes through the analytical hierarchy process (AHP) (Singh & Verma, 2019).

The high-quality development of the industrial economy calls for a sound understanding of industrial association (Berezin & Roshchupkin, 2016; Kruk & Paturej, 2020; Mohamed & Ali, 2021; Vanhamaki et al., 2019). Relying on Weaver-Thomas Index (WTI), Ou et al. (2018) numerically simulate the input-output data of regional green chemical industry, transforming the input-output matrix for complex network analysis into an adjacency matrix, and conducting a cohesive subgroup analysis on the entire network, industrial nodes, industrial subgroups, and structural holes. Through social network analysis and quadratic assignment procedure (QAP) regression, R. Chen, Zhang, Wan, Liu, and Zhang (2021) analyze the spatial correlations and influencing factors of regional high-tech industrial block model, intending to drive other industries with the knowledge and technology-intensive high-tech industry.

It is essential to understand the association of the industry for the calls of the industrial economy (Manas, Young, Fujimoto, Franklin, & Myneni, 2019). Based on the Weaver Thomas Index also interpreted as WTI, scholars simulate numerically the data regarding the green industry of the region. They are able to transform the matrix for the analysis of a complex network into a matrix that is adjacent. They also conduct a subgroup analysis that is particularly cohesive on structural holes, industrial subgroups, industrial nodes and entire networks (Ou, Sun, & Jiao, 2018). Moreover, scholars also analyze the influential factors and spatial correlation of the region block model through social network theory. Their research aims to drive the knowledge of other industry and technology-based high tech industries (B. Chen, Liu, Liu, Qin, & Peng, 2021). There are different elements upon which the quality, as well as quantity of outputs, are dependent. These elements include space, institution, resources, technology, capital and labour (B. Chen et al., 2021). Presently, most of the industrial networks are conducted with the help of tables of input and output. This approach is initially improved by scholars (Alzubaidi & Al-Shamery, 2020).

E-Sports IAN Analysis

Researchers have mentioned several physical networks that are highly common namely citation network, road network and social network. They have also mentioned subtracting networks such as neural networks, the internet and grid and many more in our real life. The pioneering work in this field is conducted by researchers in a village of Norway who present the work of social networks for the first time with a purpose to describe different social relationships which are not easily explained through traditional units which are used traditionally including workgroups and extended families (Seikkula, Arnkil, & Hoffman, 2018). Most of the early work conducted in the field of social networks is descriptive and exploratory. A knowledge base has been provided by the findings of these studies which help to identify the characteristics of the network. Generally, close networks are proved to play an instrumental and effective role. These networks also play a critical role in exerting more influence at the social level to confirm the norms of the network. Researchers also found that instrumental support and effective support is provided by the networks that are close geographically (Klyver, Honig, & Steffens, 2018). From the above discussion, it is evident that the terms social support and social networks do not reflect the theories. Whereas they are the concepts that describe the functions, processes and structures of social relationships. Several social, psychological and sociological theories namely symbolic interactionism, attachment theory and exchange theory are used by individual researchers to explain the interpersonal process at the base level which underlies sports and social relationships (Khorakian & Sharifirad, 2019).

At the international level, several countries are facing chalenges in terms of their infrastructure including the infrastructure of transport. There are several reasons for this concern. These concerns include perception of threats and risks to the infrastructure, agreements of the public and private partnership, difficulties related to the provision of the public sector to develop new infrastructure, level of using the system that already exists and conditions regarding it, and development state as well. If the infrastructure is destroyed, it will negatively affect the overall economy (Bashar, Fung, Jaillon, & Wang, 2021). Thus, it is key to find a way to identify the network. Therefore, there is a need to develop a method by which the vulnerability and risk of the networks can be assessed. The tools of the decision support are also required by which the policymaker and planner are allowed to make the assessment rationally regarding the assessment of threats regarding facilities. If the networks are planned in a good manner, it will impact the economic-social setup of the country positively, leading to an increase in trade and revenue as well (Panetti, Parmentola, Ferretti, & Reynolds, 2020).

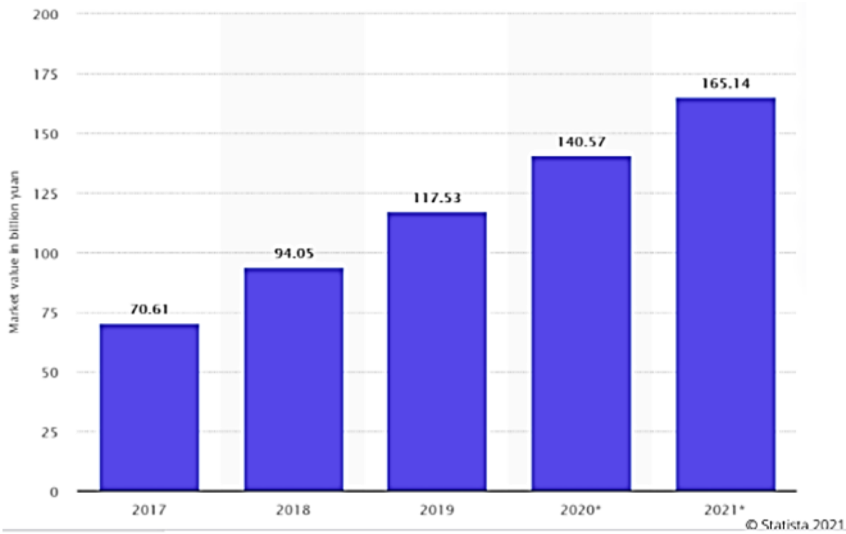
These networks can be analyzed from the perspective of network theory. The development of complex network theory provides a new research angle of industrial structural analysis in various fields. With the aid of the theory, the industrial structure can be examined from a comprehensive perspective (N. Li et al., 2021). The results thus obtained are more objective, systematic, and complete. This paper firstly processes the index data and then analyzes the global and local features of e-sports IAN.

In the last decades, China is one of the largest markets of e-sports. It is key to mention that innovation in e-sports is one of the key policies of China. Whereas, e-sports is currently the official sport of China by the General Administration of China. The e-sports industry of China illustrates the capacity of China by which they can create unique gaming and technological experience (Yang, 2018). Through e-business, China is earning revenue of millions of Dollars. It is worthy to mention that last year, China earned a revenue of 165 billion Yuan.

Key Influencing Factors

According to the development state of China's e-sports industry, and the existing theories on supply chain and complex network, the e-sports industrial network can be divided into an upstream subsystem responsible for the R&D and operation of e-sports games, a midstream subsystem responsible for organizing e-sports games, and a downstream subsystem responsible for e-sports live broadcast. This section extracts the key factors affecting e-sports industrial development, and establishes the corresponding EIS, laying the basis for e-sports IAN analysis (Otu, 2019).

Layer 1 (primary indices): $ES = \{ES_1, ES_2, ES_3, ES_4\}$ = {macro environment, upstream subsystem, midstream subsystem, downstream subsystem}.



China E-Sport Market Size (2020-21)

While Layer 2 (secondary indices): ES_1= {ES_{11}, ES_{12}, ES_{13}, ES_{14}} = {political legal environment, economic environment, social cultural environment, sci-tech environment}; ES_2= {ES_{21}, ES_{22}} = {R&D of e-sports games, operation of e-sports games}; ES_3= {ES_{31}, ES_{32}, ES_{33}} = {planning of e-sports competitions, implementation of e-sports competitions, services of e-sports competitions}; ES_4={ES_{41}} = {live broadcast of e-sports game}.

Layer 3 (tertiary indices): Under the secondary indices of macro environment, e-sports industrial development is mainly affected by four factors of political legal environment (talent cultivation policy, government incentive policy, setting of management institutions, and legal protection of competition broadcasting right), three factors of economic environment (macroeconomic level of the state, per-capita consumption, and consumption of e-sports and entertainment), two factors of social-cultural environment (social recognition of e-sports, and regional cultural integration of e-sports), and three factors of sci-tech environment (development of communication network technology, development of computer software/hardware, and development of virtual reality-VR and simulated reality-SR).

In the upstream subsystem, e-sports industrial development is mainly influenced by four factors of R&D of e-sports games (innovativeness of game design, user satisfaction of game design, maturity of game program development, and artistic beauty of game), and four factors of operation of e-sports games (understanding of market demand, professionality of product marketing, quality assurance of game services, and strength of technical supports) (Kailash & Pabalkar, 2021).

In the midstream subsystem, e-sports industrial development is mainly influenced by four factors of planning of e-sports competitions (authority, commercial reputation, organization/coordination ability, and fund/resource integration ability of the host), four factors of implementation of e-sports competitions (professionalism of competition operator, publicity and management abilities of advertisers and sponsors, formality and operation/planning ability of e-sports clubs or management enterprises, and expertise of professional players and coaches), and three factors of services of e-sports competitions (logistics quality of the operator, security guarantee, and fairness of referees).

In the downstream subsystem, e-sports industrial development is predominantly influenced by the following aspects of the live broadcast of e-sports game: the popularity of commentator, expertise of commentator, media positioning of platform, effect of platform, and supervision mechanism of platform.

Methodology

Researcher uses the experimental research design. Unit of analysis is the employees of e-sports enterprises in the region, especially the experienced ones from different departments. The response rate is 80%. According to Kiess and Bloomquist (1985) in experimental studies, the minimum response rate must be 60% (Dlalisa & Van Niekerk, 2015). Therefore, the response rate of current study is satisfactory.

The mean shortest paths and clustering coefficients of e-sports IAN are obtained through experiments, which verify the feasibility of further analysis of network associations. Node degrees and cluster density matrices are computed for the regional e-sports IAN with an actual example. Clustering coefficient trials how associated a vertex's neighbors are to one another. Then, the regional e-sports IAN is visualized in the form of cluster tree and black-and-white squares. Further, to compute the density of e-sports IAN and its change rate, the data of other regions in China of same period are introduced (Tennakoon, Luong, Mohotti, Chakravarthy, & Nayak, 2019).

Data Processing

After analyzing the completeness and cleaning the index data, the relevant data are further processed in the following steps: calculate the thresholds of the original index data of relevant e-sports enterprises and carry out thresholding on the original data; obtain the e-sports adjacency matrix for complex network analysis.

Suppose M enterprises are involved in regional e-sports industry. Let $D(i, j)$ be the data collected for evaluation index i for enterprise j. Ranking $D(i, j)$, $D(2, j)$,…,$D(M, j)$ in reverse order, the WTI of $D(i, j)$ can be described by:

$$WT(i,j) = \sum_{i=1}^{M}\left[r(a,i) - 100 \times \frac{D(a,i)}{\sum_{i=1}^{M} D(i,j)}\right]^2 \tag{1}$$

where, $r(a, i)$ can be calculated by:

$$r(a,i) = \begin{cases} 100/i, a \le i \\ 0, a > i \end{cases} \tag{2}$$

Suppose $WT(l, j) = min\{WT\{1, j), WT(2, j), \ldots, WT(M, j)\}$. Then, two enterprises with WTI>$D(l, j)$ are strongly associated in IAN.

Let $u_1, u_2, \ldots, u_M$ be the thresholds obtained through WTI calculation for the index data for the relevant enterprises; $U(i, j)$ be the data in row i and column j. According to the thresholds $u_1, u_2, \ldots, u_M$, an adjacency matrix $AD(i, j)$ can be established for complex IAN analysis:

$$\begin{cases} AD(i,j) = 1, U(i,j) \ge u_j \\ AD(i,j) = 0, U(i,j) < u_j \end{cases} \tag{3}$$

During the construction of e-sports IAN, if $AD(i, j) = 0$ in the adjacency matrix, there is no edge between two relevant enterprises, that is, the two enterprises are not associated; if $AD(i, j) = 1$, there is an edge between them, that is, the two are associated.

Analysis of the entire network

This paper uses the clustering coefficient to characterize aggregation of enterprises in e-sports IAN. The coefficient can simultaneously measure the agglomeration degree of the entire network, a part of the network, or the enterprise nodes. Let N_{TR} be the number of triangles in e-sports IAN; N_{CTR} be the number of connected triples in the network, i.e., the number of three enterprises linked up by two edges. Then, the agglomeration degree of the entire network can be defined as:

$$U_{OS} = \frac{N_{TR}}{N_{CTR}} \tag{4}$$

Formula (4) shows that U_{OS} is a constant in [0, 1]. If the e-sports IAN has a high node density, i.e., the enterprises are highly clustered, U_{OS} approaches 1; if the e-sports IAN has a low node density, i.e., the enterprises are sparsely distributed, U_{OS} approximates 0.

Let $H = (IN, CE)$ be the constructed e-sports IAN, where I and CE are an enterprise node and the edge between enterprise nodes, respectively; s_{ab} be the length of the shortest path between two enterprise nodes a and b. Then, the length of the longest path between any two enterprise nodes in H can be defined as:

$$S = max\{s_{ab}\} \tag{5}$$

Then, the mean distance s^* between any two enterprise nodes in H, i.e., the mean path length of the network, can be described by:

$$s^* = \frac{1}{M(M-1)}\sum a, b \in m, a \neq b s_{ab} \tag{6}$$

Formula (6) shows that the longer the longest path, the less efficient the resource and information transmission between enterprises in e-sports industry; the inverse is also true. The mean distance s^* can also characterize the overall efficiency of the constructed network in resource and information transmission. The value of s^* is negatively correlated with the transmission efficiency.

Comparing the actual number N_E of edges between two enterprise nodes in e-sports IAN with the maximum possible number of edges $M(M-1)$, the network density σ_{NET} can be obtained to reflect the compactness and stability of the network:

$$\sigma_{NET} = \frac{2N_E}{M(M-1)} \tag{7}$$

If the e-sports industrial network is generally stable, and if the enterprise nodes are linked up by multiple edges, then σ_{NET} takes a large value; if the network is generally unstable, and if the nodes are sparsely connected, then σ_{NET} takes a small value.

Node analysis

In the constructed e-sports IAN, the independent value of an enterprise node can be measured by node degree, i.e., the number of edges between this node with other enterprise nodes. Let $H = (I, CE)$ and $G = \{g_{ab}\}_{m \times f}$ be the e-sports IAN and its adjacency network, respectively. Then, the node degree ND_a of enterprise node a can be defined as:

$$ND_a = \sum_{b=1}^{M} g_{ab} \tag{8}$$

A large ND means the enterprise node plays a significant role in e-sports industrial network.

The centrality of enterprise nodes in e-sports IAN can be measured by three important metrics: closeness centrality, betweenness centrality, and eigenvector centrality. Let s_{ab} be the distance between two enterprise nodes a and b. Then, the closeness centrality NE_a, which highlights the network connectivity between enterprise nodes, can be expressed as:

$$NE_a = \frac{1}{\sum_{1 \le b \le M} s_{ab}} \tag{9}$$

Formula (9) shows that the NE_a value is proportional to network connectivity. If the network has a poor connectivity, then NE_a approaches 0. Let v_{bc} be the number of shortest paths between two enterprise nodes b and c; $v_{bc}(a)$ be the number of the said shortest paths passing through node a. Then, the betweenness centrality IN_a, which highlights the regulation effect of an enterprise node between other nodes, can be expressed as:

$$IN_a = \sum_{b<c} \frac{v_{bc}(a)}{v_{bc}} \tag{10}$$

This paper introduces eigenvector d to compute the eigenvector centrality, which reflects the independent value of each enterprise node in the network. Let $\mu d=Gd$ be the characteristic function, with μ being the eigenvalue. Then, the eigenvector centrality FV_a of enterprise node a can be defined as the a-th component $d_{max}(a)$ of the maximum eigenvector μ_{max} of G:

$$FV_a = d(a)_{max} \tag{11}$$

Formula (11) shows that, the FV_a value is proportional to the value of the enterprise node to the network.

This paper chooses the clustering coefficient to measure the tightness of the association between an independent enterprise node and its adjacent enterprise nodes in e-sports IAN. Let K_a and $ND_a(ND_a-1)/2$ be the number of edges between node a and its adjacent nodes, and the maximum number of edges, respectively. Then, the ratio of K_a to $ND_a(ND_a-1)/2$ is the clustering coefficient of node a:

$$U_a = \frac{2K_a}{ND_a(ND_a-1)} \tag{12}$$

Referring to the definition of the clustering coefficient for the agglomeration degree of the entire network, the agglomeration degree of an enterprise node in the network can also be calculated by:

$$U_a = \frac{N_{TR-a}}{N_{CTR-a}} \tag{13}$$

where, N_{TR-a} is the number of triangles containing node a in the network; N_{CTR-a} is the number of connected triples with node a at the center. In formula (13), U_a is still a constant in the interval of [0, 1]. If the node is closely associated with other nodes in e-sports IAN, then U_a approaches 1, and the node is relatively unimportant in the network; if the node is sparsely associated with other nodes in e-sports IAN, then U_a approximates 0, and the node is relatively important in the network.

Modularity-Based Analysis on Clustering Structure

Many real networks have clustering features, that is, inter-cluster edges are much sparser than intra-cluster edges. Based on modularity, this paper examines the clustering structure of e-sports IAN. Figure 1 illustrates the structure of the upstream subsystem (green), midstream subsystem (yellow), and downstream subsystem (purple).

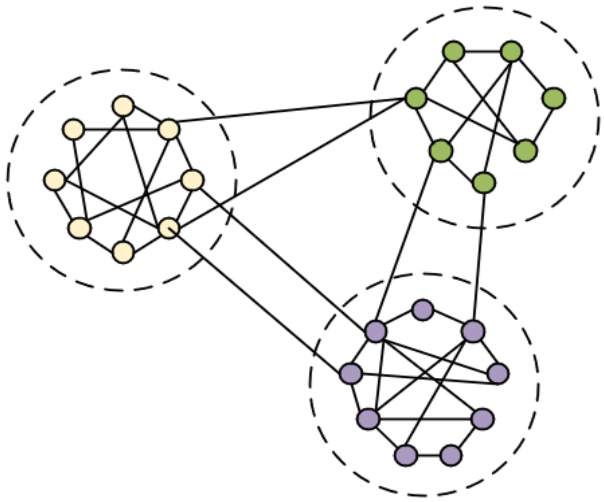


Figure 1. Clustering structure of e-sports IAN

The modularity formula is introduced by replacing the number of edges and node degree of enterprises mentioned in the preceding section with the sum of edge weights and node strength, respectively.

The strength of enterprise node a QD_a can be obtained by superposing the weights of its edges. Let θ be the sum of edge weights in the network; θ_{ab} be the weight of the edge between two enterprise nodes a and b. θ and θ_{ab} belong to cluster MO_a and cluster MO_b, respectively. Let ξ be a binary function about whether nodes a and b belong to the same cluster. If ξ=1, then the two nodes belong to the same cluster; if ξ=0, then the two nodes belong to different clusters. Thus, modularity can be computed by:

$$W = \frac{1}{2\theta}\sum_{ab}\left(\theta_{ab} - \frac{QD_aQD_b}{2\theta}\right)\xi(MO_a, MO_b), \tag{14}$$

For simplicity, the modularity matrix A can be defined as an $M\times M$ symmetric matrix:

$$A_{ab} = \theta_{ab} - \frac{QD_aQD_b}{2\theta} \tag{15}$$

Combing formulas (14) and (15):

$$W = \frac{1}{2\theta}\sum_{ab} A_{ab}\,\xi(MO_a, MO_b) \tag{16}$$

Suppose $\sum_a \theta_{ab} = QD_b$, and $\sum_a QD_a = 2\theta$. Then, the sum of all rows and columns in A equals 0:

$$\sum_a A_{ab} = \sum_a \theta_{ab} - \sum_a \frac{QD_aQD_b}{2\theta} = 0 \tag{17}$$

To divide the e-sports IAN with N_V vertices into l clusters, the binary function ξ needs to be adjusted by:

$$\xi_{MO_a,MO_b} = \sum_{QD=1}^{l} \xi_{QD,MO_a}\xi_{QD,MO_b} \tag{18}$$

Let μ_k be the eigenvalue of the symmetric modularity matrix A; Q be the orthogonal matrix; Q_{ak} be the a-th component of the eigenvector of μ_k. Then, matrix A can be written in the eigenvector decomposition form:

$$A_{ab} = \sum^{m} \mu_k Q_{ak} Q_{bk} \tag{19}$$

If there exists $\mu_1 \geq \mu_2 \ldots \geq \mu_l$, the above three formulas can be combined to update the modularity formula:

$$W = \frac{1}{2\theta}\sum_{ab}\sum_{k=1}^{N_V} \mu Q_{ak}Q_{bk}\sum_{QD}\xi_{QD,MO_a}\xi_{QD,MO_b}$$

$$= \frac{1}{2\theta}\sum_{k=1}^{N_V}\mu_k \sum_{QD}\left[\sum_a Q_{ab}\xi_{QD,MO_a}\right]^2 \quad (20)$$

The modularity can be approximated based on the maximization of the positive term:

$$W = \frac{1}{2\theta}\sum_{k=1}^{O}\mu_k \sum_{QD}\left[\sum_a Q_{ak}\xi_{QD,MO_a}\right]^2 \quad (21)$$

where, O is an integer smaller than N_V. In fact, the modularity can be approximated by the first O eigenvectors of the modularity matrix:

$$W = \frac{1}{2\theta}\sum_{QD=1}^{l}\sum_{k=1}^{O}\left[\sum_a \sqrt{\mu_k}Q_{ak}\xi_{QD,MO_a}\right]^2 \quad (22)$$

Each enterprise node a has an O-dimensional point vector t_a:

$$[t_a]_\psi = \sqrt{\mu_k}Q_{ak} \quad (23)$$

The modularity based on the point vector can be expressed as:

$$W = \frac{1}{2\theta}\sum_{QD=1}^{l}\sum_{k=1}^{O}\left[\sum_{a\in QD}[t_a]_\psi\right]^2 = \frac{1}{2\theta}\sum_{QD=1}^{l}\left|\sum_{a\in QD} t_a\right|^2 \quad (24)$$

Similar to k-means clustering, the data and distance can be replaced with node vector and inner product. The sum of point vectors of enterprise nodes in a cluster can be computed by:

$$T_{QD} = \sum_{a\in QD} t_a \quad (25)$$

Combining formulas (24) and (25):

$$W = \frac{1}{2\theta}\sum_{QD}\left|T_{QD}\right|^2 \quad (26)$$

To further explore the modularity feature, it is assumed that enterprise node moves from cluster 1 to cluster 2. The vectors of clusters 1 and 2 are denoted as C_1 and C_2, respectively. Before the movement, the cluster vectors can be described as C_1+t_a and C_2, respectively. After the movement, the cluster vectors can be described as C_1 and C_2+t_a, respectively. Then, the modularity change ΔW caused by the movement of enterprise node a can be described by:

$$\Delta W = \frac{1}{2\theta}\left[|C_1|^2 + |C_2+t_a|^2 - |C_1+t_a|^2 - |C_2|^2\right]$$
$$= \frac{1}{\theta}\left[C_2^T t_a - C_1^T t_a\right] \quad (27)$$

Formula (27) shows that the increase/decrease of modularity depends on the size of $C_2^T t_a$ and $C_1^T t_a$. Figure 2 illustrates the proposed clustering method.

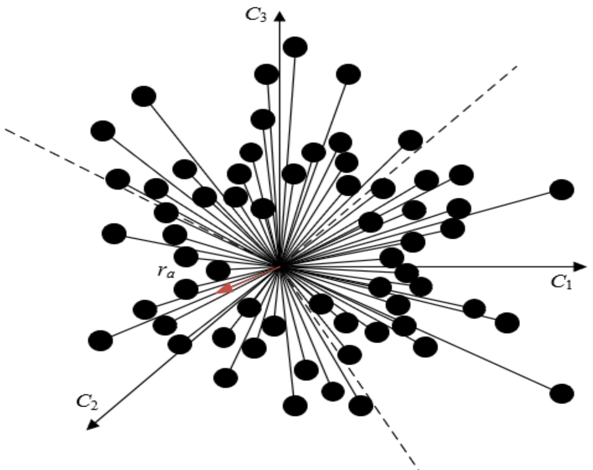


Figure 2. Sketch map of our clustering method

Experiments and Results Analysis

Table 1

Mean shortest paths and clustering coefficients of e-sports IAN

Year	2014	2016	2018	2020
Clustering coefficient	0.311	0.416	0.489	0.490
Mean shortest path	2.164	2.034	1.997	2.015

Table 1 presents the mean shortest paths and clustering coefficients of e-sports IAN. In 2014, 2016, 2018, and 2020, the clustering coefficients of regional e-sports IAN are 0.311, 0.416, 0.489, and 0.490, respectively. For e-sports enterprise nodes in any region, the ratio of actual number of edges to the maximum possible number of edges is 31.1%, 41.6%, 48.9%, and 49.0%, respectively. The ratio is relatively high.

In 2014, 2016, 2018, and 2020, the mean shortest paths of regional e-sports IAN are 2.164, 2.034, 1.997, and 2.015, respectively. On average, an enterprise node in regional e-sports industrial network needs to go through 2.164, 2.034, 1.997, and 2.015 edges, respectively, before arriving at another enterprise node. Since the established network contains 45 enterprise nodes with 1,834 edges at the most, the mean shortest paths from any node to another are relatively short, and in line with the small world features. Therefore, it is feasible to carry out further analysis on the association network.

Table 2 lists the node degrees of e-sports IAN in 2018 and 2020. The closeness centralities of the node enterprises in the network in 2018 are close to those in 2020. Comparatively, the highest node degree (27) belongs to the host of e-sports competition in the midstream subsystem, followed in turn by regional e-sports game developer (19), e-sports competition operator (18), e-sports clubs (17), and e-sports management enterprise (16). In e-sports IAN, a high node degree means a great importance of the enterprise to the network. Therefore, all these enterprises are high-value nodes in e-sports IAN in 2018 and 2019. E-sports cultural transmission enterprise has a small node degree (5), less than half of that of e-sports competition operator. There is a huge gap between this enterprise and other high-value nodes.

Figure 3 provides the clustering tree of e-sports IAN in 2020. It can be seen that the regional e-sports IAN in 2020 is divided into 3 primary parts, which contain different number of clusters. To disclose the correlations between the 5 clusters, it is necessary to derive the density matrix between them. According to the clustering density matrix of e-sports IAN in 2018 and 2020 (Table 3), the clusters are either closely or sparsely correlated. Overall, the regional e-sports IAN does not have a high inter-cluster density, suggesting a weak correlation between clusters.

Specifically, the highest density (0.913) appears between clusters 4 and 2, indicating that the two clusters are relatively close bound. In other words, the enterprises in cluster 4 have a close relationship with those in cluster 2.

Table 2

Node degrees of e-sports IAN in 2018 and 2020

Type of enterprise	Serial number	2018			2020		
		Node degree	Out-degree	In-degree	Node degree	Out-degree	In-degree
Upstream	ESE_1	12	7	4	10	8	2
	ESE_2	14	4	12	13	7	12
	ESE_3	9	3	9	7	2	5
	ESE_4	11	3	8	12	5	10
	ESE_5	14	2	11	11	6	12
	ESE_6	7	6	12	8	4	1
	ESE_7	6	5	1	5	2	2
	ESE_8	5	2	2	7	2	5
	ESE_9	13	4	4	5	1	5
Midstream	ESE_{10}	11	6	6	11	6	4
	ESE_{11}	12	12	2	6	5	2
	ESE_{12}	27	25	5	28	25	3
	ESE_{13}	16	4	9	13	3	9
	ESE_{14}	17	18	3	17	13	2
	ESE_{15}	19	16	3	17	13	3
	ESE_{16}	15	9	5	15	10	7
Downstream	ESE_{17}	14	4	9	14	6	11
	ESE_{18}	18	7	7	12	5	5
	ESE_{19}	12	13	5	15	8	8
	ESE_{20}	10	9	2	10	9	2

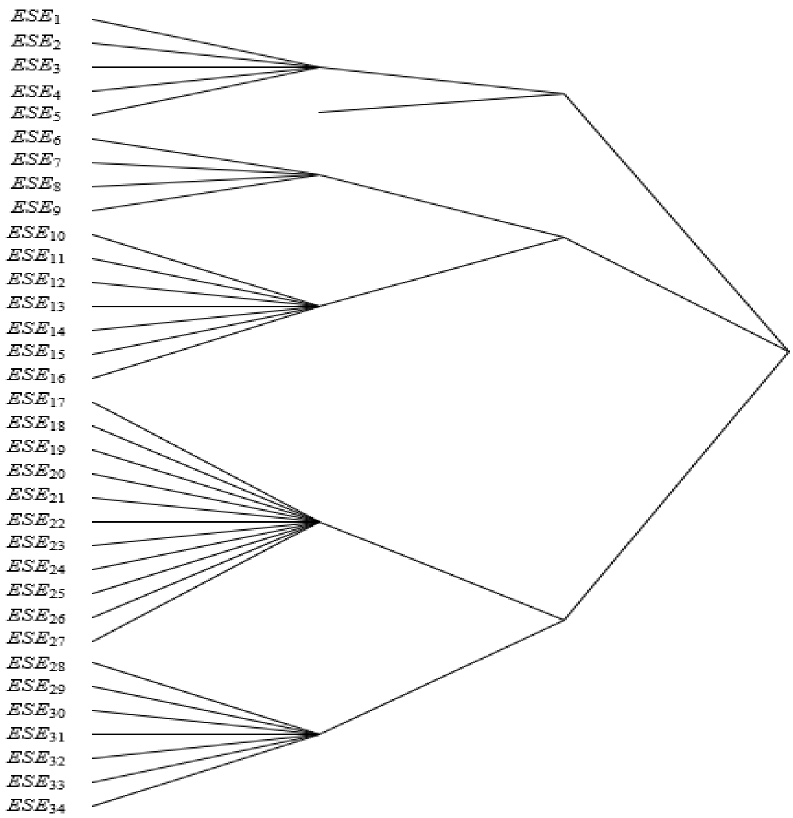


Figure 3. Clustering tree of e-sports IAN in 2020

Table 3

Clustering density matrix of e-sports IAN in 2018 and 2020

Year	Cluster number	1	2	3	4	5
	1	0.175	0.142	0.001	0.001	0.062
	2	0.135	0.261	0.125	0.001	0.235
2018	3	0.001	0.195	0.001	0.421	0.872
	4	0.001	0.913	0.001	0.506	0.621
	5	0.001	0.001	0.001	0.001	0.108
	1	0.163	0.001	0.175	0.152	0.725
	2	0.129	0.001	0.001	0.085	0.137
2020	3	0.065	0.001	0.837	0.253	0.076
	4	0.128	0.001	0.001	0.764	0.353
	5	0.032	0.001	0.001	0.001	0.125

For clarity, the elements of 1 and 0 are replaced with black squares and white squares, respectively. Then, the e-sports IAN is described in black and white squares (Figure 4). The spatiotemporal evolution and change law of e-sports industry from 2016, 2018, to 2020 can be clearly observed from Figure 4.

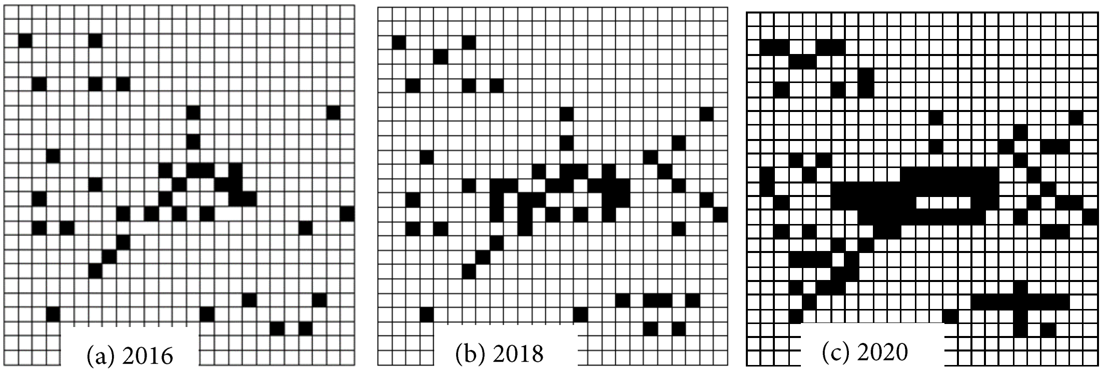


Figure 4. E-sports IAN is described in black and white squares

UCINET is adopted to simulate and compare the network densities of regional e-sports IAN in 2014, 2016, 2018, and 2024. In addition, the data of other regions in China of the four years are introduced to compute the density of e-sports IAN and its change rate (see Table 4).

Table 4

Density of e-sports IAN and its change rate

Year	Regional e-sports industrial network density	Regional change rate	National e-sports industrial network density	National change rate
2014	0.01821	-	0.01372	-
2016	0.01835	0.3759%	0.01865	71.1283%
2018	0.01972	-2.7356%	0.01938	4.0357%
2020	0.01926	0.2918%	0.02134	3.7628%

As shown in Table 4, the density of regional e-sports industrial network is 1.821% and 1.835%, respectively, in 2014 and 2016, while it is 1.972% and 1.826%, respectively, in 2018 and 2020. Therefore, the economic ties between regional e-sports enterprises enhances slightly in the six year span. Compared with the density of national e-sports industrial network, the region has a certain advantage in e-sports industrial development in 2014. However, the regional development is not as good as the national situation during 2016-2010. In the later period, the regional e-sports enterprises are not closely associated. Meanwhile, the national e-sports industrial network become denser and denser, as the density steadily rises from 1.372% in 2014 to 2.134% in 2020.

Conclusions

This paper mainly studies the structure of e-sports IAN based on the complex network theory. Firstly, the authors analyze the key factors affecting e-sports industrial development and set up the corresponding EIS. Subsequently, the overall network and enterprise nodes of e-sports IAN are investigated in detail. Finally, the network is divided into multiple clusters through modularity-based structural analysis. Through experiments, the mean shortest paths and clustering coefficients of e-sports IAN are obtained, which verify the feasibility of further analysis of network associations. With an actual example, the node degrees and cluster density matrices are computed for the regional e-sports IAN. Then, the regional e-sports IAN is visualized in the form of cluster trees and black-and-white squares. Further, the data of other regions in China of the same period is introduced to compute the density of e-sports IAN and its change rate.

The present study uses complex network theory to analyze the structure of the e-sports industry. Keeping in view the complex features of the structure of the e-sports industry, the research method used in the present study reflects the constraints and mutual dependence among the enterprises at different levels in the sports industry.

These findings of the present study fill the theoretical gaps by presenting a new way of e-sports IAN structural analysis based on the complex network theory. The findings of the present study provide the basis for stakeholders in the government to overcome the problems related to industrial structure. For future studies, these findings also provide a reference for the structural analysis of the IANs in other fields and help identify the industries and key areas in e-sports IAN.

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