



The Dynamics of Standard Cooperation: An Empirical Analysis of the Standards from ITU

Qing Zhou^{a, b}, Zhengyi Wu^a, Wenqing Chen^{a, c, *}, Wenchong Chen^{a, b}, Peifu Chen^d

^a School of Management, Hangzhou Dianzi University, Hangzhou 310018, China

^b Experimental Center of Data Science and Intelligent Decision-Making, Hangzhou Dianzi University, Hangzhou 310018, China

^c Nanyang Innovation Institute, Zhejiang University of Water Resources and Electric Power, Hangzhou 310018, China

^d School of Management, Zhejiang University of Technology, Hangzhou 310025, China

Abstract

Organizations usually engage in standardization activities by collaborating with others through participation in standard-setting organizations (SSOs), thereby giving rise to a standard cooperation network (SCN). This cooperation is dynamic rather than static; over time, organizations continuously form new variations of standard cooperation, resulting in the ongoing evolution of the SCN. However, previous studies have not thoroughly explored how SCN evolves, nor have they examined the key factors and underlying mechanisms that lead to the formation of standard cooperation driving this evolution. In this study, we employ social network analysis and a stochastic actor-based model to examine the evolution of SCN and the corresponding driving factors behind the formulation of standard cooperation within the International Telecommunication Union (ITU), one of the most influential SSOs in the ICT industry. The study's findings indicate that the SCN exhibits a significant core-periphery structure during its evolution, and the key factors driving the formation of standard cooperation fall into two categories: endogenous factors, primarily preferential attachment and transitivity; and exogenous factors, such as research and development (R&D) capacity, geographic proximity, technical proximity, and organizational proximity. These findings contribute to a new understanding that supports the sustainable development of the SCN and aids organizations in selecting standard cooperation partners based on their capabilities and strategic needs.

Keywords

Network Dynamics; Standard Cooperation Network; Network Endogeneity; Network Exogeneity; Stochastic Actor-Oriented Model

* Corresponding author. E-mail address: chenwq@zuwe.edu.cn

1. Introduction

Increasingly, standardization has become significant to organizations' competitiveness and survival. As Bloomberg's business advisor Richard Robinson observes¹, "*Standards exist across industries and create efficiencies and cost savings for many.*" To achieve standardization, organizations generally participate in the standard-setting organizations (SSOs) and cooperate with diverse partners to develop standards (Shiu *et al.*, 2023). For example, Huawei became a member of the International Telecommunication Union (ITU) and cooperated with Apple, Qualcomm, and ZTE on Information and Communication Technology (ICT) standards. This effort increased their impact in the industry, giving rise to the standard cooperation network (SCN). The SCN has attracted widespread attention in academia because such networks have been shown to facilitate the acquisition of fine-grained, high-quality knowledge and to foster knowledge complementarity among partners (Jiang *et al.*, 2020; Wen *et al.*, 2020; Yang *et al.*, 2022). However, these studies are generally based on a static network perspective, failing to account for the dynamic nature of the SCN, where organizations continually form new standard cooperation with others over time. To unpack such a "black box," it is necessary to analyze both the evolutionary trends of the SCN and the key driving mechanisms underlying the formulation of the new standard cooperation from a network dynamics perspective, providing a theoretical and practical foundation for the effective development of the SCN.

Here, network dynamics refers to a research perspective that examines network evolution by integrating insights from social network theory and organizational sociology. In network dynamics, the connections formed between network nodes (i.e., participating organizations in the SCN) are called ties (i.e., standardization partnerships between organizations). This perspective views network evolution as path-dependent, where tie formation and persistence are driven by retention mechanisms (Giuliani, 2013). Existing studies on these retention mechanisms can be broadly categorized into two types: *(i) Network Endogeneity*. It refers to the inherent structural effects within a network. Previous studies have identified preferential attachment and transitivity as the most universal structural effects driving changes in tie formation (Block, 2015). While the former reflects the centralization trend of nodes over time, the latter demonstrates the transitivity of ties between network nodes. Under the influence of these structural effects, networks are likely to exhibit a significant and stable core-periphery structure (Boschma and Martin, 2010; Sedita *et al.*, 2020; Liu *et al.*, 2021). *(ii) Network Exogeneity*. It refers to attributes beyond the inherent structural effects, including node-level and dyadic-level attributes. One of the significant node-level attributes in innovation networks is the research and development (R&D) capability, which reflects organizational knowledge and serves as a signal to attract interactions and connections (Wu and Vries, 2022). Regarding dyadic-level attributes, proximity plays a crucial role. Knoben and Oerlemans (2006) explored how geographical, technical, and organizational proximity affect the development of interactive behaviors between organizations, discovering that all these three types of proximity positively influence the formation of inter-organizational cooperation.

These research findings provide a foundational theoretical basis for exploring SCN evolution and the key factors and underlying mechanisms driving the formation of new standard cooperation that propel this evolution. However, the applicability of network dynamics to the SCN evolution has not been fully explored and verified. Within SCN, the cooperation between organizations is driven by their

¹ <https://www.bloomberg.com/professional/insights/data/how-standards-organizations-work/>

heterogeneous knowledge needs and self-interests. Each organization brings unique expertise, technical capabilities, and existing partnerships, which guide them to establish new standard cooperation at various stages of standardization to fulfil their knowledge demands and maximize benefits. Multiple factors influence this process, both endogenous structural and exogenous factors, impacting individual cooperation decision-making. Therefore, the technical challenge of this study lies in identifying both endogenous and exogenous factors and incorporating them into a model to analyse and understand the mechanisms underlying the evolution of the SCN and formulation of the new standard cooperation.

To address the challenge, this study examines the impact of preferential attachment and transitivity as aspects of network endogeneity. Additionally, we incorporate R&D capability, geographical proximity, technical proximity, and organizational proximity as aspects of network exogeneity. The standard cooperation data is collected from the official website of the ITU, which serves as the international SSO responsible for the ICT industry. In the ICT industry, organizations commonly use cooperative standard-setting to constrain and regulate the functions, performance, and compatibility of products or services, so that the SCN constructed based on standards can comprehensively reflect their standard cooperation partnerships (Mirtsch *et al.*, 2020). Besides, focusing on a specific industry contributes to avoiding the impact of industry disparities on standard cooperation, while focusing on the international industry level helps to minimize the influence of regional standard cooperation (Guo *et al.*, 2021). We use social network analysis (SNA) and the stochastic actor-oriented model (SAOM) to meet these goals. While SNA is used to analyze SCN's macroscopic evolution trend, SAOM tests the micro-level driving factors as a statistical method to model the micro-mechanisms underlying network evolution (Snijders *et al.*, 2010). Compared to traditional network methods such as exponential family random graph models, it allows for an explanation of the interaction of different driving factors from the actor perspective (Block *et al.*, 2019). Based on SNA and SAOM analyses of the evolution of the SCN and the driving factors of standard cooperation, this study makes three theoretical contributions: (i) It introduces a dynamic network perspective, overcoming the limitations of prior research that focused on static structures, and reveals both the macro-level evolution and micro-level mechanisms of SCN. (ii) It finds that the SCN exhibits a core-periphery structure with a continuing trend toward centralization. By analyzing mechanisms such as preferential attachment and network density, this study extends the traditional understanding of core-periphery structures by emphasizing the reciprocal value that the peripheral provides to the core. (iii) It shows that organizational proximity has limited influence on SCN evolution, with knowledge complementarity playing a more critical role than homogeneity. Meanwhile, it finds that R&D capacity plays a significant negative role. In contrast, knowledge advantage, industry influence, and standard-setting power are key factors, offering new insights into the dynamics of SCN evolution.

The study is structured as follows: Section 2 presents the development of the hypotheses. Section 3 outlines the methodology of data collection and analysis. Section 4 presents the results of social network analysis and empirical evidence. Finally, Section 5 discusses the findings and concludes this study.

2. Literature Review and Hypotheses

2.1. Standardization under network dynamics

Standardization aims to develop new standards and diffuse them (Blind and Mangelsdorf, 2016; Zhou *et al.*, 2022). Organizations typically participate in standardization through two main modes: joining

technical standard alliances or engaging with SSOs (Wen *et al.*, 2020; Shiu *et al.*, 2023). Compared to the former, participation in SSOs represents a more formalized standardization mode, with structured procedures and broader industry influence (Wiegmann *et al.*, 2017). As such, SSO-based standardization has been more widely examined in academic research. Within SSOs, independent organizations are required to voluntarily cooperate with competitors, suppliers, and other stakeholders to discuss, test, and design standard content and integrate complementary technologies or expand user installations to create standards as common solutions (Jiang *et al.*, 2020). Consequently, standards exhibit the characteristics of public goods, representing outcomes that maximize participants' collective benefits rather than individual private gains (Wen *et al.*, 2020; Zhou *et al.*, 2024). From a network perspective, these organizations and their mutually beneficial collaborations in standardization activities constitute a social network called SCN. Building on such a view, several studies have explored the organizational decision-making processes and behavioral drivers underlying participation in standardization efforts. They found that network position and member diversity positively impact organizational performance, product innovation, and dominant design (Jiang *et al.*, 2020; Wen *et al.*, 2020; Yang *et al.*, 2022).

Additionally, several studies indicate that the participants in the same SCN form a high level of knowledge complementarity across various domains, enabling organizations to easily decompose modular tasks based on knowledge characteristics (Su, 2022). On the one hand, it allows organizations to focus on their core competencies and specialized fields, maximizing the utilization of their expertise and technical capabilities (Grimpe and Hussinger, 2013); on the other hand, the decomposition of modular tasks makes standardization more controllable, facilitating coordination and communication among participating parties. These studies have already analyzed the characteristics of standard cooperation, network features, and the impact of static network structure. However, exploration into the evolution of SCN and the driving factors of the standard cooperation's formulation is relatively scarce in existing literature.

The perspective of network dynamics has provided theoretical and technological support for the study of network evolution. Edquist (2010) proposed that networks are adaptive systems, with their macrostructure shaped by micro-level factors and the underlying mechanisms. These factors can be classified as endogenous and exogenous factors. Endogenous factors include internal network structure (Phelps, 2010; Nepelski and Prato, 2018), while exogenous factors encompass node-level attributes such as social capital and dyadic-level attributes between network nodes such as absorptive capacity, proximity, and others (Baum *et al.*, 2010; Lazeretti and Capone, 2016). Different types of organizations form new relationships by selecting suitable partners influenced by micro-level factors, thereby driving the dynamic evolution of networks. This study examines the evolution of the SCN, considering the combined effects of endogenous and exogenous factors. Specifically, we select preferential attachment and transitivity as key endogenous factors. From a theoretical perspective, these two mechanisms are fundamental and widely recognized in the study of network dynamics (Giuliani, 2013). They explain how new ties form based on the existing network structure, reflecting phenomena such as the "rich-get-richer" cumulative advantage and the transitivity of knowledge and trust, which are significant in technological and innovation networks (Qiang *et al.*, 2021).

Meanwhile, we incorporate R&D capability and proximity as important exogenous factors. R&D capability reflects an organization's ability to acquire, absorb, and apply external knowledge, i.e., absorptive capacity (Malhotra *et al.*, 2005). In the knowledge-sharing and technology-integration processes central to standard-setting, organizations with stronger R&D capabilities are better positioned to identify cooperation opportunities, comprehend complex technical solutions, and exert greater influence during

standard discussions (Aalbers & Ma, 2023). Thus, R&D capability affects an organization's attractiveness for cooperation and may also determine its position and evolutionary trajectory within the network. Moreover, proximity—including geographical, technical, and organizational aspects—is crucial in inter-organizational cooperation. Different types of proximity play distinct yet complementary roles in fostering cooperative relationships. These proximity factors influence the likelihood of cooperation formation and the dynamic evolution of the network structure (Boschma and Martin, 2010; Marrocu *et al.*, 2013; Balland *et al.*, 2016; Kaygalak and Reid, 2016). The driving mechanisms of these factors are further analyzed, and a theoretical model illustrating their interrelationships is presented in Fig. 1. Detailed mechanism analyses can be found in Sections 2.2 and 2.3.

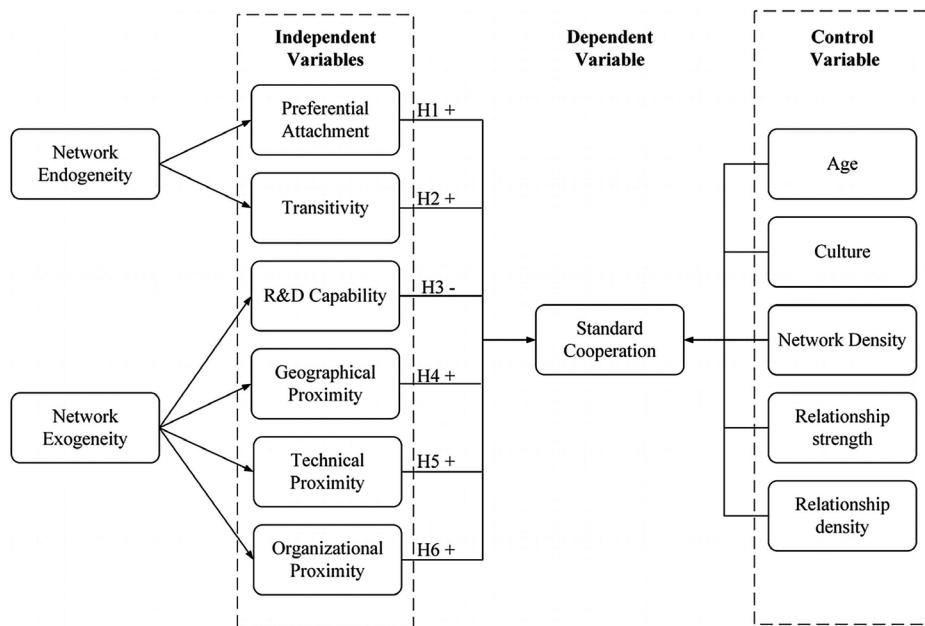


Fig. 1. Micro-driving mechanisms of SCN.

2.2. Network endogeneity drives network evolution

Network endogeneity is a crucial focal point in the study of network dynamics, encompassing the various types of network structures. This theory highlights the predictability and path-dependent nature of a network's structural evolution, indicating that the current structure is closely linked to its past structure (Giuliani, 2013). A notable consequence of network structure endogeneity is the phenomenon of preferential attachment, which elucidates the tendency of highly connected nodes to attract newly joined nodes or those already within the network but less prominent, leading to network expansion (Wu *et al.*, 2020a). In the context of SCN, where nodes represent organizations and linkages symbolize cooperation relationships, the involvement of diverse knowledge requirements and variations in individual capabilities among participating organizations makes preferential attachment a significant determinant in the evolution of SCN.

From the perspective of core organizations, they are motivated to attract new organizations to cooperate with them and foster the formation of ties. On the one hand, knowledge diversity is crucial

for achieving standardization. Standards encompass all requirements for products, processes, formats, or procedures, relying on integrating diverse knowledge resources (Jiang *et al.*, 2020; Foucart and Li, 2021). By actively obtaining new standard cooperation partners, core organizations can maintain their core position in the SCN and ensure access to adequate and diverse knowledge resources (Balland *et al.*, 2016). On the other hand, the organizations located at the center of the SCN typically possess core technical knowledge in the industry and prioritize technology innovation (Noh *et al.*, 2016). However, the integration of technical knowledge is also essential for standardization. To enhance the efficiency and potential of transforming technology into standards, core organizations must cooperate with organizations with knowledge integration capabilities to achieve vertical integration in standardization (Wen *et al.*, 2020).

From the perspective of newly joined organizations or those already within the network but less prominent, they also tend to cooperate with core organizations. Firstly, standardization is quite complex as it involves technological uncertainty, information asymmetry, and market uncertainty within the dual characteristics of products and technology (Wiegmann *et al.*, 2022; Zhou *et al.*, 2024). By collaborating with centrally located organizations, they can mitigate the risks associated with the complexity of standardization. Moreover, organizations at the center typically possess many standard-essential patents (Niezink *et al.*, 2019). Standardization is closely linked to acquiring standard-essential patents, prompting newly joined organizations to seek cooperative relationships with core organizations to obtain authorization for such patents. Based on the analysis above, we propose the following hypothesis.

H1. Preferential attachment plays a positive role in the formulation of new standard cooperation.

Transitivity is an additional network structure endogeneity effect that significantly influences network evolution. It refers to the clustering effect in a network, indicating that nodes that are not directly connected but share a common third node or are connected by a two-path have a higher probability of forming direct connections over time (Block, 2015). This closure mechanism is often represented by transitive triplets or three-cycles (Snijders *et al.*, 2010). From a knowledge base perspective, the transitivity effect enhances the flow of knowledge through formal or informal contacts (Giuliani, 2013). In this study, transitivity is considered a structural effect that influences the dynamic evolution of the entire network, impacting the formation of the microstructure and all its structural attributes of SCN (Niezink *et al.*, 2019).

In the context of SCN, transitivity is reflected in the establishment of standard partnerships, where organizations prefer to cooperate on standard-setting with partners with whom they already have established relationships. Several reasons can be summarized, including trust, opportunity, and motivation. Strong trust must be established between organizations to address the uncertainties and asymmetries associated with standardization. Transitive triplets are a stable and close cooperative relationship structure that facilitates increased interaction opportunities, information cross-validation, and reduction of potential uncertainties and risks (Blind *et al.*, 2017). Meanwhile, compared to organizations that have not yet cooperated, partners may be closer in the technical domain, making it easier to integrate knowledge and technology (Malhotra *et al.*, 2005). As a result, organizations favor this type of structure.

Furthermore, partnering through established alliances is seen as more dependable than mindlessly searching for partners. This approach mitigates the high risks of collaborating with organizations lacking standard cooperation experience (Qiang *et al.*, 2021). Based on the above analysis, the following hypothesis is proposed.

H2. Transitivity plays a positive role in the formulation of new standard cooperation.

2.3. Network exogeneity drives network evolution

Network exogeneity refers to external factors that influence the formation and evolution of a network. It emphasizes that the network dynamics are not solely determined by internal structure but also by external environments and factors (Wen *et al.*, 2020). To begin with, the node-level attributes, such as individual capability, are likely to drive the network evolution. It directly or indirectly affects their partner selection, potentially enhancing partnership quality and means of acquiring trust and commitment from partners (Lin and Wu, 2014). Based on the knowledge-based view, Wu *et al.* (2020b) argue that organizations with excellent individual capabilities can enhance their knowledge-sharing abilities, attracting other organizations to establish cooperative relationships and achieve mutually beneficial outcomes. However, recent research also suggests that willingness to share knowledge should be considered one of the factors influencing organizational cooperation tendencies. If there is a significant knowledge gap between organizations, those with knowledge advantages may avoid establishing relationships with organizations that have knowledge disadvantages due to concerns about information and knowledge leakage (Arora *et al.*, 2021). In the SCN, R&D capability is an external manifestation of organizational knowledge level and forms the foundation for organizations to participate in standard-setting and implementation (Zhou *et al.*, 2024). During standard formulation, organizations with excellent R&D capabilities are less likely to engage extensively in standard cooperation to maintain their knowledge advantage and influence in the standards. However, organizations with weaker R&D capabilities prefer to cooperate with other organizations to enhance their likelihood of participating in standardization (Gao *et al.*, 2014).

Additionally, in the subsequent iterations and upgrades of standards, organizations with strong R&D capabilities can take the lead in the standard upgrading by proposing new technical requirements and specifications. They can rely on their extensive R&D experience to validate and support these improvements, as their expertise and capabilities ensure the effective implementation and adaptability of the standards, eliminating the need to seek collaboration with other standardization organizations. Based on these insights, we propose the following hypothesis.

H3. R&D capability exerts a negative effect on the formulation of new standard cooperation.

In addition, the knowledge-based view considers multidimensional proximity as a significant external factor that facilitates knowledge exchange and establishes relationships among organizations. It encompasses various dimensions and measures individual similarity (Lazzeretti and Capone, 2016; Korbi and Chouki, 2017; Liu *et al.*, 2021). The prevailing view is that multidimensional proximity involves the similarities of geographic location, organizational affiliation, and technology (Knoben and Oerlemans, 2006). In the various dimensions of proximity, geographical proximity is considered the most prominent and fundamental factor (Petruzzelli, 2011). Geographical proximity refers to the spatial closeness between organizations and has been widely acknowledged as a key driver of organizational innovation and performance (Yang *et al.*, 2022). Standard cooperation is also inevitably influenced by geographical proximity. During the standard-setting phase, the organizations require the convergence of multidisciplinary knowledge. Geographical proximity allows organizations to interact with high-level technical information and tacit knowledge. To be specific, shorter geographical distances foster organizational agglomeration and facilitate the establishment of economic, institutional, and social connections among organizations, thereby enhancing their willingness to share technology and creating knowledge spillover (Ter Wal, 2014). Additionally, the knowledge exchange process involves certain communication costs that increase with the geographical distance between organizations (Kubick *et al.*, 2017). Therefore, cooperating with

geographically closer partners enables cost reduction and efficiency enhancement in the standard-setting.

Furthermore, geographical proximity provides the impetus for iterative upgrading of standards to maintain competitiveness. To explain, geographical proximity increases opportunities for technical knowledge exchanges among organizations, fostering knowledge interactions and stimulating innovative ideas (Kaygalak and Reid, 2016). This, in turn, drives the subsequent process of standard cooperation, leading to activities focused on upgrading standards to address any existing deficiencies. Additionally, geographical proximity facilitates interpersonal relationships and the convergence of ideas among organizations, laying the foundation for the team collaboration mindset of mutual trust and sharing (McCann *et al.*, 2016). Therefore, organizations tend to prefer geographically closer partners, as it enhances the motivation for standard iteration, fosters a conducive environment, and ensures the long-term effectiveness of standard cooperation.

Finally, geographical proximity facilitates the diffusion of standards in the market. It is well known that the diffusion of standards in the market validates their soundness and plays a crucial role in adjusting standardization strategies (Blind and Mangelsdorf, 2012). Typically, the target market for standards aligns with the market where participating organizations are located. Geographical proximity enables organizations to access timely and dynamic market information, which is crucial for making prompt and informed adjustments to their standard strategies and maximizing the benefits of standardization (Zhou *et al.*, 2024). Based on the above analysis, the following hypothesis is proposed.

H4. Geographical proximity plays a positive role in the formulation of new standard cooperation.

Technical proximity is a virtual proximity representing the overlap of knowledge on a technical basis or experience among organizational individuals. This proximity is considered a critical driver of knowledge flow and reorganization in the context of standardization activities. As pointed out by Collins and Hitt (2006), the knowledge required for standardization is tacit and idiosyncratic, which implies that organizations must possess similar knowledge structures to facilitate the transfer and exchange of knowledge. Meanwhile, a higher degree of proximity in the domain of technical knowledge implies a tighter interconnection of technical knowledge between organizations. This increases the motivation for organizations to learn from their cooperative partners (Runge *et al.*, 2022).

In the stage of standard formulation, there are challenges such as inadequate task allocation, lack of concentrated technical perspectives, and incomplete technical components among cooperative partners. By seeking collaboration with organizations with similar technical knowledge structures, deficiencies within their technical frameworks can be identified, and a better understanding of the technical architectures of their cooperative partners can also be achieved. Furthermore, standard competition has evolved into a competition between standard systems. Organizations initiating standard cooperation typically focus on patent licensing and authorization related to their technical knowledge domain, aiming to build an innovative ecosystem centered around their technology (Ranganathan *et al.*, 2018). This also drives organizations to seek collaborative relationships with organizations engaged in similar technology knowledge domains, enabling cross-licensing of patents and enhancing the potential of the standards.

In the standard iteration and upgrade stage, existing technical standard systems can be optimized and adjusted by formulating targeted standard strategies, ensuring competitiveness in the market. Additionally, collaborating organizations concentrating on the same technical knowledge domain are more likely to agree on adjusting relevant technological components. This not only reduces the cost of standard upgrades but also improves efficiency. Therefore, the following hypothesis is proposed.

H5. Technical proximity plays a positive role in the formulation of new standard cooperation.

Organizational proximity refers to the compatibility of organizations in various aspects such as

practices and management methods (Capaldo *et al.*, 2014), which has been widely recognized as a key factor in promoting innovation preference (Heringa *et al.*, 2016). It can also promote and further expand cooperation. The existing research generally explains the phenomenon from the perspective of knowledge. Organizations with similar compatibility tend to have identical learning mechanisms and organizational concepts, which promotes the flow and recombination of knowledge within the network (Caragliu and Nijkamp, 2016).

In terms of standard formulation, a prerequisite is the comprehensive and effective integration of knowledge resources from all parties involved. However, organizations often lack channels and means for knowledge integration. Similar attribution logic and foundational knowledge between organizations facilitate establishing a shared knowledge interaction system, providing a foundation and platform for in-depth knowledge fusion (Kuttim, 2016). This channel and platform reduce the time and opportunity costs associated with knowledge selection, allowing organizations to focus on core knowledge acquisition for innovation. As a result, knowledge resource allocation can be improved, and a mechanism for efficient transformation between knowledge resources and standards is created (Alpaydin and Fitjar, 2021). In addition to addressing the challenges of knowledge interaction and integration, organizations seek partners with similar organizational types to alleviate issues such as lack of trust, communication barriers, misaligned goals, and cultural conflicts in bilateral cooperation (Balland *et al.*, 2016). By doing so, they can mitigate opportunistic behaviors such as distortion of business information, non-compliance with commitments, or malicious imitation between organizations. Ultimately, the goals that promote trust, reduce uncertainty, and mitigate risks during standard-setting can be achieved.

Furthermore, organizational proximity plays a crucial strategic role in the iterative and upgrading of standards. Organizations with similar characteristics can provide more valuable information. Specifically, cooperation among proximate organizations shapes a collaborative innovation mode characterized by mutual learning, collective progress, and continuous creation (Myers, 2021). Based on this mode, standards can be constantly understood and improved, enabling them to quickly adapt to technical and market changes and derive long-term benefits. Moreover, organizations sharing similar operating patterns exhibit identical behavior patterns (Ponds *et al.*, 2007). This facilitates the formation of unified approaches to technical transformation and standard upgrading. When facing technical changes, proximate organizations can reach a consensus more quickly on optimizing standards and driving the upgrade with higher efficiency. Based on the above analysis, the following hypothesis is proposed.

H6. Organizational proximity plays a positive role in the formulation of new standard cooperation.

3. Methodology

3.1. Research setting and data

To analyze the evolution of the SCN and illustrate the influence of driving factors on the formulation of new standard cooperation, we conducted a case study on standards published by the ITU, which is responsible for developing and publishing standards within the ICT industry. The ICT industry is experiencing rapid development and has significant innovative and socio-economic implications, which have garnered substantial attention from both the academia and the industry (Chen *et al.*, 2022). The choice of ITU as a case study is particularly justified because ITU's standards affect a broad range of technological sectors and are widely accepted and complied with among countries. Compared with other SSOs, the ITU

offers a framework that transcends the limitations of specific regional or technological areas.

The study utilizes a longitudinal data set obtained from the official website of the ITU. The standards from September 2010 to September 2021 were selected for detailed analysis. A total of 1,984 samples were obtained, including 827 standards developed by two or more organizations. The processed standard data mainly includes the standard name, standard number, standard release time, standard abolition time, and the names of the organizations involved in standard development. The formulation of a standard marks the onset of cooperation, as it entails coordination, negotiation, and mutual understanding among participants to establish standards collaboratively. Conversely, the abolition of a standard signifies the conclusion of cooperation, indicating divergent interests, strategies, or priorities among participating organizations and the dissolution of the cooperative relationships forged around the standards.

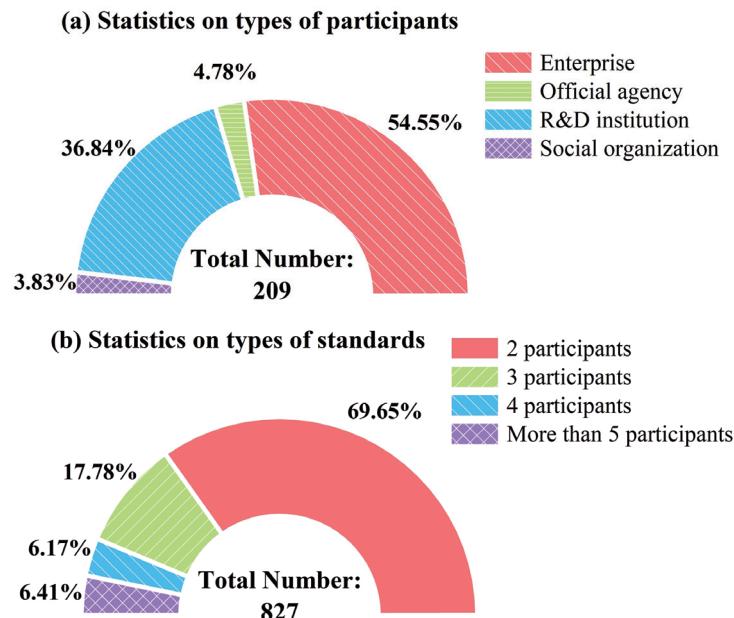


Fig. 2. Proportion statistics of participants and standard types.

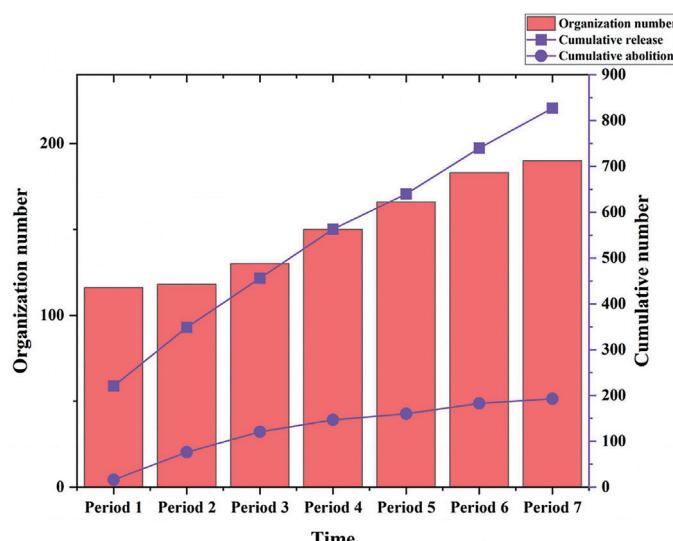


Fig. 3. Temporal statistics on organizations and standard cooperation.

Fig. 2 and 3 display crucial standard cooperation characteristics changes from 2010 to 2021. The first observation period was set to August 2015 to ensure statistical significance for subsequent analysis, as the number of standards established between 2010 and 2015 was relatively small. This first observation period should be understood merely as the starting window that provides the baseline network state for the subsequent analysis, rather than as an observation interval directly comparable to later periods. Other observation periods were set from September of each year to August of the following year, resulting in a total of seven observation periods (2010.092015.08, 2015.092016.08, 2016.092017.08, 2017.092018.08, 2018.092019.08, 2019.092020.08, 2020.092021.08). This division follows the operational cycle of the ITU, as many study groups initiate their planning and evaluation activities during the plenipotentiary conference and related meetings held in September and October each year². As such, this periodization better reflects the practical timing of standard-setting processes and helps preserve the continuity of inter-organizational collaboration.

The data collected shows that 209 organizations from different countries in the ICT industry carried out standard cooperation with others. According to the standard cooperation participants defined by Zhou *et al.* (2022), the organizations participating in standard cooperation can be divided into enterprises, R&D institutions, official agencies, and social organizations. Enterprises account for the most significant proportion (54.55%), followed by R&D institutions (36.84%). Moreover, most standard cooperation involved two organizations (69.65%), with only 6.41% of standard cooperation involving five or more organizations. As shown in Fig. 3, the number of standard cooperations experienced steady growth during the observation periods, with the establishment of large-scale new standard cooperations and some previous standard cooperations breaking up over time. Meanwhile, the number of organizations involved in standard cooperation is increasing.

Since the newly built standard cooperation is the main research object, a one-mode network is utilized to construct the SAOM, which involves only participating organizations as network nodes. The processed data was used to generate two types of one-mode symmetrical matrices, each with 209 rows and 209 columns. The rows and columns correspond to the organizations that participated in standard cooperation between Period 1 and Period 7 and are arranged according to the types of organizations. The first type of matrix describes the SCN's macrostructure, with each cell value corresponding to the number of times that two organizations have cooperated during the observation period. The second type of matrix illustrates the relationship of standard cooperation, which provides the foundation for the follow-up network dynamics analysis. The value of each cell o_{ij} indicates whether organizations i and j were engaged in standard cooperation during the observation period. Specifically, a collaboration is considered to exist if the jointly developed standard remained valid (i.e., had not been abolished). If such a collaboration exists, $o_{ij}=1$; otherwise, $o_{ij}=0$.

The analysis of network dynamics can be divided into two steps. First, a comparative analysis of the network's macrostructure in the 7 periods is conducted based on network structure indicators. Second, the proposed hypotheses are empirically tested and analyzed through SAOM. This approach can simultaneously analyze the influence of different effects on network evolution and ultimately obtain the results of statistical inference.

3.2. Social network analysis

The SNA serves as the first step towards understanding the complex dynamics of SCN. By examining the patterns of connections and interactions between organizations, SNA provides valuable insights into

² <https://pp.itu.int/2022/en/>

the structure, relationships, and knowledge flow within a cooperation network. The reason for utilizing SNA is its ability to uncover hidden relationships, identify key organizations or influencers, and analyze the overall network properties, such as core-periphery structure. The specific calculation formula for the SNA indicators and their corresponding meanings are provided in Knoke and Yang's (2019) book, and a simplified list of these variables is presented in Table 1.

Table 1

Generalized illustration of the social network indicators.

Indicator	Illustration and measure
Average Degree	“Average Degree” describes the average degree of nodes in a network, in which the degree of a node refers to the number of adjacent linkages for the node.
Average Weighted Degree	“Average Weighted Degree” describes the average of the degrees of all nodes in a weighted network, as distinct from the average degrees, which considers the weights of linkages (i.e., the times of collaborations between two nodes corresponding to organizations) in the network. The degrees of each node are equal to the sum of the weights of its adjacent linkages.
Network Diameter	“Network Diameter” refers to the maximum length of the shortest paths in the network, reflecting the tightness of the network.
Network Density	“Network Density” describes the ratio of the number of linkages that exist in a network to the number of all possible linkages ($\frac{ E }{ V \cdot (V - 1)}$).
Modularity	The measure was proposed by Newman and Girvan in 2004 to evaluate the clarity of community partitions. It can be calculated as follows: $Q = \frac{1}{2 E } \sum_{i,j} (A_{ij} - \frac{d_i d_j}{2 E }) \delta(C_i, C_j)$, where A_{ij} is any element of the adjacency matrix corresponding to the entire network, $d_{i(j)}$ is the degree of the corresponding node $i(j)$, $C_{i(j)}$ represents the community to which node $i(j)$ belongs, with $C_i \in \{1, 2, \dots, q\}$, and $\delta(C_i, C_j)$ is the Kronecker delta function, in which $\delta(C_i, C_j) = 1$ when $C_i = C_j$ and 0 otherwise.
Clustering Coefficient	“Clustering Coefficient” measures the degree to which a node’s neighbours are connected, i.e., they form a dense subgraph. For a node i , assuming it has k_i neighbours, then its clustering coefficient is defined as the ratio of dense subgraphs formed between its neighbours to $k_i(k_i - 1)/2$.
Average Distance	“Average Distance” refers to the average shortest path length between nodes in a network. It measures how closely connected nodes are and affects the speed and directness of organizational communication or interaction.
Freeman’s centralization	“Freeman’s centralization” quantifies the concentration of connectivity around a few highly connected nodes in a network. It can be calculated through the following steps: (a) Compute the total sum of centrality differences between the most central node in the network and all other nodes; (b) Divide this quantity by the theoretically maximum sum of such differences in any network of the same size.

Source: Authors’ illustration of SNA measures.

3.3. Stochastic actor-oriented model

To explain the changing trend of SCN network indicators obtained from SNA and probe into the mechanisms driving the evolution of the network, a statistical model known as the SAOM is employed for analysis (Giuliani, 2013). In the SAOM, organizations are referred to as actors, and their connections are called ties. The model views network evolution as a process in which ties (i.e., linkages) between actors change randomly, driven by

the actors' actions. The SAOM method effectively deals with problems such as multicollinearity and structural autocorrelation. The method relies on a set of fundamental assumptions (Snijders, 2010):

- The evolution of network structures is the time sequence process of the Markov chain. The network structure of the next period ($t+1$) depends only on the network structure at the current period (t), but does not depend on the past structure, such as the structure at period ($t-1$) or ($t-2$).
- The transition of observations from one time, which is called a wave in SAOM, to the next is continuous, such that the network evolution is accomplished by many sequential mini-steps at the micro level. Moreover, each actor can only change one and no more than one tie with one of the other actors between waves.
- The SAOM model is an actor-oriented model, in which actors choose to establish or eliminate ties with other actors based on their preferences and limitations. This is determined by their cognition of their position in the network and their interactive attributes.

Based on the assumption above, the Markov chain Monte Carlo for maximum likelihood estimation is used in the SAOM to estimate the variables that drive the dynamic network evolution. As an effective analytical tool to explore the dynamic evolution of networks, SAOM is widely used in analyzing the evolution of knowledge networks, industrial clusters, project-based cooperation networks, and patent cooperation networks (Wu et al., 2020a; Shiu et al., 2023). This study uses the unilateral initiative and reciprocal confirmation mode from the *R Siena* package in *R* to function the SAOM model. The change of network ties can be simulated through the node structure-based and actor attribute-based effects, and the corresponding linear combination equation is as follows (Guo et al., 2021):

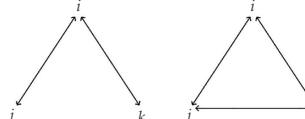
$$f_i(\beta, x) = \sum_k \beta_k S_{ki}(x) \quad (1)$$

in which x refers to the current network status, $f_i(\beta, x)$ is the objective function for actor i , $S_{ki}(x)$ is the effect function underpinning the change of network ties, β_k is the statistically weighted parameters of effects. If $\beta_k=0$, the corresponding effect does not affect the network dynamics. According to the research hypotheses, in this study the effects presented in Table 2 are taken into account.

In addition, several variables are controlled in the estimation. Network density measures the overall tendency to form connections between actors to control the cost of connections, explaining why not all nodes are connected. Culture (Cul_{ij}) measures whether the actors have a similar cultural environment. Based on the cultural distance calculation method mentioned by Kirkman et al. (2006), a cultural difference index system containing 6 indicators is constructed, including power distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence, i.e., $Cul_{ij}=1-\frac{1}{n} \sum_{l=1}^L \left[\frac{(Ind_{i,l}-Ind_{j,l})^2}{v_l} \right]$, in which L is the number of measurement indicators and l is its index, $Ind_{i,l}$ ($Ind_{j,l}$) refers to the country where the actor i (j) is located, v_l is the variance of the l -th index. Relationship strength reflects the closeness and remoteness of social relations, and measures whether there are standards of cooperation between actors i and j before. In addition to cultural factors, institutional heterogeneity is likely to influence standard cooperation. Following the illustration of Fernandez et al. (2016), we use a binary variable, i.e., whether two organizations are from different countries, as a proxy for institutional distance between two organizations. Furthermore, relationship density is the basis of the willingness and effort to transfer knowledge resources among alliance members. According to Scherngell and Hus's (2011) measurement method, the Jaccard index based on relative cooperation intensity between actors is adopted to calculate the value of relationship density. Age refers to the time elapsed from establishing these organizations until the commencement of their current standard cooperation, which is likely to affect their influence in the industry.

Table 2

Variable descriptions and data sources.

	Variables	Variable Descriptions	Source
Dependent Variables	standard cooperation	Whether there is standard cooperation between actors, expressed by the matrix o_{ij} at various periods. $o_{ij}=1$ if actor i has standard cooperation with actor j , otherwise $o_{ij}=0$.	-
Independent Variables	Preferential attachment (PA_i)	Measure the propensity of the newly joined nodes to connect with high-degree nodes in the network preferentially. The number of connections of actor j connected to actor i is used to characterize the preferential attachment, i.e., $PA_i=\sum_{j} o_{ij} \sqrt{\sum_k o_{jk}}$ (Lazzeretti and Capone, 2016).	-
	Transitivity (T_i)	Measure the clustering effects in the network evolution, referring to that once node j and node k both have connections with node i at period t , they have a high preference to create connections at period $t+1$. It is measured by the number of transfer relation triangles involving actor i , i.e., $T_i=\sum_{j < k} o_{ij} o_{jk} o_{kj}$ (Zhang et al., 2018).	-
			
	R&D capability (Rdc_i)	As the patent number is the significant index to identify and evaluate the R&D capability of the actors (Geum et al. 2013), normalization of the cumulative number of patents belonging to category H is adopted to measure R&D capability. The formula for Rdc_i can be expressed as $\frac{\sum_{n=1}^{48} f_{in}}{Rdc_{max} - Rdc_{min}}$, where f_{in} refers to the number of international patents issued by actor i under International Patent Classification n , and Rdc_{max} and Rdc_{min} represent the maximum and minimum numbers of international patents owned by one of the actors, respectively.	WIPO database
	Geographical proximity (Geo_{ij})	The difference between the natural logarithm of geographical distance between actors and the fixed value. To begin with, calculate the distance $Dist_{ij}$ between actor i and j based on the spherical distance calculation method (Ryu et al., 2018). Then, as the SAOM model limited the value range of the dependent variable from 0 to 10 such that modify the obtained $Dist_{ij}$ to conform to the data form, i.e., $Geo_{ij}=10-\ln(Dist_{ij}+1)$ (Snijders et al., 2010). The larger the value Geo_{ij} , the lower the degree of spatial aggregation of actor i and j .	Google Map
	Technical proximity (Tec_{ij})	The vector angle is based on the technology category between actors. However, Angue et al. (2014) propose that the technology classification levels directly affect the calculation results. Based on the standard data, the technology proximity between actors is calculated according to the five technology categories in the first level and forty-eight categories in the second level under the H (electrical) category, respectively. The technology proximity calculated by the former lacks discrimination such that the latter is used to calculate the technology proximity, i.e., $Tec_{ij}=\frac{f_if_j}{\sqrt{(f_if_i)(f_jf_j)}}=\frac{\sum_{n=1}^{48} f_{in}f_{jn}}{\sqrt{\sum_{n=1}^{48} f_{in}^2 \sum_{n=1}^{48} f_{jn}^2}}$. f_{in} and f_{jn} refer to the number of international patents issued by actor i and j under International Patent Classification n , respectively. Notably, each period requires recalculating Tec_{ij} because actors develop additional patents and if one of the actors involved has no patents then Tec_{ij} is considered as 0.	WIPO database
	Organizational proximity (Org_{ij})	Measures whether the actor belongs to the same organizational type according to the method proposed in the research of Marrocu et al. (2013), i.e., introduce a binary variable to demonstrate the organizational proximity according to the ownership logic. The organizational types in this study are divided into enterprises, R&D institutions, official agencies, and social organizations (Zhou et al., 2022).	-

Source: Authors' illustration of SAOM measures

4. Results

4.1. Results of descriptive analysis of network characteristics

This section presents the visual analysis results of the SCN macrostructure in ITU using *Gephi* 0.9.7, open-source software for network visual exploration (Bastian *et al.*, 2009). The macrostructure of the SCN is visualized in Fig. 4. While each node corresponds to an organization, each linkage represents the maintained cooperation between two organizations. The nodes are set as different colors and scales to distinguish the types of organizations and individual characteristics, such as node degree. The visualization clearly illustrates the trend of the macrostructure of the network over time, showing that the network is expanding gradually, and internal cooperation is becoming closer. To quantitatively analyze the evolution of the network, key structural characteristic indicators have been calculated and are presented in Table 3.

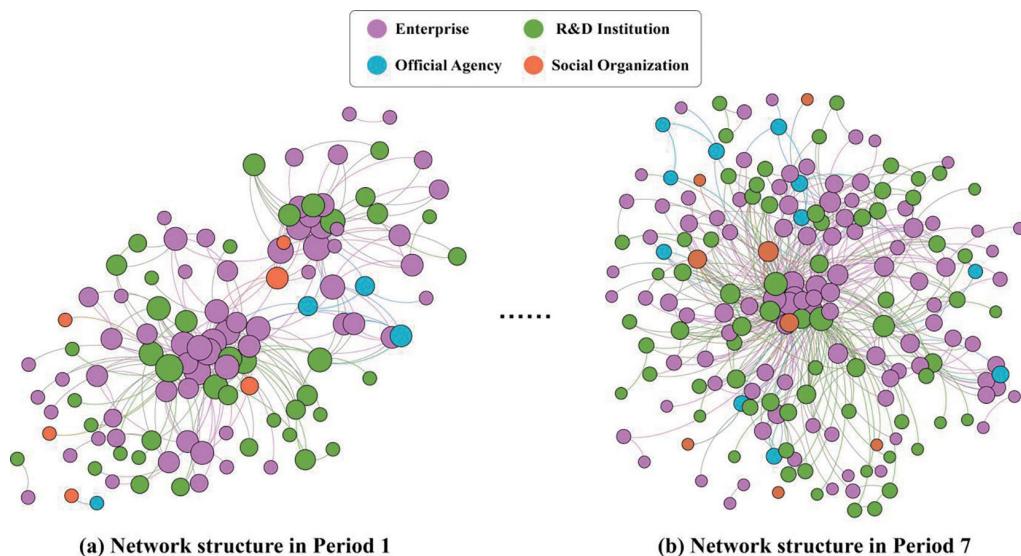


Fig. 4. The macrostructure of the SCN in partial observation periods.

Table 3
Changes in the SCN: a comparative overview from Period 1 to Period 7.

Indicators	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Average Degree	3.005	4.966	5.200	5.320	5.699	6.087	6.168
Weighted Degree	16.276	18.610	20.431	21.627	23.687	28.546	29.789
Network diameter	6.000	6.000	6.000	6.000	6.000	6.000	6.000
Network Density	0.043	0.045	0.040	0.036	0.035	0.033	0.033
Modularity	0.612	0.568	0.561	0.527	0.478	0.451	0.446
Clustering Coefficient	0.620	0.636	0.653	0.660	0.622	0.631	0.627
Average Distance	3.074	2.969	2.974	2.958	2.852	2.814	2.780
Freeman's centralization	0.083	0.081	0.091	0.137	0.178	0.222	0.237

Source: Authors' data processing based on *Gephi* 0.9.7.

Table 4

The data about the core-periphery positions in the network.

	The density of linkages		Number of core nodes	Final fit
	Core	Periphery		
Period 1				
Core	0.559	0.029	30	0.219
Periphery	0.029	0.004		
Period 2				
Core	0.976	0.056	21	0.253
Periphery	0.056	0.007		
Period 3				
Core	1.721	0.077	17	0.324
Periphery	0.077	0.010		
Period 4				
Core	2.074	0.097	17	0.340
Periphery	0.097	0.012		
Period 5				
Core	5.244	0.213	10	0.466
Periphery	0.213	0.016		
Period 6				
Core	7.556	0.298	10	0.629
Periphery	0.298	0.019		
Period 7				
Core	7.291	0.286	11	0.605
Periphery	0.286	0.020		

Source: Author's data processing based on *Gephi* 6.0.

As depicted in Table 3, the average degree and average weighted degree steadily increased from 3.005 to 6.168 and from 16.276 to 29.789, respectively, between period 1 and period 7. This finding suggests that an increasing number of organizations are engaging in standard cooperation. The network diameter remained unchanged at 6.000, indicating that the most distant organizations are connected by only five intermediary organizations, reflecting the tightly-knit nature of the network. Notably, the network density decreased from 0.043 in the first period to 0.033 in period 6 and remained stable thereafter. This phenomenon can be explained by the 23.600% increase in the average degree and the 83.006% increase in the average weight degree. This implies that more organizations prefer to continue their existing standard development cooperation relationships rather than seek out new partners. The clustering coefficient fluctuated around 6.400, with clustering coefficients of the networks from period 1 to period 7 being 0.620, 0.636, 0.653, 0.660, 0.622, 0.621, and 0.637, respectively. The average distance of the SCN gradually decreased from 3.074 to 2.780, indicating that, on average, organizations in the network can reach any other organization through a path of only 2.780 steps. The high clustering coefficient and decreasing average distance illustrate the small-world properties of the SCN (Watts and Strogatz, 1998).

Based on the presented data, it can be observed that Freeman's centralization, which measures the concentration degree of node association in the network, increases from 0.083 to 0.237 over time, indicating a gradual change in the structural characteristics of the network from a scattered structure to a high

concentration structure, such as a star type, from Period 1 to Period 7. Therefore, an in-depth analysis of the network structure trend was conducted, and the results are shown in Table 4. Further analysis shows that the network has a core-periphery structure, a typical pattern in social and organizational networks. In this structure, a small number of central (core) actors are tightly interconnected, while peripheral actors are loosely connected – mainly to core members rather than to each other. The increasing core-periphery fit over time (rising from 0.219 in Period 1 to 0.605 in Period 7, with a peak of 0.629 in Period 6) indicates that this structure becomes progressively stronger. This is further supported by the rising density of core linkages – from 0.559 in Period 1 to 7.291 in Period 7 – showing more intense collaboration within the core group. Notably, the number of core nodes declines from 30 organizations initially to just 11 in the final period. These core actors are mainly firms, representing 63.33% and 63.64% of the core in the first and last periods. This underscores the stability of organizations' dominance within the core and indicates that standardization efforts are increasingly controlled by a small number of influential organizations, potentially shaping the evolution of SCN.

4.2. Results of SAOM analysis of mechanisms underpinning network evolution

This section presents the results of the SAOM estimations and tests the proposed hypotheses using the *RSiena* 1.3.14 program on the *R* statistical platform. To ensure accurate simulation of network evolution, SAOM estimations require a Jaccard index of at least 0.2000, ideally greater than 0.3000. The Jaccard index presented in Table 5 meets this requirement. The algorithm uses the default matrix-based parameter estimation method and produces stochastic approximation results, as shown in Table 6 after 3482 iterations. The algorithm's convergence meets the expected requirements: t-ratios for all rate coefficients were less than 0.1000, and the t-ratio for overall convergence (0.2216) was below the threshold of 0.2500, indicating that the results are suitable for demonstration and further analysis.

Table 5
Descriptive statistics of connections in SCN.

Period	The change in the connections				Jaccard
	0→0	0→1	1→0	1→1	
P1→P2	21381	67	41	247	0.6960
P2→P3	21366	56	32	282	0.7620
P3→P4	21331	67	06	332	0.8200
P4→P5	21244	93	19	380	0.7720
P5→P6	21175	88	04	469	0.8360
P6→P7	21136	43	14	543	0.9050

Source: Authors' data processing based on *RSiena*.

Firstly, we test *Hypothesis 1* regarding the role of preferential attachment. The sqrt degree of alter effect, which captures this mechanism in *RSiena*, is positive and statistically significant ($\beta = 0.6728$, *s.e.* = 0.0360), supporting that actors in central network positions are more likely to attract new connections. This result also provides a micro-foundation for the observed core-periphery structure in the SCN. *Hypothesis 2*, which examines the effect of transitivity on the formation of standard cooperation, is also strongly supported. The transitive triads effect is positive and significant ($\beta = 0.4706$, *s.e.* = 0.0416), suggesting that

actors connect with their partners' partners, enhancing trust and reducing uncertainty in standard-setting processes. *Hypothesis 3* investigates whether R&D capability promotes standard cooperation. Contrary to mainstream expectations, the effect is negative and significant ($\beta = -0.2241$, *s.e.* = 0.0553), indicating that stronger R&D organizations may avoid collaboration to preserve their technological advantages and influence, rather than engage in knowledge-sharing during standardization. This aligns with the notion that standard discourse power, rather than knowledge similarity, may drive participation decisions in SCN. Next, we test *Hypotheses 4* to *6* concerning the effects of multidimensional proximity. Geographical proximity significantly and positively impacts standard cooperation ($\beta = 0.2577$, *s.e.* = 0.0395), supporting *Hypothesis 4*. Technical proximity exerts the most substantial effect among all proximity dimensions ($\beta = 0.6178$, *s.e.* = 0.1656), confirming *Hypothesis 5* and suggesting that actors with similar technological knowledge bases are more likely to cooperate. However, organizational proximity shows a slight, negative, and non-significant coefficient ($\beta = -0.0055$, *s.e.* = 0.0898), thus not supporting *Hypothesis 6*. This implies that organizational similarity (e.g., being firms or public institutions) does not play a meaningful role in forming standard cooperation ties. Among all the variables, technical proximity shows the most decisive influence on SCN formation, followed by geographical proximity, while organizational proximity appears negligible.

To ensure the robustness of the regression results, a series of control variables were incorporated into the SAOM model, including organizational age, network density, cultural distance, institutional heterogeneity, relationship strength, and relationship density. Among them, all variables except for age showed statistically significant effects. Notably, relationship density exhibited a negative and significant coefficient ($\beta = -14.7654$, *s.e.* = 2.2262), suggesting that overly dense local ties may increase redundancy and coordination burdens, thereby hindering the formation of new standard cooperation links. Cultural distance had a positive and significant effect ($\beta = 1.4239$, *s.e.* = 0.2050), indicating that cross-cultural diversity may foster cooperation in standard-setting, possibly due to broader knowledge exposure and complementary resources. In contrast, institutional heterogeneity showed a negative and significant effect ($\beta = -0.4279$, *s.e.* = 0.1153), suggesting that institutional differences between organizations may hinder the formulation of standard cooperation, potentially due to misaligned regulatory logics or operational practices. Furthermore, relationship strength was positively associated with standard cooperation ($\beta = 1.3440$, *s.e.* = 0.2359), highlighting the stabilizing role of prior collaborative ties in sustaining long-term engagement. While organizational age ($\beta = 0.6183$, *s.e.* = 0.3246) exhibited a positive but non-significant effect, network density ($\beta = 0.4706$, *s.e.* = 0.0416) showed a strong positive relationship, implying that actors embedded in more interconnected environments are more likely to engage in additional cooperative efforts.

Table 6
Drivers of network dynamic evolution: results of SAOM analysis.

Independent variables	Estimate (s.e.)	t-Value	t-Ratio
(a) Network endogeneity			
Preferential attachment	0.6728 (0.0360)	18.69***	-0.0276
Transitivity	0.4706 (0.0416)	11.31***	-0.0241
R&D capability	-0.2241 (0.0553)	-4.05***	-0.0589
(b) Network endogeneity			

Table 6. (continued)

Independent variables	Estimate (s.e.)	t-Value	t-Ratio
Geographical proximity	0.2577 (0.0395)	6.53***	0.0198
Technical proximity	0.6178 (0.1656)	3.73***	-0.0009
Organizational proximity	-0.0055 (0.0898)	-0.06	-0.0309
(c) Controls			
Age	0.6183 (0.3246)	1.90	-0.0083
Density	0.4706 (0.0416)	11.31***	-0.0395
Culture	1.4239 (0.2050)	6.95***	0.0118
Institutional heterogeneity	-0.4279 (0.1153)	-3.71***	-0.0112
Relationship strength	1.3440 (0.2359)	5.70***	-0.0107
Relationship density	-14.7654 (2.2262)	-6.63***	-0.0107

Source: Authors' data processing based on *RSiena*.

Note: The results of stochastic approximation. A total of 3482 iterations, and parameter estimates are based on 2482 iterations. The convergence of the model was good in all cases (t-ratios for all rate coefficient were all inferior to 0.10, and the t-ratio for overall convergence (0.1590) was below the threshold of 0.25 in all models).

** p < 0.01, *** p < 0.001.

Furthermore, the driving mechanisms behind standard cooperation are not static but evolve. To capture this temporal dynamic, we divide the observation window into two phases—Period 1 to Period 4 and Period 4 to Period 7—and estimate separate SAOM models for each. This division corresponds to a key technological milestone: the rollout of 5G around 2018 (aligned with Period 4), which significantly reshaped the landscape of standardization in the ICT industry. The comparative results are presented in Table 7.

Among the endogenous factors, both preferential attachment and transitivity remain strongly significant across both periods. The effect of transitivity is consistently positive ($\beta = 0.8405$, *s.e.* = 0.0772 in Period 1-4; $\beta = 0.6684$, *s.e.* = 0.092 in Period 4-7), indicating that standard cooperation continues to favor closure within triads, albeit with slightly lower intensity in the later phase. Similarly, preferential attachment remains a dominant mechanism, reflecting the tendency for well-connected organizations to attract more new ties. Regarding exogenous factors, geographical proximity exhibits an apparent increase in influence over time: it is significant in both periods, with the coefficient rising from $\beta = 0.1717$ (*s.e.* = 0.0583) to $\beta = 0.3551$ (*s.e.* = 0.0630). This suggests that spatial closeness becomes increasingly crucial in driving cooperation under the 5G regime.

Contrary to the conventional expectation that ICT advancement diminishes the role of geography, this pattern supports the idea of regionalized standard cooperation—often described as the “missing globalization puzzle” (Yilmazkuday, 2017). This is particularly evident in cases where Chinese firms deepen partnerships with countries along the Belt and Road Initiative, using regional ties to accelerate the diffusion of national standards. Technical proximity remains significant across both phases but decreases slightly in effect size. In contrast, organizational proximity remains non-significant throughout, suggesting that similarities in organizational type or function do not significantly shape standard cooperation. Notably, R&D capability shows a consistent and significantly adverse effect, indicating that high-R&D organizations may be more selective or inward-focused in their cooperative behavior.

Control variables such as culture, relationship strength, and relationship density all remain positive and significant, confirming the importance of shared values and relational embeddedness. Interestingly,

relationship strength and density influence become more pronounced over time, reinforcing the view that trust-based and structurally embedded ties are critical for sustained standard cooperation. In addition, institutional heterogeneity also reveals a temporal shift. While it has no significant effect in Period 1-4 ($\beta = -0.0045$, $s.e. = 0.1754$), it turns significantly negative in Period 4-7 ($\beta = -0.6529$, $s.e. = 0.1671$). This finding indicates that organizations are increasingly likely to collaborate with institutions from the same country in the post-5G era. This may reflect growing tendencies toward national alignment and technological decoupling, especially in light of geopolitical frictions such as the China-U.S. and EU-U.S. tech rivalry.

Table 7

Dynamics of the driving factors: results of SAOM analysis.

Independent variables	Period 1 ~ Period 4			Period 4 ~ Period 7		
	Estimate (s.e.)	t-Value	t-Ratio	Estimate (s.e.)	t-Value	t-Ratio
(a) Network endogeneity						
Transitivity	0.8405 (0.0772)	10.89***	0.0494	0.6684 (0.0924)	7.24***	0.0487
Preferential attachment	0.8471 (0.0618)	13.71***	0.0006	0.6785 (0.0480)	14.14***	0.0387
(b) Network endogeneity						
Geographical proximity	0.1717 (0.0583)	2.94**	-0.0382	0.3551 (0.0630)	5.64***	-0.0144
Technical proximity	0.6924 (0.2380)	2.91**	0.0270	0.4386 (0.2052)	2.14*	0.0614
Organizational proximity	0.0243 (0.1461)	0.17	-0.0076	-0.0820 (0.1289)	-0.64	-0.0468
R&D capability	-0.1575 (0.0736)	-2.14*	0.0350	-0.3753 (0.1005)	-3.73***	-0.0283
(c) Controls						
Age	0.4736 (0.5804)	0.82	-0.0262	-0.0298 (0.4616)	-0.06	-0.0118
Density	-6.6794 (0.3148)	-21.22***	-0.0188	-5.0791 (0.2407)	-21.09***	0.0066
Culture	1.3008 (0.3081)	4.22***	0.0009	1.3777 (0.3332)	4.14***	0.0253
Institutional heterogeneity	-0.0045 (0.1754)	-0.03	0.0133	-0.6529 (0.1671)	-3.91***	0.0281
Relationship strength	1.0707 (0.3260)	3.28**	-0.0431	1.8769 (0.4081)	4.60***	0.0271
Relationship density	28.8472 (3.8165)	7.56***	-0.0351	11.2181 (2.9976)	3.74***	0.0362

Source: Authors' data processing based on *RSiena*.

Note: The results of stochastic approximation. A total of 3060 iterations. The convergence of the models was good in all cases (t-ratios for all rate coefficient were all inferior to 0.10, and the t-ratio for overall convergence (0.1267 [0.1293]) was below the threshold of 0.25 in all models).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Discussion and Contribution

Based on standard data from the ITU, this study has investigated the dynamics of SCN. Firstly, the study provides a descriptive analysis of the macro-structure trends of SCN, finding the sustainable and stable characteristics of standard partnerships. The knowledge complementarity among standard partners makes it difficult for them to quickly find suitable alternative partners for cooperation, resulting in their prioritizing maintaining existing partnership relationships. Meanwhile, the shared knowledge base enhances the potential of standards and promotes the iteration of existing standards, creating a virtuous cycle within standard cooperation. Moreover, the SCN exhibits a prominent core-periphery structure as expected. Influenced by

preferential attachment, the network shows a trend towards centralization, with a decreasing number of organizations located at the core over time, while the number of organizations at the periphery increases.

Secondly, this study proposes micro-driving mechanisms for network evolution and empirically verifies them. Preferential attachment and transitivity have been proven to have positive impacts not only on the evolution of SCN but also on the formation of standard cooperation among organizations. The former demonstrates that peripheral and core organizations form collaborative connections driven by different knowledge needs. At the same time, the latter confirms that organizations tend to establish connections with "friends of friends" to reduce uncertainty and risks associated with standardization, forming stable three-cycle structures that facilitate cross-validation of information. However, it has been found that organizational R&D capability harms the formation of standard cooperation, which contradicts mainstream research on cooperative networks (Marek *et al.*, 2017; Giordano *et al.*, 2021). This discrepancy is due to the importance of standard discourse power for organizations within standard cooperation. Organizations with strong R&D capabilities tend to maintain their knowledge advantage and industry influence, and are unwilling to engage in standard cooperation and knowledge sharing with other organizations.

Regarding multidimensional proximity, geographic proximity and technical proximity have been proven to positively influence the formation of standard cooperation, indicating that the clustering of geographic and technical elements promotes knowledge exchange among organizations in standard cooperation, thereby driving standard iteration and upgrading. However, empirical results suggest that organizational proximity does not significantly influence the formation of standard cooperation, indicating that the effects of organizational proximity as a channel factor in the standard-setting and as a catalyst in standard iteration and upgrading are limited. This contradicts the mainstream view that organizational proximity is an essential driving factor in the evolution of cooperative networks (Marek *et al.*, 2017). However, when examined from the organizational perspective, this result is reasonable as it reveals the distinct behavioral logic underlying standard cooperation. Unlike patent cooperation or R&D alliances, standard cooperation is not solely driven by synergy among "similar partners" but also emphasizes strategic resource and capability complementarity. While organizations tend to more easily establish partnerships with others similar in technical capabilities and geographic location, they prefer collaborations across organizational differences to achieve complementarities in cognitive perspectives, institutional experience, or policy resources. This preference closely aligns with the goals of standardization, which focuses more on the broad applicability of rules rather than bilateral efficiency as in traditional collaborations (Werle and Iversen, 2006). Moreover, an organization's positioning and role in the standard-setting process may further diminish the impact of organizational proximity. Core or leading organizations often act as standard promoters and tend to select partners with diverse ownership types to leverage differentiated internal institutional routines, governance structures, and resource mobilization capabilities to enhance the efficiency of standardization. Meanwhile, peripheral organizations regard standardization as a strategy of "capability supplementation" or "market entry," actively seeking connections with strong, organizationally heterogeneous partners. In other words, it is the organization's strategic position and functional role that drive them to transcend the "homophily preference" and adopt a strategy of "heterogeneous cooperation" in standard cooperation.

5.1. Theoretical implications

This study makes three contributions to existing research. First, it provides a new perspective on the study of SCN. Previous research in this area has mainly focused on the effects of network position and

membership variety on organizational performance, product innovation, and dominant design around standards (Jiang *et al.*, 2020; Wen *et al.*, 2020; Yang *et al.*, 2022). These studies have mostly employed static network modelling to analyze the characteristics of network structures, while relatively less attention has been given to the evolution of cooperation networks. This study uses the SAOM method to investigate SCN from a dynamic network perspective, making it the first exploratory study to apply network dynamics models in standard cooperation, revealing its macro-structural changes and micro-level driving mechanisms. The in-depth exploration of the macro-structure and evolutionary trends can guide governments on how to promote standard cooperation among organizations. At the same time, analyzing micro-level mechanisms can help improve organizational management and decision-making in the standard cooperation process.

Secondly, it offers a micro-level explanation for the macro-structural evolution characteristics of SCN. The research findings demonstrate that SCN exhibits the expected core-periphery structure, and the overall network shows a significant trend towards centralization over time. At the same time, standard cooperation partners exhibit continuous and stable characteristics. This study explains the causes of network evolution phenomena through micro-level driving factors such as preferential attachment and network density, expanding upon the traditional central-peripheral structure theory. Furthermore, it enables better prediction of the future development trends of SCN based on a better understanding of its evolution. Moreover, in the discussion of preferential attachment, the study not only emphasizes the importance of core organizations to peripheral organizations within SCN but also highlights the significance of peripheral organizations to core organizations, presenting a distinct contrast to the traditional core-periphery structure theory that emphasizes the importance of the core organizations.

Finally, this study challenges the conventional view of treating organizational proximity as a key macrodynamic factor within SCN. While organizational proximity has been widely recognized as a significant factor influencing the evolution of various cooperation networks, explaining the clustering effects among similar organizations, our findings reveal its limited impact on the formation of standard cooperation. For instance, Marek *et al.* (2017) identified a significant positive effect of organizational proximity on patent cooperation. In contrast, our results highlight that other factors are more pivotal in shaping SCN. This underscores the need to move beyond the narrow focus on organizational proximity when exploring the dynamic mechanisms of SCN, offering fresh perspectives. Standard cooperation emphasizes strategic complementarity of resources and capabilities, leveraging organizational diversity to enhance the broad applicability and institutional legitimacy of standards, while also closely linked to organizations' positioning and roles. Moreover, our study questions the mainstream assumption that R&D capabilities universally promote network cooperation, confirming instead the central role of knowledge advantages, industry influence, and standard-setting discourse power in driving standard cooperation.

5.2. Managerial implications

The research findings have significant practical implications for inter-organizational standard cooperation, particularly within the ICT industry. Firstly, the managerial implications involve the influence of network endogeneity on organizational decision-making. Influenced by mechanisms such as preferential attachment and transitivity, the pronounced core-periphery structure is observed in SCN. As for core organizations possessing essential patents and technical knowledge, they should enhance their technology path iteration and optimize their standardization mode. They should expand their channels for acquiring and absorbing external knowledge resources based on exploring mechanisms that solidify

their core competitive position and improve their standard influence. As for peripheral organizations aspiring to engage in standard cooperation, they need to clarify their strategic positioning and competitive advantages. They should establish a distinctive knowledge value output system that differentiates them from other peripheral organizations, thus increasing their potential for integration into the SCN.

Additionally, such organizations should strengthen their recognition of core organizations' strengths and activate innovation capabilities based on knowledge complementarity to facilitate sustainable and stable cooperative relationships. On the other hand, while expanding their search for cooperation partners, organizations should also emphasize exploring the external networks of existing partners. This exploration will provide a basis for selecting partners, facilitating knowledge-sharing, and organic collaboration. Based on this foundation, establishing a knowledge transfer mechanism grounded in triangular cooperation will enhance inter-organizational knowledge exchange efficiency.

Secondly, the managerial implications involve the influence of network exogeneity on organizational decision-making. Organizations can prioritize selecting organizations from nearby regions when choosing standard cooperation partners. By connecting through SCN based on technology sharing and knowledge flow, they can strengthen their standard development and upgrading practices and improve standardization performance. Moreover, organizations can develop appropriate technical evaluation indicators to guide their selection of technically proximate partners. Furthermore, standards exhibit a more complex internal structure than patents, indicating a higher demand for differentiated knowledge. Therefore, organizations need to consider not only knowledge acquisition but also the heterogeneity of knowledge among organizations to promote the formation of sustained and stable standard cooperation relationships. Organizations must fully consider the combined effects of endogenous and exogenous network factors when selecting standard cooperation partners.

Lastly, the core-periphery structure observed in the SCN provides insights into macro-level policy implications. On one hand, governments need to incentivize core organizations to exert greater influence and leadership in standard cooperation, strengthening their divergent and radiative roles. Core organizations typically possess richer knowledge, resources, and experience, which give them an advantage in driving standard development and iterative upgrades. Governments can encourage core organizations to lead industry development by providing subsidies, rewards, or other forms of support. This not only facilitates the growth of peripheral organizations but also enhances the competitiveness of core organizations themselves.

On the other hand, governments and official institutions should actively provide channels and opportunities for peripheral organizations to be recognized by core organizations. Although peripheral organizations may lack resources and experience, they often possess the potential and flexibility for standardization and their knowledge advantages in specific domains. Therefore, it is necessary to strengthen the transmission and sharing of information among organizations by providing training, technical support, and collaborative opportunities. These measures will help enhance the participation capabilities of peripheral organizations in standard cooperation, enabling them to leverage their advantages and promote the healthy development of industry standards.

5.3. Limitations and further research

While this study provides valuable insights, it is essential to admit its limitations and highlight opportunities for future research. First, the focus on the ICT industry – known for its highly active and

globalized standardization activities—raises questions about the universality of the findings to other industries. While the ICT industry provides a rich and representative case for exploring the SCN, future research should extend the analysis to different industries to assess the robustness and universality of the mechanisms identified in this study. Comparative research across industries with varying levels of standardization activity could offer important insights into how industry characteristics shape SCN evolution. Another limitation is the lack of consideration for the threshold effect of multidimensional proximity and organizational R&D capability. Previous research has shown that cooperation is only possible when technical proximity reaches a certain threshold, and similar thresholds may exist for organizational R&D capability, influencing organizations' inclination towards standard cooperation. Future research could explore these thresholds and their impact on standard cooperation.

Furthermore, this study solely focuses on the micro-level mechanisms driving standard cooperation from a global perspective. Future research could explore the driving factors behind peripheral organizations becoming core actors and vice versa. A more nuanced understanding of network dynamics can be achieved by delving into the roles and evolving influences of organizations at the core and periphery of the SCN. Finally, investigating the driving factors of SCN evolution from the perspective of technological catching-up would be an intriguing avenue for research, which will enrich the understanding of standard cooperation.

Acknowledgments

This study is supported by the Major Project of the National Social Science Fund of China (Grant No. 24&ZD283).

Conflicts of Interest

The authors declare no conflict of interest.

References

Aalbers, R., & Ma, R., 2023. The Roles of Supply Networks and Board Interlocks in Firms' Technological Entry and Exit: Evidence from the Chinese Automotive Industry. *Management and Organization Review*, 19(2), 279315.

Alpaydin, U. A. R., & Fitjar, R. D., 2021. Proximity across the distant worlds of university–industry collaborations. *Papers in Regional Science*, 100(3), 689712.

Angue, K., Ayerbe, C., & Mitkova, L., 2014. A method using two dimensions of the patent classification for measuring the technological proximity: an application in identifying a potential R&D partner in biotechnology. *The journal of technology transfer*, 39, 716747.

Arora, A., Belenzon, S., & Patacconi, A., 2021. Knowledge sharing in alliances and alliance portfolios. *Management Science*, 67(3), 15691585.

Balland, P. A., Belso-Martínez, J. A., & Morrison, A., 2016. The dynamics of technical and business knowledge networks in industrial clusters: Embeddedness, status, or proximity? *Economic geography*, 92(1), 3560.

Bastian, M., Heymann, S., & Jacomy, M., 2009. Gephi: an open source software for exploring and manipulating networks[C]// *Proceedings of the international AAAI conference on web and social media*, 3(1), 361362.

Baum, J. A. C., Cowan, R., & Jonard, N., 2010. Network-independent partner selection and the evolution of innovation networks. *Management science*, 56(11), 20942110.

Blind, K., & Mangelsdorf, A., 2012. Alliance formation of SMEs: Empirical evidence from standardization committees. *IEEE Transactions on Engineering management*, 60(1), 148156.

Blind, K., Petersen, S. S., & Riillo, C. A. F., 2017. The impact of standards and regulation on innovation in uncertain markets. *Research policy*, 46(1), 249264.

Block, P., Stadtfeld, C., & Snijders, T. A. B., 2019. Forms of dependence: Comparing SAOMs and ERGMs from basic principles. *Sociological Methods & Research*, 48(1), 202239.

Block, P., 2015. Reciprocity, transitivity, and the mysterious three-cycle. *Social Networks*, 40: 163173.

Capaldo, A., & Petruzzelli, A. M., 2014. Partner geographic and organizational proximity and the innovative performance of knowledge-creating alliances. *European Management Review*, 11(1), 6384.

Caragliu, A., & Nijkamp, P., 2016. Space and knowledge spillovers in European regions: the impact of different forms of proximity on spatial knowledge diffusion. *Journal of Economic Geography*, 16(3), 749774.

Chen, H., Song, X., & Jin, Q., et al., 2022. Network dynamics in university-industry collaboration: a collaboration-knowledge dual-layer network perspective. *Scientometrics* 127, 6637-6660.

Collins, J. D., & Hitt, M. A., 2006. Leveraging tacit knowledge in alliances: The importance of using relational capabilities to build and leverage relational capital. *Journal of engineering and technology management*, 23(3), 147v167.

Edquist, C., 2010. Systems of innovation perspectives and challenges. *African Journal of Science, Technology, Innovation and Development*, 2(3), 14-45.

Fernandez, A., Ferrández, E., & León, M. D., 2016. Proximity dimensions and scientific collaboration among academic institutions in Europe: The closer, the better? *Scientometrics*, 106(3), 10731092.

Foucart, R., & Li, Q. C., 2021. The role of technology standards in product innovation: Theory and evidence from UK manufacturing firms. *Research Policy*, 50(2), 104157.

Gao, X., Guo, X., & Guan, J., 2014. An analysis of the patenting activities and collaboration among industry-university-research institutes in the Chinese ICT sector. *Scientometrics*, 98, 247263.

Geum, Y., Lee, S., & Yoon, B., et al., 2013. Identifying and evaluating strategic partners for collaborative R&D: Index-based approach using patents and publications. *Technovation*, 33(67), 211224.

Giordano, V., Chiarello, F., & Melluso, N., et al., 2021. Text and dynamic network analysis for measuring technological convergence: A case study on defense patent data. *IEEE Transactions on Engineering Management*, 70(4), 14901503.

Giuliani, E., 2013. Network dynamics in regional clusters: Evidence from Chile. *Research Policy*, 42(8), 14061419.

Grimpe, C., & Hussinger, K., 2013. Formal and informal knowledge and technology transfer from academia to industry: Complementarity effects and innovation performance. *Industry and innovation*, 20(8), 683700.

Guo, M., Yang, N., & Wang, J., et al., 2021. How do structural holes promote network expansion? *Technological Forecasting and Social Change*, 173, 121129.

Heringa, P. W., Hessels, L. K., & Van der Zouwen, M., 2016. The influence of proximity dimensions on international research collaboration: an analysis of European water projects. *Industry and Innovation*, 23(8), 753772.

Jiang, H., Gao, S., & Zhao, S., et al., 2020. Competition of technology standards in Industry 4.0: An innovation ecosystem perspective. *Systems Research and Behavioral Science*, 37(4), 772783.

Kaygalak, I., & Reid, N., 2016. Innovation and knowledge spillovers in Turkey: The role of geographic and organizational proximity. *Regional Science Policy & Practice*, 8(12), 4561.

Kirkman, B. L., Lowe, K. B., & Gibson, C. B., 2006. A quarter century of culture's consequences: A review of empirical research incorporating Hofstede's cultural values framework. *Journal of international business studies*, 37, 285320.

Knoben, J., & Oerlemans, L. A. G., 2006. Proximity and inter-organizational collaboration: A literature review. *International Journal of management reviews*, 8(2), 7189.

Knoke, D., & Yang, S., 2019. Social network analysis. SAGE publications.

Korbi, F. B., & Chouki, M., 2017. Knowledge transfer in international asymmetric alliances: the key role of translation, artifacts, and proximity. *Journal of Knowledge Management*, 21(5), 12721291.

Kubick, T. R., Lockhart, G. B., & Mills, L. F., et al., 2017. IRS and corporate taxpayer effects of geographic proximity. *Journal of Accounting and Economics*, 63(23), 428453.

Kuttim, M., 2016. The role of spatial and non-spatial forms of proximity in knowledge transfer: A case of technical university. *European Journal of Innovation Management*, 19(4), 468491.

Lazzeretti, L., & Capone, F., 2016. How proximity matters in innovation networks dynamics along the cluster evolution. A study of the high technology applied to cultural goods. *Journal of Business Research*, 69(12), 58555865.

Lin, Y., & Wu, L. Y., 2014. Exploring the role of dynamic capabilities in firm performance under the resource-based view framework. *Journal of business research*, 67(3), 407413.

Liu, Y., Shao, X., & Tang, M., et al., 2021. Spatio-temporal evolution of green innovation network and its multidimensional

proximity analysis: Empirical evidence from China. *Journal of Cleaner Production*, 283, 124649.

Malhotra, A., Gosain, S., & Sawy, O. A. E., 2005. Absorptive capacity configuration in supply chains: Gearing for partner-enabled market knowledge creation. *MIS quarterly*, 145187.

Marek, P., Titze, M., & Fuhrmeister, C., et al., 2017. R&D collaborations and the role of proximity. *Regional Studies*, 51(12), 17611773.

Marrocu, E., Paci, R., & Usai, S., 2013. Proximity, networking and knowledge production in Europe: What lessons for innovation policy? *Technological Forecasting and Social Change*, 80(8), 14841498.

McCann, B. T., Reuer, J. J., & Lahiri, N., 2016. Agglomeration and the choice between acquisitions and alliances: An information economics perspective. *Strategic Management Journal*, 10851106.

Mirtsch, M., Kinne, J., & Blind, K., 2020. Exploring the adoption of the international information security management system standard ISO/IEC 27001: a web mining-based analysis. *IEEE Transactions on Engineering Management*, 68(1), 87100.

Myers, C. G., 2021. Performance benefits of reciprocal vicarious learning in teams. *Academy of Management Journal*, 64(3), 926947.

Nepelski, D., & De Prato, G., 2018. The structure and evolution of ICT global innovation network. *Industry and Innovation*, 25(10), 940965.

Newman, M. E. J., & Girvan, M., 2004. Finding and evaluating community structure in networks. *Physical review E*, 69(2), 026113.

Niezink, N. M. D., Snijders, T. A. B., & Duijn, M. A. J., 2019. No longer discrete: Modeling the dynamics of social networks and continuous behavior. *Sociological Methodology*, 49(1), 295340.

Noh, H., Song, Y. K., & Lee, S., 2016. Identifying emerging core technologies for the future: Case study of patents published by leading telecommunication organizations. *Telecommunications Policy*, 40(1011), 956970.

Petruzzelli, A. M., 2011. The impact of technological relatedness, prior ties, and geographical distance on university-industry collaborations: A joint-patent analysis. *Technovation*, 31(7), 309319.

Phelps, C. C., 2010. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. *Academy of management journal*, 53(4), 890913.

Ponds, R., Van Oort, F., & Frenken, K., 2007. The geographical and institutional proximity of research collaboration. *Papers in regional science*, 86(3), 423444.

Qiang, G., Cao, D., & Wu, G., et al., 2021. Dynamics of collaborative networks for green building projects: Case study of Shanghai. *Journal of Management in Engineering*, 37(3), 05021001.

Ranganathan, R., Ghosh, A., & Rosenkopf, L., 2018. Competition-cooperation interplay during multi-firm technology coordination: The effect of firm heterogeneity on conflict and consensus in a technology standards organization. *Strategic Management Journal*, 39(12), 31933221.

Runge, S., Schwens, C., & Schulz, M., 2022. The invention performance implications of competition: How technological, geographical, and product market overlaps shape learning and competitive tension in R&D alliances. *Strategic Management Journal*, 43(2), 266294.

Ryu, W., McCann, B. T., & Reuer, J. J., 2018. Geographic co-location of partners and rivals: Implications for the design of R&D alliances. *Academy of Management Journal*, 61(3), 945965.

Scherngell, T., & Hu, Y., 2011. Collaborative knowledge production in China: Regional evidence from a gravity model approach. *Regional Studies*, 45(6), 755772.

Sedita, S. R., Caloffi, A., & Lizzeretti, L., 2020. The invisible college of cluster research: a bibliometric core-periphery analysis of the literature. *Industry and Innovation*, 27(5), 562584.

Shiu, J. M., Dallas, M. P., & Huang, H. H., 2023. A friend of a friend? Informal authority, social capital, and networks in telecommunications standard-setting organizations. *Technological Forecasting and Social Change*, 189, 122346.

Snijders, T. A. B., Van de Bunt, G. G., & Steglich, C. E. G., 2010. Introduction to stochastic actor-based models for network dynamics. *Social networks*, 32(1), 4460.

Su, H. N., 2022. How does distant collaboration influence R&D quality? *Technology Analysis & Strategic Management*, 34(7), 815831.

Ter Wal, A. L. J., 2014. The dynamics of the inventor network in German biotechnology: geographic proximity versus triadic closure. *Journal of Economic Geography*, 14(3), 589620.

Edward Elgar Publishing, 2015. The handbook of evolutionary economic geography. Edward Elgar Publishing.

Watts, D. J., & Strogatz, S. H., 1998. Collective dynamics of 'small-world' networks. *Nature*, 393(6684), 440442.

Wen, J., Qualls W. J., & Zeng, D., 2020. Standardization alliance networks, standard-setting influence, and new product outcomes. *Journal of Product Innovation Management*, 37(2), 138157.

Werle, R., & Iversen, E. J., 2006. Promoting legitimacy in technical standardization. *Science, Technology & Innovation Studies*, 2(1), 1939.

Wiegmann, P. M., de Vries, H. J., & Blind, K., 2017. Multi-mode standardization. *Research Policy*, 46(8), 13701386.

Wiegmann, P. M., Eggers, F., & deVries, H. J., et al., 2022. Competing standard-setting organizations: a choice experiment. *Research Policy*, 51(2), 104427.

Wu, X., Wu, J., & Li, Y., et al., 2020. Link prediction of time-evolving network based on node ranking. *Knowledge-Based Systems*, 195, 105740.

Wu, Y., & de Vries, H. J., 2022. Effects of participation in standardization on firm performance from a network perspective: Evidence from China. *Technological Forecasting and Social Change*, 175, 121376.

Wu, Y., Gu, F., & Ji, Y., et al., 2020. Technological capability, eco-innovation performance, and cooperative R&D strategy in new energy vehicle industry: Evidence from listed companies in China. *Journal of Cleaner Production*, 261, 121157.

Yang, J., Zeng, D., & Zhang, J., et al., 2022. How tie strength in alliance network affects the emergence of dominant design: The mediating effects of exploration and exploitation innovation. *Technology Analysis & Strategic Management*, 34(1), 112124.

Yilmazkuday, H., 2017. A Solution to the Missing Globalization Puzzle by Non-CES Preferences. *Review of International Economics*, 25(3), 649676.

Zhang, C., Bu, Y., & Ding, Y., et al., 2018. Understanding scientific collaboration: Homophily, transitivity, and preferential attachment. *Journal of the Association for Information Science and Technology*, 69(1), 7286.

Zhou, Q., Wu, Z., & Chen, W., et al., 2024. A new procurement and supply contract for manufacturing technology standards' diffusion from home to host countries. *International Journal of Production Research*, 62(20): 73607381.

Zhou, Q., Zhang, Y., & Yang, W., et al., 2022. Value co-creation in the multinational technology standard alliance: a case study from emerging economies. *Industrial Management & Data Systems*, 122(9), 21212141.