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RESEARCH ARTICLE

A Method to Evaluate Network Efficiency in Industrial Knowledge Transfer: Results From the Delta Region

JIAN-GUO LI[1,2], HONG LI[1], YU-WEN GONG[3], AND MIN ZHU[4]
[1]School of Management, Shanghai University, Shanghai 200444, China
[2]Department of Management Sciences, Faculty of Engineering, University of Waterloo, Waterloo, ON N2L 3G1, Canada
[3]School of Economics and Management, Southwest Jiaotong University, Chengdu, Sichuan 610031, China
[4]School of Engineering and Management, Pingxiang University, Pingxiang 337000, China

Corresponding authors: Hong Li (649796524@qq.com) and Min Zhu (945993005@qq.com)

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ABSTRACT The efficiency of industrial knowledge transfer (IKT) directly affects the level of knowledge connection and collaborative innovation in the industry. However, there is a lack of research, particularly from the perspective of network characteristics, to investigate the efficiency of IKT. Therefore, this study proposes a methodology for measuring the efficiency of weighted industrial knowledge transfer network (IKTN) by employing multiple network indicators. Firstly, based on patent data, a weighted IKTN model with node and edge weights is constructed, and the weighted clustering coefficient and path length of the network are defined. Then, considering the indicators of node weights, edge weights, weighted clustering coefficient, and path length, an efficiency measurement model for the weighted IKTN is established. Finally, we take the environmental protection industry (EPI) in the Yangtze River Delta region of China as the practical case to verify the scientific validity and applicability of the proposed method. The results show that the measurement method proposed can effectively evaluate the node efficiency and overall efficiency of IKTN, and provide a scientific basis for relevant policymaking. This study comprehensively considered multiple factors in the IKTN efficiency measurement and used existing data from the patent database in the weight setting, avoiding the problem of excessive reliance on subjective factors in previous studies that may lead to deviations in the authenticity of the evaluation.

INDEX TERMS Industrial knowledge transfer network, knowledge transfer, patent transfer, patent-intensive industry, network efficiency.

I. INTRODUCTION

The knowledge-based view holds that knowledge is a key resource for enterprises to develop and maintain their unique competitive advantages, and the improvement of the knowledge base is crucial to innovation capabilities [1], [2]. The development of an industry must rely on the continuous acquisition and creation of knowledge, and knowledge transfer (KT) within an industry is an important form to enhance its knowledge reserve level and promote industrial knowledge innovation [3], [4]. KT refers to the transfer of knowledge from one subject (source) to another subject (receiver), through knowledge acquisition, absorption, and innovation, and is a process of mutual communication and adaptation between knowledge sender and receiver [5], [6]. It's difficult for an enterprise to meet the demand for knowledge in business development only with its own knowledge stock, and inter-organizational KT has become an effective way for enterprises to quickly improve their competitiveness. KT can effectively integrate the knowledge possessed by industrial innovation subjects, expand the knowledge stock, and enhance the collaborative innovation capability of the industry [5].

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As the importance of knowledge in industrial development and innovation continues to be highlighted, KT activities among enterprises have become increasingly frequent [7]. The knowledge links between different enterprises in the industry constitute the industrial knowledge transfer network (IKTN). IKTN refers to the network structure in which different organizations communicate, share and transfer knowledge in one or more industries [8]. It describes the flow and dissemination of knowledge within and between industries. With the addition of new enterprise nodes, the exit of old enterprise nodes, and the changes in the strength of knowledge connections between enterprises, IKTN exhibits the characteristics of dynamic evolution [9]. In complex network theory, network efficiency directly reflects the connectivity and information transfer capability of the network [10]. By studying network efficiency, we can gain deeper insights into the knowledge flow process within the network and understand the influence of network structure on industrial knowledge transfer (IKT). This helps identify and address bottlenecks in IKTN and propose improvement strategies to enhance the efficiency of knowledge flow. Furthermore, we can identify key nodes and critical pathways within the network, offering decision support to policy-makers to promote knowledge flow and industrial innovation.

Currently, scholars have begun to evaluate KT activities from the perspective of network efficiency [11], [12]. However, these studies primarily focus on small innovation teams and employ subjective evaluation methods when assigning weights. Different from KT among organizations or teams, IKTN at the macro level possesses a greater number of nodes and edges. It exhibits a larger scale and a more complex structure. Hence, methods such as member or expert scoring are no longer considered reasonable or practical for assigning weights to nodes and edges. In this scenario, it becomes essential to utilize formal and quantifiable data and indicators to establish an IKTN model, and to propose a measurement method for KT efficiency from the perspective of complex networks.

Various forms of KT exist within any industry [3]. Among them, knowledge that is difficult to convey through written documents, such as experience, skills, etc., belongs to the category of tacit knowledge, while explicit knowledge, in contrast, is knowledge that can be clearly documented and recorded [13]. Hence, explicit knowledge is usually more accessible and measurable than tacit knowledge [2]. Researchers can directly process and analyze existing explicit knowledge data sources without having to rely on personal subjective interpretations or verbal descriptions. As a typical type of explicit knowledge, patents describe new inventions, technologies or innovations in written form in detail, including their principles and implementation methods, and have been regarded as a key indicator to measure the level of knowledge and technological innovation in previous studies [14], [15]. Especially in recent years, as the importance of patents in economic development has become increasingly prominent, countries have continuously strengthened the protection, management and application of intellectual property rights [16]. Industries classified by high patent density or quantity, such as patent-intensive industries, are constantly mentioned and receive increasing policy support in various countries [3].

Compared with other subjective evaluation indicators, patents are more formal and quantifiable data, which can reflect the knowledge capabilities of enterprises without being affected by human factors [15]. Especially with regard to patent transfer data, which can not only reflect the scale and direction of KT between enterprises but also provides detailed information on the technological categories to which the transferred patents belong, as well as the names and geographical locations of both parties involved. Furthermore, the transferred patents are generally considered to be of high value and high technological level. And due to their quantifiable knowledge attributes and the fact that they can be extensively accessed from public databases, they are better suited for analyzing the explicit KT within industries from a macro level [17].

As a theoretical approach that integrates the concept of complex networks into understanding mediated information flows and their effects, innovation diffusion theory explains the KT process in the diffusion of organizational innovations [18]. In this study, IKTN based on patent data is a typical innovation diffusion network, and its nodes and overall network efficiency directly affect the diffusion speed of knowledge innovation in the industry. Additionally, existing research has found that the efficiency of innovation diffusion is determined by the interaction of network strength and knowledge types [19]. Therefore, based on innovation diffusion theory, this study uses patent transfer data, which is more suitable for analyzing industrial explicit KT, as a data set, and comprehensively considers multiple network indicators in measuring network strength, and proposes an efficiency measurement method of IKTN. Then, we apply this method to a real case in a patent-intensive industry to verify its applicability. The primary reason for choosing this industry type is that, compared to other industries, patent-intensive industries generally exhibit higher growth potential and value. Moreover, the scale of patent transfers in these industries is often larger, making them more suitable for validating the effectiveness and applicability of the proposed methodology.

It is worth mentioning that, in addition to patent-intensive industries, other industries reliant on ongoing technological innovation and intellectual property protection and operation, such as clean energy, new materials and other high-tech industries or emerging technology industries, are also equally applicable for conducting network efficiency analysis using the method proposed in this paper. This study hopes that the proposed method can help grasp the development status of IKT, identify key nodes and key paths in the network,

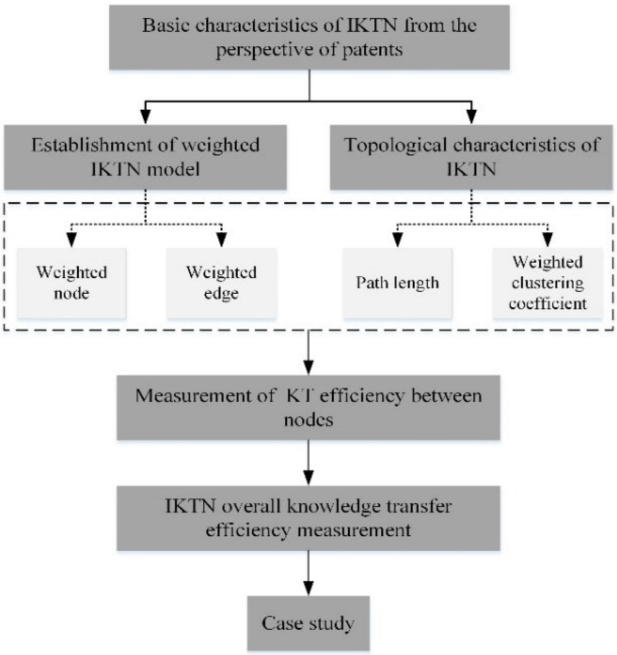

FIGURE 1. Research framework.

and provide a basis for subsequent optimization of network structure and formulation of corresponding industrial development policies from the perspective of patents as an explicit knowledge indicator.

Specifically, the goals of this study are as follows:

1) Based on the industrial patent transfer data, determine the weighting rules of nodes and edges in the network, and construct a weighted IKTN model.
2) Establish an IKTN efficiency measurement model that comprehensively considers node weights, edge weights, weighted clustering coefficients, and path lengths to comprehensively evaluate the node efficiency and overall efficiency of IKTN.
3) Verify the scientific validity and practicality of the proposed model through practical cases, with the aim of contributing to the evaluation of explicit KT network efficiency in industries that rely on continuous technological innovation and intellectual property protection and operation, and promoting collaborative innovation and the sustainable development of these industries.

The remaining part of this paper is structured as follows: Section II briefly discusses and reviews the related literature to provide the rationale of the research objectives. In section III, the topology of IKTN is analyzed and a weighted IKTN model is constructed. Section IV proposes the measurement model of inter-node and overall efficiency of IKTN. In section V, we apply the model to a practical case to verify its applicability and effectiveness. Finally, we summarize the findings of the study and propose future research prospects. The research framework of this paper is shown in Figure 1.

II. LITERATURE REVIEW

In strategic management, emphasis is placed on the fundamental role of knowledge in enabling organizations to gain competitive advantages [2], [5]. Organizations engage in research and development (R&D) activities by integrating knowledge, leading to continuous accumulation of knowledge assets and a reduction in operational costs [19]. This process culminates in a series of innovative outcomes, such as patents, resulting in sustained competitive advantages. Bataineh et al. contend that increasing R&D expenditures in enterprises facilitates the introduction of higher levels of technology transfer, enabling the acquisition of new knowledge and the creation of higher quality products [20]. The knowledge-based view posits that competitive advantage based on knowledge is sustainable, as organizations with higher levels of knowledge reserves tend to possess greater capabilities for problem-solving and environmental adaptation [21]. However, some scholars argue that relying solely on a firm's internal R&D capabilities can often fall short in meeting its knowledge demands, potentially leading to significant costs and risks for the firm [22]. In this context, inter-organizational KT has emerged as a crucial avenue for enterprises to expedite the acquisition of new knowledge and enhance their innovation capabilities, garnering increasing attention from both industry and academia [5].

In academia, the concept of KT originally came from the cross-border technology transfer between enterprises proposed by Teece. He believed that cross-regional technology transfer can help companies absorb a large amount of technical knowledge on the one hand, and on the other hand, it can also spread technology in different regions and narrow the technological gap between them [23]. Initial KT research focused primarily within organizations, exploring how knowledge is shared between individuals and teams to support organizational innovation and performance [24]. In the wave of knowledge economy, KT between enterprises has garnered increasing attention from researchers. Szulanski regards KT as a knowledge sharing activity that facilitates the dissemination of knowledge within or between organizations [25]. Li et al. state that KT activities should not only emphasize the diffusion of knowledge but also the absorption of knowledge by members [6]. Van Wijk et al. argue that transferring knowledge between different enterprises is much more complex than transferring knowledge between units within the same organization [26].

Regarding the literature on industrial knowledge transfer, researchers generally apply empirical research and case study to analyze its mechanism, performance, and influencing factors or the role in promoting economic growth and technological innovation [5], [8], [21]. Among them, Zimpel and Lettice conducted in-depth interviews to explore the mechanisms and sustainability of KT in the food industry [27]. Shi et al. found through empirical analysis that centrality in innovation networks significantly impacts the KT performance in the artificial intelligence industry [8]. Liao and Hu conducted empirical research on the semiconductor industry and confirmed that efficient KT can enhance the industry's core competitiveness [22]. In addition, the trust mechanism and contract mechanism between enterprises are regarded as the internal driving mechanism for the generation and continuation of IKT because they can prevent opportunistic behavior [28], [29]. In terms of knowledge characteristics, explicit knowledge is the main component of formal KT in the industry because it has been codified and is easily subject to contract mechanisms [30]. Tacit knowledge, on the other hand, is more suitable for transfer between cooperative teams and individuals, and is difficult to measure and evaluate [13].

With the continuous development of complex network theory and computer technology, a substantial influx of research on IKTN has surfaced. Bunnell and Coe were the first to propose considering the characteristics of networks in the study of KT and identified network structure as an important factor [31]. As subsequent research has delved deeper, the significant impact of network structure on IKTN has been continuously confirmed [9], [10]. Among them, Ernst and Kim argued that the positioning of network nodes is closely related to IKTN performance [32]. Ye et al. analyzed the data of joint patent applications and found that the central positions of key nodes in IKTN are difficult to be replaced [33].

In terms of research methodology, Byosiere et al. combined social network theory and organizational knowledge creation theory, and through case studies found the cross-influence of network connection strength and knowledge type on the effectiveness of innovation diffusion in the European telecommunications industry [19]. Xie et al. adopted the fuzzy set qualitative comparative analysis and found that the existence of network size, network relationship strength and network centrality determines the IKTN performance, while the effect of network heterogeneity on performance is not significant [34]. Ter Wal employed an empirical research method and obtained the conclusion that the importance of network node proximity is continuously diminishing [35]. Studies have also revealed that IKTN tends to exhibit high clustering, which means that participants are more likely to be connected to other members who are already connected to each other [36]. This clustering phenomenon can be attributed to participants' inclination to seek and depend on familiar partners. Also, IKTN tends to be highly dynamic and constantly evolving due to changes in enterprise technology needs, new technologies emerging, and entry of new players [37], [38]. It is evident that the current research on IKTN primarily concentrates on the analysis of the network's structural characteristics and their impact on performance, while the research on IKTN efficiency is less involved.

The efficiency of IKTN directly affects the speed and scope of knowledge dissemination in the network [39]. In the field of network research, the network efficiency between nodes is defined as the reciprocal of the shortest path length between two nodes, and the global efficiency of the network is the average of the reciprocal of the shortest path length between each pair of nodes in the network [39]. This network efficiency measurement method intuitively and simply reflects the speed and efficiency of information dissemination in the network, and is widely used in social networks and logistics networks [40]. With the deepening of research on complex network theory, scholars find that small-world networks characterized by high clustering and short path lengths are more conducive to information transmission within the network and are considered efficient [41]. In addition, in the case of weighted networks, the weights of nodes and edges also have an impact on KT efficiency. Some scholars have begun to explore the influence of node, edge, and network topology characteristics on the efficiency of knowledge networks in their research. Su et al. and Jiafu et al. considered indicators such as weighted path length and clustering coefficient, established weighted knowledge cooperation network and open innovation network respectively, and measured the knowledge diffusion efficiency of these networks [12]. The above research further considered the node weights and topological characteristics of the network in the network efficiency analysis, which enriches the results of knowledge network efficiency study and provides valuable ideas for subsequent related research. However, these studies mainly focus on the tacit knowledge flow efficiency of innovation teams or member cooperation networks from the micro level, and tend to use highly subjective methods such as members scoring in the selection of indicators and the determination of weights.

IKT activities based on trust and contract mechanisms are more formal and explicit forms of KT, such as the transfer of patent rights between enterprises. Their networks are massive and rely on measurable and batch-acquired metrics from large databases for characterization. Driven by the knowledge economy, the scale of IKTN continues to expand, and it has become increasingly urgent to explore its network efficiency based on indicators such as node and edge weights and network topology. However, current research on evaluating the efficiency of KT networks at the industry level based on more formal and quantifiable indicators is still lacking. Hence, this paper attempts to study the efficiency of IKTN at the macro level by utilizing patent data and considering multiple network indicators.

Based on the above literature analysis results, this study proposes the following hypotheses:

H1: The new methodology based on the patent perspective can effectively evaluate the network efficiency of explicit KT in the industry.

H2: The new methodology that integrates node weights, edge weights, path lengths and weighted clustering coefficients is more applicable than traditional method in measuring network efficiency in IKT.

III. THE ESTABLISHMENT OF IKTN MODEL

A. BASIC CHARACTERISTICS OF IKTN FROM THE PERSPECTIVE OF PATENTS

Patent information is widely recognized as an indicator to measure KT [42]. Some studies believe that patent citations between organizations can be used to represent explicit KT [14], while the cooperative invention relationship among patent inventors can be used to measure implicit KT [13]. In addition, numerous studies have shown that patent transfer is also an important channel [15], [43]. Patent transfer refers to the process by which an organization or individual, as a recipient of knowledge, acquires patented technology from a knowledge provider in order to enhance their knowledge reserves and improve their technological innovation capabilities [15]. Patent transfer can be a channel for knowledge and technology transfer, which improves the efficiency of the innovation process by promoting the division of innovative labor and diffusion of technology [17]. Compared with indicators such as patent citation data, which are more suitable for studying the evolution of specific technologies, patent transfer data records the changes in patent ownership between enterprises, which can reflect the flow of knowledge between different enterprises [44]. Moreover, it is generally only when a patent holds high value that others will consider purchasing it from the inventor or patent holder, thereby leading to the transfer of patent rights [15]. For these reasons, patent transfer data can relatively better reflect the economic value of knowledge and is more appropriate for studying the efficiency of IKTN.

Regarding the characteristics of the patent transfer network, it exhibits clear originating and arriving nodes. For instance, if enterprise A transfers its patents to enterprise B, then A serves as the originating node while B represents the arriving node. Therefore, the edges in the ITKN are directed edges. Furthermore, the process of patent transfer is typically accompanied by the transfer of knowledge value, which imbues it with not only direction but also weight. For instance, the number of patents transferred, the technical content of patents, and the value of patents can serve as edge weights to reflect the importance of knowledge. Therefore, the IKTN based on patent transfer information is a typical directed weighted network.

B. ESTABLISHMENT OF WEIGHTED IKTN MODEL

1) NODE WEIGHTING METHOD OF WEIGHTED IKTN

A node is the basic unit of a complex network, which represents an individual, group or event in the network [45]. In IKTN, each node represents an enterprise entity or regional entity in the industry. Due to the differences in the knowledge capabilities of each node, they have different node weights in the network [46]. Specifically, one of the core factors affecting the efficiency of IKT lies in the transfer capability of knowledge of each enterprise. When enterprises lack sufficient transfer capabilities, it may seriously hinder the transmission and sharing of knowledge resources within the industry, and weaken the cooperation between enterprises [7]. The knowledge absorption capacity of an enterprise determines whether the enterprise can quickly grasp external advanced technology and experience and apply it to production and operation [47]. It is also a key factor affecting the efficiency of industrial knowledge flow. Therefore, in this study, the node attributes in IKTN include the enterprise's knowledge transfer capacity and knowledge absorption capacity.

Organizations with high patent transfer-out data usually have strong technical exchange, cooperation and transfer capabilities, while organizations with high patent transfer-in data typically exhibit excellent abilities in learning, absorbing, and integrating external knowledge [48]. Hence, we use the total number of patent transferred-out of enterprises to represent the knowledge transfer capacity of nodes, and the total number of patent transferred-in of enterprises to represent the knowledge absorption capacity. Due to the large gap in the scale of KT between different enterprises in the industry, it is necessary to normalize the weights of nodes. Yoon and Hwang proposed a cost-based and benefit-based index normalization method, which has been widely used [49], as shown in formula (1) and (2).

$$k_{i-benefit} = \frac{k_i - k_{min}}{k_{max} - k_{min}} \tag{1}$$

$$k_{i-cost} = \frac{k_{max} - k_i}{k_{max} - k_{min}} \tag{2}$$

where, (1) for benefit-based and (2) for cost-based index normalization method, $k_{max} = max\{k_i|\ i = 1,2,\ldots,n\}$, $k_{min} = min\{k_i|\ i = 1,2,\ldots,n\}$.

Numerous studies have shown that the transfer and absorption of knowledge play an important role in promoting the effect of KT in the entire industry [47], [50]. Thus, this paper adopts a benefit-based normalization method. Let the total number of patent transferred-out of node enterprise i be t_i, then the normalized knowledge transfer capacity t_i' can be expressed as:

$$t_i' = \frac{t_i - t_{min}}{t_{max} - t_{min}} \tag{3}$$

In the formula, $t_{max} = max\{t_i|\ i = 1, 2, \ldots, n\}$, $t_{min} = min\{t_i|\ i = 1, 2, \ldots, n\}$. Let the total number of patents transferred into enterprise i be a_i, then the normalized knowledge absorptive capacity a_i' can be expressed as:

$$a_i' = \frac{a_i - a_{min}}{a_{max} - a_{min}} \tag{4}$$

In the formula, $a_{max} = max\{a_i|\ i = 1, 2, \ldots, n\}$, $a_{min} = min\{a_i|\ i = 1, 2, \ldots, n\}$.

The node weight is composed of its knowledge transfer capacity and knowledge absorption capacity. Since t_i' and a_i' are relative values, and t_{max} and a_{max} may have large differences in values, resulting in unreasonable node weights. To avoid this situation, t_{max} and a_{max} need to be further normalized. Hence, refer to the research of [51] and [52], this study adopts the following weighting method to determine the node weight of IKTN:

$$A_i = \frac{t_{max}}{t_{max} + a_{max}} \cdot t_i' + \frac{a_{max}}{t_{max} + a_{max}} \cdot a_i' \tag{5}$$

In the formula, A_i is the comprehensive weight of node i in IKTN, and it is not difficult to see that the value range of A_i is between 0 and 1.

2) EDGE WEIGHTING METHOD OF WEIGHTED IKTN

Edges in complex networks, also known as network links, represent the connection relationship between nodes [53]. The degree of mutual trust and relationship between enterprises is an important factor that cannot be ignored to affect the efficiency of KT and it is regarded as the edge connecting enterprises in many studies of inter-enterprise KT network [54]. In IKTN, the scale of patent transfer between enterprises constitutes an edge with weight characteristics. By calculating the weight of the edge, the intensity of knowledge exchange and relationship level between nodes can be grasped, which is helpful to further explore the efficiency of network.

In the KT network, knowledge flows from nodes with high knowledge potential energy to nodes with low knowledge potential energy [55]. Since each node may have different knowledge potential energy in different knowledge fields, each node acts as both a knowledge sender and a knowledge receiver [6]. Similar to this, each enterprise node in IKTN may be either the assignor or the assignee of the patent right, which has typical directed network characteristics. Set the edge of knowledge flowing from node i to node j in IKTN as e_{ij}, and the edge from node j to node i as e_{ji}, and normalize them as follows:

$$e'_{ij} = \frac{e_{ij} - e_{min}}{e_{max} - e_{min}} \tag{6}$$

$$e'_{ji} = \frac{e_{ji} - e_{min}}{e_{max} - e_{min}} \tag{7}$$

In the formulas, $e_{max} = max\{e_{ij}|\ i, j = 1, 2, \ldots, n\}$, $e_{min} = min\ \{e_{ij}|\ i, j = 1, 2, \ldots, n\}$.

From this, the comprehensive edge weight B_{ij} between node i and node j in IKTN can be obtained:

$$B_{ij} = \frac{e'_{ij} + e'_{ji}}{2} \tag{8}$$

C. TOPOLOGICAL CHARACTERISTICS OF IKTN

From both empirical and evolutionary simulation perspectives, numerous studies have demonstrated that the efficiency of KT is significantly influenced by the network's topological structure [11], [56]. Path length and clustering coefficient are regarded as two crucial topological structures in complex network and are often taken into account in studies of team collaboration networks and innovation networks [57]. Therefore, on the basis of previous studies, this paper takes the path length and clustering coefficient between nodes into the key factors affecting the efficiency of IKTN.

1) PATH LENGTH

Path length in a network generally refers to the number of edges on the shortest path connecting two nodes [58]. The reason for considering this feature in efficiency research in IKTN is that complex networks contain highly connected nodes (key nodes) that facilitate short-path connections between a large number of nodes. These short paths result in a smaller average path length, making information dissemination and interaction between nodes relatively easier in the network [59]. In some complex networks, such as transportation networks, the length of roads may affect the choice of routes. Currently, the widely used algorithm for weighted path length in social network research is to calculate the sum of the inverse weights of all edges along the shortest path between two nodes, as shown in the following formula:

$$d_{ij} = min_{p\in paths(i,j)} \sum_{(u,v)\in p} \frac{1}{w\,(u,\,v)} \tag{9}$$

In the formula, d_{ij} represents the weighted path length from node i to node j, $paths(i, j)$ represents the set of all paths from node i to node j, $w(u, v)$ represents the weight of the edge between node u and node v.

It needs to be emphasized here that the IKTN based on patent transfer data is different from the general weighted cooperation network in connotation. Due to the fact that the transfer of patent rights is constrained by the trust mechanism and contract mechanism between enterprises and is a formal explicit KT method, both parties in the transaction need to invest more effort and resources in terms of business operations, competitive relationships, and the evaluation of patent value [17]. Once the transfer of patent rights occurs between enterprises, it means that the two parties have established a certain degree of trust [60]. Therefore, in IKTN, the path length does not solely depend on the scale of patent transfers between nodes, but rather emphasizes whether there can be direct knowledge connections between nodes or knowledge connections that only pass through a few nodes, thereby forming a highly efficient small-world network [59].

In summary, when exploring the KT efficiency in IKTN, it is more suitable to use the definition of general path length, that is, the weight of all edges on the shortest path between nodes $w\,(u,\,v) = 1$, which can be expressed by the following formula:

$$d_{ij} = min_{p\in paths(i,j)} \tag{10}$$

The average path length L of IKTN refers to the average length of the shortest path between two nodes in the network, which can be obtained according to the algorithm proposed by [61]:

$$\mathrm{L} = \frac{1}{N(N+1)} \sum_{i\neq j} d_{ij} \tag{11}$$

2) WEIGHTED CLUSTERING COEFFICIENT

The clustering coefficient refers to the probability that neighbors of a node in a complex network are connected [62]. The reason for considering this feature in efficiency research in IKTN is that nodes in complex networks tend to form clustered connectivity patterns. This clustering propensity increases the likelihood of connections between neighboring nodes, thereby facilitating efficient KT [45]. It is used to describe the degree of closeness between the nodes surrounding a certain node in the network. The clustering coefficient of a node is equal to the ratio of the actual number of edges between its neighbors to the possible number of edges [57]. It can be expressed by the following formula:

$$C_i = \frac{2e_i}{k_i\left(k_i - 1\right)} \tag{12}$$

In the formula, C_i is the clustering coefficient of node i, k_i represents the number of neighbor nodes of node i, and $k_i\left(k_i-1\right)/2$ represents the number of triples centered on node i.

The weighted clustering coefficient refers to the weighted proportion of connections between the neighbor nodes of node i [51]. In order to solve the problem that the unweighted clustering coefficient does not consider that some neighbor nodes in the weighted network are more important than other nodes, refer to the research of [12] and [57], we define the weighted clustering coefficient of node i in IKTN as:

$$C_i^w = \frac{1}{(k_i-1)\sum_{j\in V(i)} B_{ij}} \sum_{j,k\in V(i)} \frac{w_{ij}+w_{ik}}{2} a_{ij}a_{ik}a_{jk} \tag{13}$$

In the formula, $\sum_{j\in V(i)} B_{ij}$ is the weighted strength of node i, $V(i)$ is the set of neighbor nodes of node i, w_{ij} and w_{ik} are the weights of edges between node i and nodes j and k. a_{ij}, a_{ik} and a_{jk} represent the connection relationship between nodes, if its value is 1, it means there is an edge between nodes; otherwise, its value is 0. $(k_i-1)\sum_{j\in V(i)} B_{ij}$ is the normalization factor to ensure that $0 \leq C_i^w \leq 1$.

IV. THE MEASUREMENT METHOD OF IKTN EFFICIENCY

A. MEASUREMENT OF KT EFFICIENCY BETWEEN NODES

As stated above, the KT efficiency between nodes is affected by the node's own knowledge capacity and the strength of knowledge connection between nodes. Among them, the enterprise's own knowledge transfer capacity and knowledge absorption capacity constitute the index of node weight, and the scale of KT between nodes constitutes the index of edge weight. Opsahl et al. pointed out that the larger the node weight and edge weight in a weighted knowledge network, the smaller the cost of KT, which in turn can promote the flow of knowledge between nodes [53].Therefore, these two types of indexes are positively correlated with the efficiency of KT. In addition, the topological characteristics of the network have also been confirmed to have an impact on the efficiency of knowledge flow and transfer [12]. Clustering coefficient and path length are two basic indicators to describe the topology of complex networks. Among them, when the clustering coefficient of the network is higher, the connection between nodes is more closely. In this case, the network will be more open and transparent, and the reputation and cooperation norms of network nodes will be easier to form, making it easier for knowledge to spread in the network [62]. Therefore, the clustering coefficient is positively correlated with the KT efficiency of the network. The shorter path length indicates that the distance between any two nodes is closer and the distance traveled by knowledge is shorter [41]. Thus, the path length is negatively related to the KT efficiency of the network. Consequently, the KT efficiency of the network can be regarded as a function of the combined effect of node weight, edge weight, path length between nodes and clustering coefficient. Under the combined influence of these network indicators, the KT efficiency between different nodes presents heterogeneous characteristics [57]. The explanation of each measurement indicator and its impact on the KT efficiency of the network are shown in Table 1.

TABLE 1. Explanation of measurement indicators.

Indicators	Explanation	Impact on KT efficiency
Node weights	Knowledge transfer and absorptive capacity of nodes	Positive impact
Edge weights	The strength of knowledge exchange and relationship level between nodes	Positive impact
Weighted clustering coefficient	The degree of connectivity between the neighbors of a network node	Positive impact
Path length	The number of edges on the shortest path connecting two nodes	Negative impact

It should be noted that, driven by the knowledge economy, IKTN will continue to grow. However, in the early stage of its development, due to the lack of extensive knowledge connections between enterprise nodes, the network is relatively scattered. In this case, there may be cases where the clustering coefficient is theoretically 0 due to the fact that no triangular structure connection has been formed between the nodes. Therefore, combining the actual characteristics of IKTN from the perspective of patents, and referring to the research of [11] and [12], this paper constructs the following analysis model for the efficiency of KT between nodes in IKTN:

$$T_{ij} = \frac{(A_iA_j)^{\alpha} B_{ij}^{\beta} e^{\left(C_i^w \cdot C_j^w\right)^{\theta} - 1}}{d_{ij}^{\varphi}} \tag{14}$$

In the formula, T_{ij} represents the KT efficiency between nodes i and j, A_i and A_j represent the individual knowledge capacity of nodes i and j. B_{ij} denotes the strength of knowledge connection between nodes i and j. C_i^w and C_j^w represent the weighted clustering coefficients of nodes i and j, d_{ij} is the path length between nodes $i$and j. Besides, α, β, θ, φ are the adjustment parameters of node knowledge ability, communication relationship strength, weighted clustering coefficient and path length respectively, so as to ensure that T_{ij} is in the range of (0,1).

B. IKTN OVERALL KNOWLEDGE TRANSFER EFFICIENCY MEASUREMENT

To evaluate the overall performance and efficiency of specific complex networks in terms of information transmission and resource sharing, Latora and Marchiori studied the characteristics of small-world networks, and proposed the following calculation formula (L-M model) for network efficiency [41]:

$$\mathrm{E} = \frac{1}{N\left(N-1\right)}\sum_{i\neq j}\varepsilon_{ij} = \frac{1}{N\left(N-1\right)}\sum_{i\neq j}\frac{1}{d_{ij}} \tag{15}$$

In the formula, E is the network efficiency, ε_{ij} is the efficiency of information transmission between nodes, and its value is equal to the reciprocal of the path length between nodes. In this paper, the node KT efficiency T_{ij} in IKTN is used instead of ε_{ij} to obtain the overall KT efficiency measurement model of IKTN from the patent perspective:

$$\begin{aligned} \mathrm{E}_{IKTN} &= \frac{1}{N\left(N-1\right)}\sum_{i\neq j\in G} T_{ij} \\ &= \frac{1}{N\left(N-1\right)}\sum_{i\neq j\in G}\frac{(A_iA_j)^{\alpha}B_{ij}^{\beta}e^{\left(C_i^w\cdot C_j^w\right)^{\theta}-1}}{d_{ij}^{\varphi}} \end{aligned} \tag{16}$$

In the formula, E_{IKTN} represents the overall KT efficiency of IKTN. By comparing (15) and (16), it can be observed that the IKTN overall efficiency measurement model not only considers path length and network size like the L-M model, but also incorporates key features such as node weights, edge weights, and weighted clustering coefficient into the model. This model can better reflect the actual characteristics of IKTN based on patent data, ensuring that the results obtained are more scientific and reasonable.

C. MEASUREMENT OF REGIONAL IKTN EFFICIENCY

The IKTN efficiency measurement model established can not only analyze the KT efficiency between enterprise nodes and the overall network, but also explore the KT efficiency of industries in different regions and the overall regional network from a geographical perspective [64]. As the patent transfer data contains geographical location information such as zip codes and addresses of both parties involved in the transaction, it can also be used to create a regional IKTN with different regions as nodes and cross-regional patent transfer information as edges. The number of patent transfers within and between regions can be used as the weight of nodes and edges, forming a directed and weighted regional IKTN. In this case, the enterprise nodes i and j in formula (16) represent regional nodes.

When studying the efficiency of the IKTN in a specific region, the network's nodes represent a certain unit within that region [36]. Unlike enterprise-based IKTN, whose scale continues to expand as more enterprises enter the network, the maximum size of a regional IKTN is generally considered constant. For example, the number of urban nodes in a region remains unchanged. Thus, as the network undergoes further development and all urban nodes become part of IKTN, modifications are observed solely in the weight of urban nodes and edges, without any proliferation in the number of urban nodes. Compared to enterprise-based IKTN, regional IKTN have a smaller network size but a higher scale of patent transfers between nodes and a higher network clustering coefficient. They can be viewed as a categorization of the IKTN from a spatial perspective. Studying the efficiency of KT in regional IKTN is of great significance for understanding the trends of regional industry KT and promoting coordinated development of regional industries.

V. CASE STUDY

A. CASE SELECTION AND DATA PROCESSING

Enterprise-based IKTN are often of a massive scale, encompassing thousands of enterprise nodes. Due to the limited scope of this article, in this section we choose to analyze the efficiency of IKTN from a regional perspective, focusing on city nodes with same applicability as a practical case study.

Regional urban clustering has become important geographical units for countries to participate in global competition and division of labor [36]. In recent years, there has been a continuous emergence of studies analyzing IKT from a regional perspective [38]. Among them, the Yangtze River Delta region, located at the intersection of the Yangtze River Economic Belt, which is one of the most economically and innovatively powerful regions in China, has consistently been the focus of research by scholars [44]. It includes three provinces and one municipality, namely Anhui province, Jiangsu province, Zhejiang province and Shanghai. As the integrated development of the Yangtze River Delta region has become a national strategy in 2019, enterprises in the region are engaging in increasingly close knowledge cooperation.

In addition, due to the increasingly prominent importance of environmental protection, the environmental protection industry (EPI) in the Yangtze River Delta has developed rapidly in recent years although it started late. Taking this as an example can more clearly reflect the changes in the regional IKTN and make the research results more intuitive. Hence, this study selects the KT network within the EPI, which belongs to the patent-intensive industries in the Yangtze River Delta region of China, for efficiency analysis in the years 2010, 2014, 2018, and 2021, to verify the applicability and effectiveness of the proposed model.

This study uses patent transfer data as the indicator to measure the efficiency of IKTN, and the data comes from the "Patent Information Service Platform (PISP)" database under the China National Intellectual Property Administration (CNIPA). PISP is a public-oriented patent information retrieval database in China, which contains information on the transfer of all registered patent rights in China. The process

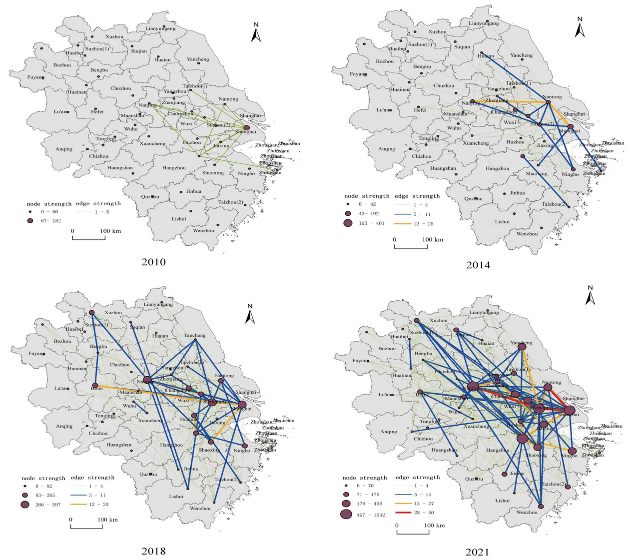

FIGURE 2. Spatial distribution of the Yangtze River Delta's IKTN.

of data acquisition and processing is as follows: (1) Data retrieval and mining: Firstly, in the PISP database, we conducted a search using "patent transfer" as the keyword to retrieve patent transfer data in China between 2010 and 2021. Subsequently, the "Octopus" data mining software is used to perform batch crawling to obtain the required research data. Each patent transfer record includes information such as "IPC number", "right holder before change", "right holder after change", "address before change", and "address after change". (2) Data Cleaning: Since the scope of the case is the Yangtze River Delta region in China, to ensure the validity of the obtained data, we conducted manual verification and auditing to eliminate missing or irrelevant information. (3) Data Matching: As the internationally recognized patent classification system, IPC does not align with the classification of China's national economic industries. Therefore, based on the "Statistical Classification of Intellectual Property (Patents) Intensive Industries (2019)" and the "IPC and National Economic Industry Classification Reference Table (2018)" published by CNIPA, we established the correspondence between China's patent-intensive industries and IPC. Ultimately, we matched a total of 18,147 patent transfer records related to the EPI in the Yangtze River Delta. To visually present the distribution of IKT in each city, Arcgis spatial geographic analysis software is used to obtain the spatial distribution maps of the Yangtze River Delta's IKTN at four time periods, with the total number of patent transfers in each city's EPI as the node intensity and the number of patent transfers between cities as the edge intensity, as shown in Figure 2.

It shows that the KT scale of the EPI in the Yangtze River Delta has been expanding in recent years, but the efficiency of the overall network and between different nodes at each time period still needs to be further explored. To this end, we apply the IKTN efficiency measurement method proposed above to this case.

B. MEASUREMENT METHOD APPLICATION PROCESS

According to formula (3) - (8), we determine the weights of nodes and edges in the regional IKTN. At this stage, we use the total number of transferred-out patents and transferred-in patents of EPI in each city to represent the knowledge transfer capacity and knowledge absorption capacity of the city node respectively, and we denote the strength of an edge by the number of patent transfers that occur between two city nodes. The normalized results are illustrated in Figure 3.

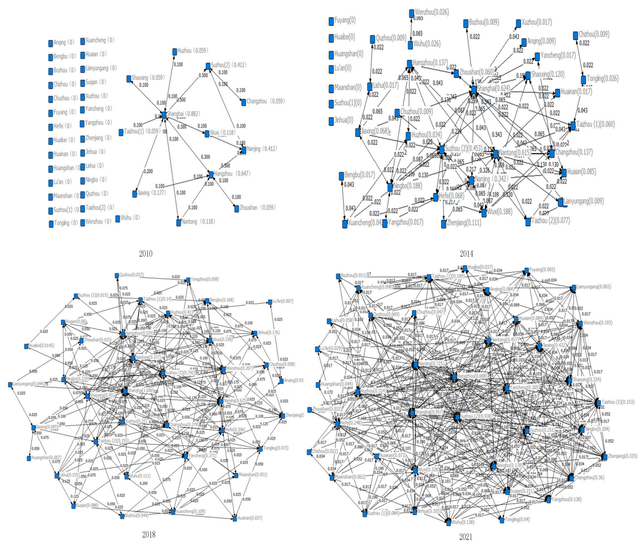

FIGURE 3. Weighted IKTN.

It can be seen that in 2010, IKTN only contained a small number of city nodes, and there were few edges between nodes. Subsequently, more cities joined the network, and by 2018, the network had covered all city nodes in the region, and since then its network density has gradually increased, and the connections between nodes have become closer. In 2010, Shanghai with a node weight of 0.882 and Shanghai-Suzhou with an edge weight of 0.5 became the most important node and edge in IKTN respectively, but the weights of other nodes and edges were low. By 2021, the number of cities with node weights higher than 0.5 in the IKTN had reached four, namely Shanghai (0.957), Suzhou (0.938), Nanjing (0.725), and Hangzhou (0.688). Meanwhile, there were also four city pairs with edge weights higher than 0.5, including Shanghai-Suzhou (0.862), Suzhou-Changzhou (0.603), Shanghai-Nantong (0.534), and Nanjing-Suzhou (0.534). According to the evolutionary trend of weighted IKTN, it can be observed that economically underdeveloped cities in the Yangtze River Delta region generally joined the network later and consistently remained at the periphery. Furthermore, the role of the key nodes that occupied core positions in the early stages of network formation were less likely to be replaced, which was also verified by Ye et al. [33].

TABLE 2. Top 5 node pairs of KT efficiency.

Rank	2010		2014		2018		2021	
	Links	Efficiency	Links	Efficiency	Links	Efficiency	Links	Efficiency
1	Shanghai-Hangzhou	0.547	Shanghai-Nanjing	0.584	Shanghai-Suzhou	0.636	Shanghai-Suzhou	0.759
2	Shanghai-Suzhou	0.539	Nantong-Nanjing	0.492	Shanghai-Shaoxing	0.592	Suzhou-Nanjing	0.620
3	Hangzhou-Nanjing	0.512	Shanghai-Suzhou	0.482	Suzhou-Hefei	0.575	Shanghai-Nanjing	0.633
4	Shanghai-Jiaxing	0.402	Nantong-Suzhou	0.441	Nanjing-Suzhou	0.561	Shanghai-Nantong	0.629
5	Suzhou-Nanjing	0.363	Suzhou-Nanjing	0.434	Shanghai-Nanjing	0.555	Suzhou-Changzhou	0.620

Furthermore, based on formula (10) and (13), the path length and weighted clustering coefficient between nodes in the IKTN are calculated, and the KT efficiency among nodes is obtained according to the IKTN efficiency analysis model proposed by formula (14).

Table 2 lists the top five node pairs of KT efficiency in the four time periods. It can be seen that the areas with the highest KT efficiency are mainly concentrated between Shanghai, Suzhou, Nanjing and other economically developed super-large cities, and the KT efficiency is increasing year by year. Moreover, the KT efficiency of the EPI in links such as Shanghai-Nantong and Suzhou-Changzhou has also been continuously improved in recent years. Especially since all cities have joined the Yangtze River Delta IKTN, the number of network nodes no longer increases, but the node weight, edge weight, and network density continue to increase, while the path length between nodes gradually decreases and tends to 1. This has resulted in closer connections between EPIs in various cities, thereby continuously promoting the improvement of KT efficiency. But at the same time, except for these high-efficiency nodes, the KT efficiency among most nodes in the network is still at a low level, and there are still a large number of cities that have not directly transferred patents.

It is worth mentioning that the node pairs with high KT efficiency in the EPI in the Yangtze River Delta region are increasingly concentrated between Shanghai and cities in Jiangsu Province. For example, Table 2 shows that among the node pairs with high KT efficiency in 2018, Shanghai appeared three times, cities in Jiangsu Province appeared four times (Suzhou, Nanjing), and cities in Zhejiang Province and Anhui Province appeared once each (Shaoxing, Hefei). However, by 2021, there were no cities from Zhejiang Province and Anhui Province in the high KT efficiency node pairs. Under the regional integrated development strategy of the Yangtze River Delta, although the scale of IKT continues to expand, problems such as the uneven distribution of high-efficiency nodes and the excessive presence of low-efficiency nodes may hinder the coordinated and sustainable development of industries in this area.

C. VALIDATION OF THE METHODOLOGY

According to formula (16), the overall efficiency of IKTN is measured, and compared with the traditional network efficiency calculation results that only consider the path length, the results are shown in Table 3. It can be seen that from 2010 to 2014, when the network scale continued to expand, both methods showed that the efficiency was in a declining stage. After the network scale is fixed, as the connection between nodes becomes closer, the KT efficiency begins to gradually increase. Both methods reflect that the overall efficiency of IKTN between 2010 and 2021 shows a trend of first decreasing and then increasing. It should be noted that the KT efficiency measurement model proposed in this paper is not proportionally reduced based on the traditional network efficiency value. For example, as shown in Table 3, the network efficiency calculated by traditional methods in 2018 was 0.590, higher than the level of efficiency in 2010 (0.569). However, the results obtained by the new method were the opposite, and the decline in network efficiency calculated by the latter method after 2014 was significantly higher than that of the former method. These differences are the result of the combined effects of multiple factors. Besides, as shown in the table, the traditional network efficiency score of the Yangtze River Delta EPI in each year is higher than the weighted IKTN measurement efficiency. Based on the perspective of traditional network efficiency, when all nodes in the network are directly connected, that is, when a fully connected graph is developed, the network efficiency reaches 1 [40]. In fact, unlike unweighted networks, the efficiency of IKTN not only depends on the path length between nodes, but also is affected by the knowledge capabilities of nodes, the strength of relationships between nodes, and the degree of clustering. Under the combined influence of multiple indicators, the overall efficiency of IKTN is lower than that of traditional networks.

TABLE 3. The comparison of two methods.

Method comparison	2010	2014	2018	2021
Traditional method	0.569	0.483	0.590	0.694
New method	0.235	0.149	0.212	0.247

To sum up, by applying the IKTN efficiency measurement model proposed in this paper to the practical case analysis, we found that the scale of IKTN in the Yangtze River Delta region has been expanding in recent years, and the strength of KT between nodes and network efficiency have been further improved, but the overall network efficiency is still low. Although all city nodes in the region have joined the network after 2018, there are still a large number of cities that have not established knowledge cooperation or are not closely connected with each other. In addition, there is a large gap in KT efficiency between urban nodes. High-efficiency node pairs are mainly concentrated in Shanghai, Jiangsu Province, and Zhejiang Province, while KT between most cities in Anhui Province is inefficient.

Hypothesis 1 states that the new method based on the patent perspective can effectively evaluate the network efficiency of explicit KT in the industry. In previous studies, patents have been repeatedly employed to evaluate inter-organizational or inter-regional explicit KT, and their representativeness has been validated [43]. This study uses patent transfer as the indicator of industrial explicit KT and applies it to a real IKTN case, identifying key nodes and measuring the overall efficiency of the network. Therefore, Hypothesis 1 is confirmed.

According to the current development trend of the KT scale of the EPI in the Yangtze River Delta region, in the near future, there will be a high probability that all nodes will be directly connected, that is, a fully connected graph. To further verify the effectiveness of the method proposed in this paper, here we consider the applicability of the IKTN efficiency measurement model in the special case of a fully connected graph. Due to the limitation of the length of the article and for the ease of understanding, we only consider the fully connected network with four nodes, as shown in Figure 4. In (x, y) next to the node, x and y represent the amount of knowledge transferred and absorbed by the node respectively, and the number next to the edge represents the amount of knowledge transferred between the two nodes. Examples (a) and (b) are both fully connected networks, and (b) has a closer knowledge connection between BD and BC nodes than (a). After analyzing each node pair and overall efficiency in (a) and (b), the results are shown in Table 4. In the table, T represents the node efficiency, E_{new} and E_{tra} represent the overall efficiency analysis method proposed in this paper and the traditional method respectively.

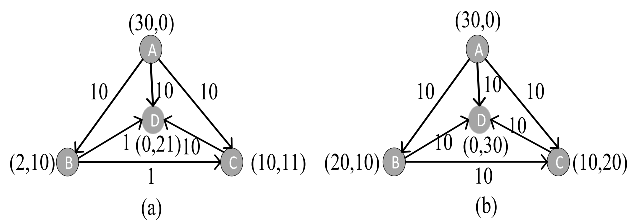

FIGURE 4. Fully connected IKTN.

Combining Figure 4 and Table 4, it can be seen that after the fully connected graph is formed, the network efficiencies of (a) and (b) obtained by using the traditional network efficiency measurement method are both 1. Because the frequency and scale of knowledge exchange between nodes have a direct impact on mutual trust, relationship level, knowledge transfer and absorption capacity, which in turn affects KT efficiency [11], [39]. Therefore, in IKTN, the fully connected graph is not the highest stage of industrial development. Only by further deepening and strengthening cooperation between nodes after establishing knowledge connections can the rapid flow and innovation of knowledge be promoted and the efficiency of IKT be improved [66]. The analysis results of the measurement model proposed in this paper show that in case (a), due to the small size of KT between BC and BD, the KT efficiency between them is lower than that of other node pairs, which in turn affects the overall efficiency of the network. In (b), when the size of KT between BC and BD increases, its KT efficiency also increases. Besides that, it also improves the KT efficiency of other node pairs in the network to a certain extent, thereby increasing the overall network efficiency from 0.468 in example (a) to 0.599. This indicates that compared with the traditional method, the IKTN efficiency measurement model based on the patent perspective can not only comprehensively consider various objective network indicators, but also solve the limitation of the former that the efficiency is always 1 after the network reaches a fully connected graph. Moreover, the new method can also identify key nodes that affect the efficiency of IKTN. Therefore, the effectiveness and applicability of the proposed measurement model in this paper are validated. This method can provide references and insights for understanding and evaluating the efficiency of IKT and for policymakers to take appropriate measures to promote industrial development.

TABLE 4. Model validation.

Examples	T_{AB}	T_{AC}	T_{AD}	T_{BC}	T_{BD}	T_{CD}	E_{new}	E_{tra}
(a)	0.542	0.595	0.595	0.348	0.348	0.382	0.468	1
(b)	0.599	0.599	0.599	0.599	0.599	0.599	0.599	1

Hypothesis 2 states that the new method, which integrates node weight, edge weight, path length, and weighted clustering coefficient, demonstrates greater applicability in measuring the network efficiency of IKT compared to traditional methods. Combining the results from Table 3, Figure 4, and Table 4, it can be observed that the proposed IKTN efficiency measurement method, which considers multiple network indicators, provides a more objective reflection of the actual network efficiency situation. Furthermore, it avoids the situation, observed in traditional methods, where the evaluation results remain constantly at 1 after the network reaches a certain stage of development. Thus, Hypothesis 2 has also been confirmed.

VI. DISCUSSION

KT is the key link of industrial coordination and innovation. Previous studies have analyzed the efficiency of IKT and innovation from the perspective of input-output, using methods such as DEA and SFA [65], [67]. With the rise of complex network theory, the significant impact of network structure characteristics on organizational KT has been continuously verified [34]. Therefore, it becomes necessary to explore the efficiency of IKTN from a network level. IKTN efficiency reflects the cost and difficulty of KT between enterprises.

Exploring it is helpful to identify key nodes and low-efficiency nodes in the network and grasp the evolution of IKT, so as to take corresponding measures to further reduce the cost, optimize the network, and improve industrial innovation capabilities [39]. According to the actual characteristics of IKTN, this paper proposes an IKTN efficiency analysis model based on a patent perspective. This study finds that:

(1) In terms of network knowledge flow efficiency research, traditional methods only consider single factors such as network path length, or rely too much on subjective evaluation indicators in weight analysis. In fact, different from the measurement of KT efficiency within the organization, IKTN efficiency needs to be reflected from a macro perspective through objective data, and the construction of indicators needs to be more comprehensive. At this time, the network efficiency calculation method based only on the path length is no longer applicable. This study comprehensively considered multiple factors in the IKTN efficiency measurement, and used objective data in the weight setting, avoiding the problem of excessive reliance on subjective factors in previous studies that may lead to deviations in the authenticity of the evaluation, so that the results can better reflect the actual industry feature.

(2) During the development and expansion of IKTN, with the continuous addition of a large number of new nodes, the overall network efficiency will show a downward trend compared with the initial stage. As the network scale tends to be stable, the connection between nodes becomes closer, the path length decreases, and the degree of clustering increases, and the overall KT efficiency will increase.

(3) In the case study section, we found that the KT network of the EPI in the Yangtze River Delta region has been growing in recent years, and city nodes with high KT efficiency have gradually increased, and most of them are concentrated in developed cities located in the east of the Yangtze River Delta, such as Shanghai, Suzhou, and Nanjing. But at the same time, there are still many nodes in the network that have not yet established close knowledge connections with other nodes, and lack effective KT between each other. In the future, there is still a lot of room for improvement in the KT efficiency of the EPI in the Yangtze River Delta.

Our research holds both theoretical and practical implications. In a theoretical sense, scholars have been continuously making efforts to explore the phenomena of cross-organizational KT and cooperative innovation from multiple perspectives, aiming to improve the efficiency of KT [39], [56]. This paper investigates the problem of IKT efficiency from the theoretical perspective of complex networks, which can provide new method for future research on KT efficiency. We analyze the applicability of using patent transfer data as an indicator to study IKTN efficiency, and establish a weighted IKTN model and an efficiency measurement model, which comprehensively reflect the impact of network topology and the relationship between nodes on KT efficiency. The proposed methodology can measure both the overall KT efficiency of the weighted network and identify key nodes within the network. Additionally, it allows for the analysis of the IKTN based on individual or enterprise nodes, as well as from a regional perspective by considering the geographical location information contained in the patent transfer data. These findings theoretically enrich the framework of IKTN efficiency study and provide new ideas for related research.

Practically, measuring the efficiency of KT networks in various industries, especially in patent-intensive industries with high growth and high value, can grasp the development status of industrial collaborative innovation and identify the transfer path of knowledge in the network. In addition, through further analysis of the key nodes and evolution process in IKTN, it will help to find the bottleneck of industrial development and summarize development experience, and provide scientific basis for the government to formulate industrial policies and development plans. This study validates the effectiveness and applicability of the proposed method through practical case studies, and identifies potential issues such as significant disparity in KT efficiency among nodes in the process of IKTN development. By utilizing the proposed methodology in this paper, policymakers can gain insight into the evolving trend of IKTN efficiency based on objective patent data, enabling them to continuously adjust industrial policies and optimize resource allocation to promote the coordination and sustainable development of IKTN.

VII. CONCLUSIONS, LIMITATIONS AND FUTURE WORKS

Based on complex network theory and innovation diffusion theory, this study comprehensively considered various network indicators and proposed a method for evaluating the network efficiency in IKT. By applying this method to a practical case, the study validated that the proposed measurement method, compared to traditional network efficiency models, is more effective in assessing both node and overall efficiency of IKTN.

This study also has certain limitations. First of all, the selection of patent transfer as the sole indicator to measure IKTN efficiency in this study introduces a certain level of subjectivity. In addition to patent transfer information, indicators like academic papers and patent cooperation and invention relationships are also regarded as indicators to measure the efficiency of IKT. To comprehensively and accurately reflect the actual situation of IKT, it is necessary to integrate explicit and tacit KT indicators and establish a complete evaluation system. In the practical case study, we selected a specific patent-intensive industry and verified the proposed method from the perspective of regional nodes without applying the model more broadly. This may result in a degree of subjectivity in the study results. In fact, patent output and transfer exist in any industrial category, but there are differences in the representativeness and applicability of using patent transfer to characterize KT in different industries. This leads to a problem, that is, in industries with low demand for technological innovation, such as tourism, hotels, and creative industries, there often lacks large-scale patent output and transfer activities. Instead, they rely on the dissemination and transfer of tacit knowledge in areas such as successful experiences and skills, and best practices. Therefore, the representativeness and replicability of the method proposed in this study in measuring the efficiency of IKTN in labor-intensive industries with small-scale patent output or in countries with slow patent growth are limited. Furthermore, in the weight measurement index of nodes, we only considered two attributes, namely knowledge transfer capability and knowledge absorption capability. Other factors such as knowledge transfer willingness and knowledge absorption willingness also influence node weights. Therefore, incorporating more representative indicators to comprehensively measure IKTN efficiency is the direction of our future efforts.

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JIAN-GUO LI received the M.S. degree in management science and engineering from the Kunming University of Science and Technology, Kunming, China, in 2020. He is currently pursuing the Ph.D. degree in management science and engineering with Shanghai University, Shanghai, China. His research interests include industrial knowledge transfer and innovation management.

HONG LI received the Ph.D. degree in management from Tongji University, Shanghai, China. She is currently a Professor and a Doctoral Supervisor with the Department of Business Administration, School of Management, Shanghai University, Shanghai. Her research interests include intellectual property management and innovation management.

YU-WEN GONG received the M.S. degree in management science and engineering from the Kunming University of Science and Technology, Kunming, China, in 2020. She is currently pursuing the Ph.D. degree with the School of Economics and Management, Southwest Jiaotong University, Chengdu, China. Her research interests include blood donation and data mining.

MIN ZHU received the M.S. degree in management from the Jiangxi University of Science and Technology, Nanchang, China, in 2012. She is currently a Lecturer with Pingxiang University, Pingxiang, China. Her research interests include urban renewal and knowledge graph analysis.