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Measuring China's International Competitiveness in Digital Services Trade: A Complex Network Perspective

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Measuring China's International Competitiveness in Digital Services Trade: A Complex Network Perspective

Abstract: Digital technology is transforming trade in services and reshaping global digital services trade and international cooperation. Using global bilateral digital services trade data for 2010-2025, we constructed a directed weighted complex network and assessed China's international competitiveness in terms of market size, network position, and trade security. We then conducted scenario simulations based on a knowledge-flow model and an evolutionary dynamics model. The results showed a relatively stable single-core, multicenter structure in the global network. China's market size expanded, its network position improved markedly, and its capacity to safeguard trade security remained strong. In the simulations, greater digital technological capability directly increased trade volumes; lower trade barriers had substantial cumulative effects on network position; and higher link formation intensity helped diversify trading partners. We tentatively proposed pathways for improving international competitiveness, with practical implications for the high-quality development of China's digital services trade.

Keywords: digital services trade; complex networks; trade network; international competitiveness; network evolution; trade security

1 Introduction

Digital technology has increasingly permeated the production, transaction, and delivery of services, accelerating the shift toward digital, platform-based, and intelligent trade in services (Herman and Oliver 2023; Sheng and Gao 2021). As cross-border data flows, digital platform governance, and intellectual property protection move to the forefront of international trade rule negotiations, global digital services trade is entering a new phase of simultaneous market expansion and regulatory restructuring (Shen et al. 2022). As a major participant in global trade in services, China has introduced reforms to promote digital trade, including relaxing foreign equity restrictions in value-added telecommunications services, expanding opening-up in healthcare, establishing digital trade demonstration zones, and fostering new forms of cross-border e-commerce (General Office of the Communist Party of China Central Committee and General Office of the State Council 2024; Ministry of Industry and Information Technology 2024). Its digital services trade has continued to expand, its trade structure has improved, and its position in the international division of labor in services has risen substantially (Ministry of Commerce 2025). Looking ahead, developing digital services trade on the basis of international competitiveness has become a priority for China's foreign trade policy. This priority reflects both its commitment to high-standard opening-up and its responsibilities as a major country, as it responds to increasingly complex

domestic and international trade conditions and seeks sustained development. Assessing the current level and changing pattern of China's international competitiveness in digital services trade is therefore essential to evaluating trade development quality, its position in the international division of labor, and the security of opening-up. Such assessment provides a foundation for improving trade policies and promoting high-quality development in trade in services.

International trade inherently involves cross-border linkages and international comparison. Competitiveness develops through the international division of labor and interactions involving both competition and cooperation among multiple actors. As digitalization deepens, cross-country flows of services, data, and knowledge interact with platform connections, changing how trade in services is organized and connected (Hu et al. 2024). First, cross-border data flows span the entire service transaction process, extending countries' digital services trade relationships beyond final delivery to information transmission and service coordination (Wu et al. 2021). Second, digital platforms integrate dispersed cross-border supply and demand through open interfaces, coordinated rules, and aligned standards. They thereby create trade networks with multiple connected nodes and transmission pathways (Ma et al. 2019). Both the cross-border linkages inherent in international trade and the restructuring of service trade relationships by digital technology give digital services trade typical complex network characteristics. Its international competitiveness depends not only on a country's resource endowments and development conditions but also on its position and relationships in the global trade network. It must therefore be examined within that global network.

Building on this analysis, we used bilateral digital services trade data for 159 sovereign countries over 2010-2025. We applied a sector-based identification approach to measure bilateral digital services trade and constructed a global directed weighted network. We assessed China's international competitiveness along three dimensions: market size, network position, and trade security. Drawing on complex network theory and international trade theory, we classified the mechanisms underlying trade link formation into technological endowments, market size, and the institutional environment. Historical backtesting assessed their ability to explain new trade links. Scenario simulations then examined changes in China's competitive position under alternative evolutionary conditions and the scope for improvement through greater digital technological capability, lower institutional restrictiveness, and higher link formation intensity. This approach identified the foundations, constraints, and potential pathways for improving China's international competitiveness in digital services trade.

2 Literature Review and Research Design

2.1 Literature Review

This study examined the measurement of China's international competitiveness in digital services trade from a complex network perspective. As discussed above, digital services trade features expanding boundaries, stronger cross-border connections, and evolving network structures. Competition has shifted from scale expansion and cost advantages toward a combination of technological, market, and institutional factors. Trade links continue to form, network positions change, and competitive advantages evolve. Accordingly, we organized the literature review around three themes: definitions, statistical coverage, and the measurement of digital services trade; approaches to assessing international competitiveness and their extension to network-based measurement; and trade link formation, network evolution, and the underlying mechanisms. This review established the theoretical foundations, indicator selection, and analytical approach, and clarified gaps in the literature and the study's potential incremental contributions.

Digital services trade is a new form of trade arising from the integration of digital technology into service production, transactions, and delivery. Its conceptual boundaries directly determine statistical coverage and the scope of empirical analysis (Sheng and Gao 2021). Ma et al. (2019) argue that digital trade combines digitally conducted transactions with digitally delivered content. Its value lies not only in greater transaction efficiency but also in changes to the objects of trade, organizational arrangements, and rule systems. Existing studies generally define digital services trade in broad or narrow terms. The broad definition emphasizes digital technology's role throughout the service trade process. The narrow definition uses digitally deliverable services as its statistical basis and is better suited to cross-country comparisons and long-term trend analysis (International Monetary Fund et al. 2023; Wen et al. 2021). Two common measurement approaches are the measurement of trade in digitally delivered services and the sector-based identification approach. The former follows international organizations' statistical definitions and facilitates consistent comparisons across countries and periods. The latter extends sample coverage by identifying the digital attributes of service sectors and accommodates the lack of fully harmonized statistical classifications (Jia et al. 2021; Vollrath 1991). Drawing on this literature and the sector-based identification approach, we selected service sectors within EBOPS 2010 according to their digital delivery attributes. We aggregated bilateral trade in these sectors to measure bilateral digital services trade flows.

Research on trade competitiveness mainly addresses comparative advantage and market performance. Comparative advantage indicators, notably the revealed comparative advantage (RCA) index, compare a product's or service's share of a country's exports with its corresponding

share of world exports to measure export specialization (Fagerberg 1988). Market performance indicators include the trade competitiveness index (TC), international market share (IMS), export growth rate, and trade balance. They capture competitive outcomes through the relationship between exports and imports, market shares, export expansion, and net exports, respectively (Gao 2023). Most studies of digital services trade competitiveness adopt these two groups of indicators. They compare countries or regions using the RCA index, TC, and IMS (Jiang and Luo 2019; Wu and Bi 2024). Digital services trade relies on digital platforms, ICT infrastructure, and cross-border data flows. Transactions involve sustained connections among countries and market participants and thus exhibit strong cross-border and network characteristics (Lyu et al. 2021). Studies have used core–periphery structure, centrality, and structural holes to identify the clustering of global trade links, countries' connection patterns, and their intermediary positions (Chen and Song 2023; Hu et al. 2024). Building on established approaches to trade competitiveness assessment, we incorporated network indicators into the measurement framework to assess China's international competitiveness within the global digital services trade network.

Existing studies explain digital services trade link formation through bilateral trade conditions, network structural effects, and institutional rules. Gravity models explain bilateral trade relationships through economic size, market demand, geographical distance, and trade costs (Anderson and van Wincoop 2003). As digital technology enters service production and cross-border supply, digital connectivity partly substitutes for geographical proximity. Digital infrastructure, digital capabilities, platform development, and rules governing cross-border data flows change supply, demand, and transaction costs (Wu and Yang 2019). Once trade links have accumulated, existing partners, shared connections, and network positions influence the formation and intensity of new relationships through path dependence, preferential attachment, and structural embeddedness. Digital services trade networks exhibit small-world and core–periphery structures, making endogenous network structure an important driver of trade relationship evolution (Ma et al. 2024; Yang and Yin 2024). As rule networks and trade networks coevolve, institutional rules become endogenous to digital services trade link formation. They regulate link intensity through positions in rule networks, data flow arrangements, and differences in agreement templates (Mi and Wang 2024). For example, heterogeneity in digital trade rules within regional trade agreements helps explain differences in exports (Peng et al. 2021; Wu et al. 2023). Barriers to cross-border data flows increase transaction costs and affect both the establishment of digital services trade relationships and the expansion of existing ones (Zhou et al. 2022). Regional trade agreements differ in their institutional approaches to cross-border data flows, electronic transactions, personal information protection, and regulatory cooperation. Digital services trade networks therefore evolve within differentiated institutional environments (Shen et al. 2022). Network evolution reflects

national capabilities that underpin connections, bilateral conditions that enable relationships, existing network structures that influence subsequent connections, and continuing institutional regulation. These studies provided the theoretical basis for identifying bilateral digital services trade relationships, setting network construction parameters, and analyzing changes in competitive positions.

Existing studies have advanced the definition, measurement, and network analysis of digital services trade, providing a basis for assessing competitiveness from a complex network perspective. This study made three contributions. First, we refined existing trade competitiveness indicators using complex network methods and developed an assessment framework covering market size, network position, and trade security to evaluate China's competitive standing in global digital services trade. Second, we examined how technological endowments, market size, and the institutional environment influenced new trade links. Historical backtesting compared the explanatory power of these mechanisms and informed our analysis of digital services trade network evolution. Third, given the continuing evolution of the network, we examined how alternative evolutionary scenarios and changes in key parameters affected China's competitive position. This analysis identified priorities for strengthening network competitiveness and provided a basis for improving digital services trade policies.

2.2 Research Design and Data Sources

2.2.1 Research Design

We defined the scope of digital services trade using the Extended Balance of Payments Services Classification 2010 (EBOPS 2010), the functional attributes of digital services, and cross-border supply settings. We selected bilateral digital services trade data for 159 countries and territories over 2010-2025 from the World Trade Organization database and used interpolation to address some missing observations. Countries and territories formed the nodes, and bilateral export values provided directed edge weights. A threshold excluded weak trade links. We used Gephi and UCINET to construct the global directed weighted digital services trade network and calculate network indicators. Drawing on global trends and existing studies, we divided the study period into four stages: emergence and start-up in 2010-2013, rapid expansion in 2014-2017, structural reshaping in 2018-2021, and deepening rules in 2022-2025. Based on complex network theory, we assessed competitiveness in terms of market size, network position, and trade security, represented by relative node strength, PageRank centrality, and effective size, respectively. We examined the characteristics and changes in China's international competitiveness in digital services trade. We then introduced a simulation model of trade-network evolution to examine how digital technological capability, market-size-based preferential attachment, and institutional-gravity-based

link formation affected trade link formation. Alternative intervention scenarios assessed how changes in digital technological capability, trade restrictiveness, and link formation intensity affected China's market size, network position, and trade security. The analysis informed pathways for improving China's international competitiveness in digital services trade. Figure 1 presents the research framework.

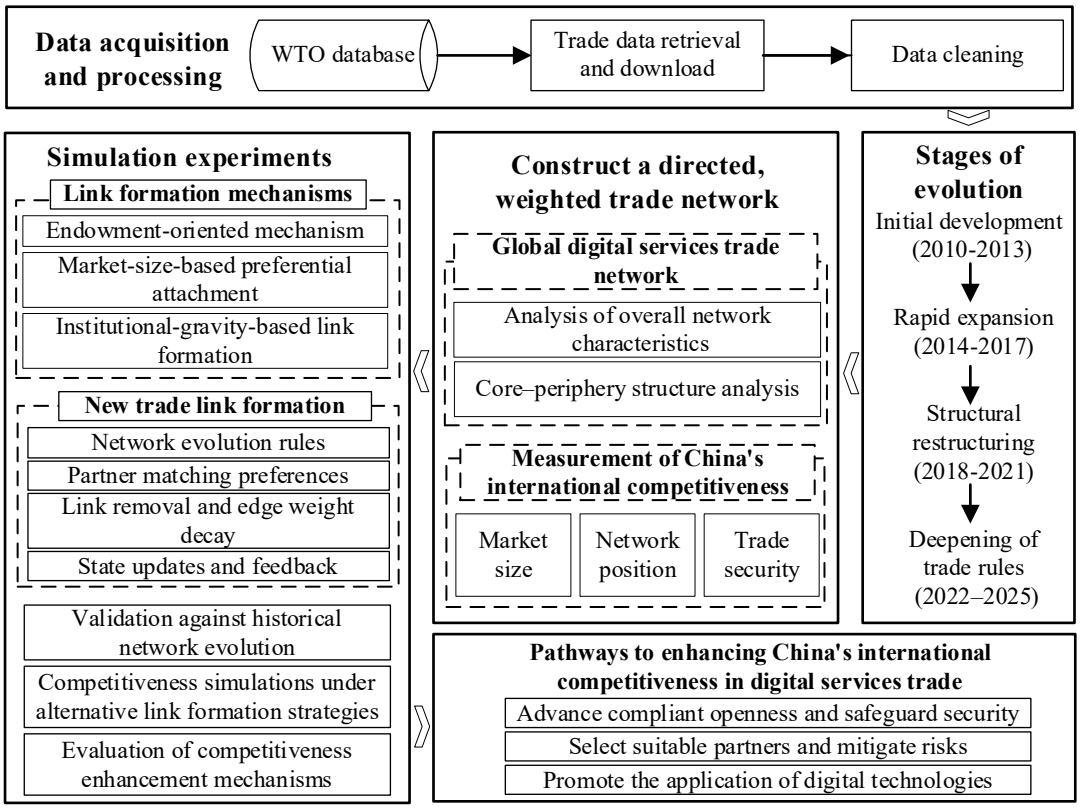


Fig. 1 Research framework

2.2.2 Sectoral Statistical Coverage

We used a sector-based identification approach to define the sectors covered by digital services trade, drawing on definitions from UNCTAD, the OECD, and the China Digital Services Trade Development Report 2018. Digital services trade refers to service transactions delivered across borders through digital channels, including electronic networks, information and communication technology, and digital platforms. Under these criteria, the following categories within the 12 broad sectors of trade in services were included: insurance and pension services; financial services; charges for the use of intellectual property n.i.e.; telecommunications, computer and information services; personal, cultural and recreational services; and selected subsectors of other business services.

Digital services trade sectors fall into two categories: digital technology services and digitally enabled services. Telecommunications, computer and information services depend directly on digital technology and constitute digital technology services. The remaining sectors rely primarily

on digital technology for the cross-border delivery of service content and constitute digitally enabled services. Digitally enabled services comprise digital content services and other digitally deliverable services. Personal, cultural and recreational services mainly involve digital cultural products, audiovisual content, and online entertainment and therefore constitute digital content services. Insurance and pension services, financial services, charges for the use of intellectual property n.i.e., and selected subsectors of other business services fall within other digitally deliverable services. These subsectors include research and development services; professional and management consulting services; architectural, engineering, scientific and other technical services; and trade-related services. They use digital networks for transactions, settlement, licensing, research and development, consulting, technical services, or trade support activities. Table 1 lists the digital services trade subsectors.

Table 1. Digital services trade subsectors

Type of digital services trade	**Subtype**	**Industry code and description**
Digital technology services	Digital technology services	SI Telecommunications, computer, and information services
Digitally enabled services	Digital content services	SK Personal, cultural, and recreational services
	Other digitally deliverable services	SF Insurance and pension services
		SG Financial services
		SH Charges for the use of intellectual property n.i.e.
		SJ1 Research and development services
		SJ2 Professional and management consulting services
		SJ31 Architectural, engineering, scientific and other technical services
		SJ34 Trade-related services

2.2.3 Data Sources

The data mainly came from WTO statistics on trade in services. We first extracted bilateral trade data for disaggregated service categories covering 159 sovereign countries over 2010-2024. Following the sector-based identification approach, we aggregated service categories with digital delivery attributes to obtain bilateral digital services export values. The 159 sovereign countries formed the nodes, and bilateral digital services export values provided the edge weights of a global directed weighted network. If country i exported digital services to country j, a directed edge ran from node i to node j, weighted by the corresponding export value. Following the trade threshold used by Li et al. (2017), we treated bilateral digital services exports below US$100 million as weak links and assigned them a value of 0. Trade flows of at least US$100 million were retained with their original weights.

Because complete bilateral data for disaggregated service categories in 2025 had not yet been released, we supplemented the 2025 bilateral data using a Holt's linear trend method combined with

proportional calibration subject to an aggregate constraint (Zhang et al. 2021; Zhang and Zheng 2009). We first constructed a global trade aggregate from the series of total global digital services exports for 2010-2024:

$$Y_t = \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ijt} \tag{1}$$

We fitted a Holt's linear trend method with level and trend components. By capturing the smoothed level and continuation of the trend, the model yielded a forecast of total global exports in 2025, $\hat{Y}_{2025}$. We then fitted a separate Holt's linear trend method to each bilateral trade flow series among the 159 sovereign countries to obtain an initial forecast, $\tilde{x}_{ij,2025}$, of country i's exports to country j in 2025. For edges with historical observations that were all zero, the forecast was set to 0. For the few anomalous series that could not be fitted, we extrapolated from the changes over the latest two years. Finally, we introduced a global scaling factor to eliminate the discrepancy between the sum of the edge-level forecasts and the global aggregate forecast:

$$\lambda = \hat{Y}_{2025} \Big/ \sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{x}_{ij,2025} \tag{2}$$

We applied a global proportional adjustment to the initial bilateral forecasts to obtain calibrated bilateral digital services export values for 2025, $x^{*}_{ij,2025} = \lambda \tilde{x}_{ij,2025}$, consistent with the aggregate constraint.

2.2.4 Sectoral Trade Scale

Figure 2 shows total global digital services trade and its growth rate over 2010-2025. Global digital services trade expanded continuously over the past decade, with growth rates fluctuating across stages. Growth was relatively rapid in 2010-2014, followed by a period of comparatively steady expansion in 2017-2019. External shocks changed how global trade in services operated after 2020 and increased demand for digital delivery. Growth rose markedly in 2021, and digital services trade played a stronger role in the recovery of global trade in services. After 2022, total trade continued to rise while growth moderated. Global digital services trade thus shifted from rapid substitution-driven growth under external shocks toward more regular expansion.

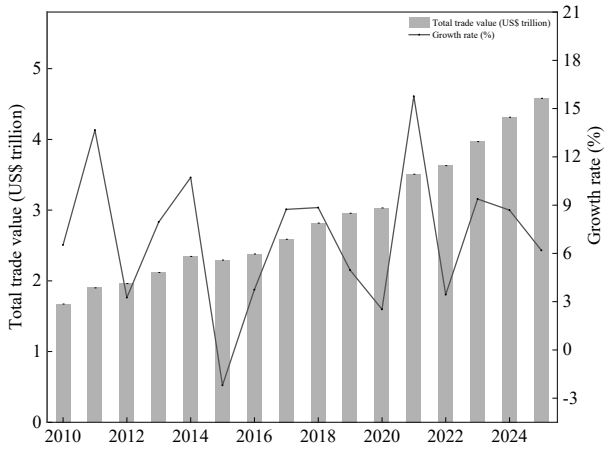


Fig. 2 Global digital services trade: total value and growth rate, 2010-2025

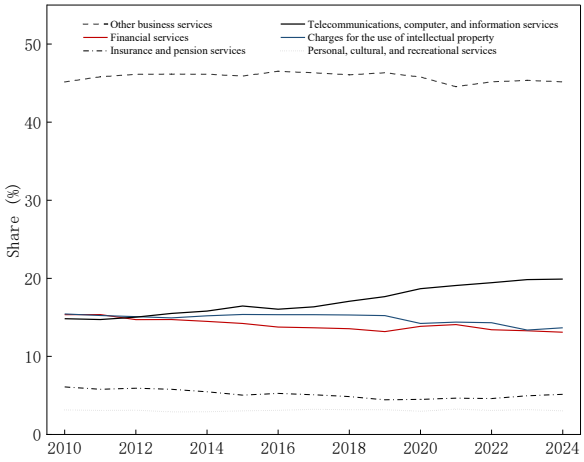


Fig. 3 Sectoral shares of global digital services trade, 2010-2024

Figure 3 shows the sectoral shares of global digital services trade over 2010-2024. Other business services consistently accounted for the largest share, at approximately 45%, and remained the dominant sector. Research and development, consulting, technical services, and trade-related services therefore formed the main basis for the expansion of digital services trade. The share of telecommunications, computer and information services generally increased from approximately 15% to nearly 20%, indicating the growing importance of digital technology services. The shares of financial services and charges for the use of intellectual property n.i.e. remained relatively stable, together supporting high-value-added digitally delivered services. Insurance and pension services and personal, cultural and recreational services accounted for smaller shares and made relatively limited contributions. Overall, other business services dominated, while the share of information technology services gradually increased.

Following existing approaches to identifying stages in digital trade development (Ma et al. 2019), we divided global digital services trade over 2010-2025 into four stages, considering changes in trade scale, growth fluctuations, and external shocks. The first was initial expansion (2010-2013), when digital technology entered the entire service trade process and cross-border digital delivery capabilities gradually developed. The second was accelerated development (2014-2017), when digital platforms, services outsourcing, and information and communication technology spread rapidly, substantially strengthening links between trade network nodes. The third was shock adjustment (2018-2021), when the COVID-19 pandemic profoundly changed the operation of global trade in services and demand surged for teleworking, online education, digital finance, and cloud computing services. The fourth was recovery and restructuring (2022-2025), when global digital services trade entered a new stage combining a recovery in trade scale with extensive network restructuring, alongside faster adjustments to international trade rules.

3 Evolution of the Global Digital Services Trade Network

The global digital services trade network captures the spatial pattern of trade links among countries and forms an important external environment for national competitiveness. Overall network characteristics describe the extent of trade link expansion, connection intensity, clustering, and transmission efficiency. The core–periphery structure further reveals countries' hierarchical distribution and differentiated positions within the global network. Together, these features provide a basis for identifying differences in network positions and their evolution.

3.1 Overall Network Characteristics

To identify the evolution of the global digital services trade network over 2010-2025, we selected average degree, network density, average clustering coefficient, average shortest path length, and modularity as indicators of overall structural change. Table 2 reports their calculations and economic interpretations.

Table 2. Global digital services trade network indicators and their interpretations

Indicator	Formula	Definition	Economic interpretation
Average degree	$K_k^{inandout}(t)=\frac{1}{n}\sum_{j=1}^{n}d_{ji}(t)$	n is the number of nodes in the network; d_{ji} is the number of edges from node j to node i.	The average number of edges per node, reflecting overall trade network connectivity.
Network density	$D=\mathrm{m}/n(n-1)$	m is the number of observed edges in the network.	Measures the overall saturation and intensity of trade linkages.
Average clustering coefficient	$C=\frac{1}{n}\sum_{i=1}^{n}\frac{2m_i}{k_i(k_i-1)}$	k_i is the degree of node i; m_i is the number of observed edges among the neighbors of node i.	Measures the local clustering of trading partners and their tendency to form groups.
Average shortest path length	$L=\frac{1}{n(n-1)}\sum_{i\neq j}^{n}d_{ij}$	d_{ij} is the shortest path between nodes i and j.	Measures overall network accessibility and the efficiency of trade flows.
Modularity	$Q=\sum_{c=1}^{C}\left(e_c-a_c^2\right)$	e_c is the share of edge weights within community c; a_c is the share of node strength in community c; C is the total number of communities identified in the network.	Identifies community structure, indicating regional clustering or globalization in the network.

Using these indicator definitions, we calculated the overall network indicators for the four stages over 2010-2025. Table 3 reports the results.

Table 3. Overall structural indicators of the global digital services trade network, 2010-2025

	Stage 1: 2010-2013	Stage 2: 2014-2017	Stage 3: 2018-2021	Stage 4: 2022-2025
Number of nodes	121	128	130	134
Number of edges	1760	1917	2188	2469
Average degree	14.545	14.977	16.831	18.425
Network density	0.121	0.118	0.13	0.139
Average clustering coefficient	0.632	0.643	0.697	0.731

	Stage 1: 2010-2013	Stage 2: 2014-2017	Stage 3: 2018-2021	Stage 4: 2022-2025
Average shortest path length	1.928	1.92	1.902	1.899
Modularity	0.119	0.105	0.074	0.006

Table 3-2 shows that the global digital services trade network expanded continuously over 2010-2025 and that trade links among countries became closer. The number of nodes increased from 121 to 134, the number of edges from 1760 to 2469, and average degree from 14.545 to 18.425. These changes indicate that wider digital infrastructure coverage and expanding cross-border e-commerce and platform services lowered barriers to cross-border supply, allowing more economies to enter the global digital services trade system. Network density rose from 0.121 to 0.139 but declined to 0.118 in the second stage. This suggests that high-standard rules, including the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP) and the General Data Protection Regulation (GDPR), strengthened institutional standards while imposing compliance constraints on some economies. The average clustering coefficient rose from 0.632 to 0.731, while average shortest path length fell from 1.928 to 1.899. These changes reflected stronger regional digital industry chain connections and lower trade connection costs through cross-border remote delivery and platform matching. Small-world characteristics became more pronounced. Modularity declined from 0.119 to 0.006, indicating a marked weakening of the boundaries initially shaped by differences in rules and regional agreements. With the diffusion of 5G, cloud computing services, new digital trade rules such as the Digital Economy Partnership Agreement (DEPA), and generative AI applications, global digital services trade increasingly transcended regional divisions, exhibiting stronger cross-regional connections and multicenter interaction.

3.2 Core–Periphery Structure

In the global digital services trade network, the core–periphery structure comprises a small number of central, densely interconnected core nodes and more sparsely connected peripheral nodes. Coreness measures a node's importance and the closeness of its connections. We used the core–periphery function in UCINET to calculate coreness for each stage. Drawing on the three-tier approach of Wang et al. (2015), we applied the natural breaks method to descending coreness scores. With breaks at 0.5, 0.15, and 0.07, countries were classified into four tiers: core, intermediate, peripheral, and outermost. Figure 4 shows the resulting core–periphery structures.

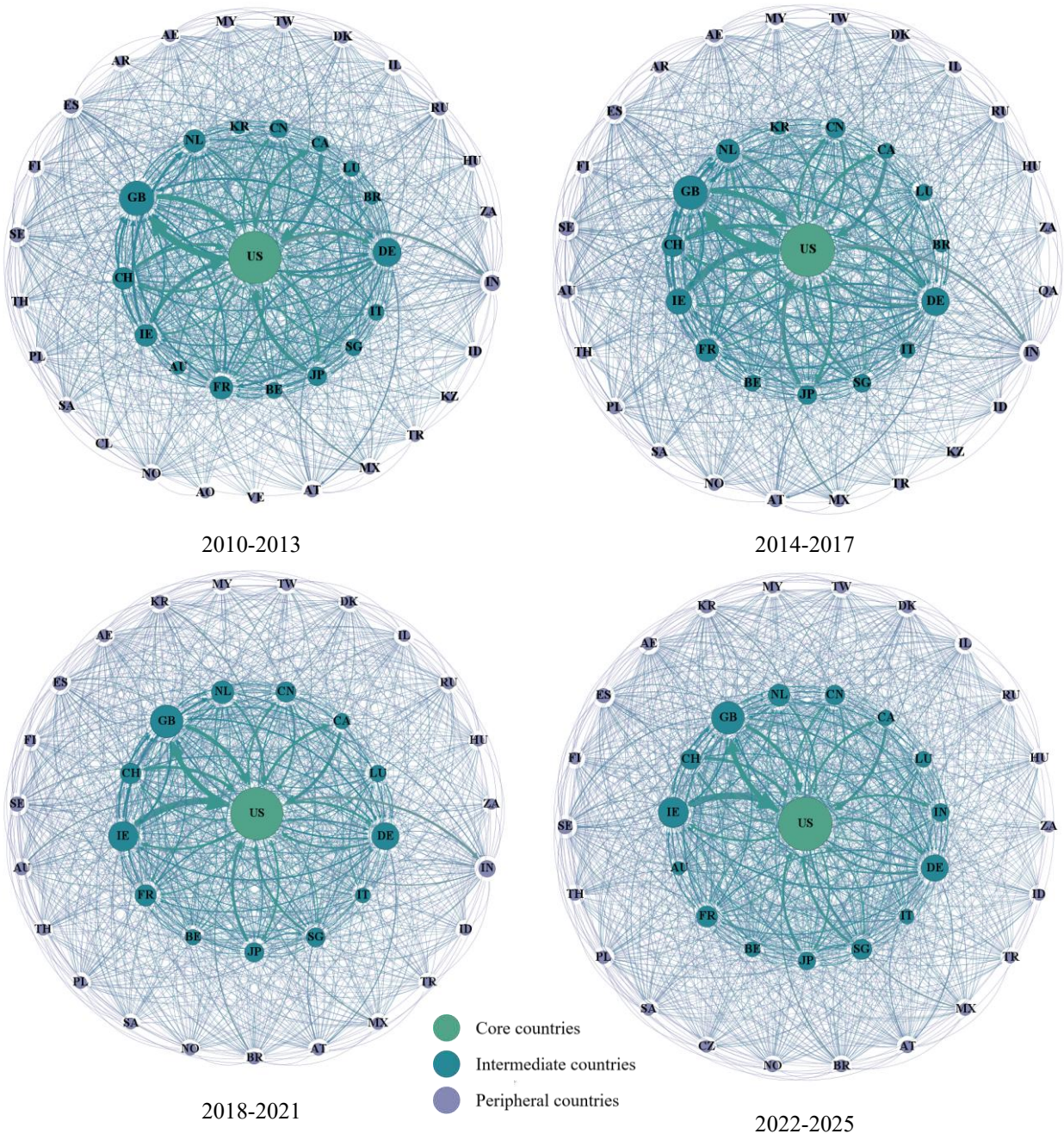


Fig. 4 Evolution of the core–periphery structure of the global digital services trade network across stages

The global digital services trade network exhibited a stable core–periphery pattern over 2010-2025. The United States alone occupied the core tier throughout, and no other country entered it. The highest tier therefore remained single-core. The intermediate tier mainly comprised the United Kingdom, Ireland, Germany, Switzerland, Japan, France, the Netherlands, Canada, Singapore, and China. Its membership remained broadly stable, indicating that the subcore continued to be dominated by economies with strong digital industries, well-developed institutional environments, and substantial cross-border service connectivity. Most changes occurred between the intermediate and peripheral tiers: India moved upward, Australia returned to the intermediate tier, and South Korea and Brazil moved downward. Competition in digital services trade was thus reflected mainly in adjustments to subcore positions. China remained in the intermediate tier in all four stages, with

coreness between 0.127 and 0.149 and a ranking between 10th and 11th. This indicated substantial integration into the global digital services trade network and a relatively stable connection base. Relative to high-coreness economies such as the United States, the United Kingdom, Germany, and Ireland, China still had room to improve its supply of high-end digital services, connection intensity with core markets, and influence over international rules.

4 Assessing China's International Competitiveness in Digital Services Trade

Existing studies mainly use four indicators to measure China's trade competitiveness: international market share (IMS), the revealed comparative advantage (RCA) index, the trade competitiveness index (TC), and the Herfindahl–Hirschman Index (HHI). Table 4 explains these indicators.

Table 4. Trade competitiveness indicators used in existing studies

Indicator	Formula	Definition	Economic interpretation
International market share (IMS)	$\mathrm{IMS}_i = X_i / X_w$	X_i denotes the country's exports; X_w denotes world exports.	Measures absolute export scale and market share.
Revealed comparative advantage index (RCA)	$RCA_{ik} = \frac{X_{ik} / X_{it}}{X_{ik} / X_{wt}}$	X_{ik} and X_{wk} denote exports by country i and world exports in sector k, respectively; X_{it} and X_{wt} denote exports by country i and world exports in sector t, respectively.	Measures the relative international competitive advantage of a given industry.
Trade competitiveness index (TC)	$TC = \frac{X_{exp} - X_{imp}}{X_{exp} + X_{imp}}$	X_{exp} denotes the country's exports; X_{imp} denotes its imports.	Uses the trade balance to identify an industry's inward- or outward-oriented character.
Herfindahl–Hirschman Index (HHI)	$HHI = \sum_{i=1}^{N} s_i^2$	s_i is the market share of firm i; N is the total number of firms in the market.	Assesses dependence on a single market and the associated risks.

These trade competitiveness indicators rely on country-level aggregate data and mainly measure national attributes such as trade scale, advantages in the division of labor, and market concentration. Because competitiveness in digital services trade emerges through bilateral trade links and their structural relationships, we followed Xu and Zhao (2025) in introducing complex network indicators to identify a country's position in global trade. IMS captures scale and market share. Node strength measures trade scale and network connectivity through the volume of trade relationships and weighted connections. The RCA index and TC emphasize advantages in the division of labor. PageRank centrality additionally incorporates the structural weights of trading partners to measure network influence. HHI reflects market concentration risk. Effective size measures a country's ability to connect with diverse partners and diversify external risks through nonredundant trade links. Accordingly, we selected node strength, PageRank centrality, and

effective size to measure market size, network position, and trade security, respectively. Table 5 presents the corresponding formulas and economic interpretations.

Table 5. Indicators of China's international competitiveness in digital services trade

Dimension	Indicator	Formula	Definition
Market size	Node strength	$s_i = \sum_{j=1}^{n} a_{ij} w_{ij}$	a_{ij} is an adjacency matrix element; w_{ij} is the edge weight in the weighted network, representing the bilateral trade flow between nodes.
Network position	PageRank centrality	$PR_i = \frac{1-d}{n} + d\sum_{j=1}^{n} PR_j \frac{w_{ji}}{s_j^{out}}$	The damping factor d is 0.85. The measure is the reputation and influence score of country i in the network. s_j^{out} is the out-strength of node j.
Trade security	Effective size	$E_i = \sum_{j=1}^{n}(1 - \sum_{k=1,k\neq i\neq j}^{n} p_{ik} m_{jk})$	p_{ik} is the share of trade between country i and intermediary country k in its total trade; m_{jk} is the ratio of trade between partner j and intermediary country k to the edge strength of its largest trading partner.

4.1 Market Size

Node strength measures the scale of a node's trade relationships in a weighted trade network. Greater node strength in the global digital services trade network indicates larger trade flows. To remove the effect of overall network expansion on comparisons across periods, we used relative node strength: the ratio of a country's node strength to the network-wide average. It captures a country's relative scale within the global digital services trade network at different stages.

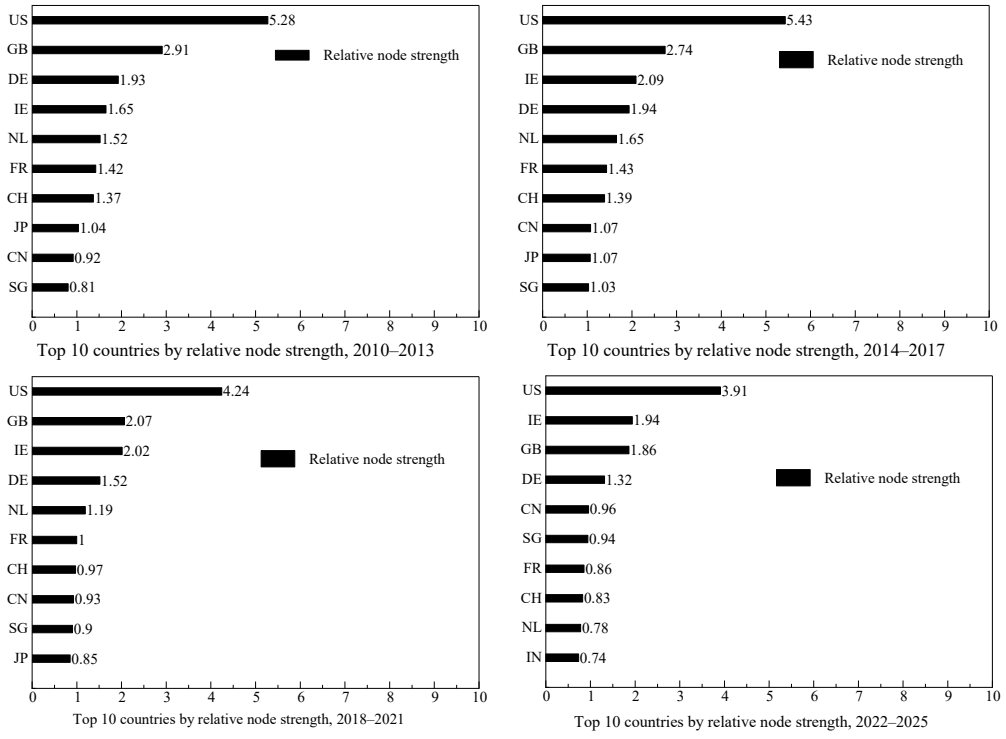


Fig. 5 Top ten countries by relative node strength in the global digital services trade network, 2010-2015

Figure 5 shows the top ten countries by relative node strength over 2010-2025. Market size advantages in global digital services trade remained concentrated in a few countries. US relative node strength rose from 5.28 in the first stage to 5.43 in the second, before declining to 3.91 in the fourth. Although the United States remained first, its lead narrowed markedly. It retained the strongest capacity to attract trade flows, but flows gradually dispersed across multiple nodes as more economies entered the network. The United Kingdom, Ireland, and Germany consistently ranked highly, maintaining a strong scale base in digital service supply, cross-border financial services, software services, and international market coverage. China's relative node strength increased from 0.92 to 0.96, and its ranking rose from 9th to 6th, indicating a sustained improvement in its relative trade scale. Policy support for the digital economy, a very large domestic market, platform firms' overseas expansion, and the upgrading of services outsourcing broadened the base of China's digital services trade flows.

4.2 Network Position

Table 6 reports the top ten countries by PageRank centrality and effective size across the four stages. PageRank centrality emphasizes partner quality and structural weights and captures a country's structural influence in global digital services trade. As Table 6 shows, US PageRank centrality remained above 0.179 and ranked first in all four stages. Its advantage therefore reflected not only trade scale but also stable connections with highly weighted partners. UK centrality declined from 0.105 to 0.090 but remained second, closely related to its service-oriented economic structure. London's long-standing role as a global center for finance, legal services, accounting, and consulting, together with English-speaking markets, common law institutions, the concentration of multinational headquarters, and international financial transaction networks, enabled the United Kingdom to maintain connections with the United States, the European Union, and major offshore service markets. It therefore retained a high structural weight in digital services trade. China's PageRank centrality increased from 0.032 to 0.040, and its ranking rose from 8th to 5th. Its competitiveness gains thus reflected both larger trade flows and improved connections with highly weighted partners. China's entry into the top five in the fourth stage indicated a continuing rise in network position. Nevertheless, gaps remained relative to the United States, the United Kingdom, and Ireland in the depth of core partner connections and influence over rules.

4.3 Trade Security

In the global digital services trade network, structural holes arise when a country connects different trade subgroups through diverse, nonduplicative trade relationships. Common measures include effective size, efficiency, constraint, and hierarchy. Effective size measures the number of

nonredundant ties and captures the diversity of trading partners, making it suitable for measuring trade security.

Table 6. Top ten countries by PageRank centrality and effective size across four stages

Indicator	Rank	Stage 1		Stage 2		Stage 3		Stage 4	
		Country	Index	Country	Index	Country	Index	Country	Index
PageRank centrality	1	United States	0.185	United States	0.187	United States	0.179	United States	0.182
	2	United Kingdom	0.105	United Kingdom	0.096	United Kingdom	0.092	United Kingdom	0.090
	3	Germany	0.064	Germany	0.063	Ireland	0.065	Ireland	0.071
	4	France	0.047	Ireland	0.048	Germany	0.060	Germany	0.054
	5	Netherlands	0.041	France	0.044	Netherlands	0.042	China	0.040
	6	Ireland	0.038	Netherlands	0.043	France	0.040	India	0.040
	7	Switzerland	0.038	Switzerland	0.037	China	0.038	France	0.038
	8	China	0.032	China	0.035	India	0.035	Netherlands	0.037
	9	Japan	0.029	Japan	0.030	Singapore	0.031	Singapore	0.035
	10	India	0.028	India	0.029	Switzerland	0.029	Switzerland	0.028
Effective size	1	United States	99.698	United States	103.151	United States	96.628	United States	99.221
	2	United Kingdom	63.256	United Kingdom	68.191	United Kingdom	70.024	United Kingdom	72.164
	3	France	48.486	Germany	52.326	Germany	60.848	China	61.559
	4	Switzerland	45.499	France	52.049	France	55.962	Germany	61.068
	5	Netherlands	45.424	Netherlands	51.954	Singapore	55.375	Netherlands	59.281
	6	China	44.546	China	49.124	China	54.964	India	59.176
	7	Singapore	44.44	Singapore	47.528	India	50.971	France	58.555
	8	Germany	43.125	Switzerland	46.314	Ireland	49.513	Ireland	55.804
	9	India	43.096	Ireland	44.971	Netherlands	48.364	Singapore	55.394
	10	Italy	37.676	India	40.616	Switzerland	47.252	Switzerland	49.465

Effective size is a social network analysis measure of a node's bridging capacity. It captures a country's ability to connect diverse trading partners, occupy intermediary positions, and reduce relational redundancy. Table 6 shows that US effective size remained around 100 and ranked first in all four stages. Its digital services trade connections had the broadest coverage and the lowest partner overlap, enabling it to connect different market groups. UK effective size increased from 63.256 to 72.164 and remained second, indicating a stable advantage in cross-regional service network channels. Germany, France, the Netherlands, and Singapore consistently ranked highly. Their connectivity advantages reflected the combined support of European market integration, multinational corporate networks, and high-end service supply. China's effective size increased markedly from 44.546 to 61.559, and its ranking rose from 6th to 3rd. Its intermediary capacity strengthened as it moved from scale expansion toward the optimization of network position. Since the Regional Comprehensive Economic Partnership Agreement (RCEP) entered into force in 2022,

China has continued to improve its cross-border data flow regime, accelerate digital trade reform and innovation, and pilot greater opening-up in value-added telecommunications services. These measures expanded international market opportunities for platform services, data services, cross-border e-commerce, and digital content. China's digital services trade links shifted from scale expansion toward partner diversification and market dispersion. Dependence on a few core markets declined, while the capacity to reorganize partners increased amid diverging external rules and technological restrictions.

5 Network Evolution Simulation Model

Complex network theory holds that network topology emerges endogenously through continuing interactions among node attributes, link formation rules, and flow feedback. In digital services trade networks, countries' existing digital technological capability, market size, and institutional openness affect partner selection and bilateral link formation probabilities. Once established, trade links can in turn affect national digital technological capability through digital services outsourcing, cross-border data flows, knowledge transfer, technological imitation, and the diffusion of platform capabilities. On this basis, we constructed a dynamic simulation model of the digital services trade network. Let t denote simulation time. The global digital services trade network was represented as:

$$G_t = (N, A_t, W_t) \tag{3}$$

Here, N denotes the set of country nodes, which remained fixed throughout the simulation. $A_t = (a_{ij,t})$ denotes the directed adjacency matrix at time t. If country i has a digital services trade link to country j, $a_{ij,t} = 1$; otherwise, $a_{ij,t} = 0$. $W_t = (w_{ij,t})$ denotes the directed weighted adjacency matrix, and w_{ij} denotes the trade intensity of digital services supplied by country i to country j. The set of potential partners with which exporter i had not established a direct trade link at time t was defined as:

$$C_i(t) = \{ j \mid j \neq i, a_{ij,t} = 0 \} \tag{4}$$

$C_i(t)$ denotes the set of candidate importers with which country i may establish new digital services trade links in the next period. It excludes the home country and pairs with existing direct trade links, so that new links form only between previously unconnected countries. Existing trade links strengthen, weaken, or dissolve through the edge weight update mechanism.

5.1 Node Link Formation Strategies

To examine evolutionary paths in the global digital services trade network, we drew on classical trade theories and the link formation strategies used by Ma and Zhang (2017) for knowledge networks. We simulated and compared how alternative strategies affected nodes' market size, network position, and trade security. Table 7 summarizes the link formation rules and their theoretical foundations.

Table 7. Node link formation rules based on trade theories

Link formation strategy	Trade theory	Logic of link formation
Endowment-oriented link formation strategy	Theory of comparative advantage emphasizes factor endowment differences as the fundamental driver of trade. Differences in digital technological capability promote resource complementarity and a vertical specialization.	One country's capacity to supply digital technology matches another country's demand for industrial transformation, creating links through a vertical specialization.
Market-size-based preferential attachment strategy	New trade theory emphasizes the Matthew effect generated by increasing returns to scale. Strong attraction channels trade toward core hubs.	Nodes tend to connect with partners with greater node strength to obtain economies of scale and reduce search costs.
Institutional-gravity-based link formation strategy	The gravity model of trade emphasizes institutional barriers and cost frictions. Trading partners are selected by assessing the extent to which policy barriers offset attraction.	A bilateral trade relationship forms only when potential attraction exceeds the link formation threshold determined by digital trade restrictiveness.

5.1.1 Endowment-Oriented Link Formation Strategy

Digital services trade links have a clear direction of technological supply. Let $V_i(t)$ and $V_j(t)$ denote the digital technological capability of country i and country j, respectively, at time t. When $V_i(t) > V_j(t)$, country i has an advantage in digital service supply over country j. When $V_i(t) < V_j(t)$, the technological gradient in this direction does not provide an effective incentive for link formation. The bilateral gap in digital technological capability was defined as:

$$\Delta V_{ij}(t) = \max\left(0, \frac{V_i(t) - V_j(t)}{V_{\max}(t) + \varepsilon}\right) \tag{5}$$

Here, $\Delta V_{ij}(t)$ denotes the directional technological capability gap of country i relative to country j; $V_{\max}(t) = \max_{p,q \in N} |V_p(t) - V_q(t)|$ denotes the maximum network-wide technological capability gap[1]; and ε is a small positive constant that prevents division by zero. Under the endowment-

[1]Digital technological capability $V_i(t)$ and $V_j(t)$ were represented by the Global Innovation Index (GII), published by the World Intellectual Property Organization (WIPO). Data were obtained from the annual Global Innovation Index reports.

oriented strategy, the probability $P_{ij}^{\mathrm{E}}(t)$ that exporter initiates a digital services trade link with importer j was defined as:

$$P_{ij}^{E}(t)=\frac{\Delta V_{ij}(t)e^{-\gamma\Delta V_{ij}(t)}}{\sum_{k\in C_i(t)}\Delta V_{ik}(t)e^{-\gamma\Delta V_{ik}(t)}+\varepsilon} \tag{6}$$

E denotes factor endowments, and $\gamma>0$ is the technological-distance damping coefficient. The exponential term $e^{-\gamma\Delta V_{ij}(t)}$ captures the inhibition of link formation when an excessive technological gap leads to insufficient absorptive capacity, infrastructure differences, and mismatched industrial ecosystems. The denominator normalizes probabilities over the candidate importer set $C_i(t)$.

5.1.2 Market-Size-Based Preferential Attachment Strategy

Digital services trade links exhibit cumulative advantage. Countries with larger existing import markets generally have more developed digital platforms, payment systems, data circulation environments, and market demand. We used national in-strength $S_j^{in}(t)$ to represent digital services import market size. Under market-size-based preferential attachment, the probability $P_{ij}^{S}(t)$ that exporter i chooses importer j at time t was expressed as:

$$P_{ij}^{S}(t)=\frac{S_j^{in}(t)+\varepsilon}{\sum_{k\in C_i(t)}\left[S_k^{in}(t)+\varepsilon\right]} \tag{7}$$

$$S_j^{in}(t)=\sum_{i=1,i\neq j}^{N}w_{ij,t} \tag{8}$$

S denotes scale, and ε is a small positive constant that prevents the complete exclusion of zero-strength nodes. This probability increases with the target country's existing import market size, capturing preferential attachment toward nodes with greater market capacity.

5.1.3 Institutional-Gravity-Based Link Formation Strategy

Digital services trade depends heavily on cross-border data flows, intellectual property protection, platform regulation, and the digital compliance environment. Institutional restrictions inhibit potential trade link formation. Incorporating the importer's digital services trade restrictiveness, we defined potential institutional attraction $G_{ij}(t)$ between country i and country j as:

$$G_{ij}(t)=V_i(t)V_j(t)e^{-\eta R_j(t)} \tag{9}$$

$\eta > 0$ is the institutional-friction sensitivity coefficient, and $R_j(t)$ denotes digital services trade restrictiveness in importer j[2]. Stronger bilateral digital technological foundations increase potential attraction, whereas greater institutional restrictiveness in the importing country reduces it. Institutional barriers thus screen potential trade links. Under the institutional-gravity-based link formation strategy, the link formation probability $P_{ij}^{G}(t)$ was defined as:

$$P_{ij}^{G}(t) = \frac{G_{ij}(t)\mathrm{I}[G_{ij}(t) \geq \tau]}{\sum_{k \in C_i(t)} G_{ik}(t)\mathrm{I}[G_{ik}(t) \geq \tau] + \varepsilon} \tag{10}$$

Here, G denotes institutional attraction. $\mathrm{I}(\cdot)$ is an indicator function that tests whether institutional attraction reaches the link formation threshold τ. If $G_{ij}(t) \geq \tau$, it takes the value 1 and retains the original attraction score; otherwise, it takes the value 0. The function provides a hard-threshold screening mechanism, excluding candidates below the link formation threshold from the normalization of link formation probabilities.

5.1.4 Hybrid Link Formation Strategy

Actual digital services trade links are jointly driven by technological endowments, market size, and the institutional environment. We therefore constructed a hybrid link formation probability:

$$P_{ij}^{M}(t) = \lambda_E P_{ij}^{E}(t) + \lambda_S P_{ij}^{S}(t) + \lambda_G P_{ij}^{G}(t) \tag{11}$$

Here, $P_{ij}^{M}(t)$ is the overall probability that exporter i forms a trade link with importer j. The weights $\lambda_E, \lambda_S, \lambda_G$ represent the relative contributions of comparative advantage, market-size-based preferential attachment, and institutional attraction to micro-level link formation decisions. The weights satisfy normalization and nonnegativity constraints: $\lambda_E + \lambda_S + \lambda_G = 1$ and $\lambda_E, \lambda_S, \lambda_G \geq 0$.

5.2 Link Formation and Edge Weight Updates

After obtaining the link formation probability $P_{ij}^{(m)}(t)$ under strategy m, we generated new edges in two steps: determining the number of new links and sampling candidate partners. To reflect the stochastic and sparse nature of digital services trade link formation, we assumed that the number of new partners planned by exporter i in period t followed a Poisson distribution:

$$K_i(t) \sim \mathrm{Poisson}\left(\beta_i(t)\right) \tag{12}$$

[2]The importing country's policy barrier variable $R_j(t)$ was represented by the overall Digital Services Trade Restrictiveness Index (Digital STRI) score published by the Organisation for Economic Co-operation and Development (OECD). The score lies strictly within $[0,1]$. Higher scores indicate stricter data sovereignty regulation and higher barriers to cross-border digital flows. Data were obtained from the OECD iLibrary official statistical database.

Here, $K_i(t)$ denotes the number of new trading partners planned by exporter i in period t, and $\beta_i(t)$ is the node's link formation intensity. In the baseline simulation, countries were assigned the same basic link formation intensity, $\beta_i(t) = \beta_0$. Differences in network evolution across scenarios therefore arose mainly from link formation strategies rather than differences in node activity. Because the candidate importer set was finite, the actual number of new links could not exceed its size and was defined as:

$$K_i^*(t) = \min\left\{K_i(t), |C_i(t)|\right\} \tag{13}$$

$K_i^*(t)$ denotes the actual number of new trading partners available to country i in period t. Given $K_i^*(t)$, we sampled from the candidate set $C_i(t)$ according to the link formation probabilities using weighted sampling without replacement[3], obtaining the set of new trading partners:

$$B_i^{(m)}(t) = \text{SampleWOR}\left(C_i(t), K_i^*(t), \left\{P_{ij}^{(m)}(t)\right\}_{j \in C_i(t)}\right) \tag{14}$$

$B_i^{(m)}(t)$ denotes the new trading partners actually selected by country i under strategy m in period t. SampleWOR denotes weighted sampling without replacement, which prevents a country from being selected more than once in the same period. If all candidate scores were zero, no new trade link formed in that period. If any candidates had positive scores, normalization and sampling were restricted to those candidates. Following link formation, edge weights were determined jointly by potential trade intensity, the existing trade base, and institutional restrictions in the importing country. The potential trade intensity of digital services supplied by country i to country j under strategy m was denoted by $\Phi_{ij}^{(m)}(t)$ and jointly determined by link formation probabilities and base-period trade scale. Intermediate edge weights before updating existing weights were given by:

$$\tilde{w}_{ij}(t+1) = a_{ij,t} w_{ij,t}[1 + g_{ij}^{(m)}(t)] + x_{ij}^{(m)}(t+1)\Phi_{ij}^{(m)}(t) \tag{15}$$

$$g_{ij}^{(m)}(t) = \mu \Phi_{ij}^{(m)}(t) - \chi R_j(t) \tag{16}$$

$\tilde{w}_{ij}(t+1)$ denotes the intermediate edge weight before testing for link dissolution. $a_{ij,t} w_{ij,t}[1 + g_{ij}^{(m)}(t)]$ represents the continuation and growth of an existing trade link in the current period, while $x_{ij}^{(m)}(t+1)\Phi_{ij}^{(m)}(t)$ captures the initial potential trade flow generated by a new link. $g_{ij}^{(m)}(t)$ denotes the growth rate of existing trade intensity from country i to country j under strategy m. $\mu > 0$ is the coefficient of potential trade intensity in existing-link growth, and $\chi > 0$ is the coefficient of institutional barriers in trade-growth inhibition. To prevent the network from

[3]To avoid undefined sampling probabilities when all candidate scores are zero, an exporting country formed no new trade links in a period if all candidate partners received a score of 0 under a given strategy. If any candidates had positive scores, normalization was restricted to that set.

converging irreversibly toward complete connectivity during long-run simulations, we introduced a minimum trade-link maintenance threshold θ. A trade link was considered unsustainable if its intermediate edge weight fell below this threshold:

$$a_{ij,t+1} = \mathrm{I}\left[\tilde{w}_{ij}(t+1) \geq \theta\right] \tag{17}$$

$$w_{ij,t+1} = a_{ij,t+1}\tilde{w}_{ij}(t+1) \tag{18}$$

Here, $\mathbf{I}(\cdot)$ is an indicator function testing whether potential trade intensity in the next period is at least the trade-link maintenance threshold. It takes the value 1 when potential trade intensity reaches or exceeds the threshold, indicating that an edge forms or persists between the pair of nodes. Otherwise, it takes the value 0, indicating that the link cannot form or is dissolved. This mechanism allows new digital services trade links to emerge, while existing links can weaken or dissolve because of high institutional restrictiveness, insufficient potential trade intensity, or weak growth.

5.3 Updating Nodes' Digital Technological Capability

Network evolutionary dynamics and knowledge-flow models emphasize feedback between network structure and node attributes. By importing digital services from technologically advanced countries, importers can receive spillovers in technological knowledge, platform experience, data processing capabilities, and organizational management experience. These spillovers affect domestic digital technological capability. Country j's digital technological capability in period $t+1$ was determined jointly by technological depreciation and external technological spillovers and was updated as follows:

$$V_j(t+1) = (1-\delta)V_j(t) + \alpha\sum_{i\neq j}\frac{w_{ij,t+1}}{\sum_{p\neq j} w_{pj,t+1} + \varepsilon}\max\left[0, V_i(t) - V_j(t)\right] \tag{19}$$

Here, $\delta \in [0,1]$ is the technological depreciation or competitive-decay coefficient, capturing the possible natural erosion of technological advantages over time. $\alpha > 0$ denotes technology absorption efficiency. The fractional term represents the relative weight of country j's digital services imports from country i. A higher weight indicates greater dependence of country j on digital services from country i and stronger potential technological spillovers. $\max\left[0, V_i(t) - V_j(t)\right]$ captures the direction of technological spillovers: learning from more technologically advanced partners and catch-up effects arise only when the exporter has greater digital technological capability than the importer. To maintain a common scale throughout the simulation, we normalized updated digital technological capability:

$$\bar{V}_i(t+1) = \frac{V_i(t+1) - V_{\min}(t+1)}{V_{\max}(t+1) - V_{\min}(t+1) + \varepsilon} \tag{20}$$

Here, $V_{\min}(t+1)$ and $V_{\max}(t+1)$ denote the minimum and maximum digital technological capability among country nodes at time $t+1$, respectively. Min–max normalization maps digital technological capability onto the interval from zero to one, achieving nondimensionalization and removing the influence of differences in units on dynamic evolution. The normalized value $\bar{V}_i(t+1)$ enters the system in the next period. For notational simplicity, we use $V_i(t+1)$ in place of the dimensionless value hereafter.

6 Simulation Experiments and Results

6.1 Data Processing and Simulation Settings

6.1.1 Data Processing

The simulation data comprised bilateral digital services trade flows $w_{ij,0}$, the Global Innovation Index (GII), and the Digital Services Trade Restrictiveness Index $R_{j,0}$. We matched the three datasets by country or territory name and year and harmonized trade direction, statistical coverage, and units. The simulation covered 159 country or territory nodes, with an evolution horizon of T=100. The 2024 bilateral digital services trade network provided the initial state. For bilateral digital services trade flows $w_{ij,0}$, exporter i was the origin of a directed edge, importer j was its destination, and the trade flow was its weight. Edge weights were set to zero for country pairs with no observed trade flow.

6.1.2 Simulation Rules and Procedure

We implemented the simulation model of trade-network evolution for digital services trade in Python using libraries including Matplotlib and NumPy. Four link formation strategies were specified: endowment-oriented, market-size-based preferential attachment, institutional-gravity-based link formation, and hybrid. Drawing on expert assessment, relevant network simulation studies, and historical backtesting, we set the parameters to $\beta_0 = 1.4$, $\rho = 0.85$, $\mu = 0.18$, $\chi = 0.001$, $\alpha = 0.08$, $\delta = 0.02$, $\gamma = 3.0$, $\eta = 2.0$, $\tau = 0.03$, and $\theta_{\text{ratio}} = 0.006$. The trade scale benchmark was the median positive trade flow in 2024, US$354.04 million. The minimum trade-link maintenance threshold was US$2.12 million, calculated as the product of the trade scale benchmark and θ_{ratio}.

Figure 6 shows the simulation procedure. During initialization, we specified the country or territory nodes, trade links, and edge weights; imported the GII and Digital STRI; assigned node

and environmental parameters according to the link formation strategy; and set the initial time to $t=0$. We then calculated potential trade link formation probabilities and generated new trade edges $X_{ij,t}$ through random sampling. Edge weights were adjusted for growth in existing trade flows, new trade links, and institutional inhibition. Weak links below the trade-link maintenance threshold were removed to update the trade network. We then updated nodes' digital technological capability $V_{i,t}$, set $t=t+1$, and calculated relative node strength, PageRank centrality, and effective size to measure China's market size, network position, and trade security, respectively. After each round, we checked whether the specified evolution horizon had been reached. If $t<T$, the procedure returned to trade link generation, using the updated network and node attributes for the next round. When $t=T$, the simulation ended, and changes in China's trade competitiveness were compared across the four scenarios.

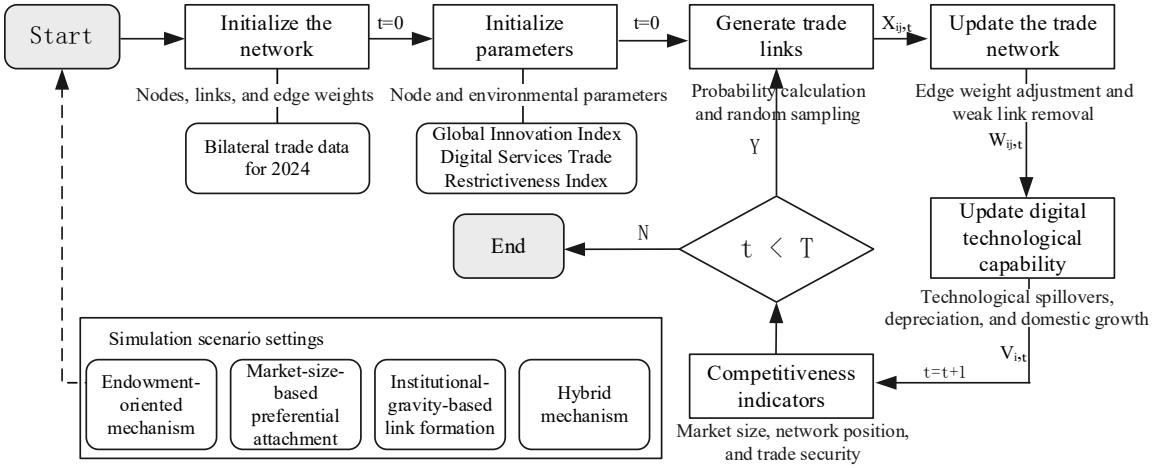


Fig. 6 Simulation procedure

6.2 Historical Backtesting of Link Formation Mechanisms

To assess how well the link formation mechanisms explained actual network evolution, we conducted historical backtesting using bilateral digital services trade data for 2014-2024 and constructed 10 rolling forecasting windows. Each window used the observed network in year t as its baseline and identified candidate edges without existing direct trade links. We calculated link formation probability scores under the endowment-oriented, market-size-based preferential attachment, institutional-gravity-based link formation, and hybrid mechanisms and compared them with actual new links in year $t+1$. Following evaluation frameworks for link prediction in complex networks (Bi et al. 2024; Zhu et al. 2022; Zhu et al. 2023), we selected AUC, precision, lift, and top-k coverage. Table 8 defines these indicators.

Table 8. Evaluation indicators for the digital services trade network evolution model

Indicator	Definition	Formula

Indicator	Definition	Formula
AUC	Measures the overall ability to distinguish and rank actual new edges relative to non-new edges. Values range from 0.5 to 1; values closer to 1 indicate higher predictive accuracy.	$AUC = \frac{n' + 0.5n''}{n}$
Precision	The share of actual new edges among the top L candidates. Higher values indicate greater local precision.	$Precision@L = \frac{M_{hit}}{L}$
Lift	Measures the gain in identification relative to random ranking. The benchmark is 1; larger values indicate more effective identification of high-confidence new edges.	$Lift@L = \frac{Precision@L}{P_{random}}$
Top-k coverage	Measures how well the high-score candidate set captures actual new edges. Values closer to 1 indicate greater concentration of target relationships in the high-score range.	$Coverage = \frac{N_{captured}}{N_{total}}$

These indicators assessed simulation accuracy from complementary perspectives: global discrimination, precision among top-ranked candidates, and concentration in high-score groups. We calculated their means and standard deviations across the 10 rolling windows to reduce random perturbations associated with exogenous macroeconomic shocks in particular years. Table 9 compares the historical backtesting performance of the link formation mechanisms under this evaluation framework.

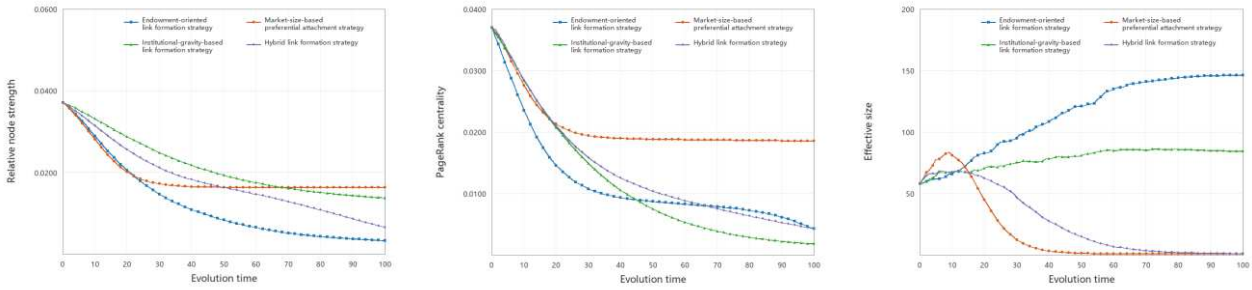
Table 9. Historical backtesting performance of alternative link formation mechanisms

Link formation strategy	Mean AUC	AUC standard deviation	Precision	Lift	Top-10% coverage	Top-20% coverage
Endowment-oriented	0.53	0.06	0.01	1.72	15%	29%
Market-size-based preferential attachment	0.81	0.03	0.05	7.88	40%	61%
Institutional-gravity-based	0.86	0.01	0.08	15.20	57%	76%
Hybrid mechanism	0.89	0.01	0.06	10.57	63%	80%

Table 6-2 shows that all four link formation strategies clearly outperformed the random benchmark of 0.5, indicating that the mechanisms captured the general direction of actual digital services trade network evolution. The hybrid mechanism achieved a mean AUC of 0.89 with a standard deviation of only 0.01, combining strong predictive performance with stability. Among the individual strategies, institutional-gravity-based link formation performed particularly well in identifying high-confidence candidate edges, with precision of 0.08 and lift of 15.20. This indicated a pronounced screening role for the institutional environment in new trade link formation. The hybrid mechanism also showed an overall coverage advantage: the top 10% and top 20% of candidate edges captured 63% and 80% of actual new links, respectively. Actual new edges were therefore relatively concentrated in high-score ranges. We further searched over the three mechanism weights in increments of 0.05. Subject to $w_E + w_S + w_G = 1$, we selected the combination that maximized mean historical backtesting AUC. The resulting weights were w_E 0.05 for the endowment-oriented mechanism, w_S 0.50 for market-size-based preferential attachment, and w_G 0.45 for institutional-gravity-based link formation. These weights determined the hybrid link formation probabilities in subsequent baseline simulations.

6.3 Changes in China's Trade Competitiveness under Alternative Link Formation Strategies

To identify how alternative link formation mechanisms affected the evolution of China's digital services trade competitiveness, we used the 2024 bilateral digital services trade network as the initial state and specified four simulation scenarios: endowment-oriented, market-size-based preferential attachment, institutional-gravity-based link formation, and hybrid. The three individual strategies isolated the influence of each mechanism on China's competitiveness. The hybrid strategy served as the baseline, with weights determined by historical backtesting to approximate the actual trade network formation process more closely. Figure 7 shows changes in China's trade competitiveness under the three strategies. We compared the direction and extent of each individual strategy's deviation from the hybrid strategy to identify their differentiated effects on market size, network position, and trade security.



(a) Market size: relative node strength

(b) Network position: PageRank centrality

(c) Trade security: effective size

Fig. 7 Changes in China's trade competitiveness under three strategies

The three individual link formation strategies deviated from the hybrid baseline in different directions, and their relative advantages varied across stages. Under the endowment-oriented strategy, relative node strength remained below the baseline. Under the current parameters, link formation driven solely by gaps in digital technological capability therefore struggled to translate technological advantages directly into market share advantages. PageRank centrality remained below the baseline in the early and middle stages, exceeded it intermittently in the later stage, and ended slightly below it, showing no sustained advantage. Effective size exceeded the baseline in the middle and later stages, following a different trajectory from trade share. Under institutional-gravity-based link formation, relative node strength remained above the baseline, and effective size exceeded it in the middle and later stages. PageRank centrality, however, remained below the baseline and was the lowest at the end. A higher trade share therefore did not coincide with greater network influence. Relative node strength includes both exports and imports, whereas PageRank also depends on the centrality of incoming partners and their export allocation shares. The two indicators capture different dimensions of competitiveness. Under market-size-based preferential attachment, relative node strength and PageRank centrality remained above the baseline in the middle and later stages. Its relative advantages in trade share and network position gradually

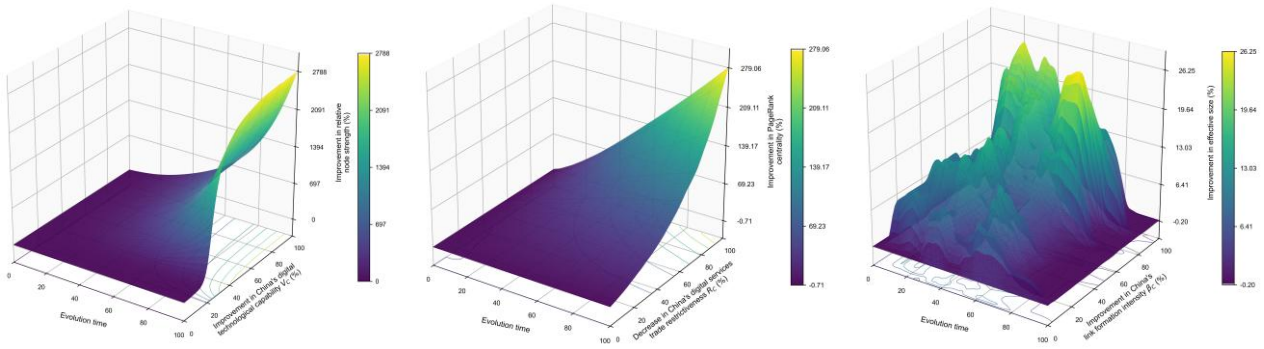
emerged. Effective size initially increased and then declined, falling below the baseline in the middle and later stages. Relative advantages in trade share and centrality thus did not extend to effective size. These results informed the subsequent intervention scenarios for improving China's digital services trade competitiveness, focusing on translating digital technological capability into trade outcomes, reducing institutional constraints, and expanding nonredundant partner connections.

6.4 Testing Intervention Effects on China's Trade Competitiveness

The network assessment for 2010-2025 indicated substantial scope for improving China's market size and network position. Based on the deviations of individual strategies from the hybrid baseline, we specified corresponding pathways for improving the competitiveness of the Chinese node[4]. Under the endowment-oriented strategy, low relative node strength revealed the limitations of expanding trade share solely through technological capability gaps and factor complementarity. We increased digital technological capability V_C to assess its contribution to market expansion. Under institutional-gravity-based link formation, low centrality indicated that institution-led link formation did not generate an advantage in network position. We reduced digital services trade restrictiveness R_C to examine potential improvements in network topology. Under market-size-based preferential attachment, relatively high node strength and centrality coexisted with low effective size, highlighting the distinction between trade concentration and the expansion of nonredundant ties. We increased link formation intensity β_C to examine how nonredundant connections could improve trade security. All three scenarios used the hybrid mechanism as their baseline and adjusted one factor at a time to assess the corresponding improvement pathway.

The simulations used the 2024 digital services trade network as the initial structure and ran for 100 time steps. All indicators initially matched the no-intervention baseline. During initialization, digital services trade restrictiveness R_C was determined by the normalized 2024 restrictiveness index. Baseline digital technological capability V_C was 0.805, and baseline link formation intensity β_C was 1.40. We applied three one-factor-at-a-time interventions: increasing the initial value of V_C, reducing R_C, and increasing β_C. Changes were evenly distributed over the 0 to 100% range. Other parameters followed the previously calibrated hybrid network weights and baseline rules. Improvement was measured as the percentage increase in each indicator relative to the no-intervention baseline at the same time step. Figure 8 shows the evolutionary outcomes.

[4]Only factors related to the Chinese node were changed. Other countries continued to evolve under the hybrid link formation mechanism determined by historical backtesting, allowing potential pathways for improving China's competitiveness in digital services trade to be identified.



(a) Market size (b) Network position (c) Trade security

Fig. 8 Intervention effects on China's digital services trade competitiveness

Figure 8 shows that, under the technological capability intervention, higher digital technological capability progressively widened the advantage in relative node strength over the baseline in the middle and later stages. A 100% increase in digital technological capability yielded an end-period increase of approximately 2838.46%. This increase also reflected the declining trade share in the baseline scenario. Improved technological conditions thus helped generate a relative share advantage. Under reduced institutional constraints, lower digital services trade restrictiveness had a cumulative effect on centrality. When restrictiveness fell to zero, end-period centrality was approximately 282.39% above the baseline. Lower institutional barriers improved the conditions for cross-border trade link formation and helped strengthen the Chinese node's network influence. Under higher link formation intensity, effective size generally increased during some stages and declined later. The maximum relative increase during the simulation was approximately 27.73%. In the later stages, the effects of different intervention levels gradually converged, with end-period deviations from the baseline ranging from approximately -0.10% to 0.09%. More link formation opportunities therefore expanded nonredundant ties during certain stages. Their effectiveness still depended on the new partners and their connection structures. Increasing link formation intensity alone was insufficient to sustain a long-term advantage in effective size.

7 Conclusions and Recommendations

We constructed the global digital services trade network for 2010-2025 to measure China's international competitiveness and used a simulation model of trade-network evolution to examine its formation mechanisms and improvement pathways. The global network exhibited a stable single-core, multicenter structure. China ranked among the world's leading countries in market size, network influence, and trade security, placing 6th, 5th, and 3rd, respectively. As trade scale expanded, network influence and resilience to trade risks also strengthened. Among the link formation mechanisms, the hybrid mechanism combining digital technological capability, market-size-based preferential attachment, and institutional-gravity-based link formation had the greatest explanatory power for trade link formation, with an AUC of 0.89. Institutional-gravity-based link

formation, centered on digital services trade restrictiveness, played a pronounced screening role in new trade link formation. Intervention simulations showed that digital technological capability V_C positively affected market size, with diminishing marginal effects. Reducing trade restrictiveness R_C continuously strengthened China's influence in the international digital services trade network. Higher link formation intensity β_C, however, was not always preferable. Excessive trade link expansion could duplicate cooperation, disperse resources, and accumulate risks, weakening trade security.

The simulations identified China's digital technological capability V_C, digital services trade restrictiveness R_C, and link formation intensity β_C as the main factors affecting its digital services trade competitiveness. Policy interventions can target the dynamic responses of these model parameters through coordinated, in-depth measures along the following dimensions.

First, balance development and security to improve the environment for cross-border digital services trade operations. Firms expanding overseas need to transfer data across borders and provide digital services while complying with national requirements for data security, personal information protection, and important data management. Rules on data flows, privacy protection, electronic signatures, digital payments, and intellectual property protection differ across countries and territories. Firms, particularly small and medium-sized enterprises, often lack sufficient knowledge of applicable rules, compliance procedures, and risk boundaries and face high costs of adapting to institutional requirements. The government should steadily advance international cooperation in digital services trade while safeguarding national data security and rights and interests relating to personal information. Policies can differentiate management by data type, business setting, and risk level. Cross-border procedures should be more efficient for general, low-risk activities. Activities involving personal privacy, important data, and critical infrastructure should remain subject to strict security assessments, authorization management, and necessary data localization requirements. Pilot programs in suitable key regions and sectors can generate replicable regulatory experience. Meanwhile, greater alignment of standard contracts, certification and accreditation, electronic signatures, and dispute settlement rules should be supported by compliance guidance, risk assessment, and professional consulting services for firms. Clearer regulatory boundaries and procedures can reduce the costs of adapting to institutional requirements and support steady digital services trade development on a secure basis.

Second, develop digital technology products around industrial applications to strengthen firms' digital service supply capabilities. In some Chinese digital services trade firms, research and development remain insufficiently connected to market demand. Investment concentrates on

general-purpose platforms and individual technologies, while industry processes in finance, manufacturing, logistics, and healthcare and the needs of overseas customers are not fully translated into product requirements. Whether technological investment generates innovation performance and business returns depends on its integration with business processes, organizational coordination, resource allocation, and specific applications. Firms should bring together technology, marketing, and service teams to develop products for cross-border payments, smart logistics, remote operation and maintenance, and digital marketing. Overseas customers and local partners should participate in requirements validation, testing, and improvement. New solutions should first undergo small-scale trials, with further investment based on customer feedback and service returns. Research and development should be redirected promptly where demand is unclear, functions overlap, or returns are insufficient. Firms should also improve data interfaces, information security, product modularity, and localized operation and maintenance. These measures can improve adaptation to national industry standards and customer needs, supporting the commercialization of technological achievements as digital service products that generate sustainable sales, support reliable delivery, and can be replicated at scale.

Third, pursue targeted international partner development and shift overseas market connections from quantity toward quality. A larger international cooperation network does not necessarily create more opportunities. When partners are highly homogeneous and business channels overlap, firms may gain few new market resources while incurring higher coordination costs and business risk. Given differences in overseas market environments, excessive dependence on a single platform, region, or small group of partners can leave firms vulnerable to channel adjustments, policy changes, and market fluctuations. Firms should select partners according to customer demand, institutional environments, and service conditions in different markets. Priority should go to partners offering new channels, technical support, and local resources. Backup arrangements for critical activities should be incorporated into internationalization plans. Firms can maintain partner registers recording new customers, order revenue, payment collection, technical support, local resources, compliance capabilities, and replacement difficulty. The head of international business should lead quarterly or semiannual reviews involving sales, finance, legal, and delivery departments. Through dynamic assessment and differentiated governance, firms can concentrate limited resources on markets with sustained demand and partner complementarity, building a stable, diversified international cooperation system that continues to create market opportunities.

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