



Comprehensive assessment of the performance of major ports in China

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Abstract

Against China's drive to build world-class ports, and addressing the issue of the separation of competitiveness and network attributes in existing research, this study targets major Chinese ports to construct an integrated evaluation framework. To that effect, port connectivity is measured using four standard network centrality indicators: degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Connectivity and competitiveness are evaluated, with competitiveness covering infrastructure, productivity and the economic environment, to identify performance gaps and provide differentiated improvement paths. The results show Shanghai, Ningbo, Shenzhen, and Guangzhou being in the first tier, with connectivity and competitiveness as the core factors influencing port performance. The findings suggest that hub ports should prioritize the growth of international direct routes, while other major ports should strengthen weak infrastructure and pursue differentiated quality upgrading. Local port and maritime authorities are advised to allocate resources based on tiered differentiation, in order to avoid homogeneous competition and the waste of scarce resources. By integrating connectivity and competitiveness into a unified framework, this study offers a more holistic approach to port performance evaluation.

Keywords Port performance · Port connectivity · Port competitiveness · Entropy–TOPSIS method · Social network analysis · Spearman correlation coefficient

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1 Introduction

As a strategic pivot for the economic and social development of hinterlands, the port is an important node connecting inland and maritime transport networks. According to the *Guideline to Build World-class Ports* (Ministry of Transport of China et al. 2019), China aimed to achieve breakthroughs in the green, smart, and safe development of major ports by 2025, with enhanced scale at regional and other ports. By 2035, major ports should achieve world-class performance in terms of green and smart development, setting a global benchmark. By 2050, several world-class port clusters should have been formed.¹ Under the influence of this guideline, Chinese ports handled approximately 15.5 billion tons of cargo in 2021, and China occupied seven of the top ten ports globally in terms of throughput.

Figure 1 shows the Hirschman–Herfindahl Index (HHI) and Gini coefficient for 15 major coastal ports in China from 2012 to 2021. The HHI ranges from $1/n$ to 1 ($n=15$), with higher values indicating greater market concentration. The Gini coefficient ranges from 0 to 1, with larger values indicating greater imbalance. These two indices focus on coastal ports, indirectly reflecting market competition (the below network and comprehensive evaluation use 19 major ports² for a fuller analysis). Both indices declined to very low levels in 2017 and 2018, then increased from 2019, surpassing 0.1 and 0.4, respectively. Throughput distribution became increasingly

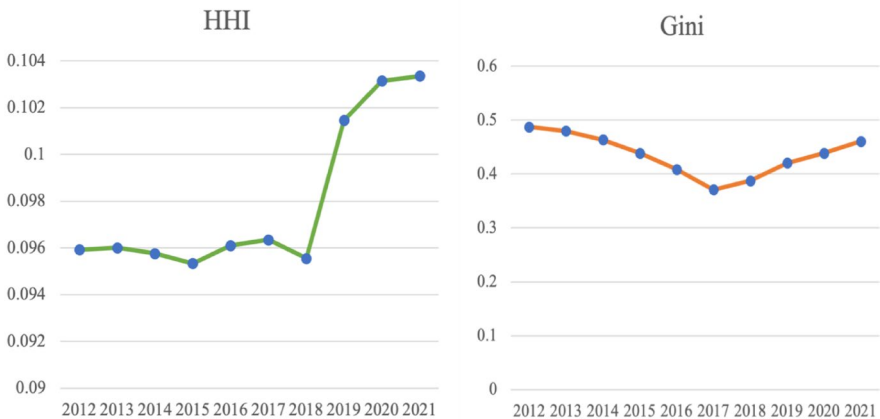


Fig. 1 Concentration at major Chinese ports. Source: Collection of cargo throughput at major ports in the China Statistical Yearbook and calculations to obtain the annual values of the HHI and Gini

¹ Ministry of Transport: https://www.mot.gov.cn/zhengcejiedu/gjssjylgk_zdyj/xiangguanzhengce/201911/t20191113_3430361.htm.

² Major ports refer to the ports included in the national list of major ports (Outline for the Planning of the National Comprehensive Stereo-dimensional Transportation Network). Based on data availability, 19 ports were selected for this study. The 19 ports are Dalian, Fangchenggang, Fuzhou, Guangzhou, Lianyungang, Nanjing, Nantong, Ningbo, Qingdao, Qinhuangdao, Shanghai, Shantou, Shenzhen, Tianjin, Wenzhou, Xiamen, Yantai, Yingkou, Zhanjiang. Since route data are available only for Ningbo Port and not for Zhoushan Port, the infrastructure and productivity data are based on the Ningbo Port section of Ningbo–Zhoushan Port.



concentrated in a few leading ports such as Shanghai and Ningbo-Zhoushan, indicating an oligopolistic market structure.

Improving the development of Chinese ports and building world-class ports requires clarifying their roles and positions within the overall port system and determining their functional positioning and development priorities. Compared to the use of one or two only specific indicators, such as the HHI and Gini coefficient, a comprehensive evaluation method can better assess the positions of individual ports from a global perspective.

Existing literature mainly adopts two approaches to port evaluation. The first focuses on internal conditions and assesses factors such as production capacity and hinterland economy (De Martino and Morvillo 2008; Yeo et al. 2008; Kim 2016). The second evaluates port position within maritime networks (Wang and Cullinane 2016; Kang and Woo 2017; Lu et al. 2018). The first approach measures port strength from an absolute perspective but neglects synergies and competitive relationships within global shipping networks (Nguyen and Woo 2022). The second evaluates port location from a relative perspective but ignores ports' ability to leverage network advantages based on their own functions (Wiegman et al. 2008).

A separate application of the two approaches makes it difficult to reveal the drivers of port performance. It cannot explain, for instance, why ports with similar resource endowments and operational conditions show different performance because of differences in network status, nor why some ports with high network status fail to realize their performance potential (Lu et al. 2018). This separation reduces the practical implications of existing research on port development and management (Yap and Ho 2023). Therefore, this study aims to overcome this limitation by developing an evaluation framework that integrates port attributes such as resource endowments and operational conditions with network status.

Research on port performance encompasses multiple aspects. This study examines port performance primarily from two perspectives: competitiveness and shipping networks. In the existing literature, the definitions of port performance and port competitiveness are often ambiguous. Some scholars define port competitiveness as a port's ability to obtain obvious advantages, over and above other ports, in terms of comprehensive shipping services, cargo throughput, core values, and regional growth, by optimizing port resource allocation and integration of supply chain resources (Parola et al. 2017; Yu et al. 2025). Notteboom and Yap (2012) argued that port competitiveness refers to a port's ability to attract various production and shipping factors based on its geographical conditions, terminal facilities and hinterland economy, achieving comparative advantage in the transport market, developing value-added logistics, and maintaining sustainable development. In our study, port competitiveness refers to a port's comparative advantage in transport, value-added logistics, and sustainable development, derived from its geographic conditions, infrastructure endowment, and hinterland economic development. Port performance refers here to a port's comprehensive capacity to achieve its strategic objectives, including network connectivity, infrastructure conditions, operational efficiency, and hinterland economy. In short, port performance is jointly determined by port competitiveness and port network connectivity.



Against this background, this study uses the entropy–TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method to evaluate and rank major ports in China, with the aim of identifying their performance gaps and competitive advantages. By adopting a shipping network perspective, the study constructs a port performance evaluation system that includes connectivity, infrastructure, productivity, and economic environment. Port connectivity is measured using social network analysis (SNA). This network perspective complements the HHI analysis of market concentration and helps reveal the structural evolution of the port system.

The remainder of this study is organised as follows. Section 2 reviews the port performance literature and identifies research directions. Section 3 describes the methods, data sources, and indicator selection. Section 4 presents the empirical analysis and identifies port performance rankings and influencing factors. Section 5 presents the main conclusions.

2 Literature review

Research on port competitiveness emerged in the 1960s and became prominent in academic and industrial fields after the 1980s (Heaver 1995). Relevant studies have gradually formed two main branches. The first focuses on the quantitative ranking of port competitiveness, primarily through constructing indicator systems to differentiate performance levels. Some scholars have integrated multi-dimensional data, including port operations, spatial capacity, and mainline route layouts, to analyze the dynamics of hub port competitiveness (Tai and Hwang 2005), while others have combined the TOPSIS method with k-means clustering to rank the competitiveness of Southeast Asian ports (Nguyen and Woo 2022).

The second branch focuses on identifying influencing factors of port competitiveness, with their research scope expanding from the port itself to the container shipping market and liner shipping network. Studies have examined factor impacts on port competitiveness, including hinterland overlaps (Hoare 1986), service efficiency (Bird and Bland 1988), resource integration capability (Gordon et al. 2005), and changes in the maritime industry (Parola et al. 2017). Subsequent research has further deepened this analysis from the perspective of shipping companies, revealing the influence of market demand on port competitiveness (Kaliszewski et al. 2020).

With the increasing integration of the global shipping network, the network attributes of ports have become key variables affecting performance. Such research can be divided into two streams. The first involves evolutionary analysis of port concentration (Nguyen et al. 2020; Theodore 2019). The second focuses on measuring port connectivity based on SNA, which has become the mainstream research paradigm. Some works have developed analytical frameworks that consider the directionality and weighting characteristics of maritime networks, verifying the effectiveness of network indicators in measuring port connectivity (Wang and Cullinane 2016). Subsequent studies expanded the application of SNA and explored the mechanisms underlying the relationship between network attributes and port development. More recent research has confirmed a significant correlation between port throughput and network centrality (Kang and Woo 2017). It has also been found that the throughput



of small and medium-sized ports is highly dependent on network linkages with surrounding hub ports (Lu et al. 2018). Another study has analyzed regional imbalances in global shipping networks, revealing differentiated development patterns between core and peripheral regions (Xu et al. 2015).

Although these two research streams have advanced understanding of port performance from the perspectives of competitiveness and shipping networks, they have largely remained separate, creating a clear research gap. Competitiveness studies focus on internal attributes and hinterland conditions without situating ports within the global shipping network, thus failing to explain why some ports with strong infrastructure and operational capacity underperform. Shipping network research emphasises the network position of ports, while neglecting the role of internal competitiveness in transforming network advantages, preventing a full explanation of port performance mechanisms. Even studies applying the TOPSIS method for comprehensive ranking rarely incorporate network connectivity, resulting in evaluations that fail to balance internal functional strength with external network advantages. This separation limits the explanatory power and practical value of existing research.

To address these limitations, this study draws on SNA-based approaches to construct a port connectivity evaluation framework (Wang and Cullinane 2016; Kang and Woo 2017). It also adopts economic environment, productivity, and infrastructure as traditional competitiveness indicators based on existing studies (Chang et al. 2008; De Martino and Morvillo 2008; Wiegman et al. 2008; Yeo et al. 2008; Kim 2016; Wang et al. 2023). The entropy weight method is used to assign objective weights to connectivity and competitiveness indicators, combined with the TOPSIS method, to integrate multi-dimensional indicators and generate a comprehensive ranking of port performance. This integrated design reveals more clearly the core driving mechanisms of port performance and provides a stronger theoretical basis for differentiated port development strategies. Table 1 summarises the literature on port performance from the perspectives of competitiveness and shipping networks.

3 Methodology and data

3.1 Data

In 2021, the Communist Party of China Central Committee and the State Council issued the *Outline for the Planning of the National Comprehensive Stereo-dimensional Transportation Network*, listing 27 major coastal ports. Based on data availability, 19 ports were selected for this study.

The port-routes data (including port calls, route frequency and port connections) were obtained from the China Port Network.³ That platform covers 90 shipping companies worldwide (including the world's top 20), more than 90,000 logistics companies, over 300,000 basic ship records, and more than 100,000 detailed professional ship records, making it China's most comprehensive logistics information and port business platform. We collected data on 18,369 routes across 24 major global routes.

³ <http://www.chinaports.com>.



Table 1 Survey of the existing literature on port performance from the perspectives of competitiveness and shipping networks

Categories	Study	Results
Port competitive- ness perspective	Hoare (1986)	Competition between ports is based on overlapping hinterlands.
	Bird and Bland (1988)	Port service efficiency is a primary concern for freight forwarders in selected ports.
	Gordon et al. (2005)	This study observes the continued competitive advantage of ports arising from resource consolidation.
	Tai and Hwang (2005)	East Asia and North America account for the largest container flows in the global liner shipping market. Competition exists among hub ports in the region.
	Parola et al. (2017)	This study argues that port competitiveness and its drivers are significantly affected by major changes in the maritime industry.
	Kaliszewski et al. (2020)	This study complements the findings of other competitiveness studies by examining the perceptions of decision-makers in shipping companies.
	Nguyen and Woo (2022)	Southeast Asian ports are divided into three groups. Ports in Groups 2 and 3 may be able to improve competitiveness by developing cargo-handling facilities and infrastructure.
	Baştuğ et al. (2022)	According to port operators, the factors that are important to port competitiveness are not necessarily equally important to shipping companies when choosing ports.
Port shipping network perspective	Xu et al. (2015)	This study shows that indicators in network analysis can provide a more nuanced understanding of port area development than measures based solely on total traffic volume.
	Wang and Cul- linane (2016)	This study indicates that foreland market coverage has a particularly strong impact on port demand and closeness centrality.
	Kang and Woo (2017)	Port throughput is influenced by macroeconomic, infrastructure, and port network factors.
	Lu et al. (2018)	The throughput of small and medium-sized ports is closely related to the connectivity of surrounding hubs.
	Theodore (2019)	Ports in the U.S. have evolved from dispersed to highly concentrated and then to moderately concentrated port ranges.
	Nguyen et al. (2020)	Singapore is the busiest container port in the region, but the emergence of other container ports in neighbouring countries threatens its premier position.

Ports of departure and destination serve as the main starting and ending points of cargo and service flows and key gateway nodes in shipping networks, where unloading and modal transfer occur; they are therefore the focus of this study. Ports of call are intermediate points and do not function as transfer hubs. Accordingly, route frequency provides a realistic benchmark for evaluating the intermediary function of port nodes. Based on this rationale, traffic flows between China's major ports and major global ports in 2021 were determined.⁴

⁴ Ports with multiple port areas, such as Shekou Port, Chiwan Port, and Yantian Port in Shenzhen, are collectively referred to as Shenzhen Port.



3.2 Entropy–TOPSIS

TOPSIS ranks the objects to be evaluated according to their similarity to an ideal optimal value. These solutions include the positive ideal solution and the negative one. In complex networks, node importance evaluation becomes an integrated decision-making problem when each node is treated as a research scheme and its importance is treated as a scheme attribute.

The entropy weight method determines weights based on the amount of information reflected in the degree of variation in each evaluation index. Entropy-weighted TOPSIS uses the entropy assignment method to determine the weight of each index in multi-attribute decision-making. This study uses the entropy–TOPSIS method to rank China's major ports in the maritime transport network. Entropy weight theory is applied to determine the centrality weights of ports within this network and to derive the comprehensive ranking of the influence of each type of centrality on decision-making. This method overcomes the one-sided and inadequate ranking based on single indicators.

We use the Entropy–TOPSIS method for integrated evaluation (Shih et al. 2007). Detailed calculation procedures are provided in the Appendix 1.

3.3 Social network analysis (SNA)

Commonly used node centrality indices include degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Degree centrality considers the near neighbours of nodes and analyses the degree of centredness of the nodes in the network. Closeness centrality is a central index, and betweenness centrality is based on the nodes in the path analysis network. Finally, eigenvector centrality is a central index that considers the number and quality of neighbouring nodes. (Freeman 1978; Woo 2013; Kang and Woo 2017). Detailed definitions and interpretations of these centrality measures in the shipping network are provided in Appendix 2.

3.4 Indicator system and selection

The *Guideline to Build World-class Ports* emphasizes promoting the integration of industry, cities, and ports and creating comprehensive hub ports with advanced facilities and high economic efficiency. To identify core evaluation indicators of port performance, this study reviewed literature in port economics using keywords such as 'port performance evaluation', 'port performance', and 'port efficiency'. The selected studies present clear indicator systems and cover East Asian and global ports, ensuring representativeness. Statistical analysis indicated that connectivity, infrastructure, productivity, and economic environment are the most frequently used dimensions. Secondary indicators, including degree centrality, number of berths, cargo throughput, and city GDP, have been repeatedly validated in empirical studies and are therefore selected as initial indicators to ensure academic universality. Unlike Wiegman et al. (2008) and Kim (2016), who apply broad connectivity concepts or single centrality measures, this study incorporates four SNA indicators: degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality (Chen et al.



2020). Combined with the characteristics of China's port network, these indicators capture node importance, accessibility, resource control capability, and core correlation within the maritime network, enriching connectivity evaluation.

Due to fragmented public data on indicators such as average berth depth and number of international routes proposed by Yeo et al. (2008) and De Martino and Morvillo (2008), unavailable indicators are excluded. The economic environment dimension, measured by city GDP, the contribution rate of the tertiary industry and total import and export volumes, address the limitation of studies relying solely on city GDP to represent hinterland conditions (Kaliszewski et al. 2020). The contribution rate of the tertiary industry is added to better reflect industrial linkages between ports and cities, balancing academic universality and data operability. Unlike Wiegman et al. (2008), who emphasize common global indicators, thus overlooking the Chinese context, this study adapts consensus indicators to Chinese data. The resulting indicator system adopts a four-dimensional framework—connectivity, infrastructure, productivity, and economic environment, while supporting empirical comparison of Chinese port performance and avoiding incompatibility with international indicators. The comprehensive port capacity evaluation indicator system is shown in Table 2, ensuring both academic universality and empirical operability for Chinese ports.

In connectivity, degree centrality determines the breadth of cargo flow access, closeness centrality affects transit time efficiency costs, betweenness centrality relates to transit revenue, and eigenvector centrality helps attract high-quality cargo flow, collectively forming the external network support for port performance. In infrastructure, the number of berths and quay length are both included as separate indicators: the number of berths ensures the reception of vessels and the handling of cargo volumes, while the length of the quay line supports operational efficiency, forming the hardware foundation for port performance implementation. In productivity, the throughput of goods and containers directly reflects the scale of operations and income level, and their year-on-year growth rate indicates the potential for operational growth, which is the core output indicator of port performance. Although the shipping network is based on liner container routes, port performance is measured by total cargo throughput (container and bulk cargo) to reflect each port's actual overall operation. In the economic environment, GDP provides the foundation for local freight flow; the contribution of the value of the tertiary sector to the city's GDP enhances service added value; and the total value of imports and exports supports international freight flows, offering stable hinterland support for port performance. These indicators address performance evaluation needs across multiple dimensions.

This study uses complete data from 19 major coastal ports in China for 2021. Descriptive statistics are presented in Table 3. In terms of connectivity, the average degree centrality of ports reaches 29.05. The distribution is extremely wide. The highest value, 111, is approximately 100 times the lowest value, 1. Combined with differences in closeness centrality, this shows a clear hierarchical structure in the shipping network, whereby hub ports hold a more central position than other major ports. This helps to identify key nodes for port development and resource allocation. Infrastructure data further confirm this pattern. The total number of berths ranges from more than 1,000 to fewer than 40, and 10,000-ton-class berths (berths capable of accommodating large vessels of 10,000 deadweight tons and above) and quay length



Table 2 Port integrated capacity index system

Primary indicators	Secondary indicators	Data sources	References
Connectivity	Degree centrality	China Port Network	Yeo et al. (2008), Wiegmans et al. (2008), Kim (2016)
	Closeness centrality		
	Betweenness centrality		
	Eigenvector centrality		
	Infrastructure	China Ports Yearbooks, China Statistical Yearbooks, China City Statistical Yearbooks, local government statistical yearbooks, statistical bulletins	Wiegmans et al. (2008), De Martino and Morvillo (2008), Kim (2016)
	Productivity	China Ports Yearbooks, China Statistical Yearbooks, China City Statistical Yearbooks	Yeo et al. (2008), De Martino and Morvillo (2008), Chang et al. (2008), Kim (2016), Kang and Woo (2017), Wan et al. (2022)
	Economic environment	China City Statistical Yearbooks	Kang and Woo (2017), Wang et al. (2023)
			Yeo et al. (2008)

Port connectivity is calculated using a social network analysis model

TEU: twenty-foot equivalent unit

show similar concentration trends. These findings indicate that hub ports possess larger-scale infrastructure, which supports higher shipping connectivity and greater handling capacity. Most ports maintain stable production. The average growth rate of cargo throughput is 6.65%. Port cities exhibit a strong economic base. The average GDP provides sufficient freight demand, while the tertiary industry (service sector) accounts for more than 54% of GDP. A high share of services indicates more developed logistics, finance and trade, which help support port operations. Total import and export volume is large, implying substantial cross-border cargo flows that underpin



Table 3 Descriptive statistics

Variables	<i>N</i>	Mean	SD	Min	Max
Degree centrality	19	29.05	31.67	1	111
Closeness centrality	19	0.303	0.0844	0	0.398
Betweenness centrality	19	0.0109	0.0230	0	0.0952
Eigenvector centrality	19	0.277	0.240	0.000909	0.747
Number of berths	19	250.1	245.1	37	1,037
Number of productive-use berths	19	198	152.8	37	619
Number of 10,000-ton-class berths	19	81.26	48.36	14	198
Length of quay line	19	36,485	26,672	6,029	109,151
Length of productive-use quay line	19	32,882	21,812	6,029	98,307
Cargo throughput	19	34,000	19,436	4,138	69,827
Container throughput	19	1,145	1,342	64	4,703
Cargo throughput year-on-year growth	19	0.0665	0.0707	−0.0553	0.235
Container throughput year-on-year growth	19	0.0526	0.109	−0.282	0.283
City GDP	19	12,164	11,288	815.9	43,653
Contribution of the tertiary sector to city GDP	19	0.544	0.0951	0.365	0.733
Total value of imports and exports	19	8,044	11,223	401.1	40,610

port throughput. This economic structure supports stable cargo demand and efficient shipping services and thus matches the requirements of modern port development.

4 Results analysis

4.1 Social network analysis results

Data on 18,369 routes from 601 ports were collected to map the global port-shipping network (Fig. 2). The existence of a directional line between ports A and B indicates a route. Line thickness is proportional to the number of shipping routes; thicker lines indicate a higher number of routes. The size and colour depth of the network nodes are proportional to the degree centrality of the port. Larger nodes and deeper colours indicate higher port degree centrality.

As shown in Fig. 2, the ports of Shanghai, Shenzhen, Ningbo, Qingdao, Xiamen, Tianjin, and Dalian are prominent, indicating their high global network centrality.

To describe the network characteristics of Chinese ports in detail, degree, closeness, betweenness, and eigenvector centrality values are shown in Table 4.



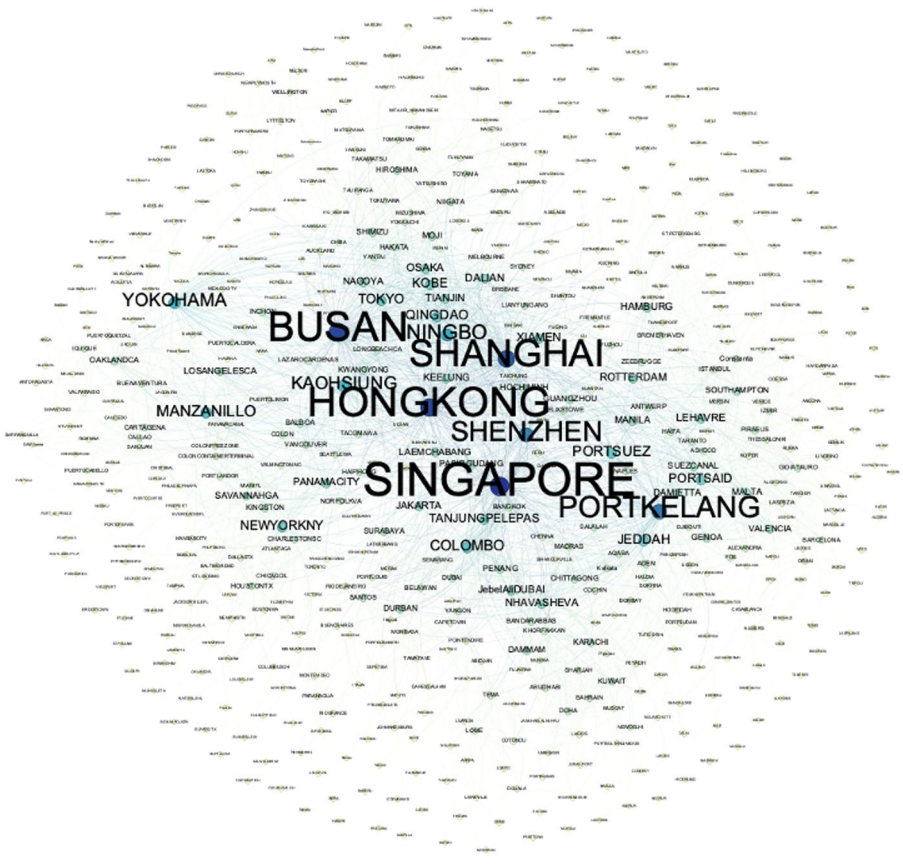


Fig. 2 Global port shipping network. Source: Authors, based on UNCTAD (<https://unctadstat.unctad.org/datacentre/dataviewer/US.PLSCI>). Software: Gephi

4.1.1 Degree centrality

As shown in Columns (1)– (3) of Table 4, Shanghai (111) has the largest degree in the analysis of degree centrality, indicating that the largest number of ports are connected to Shanghai. Shanghai (111), Shenzhen (89), Ningbo (70), Qingdao (48), and Xiamen (42), the five most central ports by degree, are much larger than their in-degree counterparts. The larger the difference between the out-degree and in-degree, the greater the trade imbalance on the route.

4.1.2 Closeness centrality

As shown in Column (4) of Table 4, the ports with high closeness centrality are again Shanghai, Shenzhen, Ningbo, Qingdao, and Xiamen, consistent with degree centrality. These ports are important hubs in China’s port network. In general, port closeness centrality values do not vary significantly, and all ports have strong spatial advantages in shipping networks.



Table 4 The network characteristics of major Chinese ports

	In-degree	Out-degree	Degree	Closeness centrality	Betweenness centrality	Eigen-vector centrality
Dalian	12	27	39	0.340353	0.004715	0.322760
Fangchenggang	2	3	5	0.290010	0.001445	0.071626
Fuzhou	7	8	15	0.315901	0.001691	0.180564
Guangzhou	15	13	28	0.320643	0.004564	0.527485
Lianyungang	8	11	19	0.321678	0.000334	0.220305
Nanjing	2	3	5	0.285988	0.004323	0.074333
Nantong	1	1	2	0.244082	0.000008	0.000909
Ningbo	25	45	70	0.371891	0.028222	0.554702
Qingdao	17	31	48	0.352802	0.011248	0.462005
Qinhuangdao	1	1	2	0.252108	0	0.018578
Shanghai	31	80	111	0.398401	0.095208	0.747334
Shantou	7	4	11	0.303399	0.001656	0.218333
Shenzhen	23	66	89	0.395503	0.041036	0.665624
Tianjin	22	16	38	0.336712	0.007968	0.464494
Wenzhou	2	2	4	0.293857	0	0.094251
Xiamen	16	26	42	0.340547	0.004255	0.449150
Yantai	6	12	18	0.306196	0.000969	0.133507
Yingkou	2	3	5	0.286811	0	0.045490
Zhanjiang	1	0	1	0	0	0.004445

4.1.3 Betweenness centrality

As shown in Column (5) of Table 4, Shanghai has the largest betweenness centrality and differs significantly from Shenzhen, which ranks second. Shanghai is an important transportation hub in the shipping network with strong cargo transit capability. Shanghai, Shenzhen, Ningbo, Qingdao, and Tianjin are the top five ports by betweenness centrality. The betweenness centrality of four ports in the network is 0, indicating significant differences in betweenness capacity and uneven development of maritime transport networks.

4.1.4 Eigenvector centrality

As shown in Column (6) of Table 4, Shanghai has the highest eigenvector centrality, followed by Shenzhen, Ningbo, Guangzhou, and Tianjin, indicating that these five ports are linked to many high-scoring ports. Shanghai, Shenzhen, and Ningbo rank among the top three for degree, closeness, betweenness, and eigenvector centrality. This demonstrates the importance of these three ports, which are stable transport hubs in China.

4.2 Results of Entropy-TOPSIS analysis

First, the index weights of the measurement index system are calculated using the entropy method (Eq. 1), and the results are presented in Table 5. Port connectivity indicators are heavily weighted, except for closeness centrality, particularly between-



Table 5 Indicator weights

Indicator	Entropy value	Variability index	Weight (%)
Degree	0.809	0.191	8.872
Closeness centrality	0.979	0.021	0.986
Betweenness centrality	0.581	0.419	19.433
Eigenvector centrality	0.865	0.135	6.269
Number of berths	0.846	0.154	7.131
Number of productive-use berths	0.883	0.117	5.418
Number of 10,000-ton-class berths	0.917	0.083	3.855
Length of quay line	0.898	0.102	4.711
Length of productive-use quay line	0.909	0.091	4.226
Cargo throughput	0.926	0.074	3.433
Container throughput	0.77	0.23	10.657
Cargo throughput year-on-year growth	0.941	0.059	2.733
Container throughput year-on-year growth	0.975	0.025	1.178
City GDP	0.854	0.146	6.77
Contribution of the tertiary sector to city GDP	0.948	0.052	2.409
Total value of imports and exports	0.743	0.257	11.919

ness centrality, which has the highest weight (19.433%). This indicates the need for ports to prioritize increased navigational capacity to enhance integrated capacity.

Then, using the TOPSIS method, a weighted normalisation matrix is constructed using indicator weights and raw data to determine the positive and negative ideal solutions. The Euclidean distances of the positive and negative ideal solutions and the comprehensive capability measurement values of each port are calculated, as shown in Table 6.

We divide all ports into three groups based on the entropy-TOPSIS results. Group 1 scores above 0.4 and includes Shanghai, Ningbo, Shenzhen, and Guangzhou. The ports in this group are located in highly developed socio-economic areas; growth of urban trade has promoted port operations, integration has been effective, and infrastructure and turnover capacity are strong. Group 2 scores 0.25–0.4 and includes Tianjin, Qingdao, Xiamen, and Dalian. Most ports in this group are in Tier 2 cities or areas with average economic development. The ports are modest in size but perform extremely well in specific aspects, such as Tianjin, where the country's first fully automated docks were built. Group 3 scores below 0.25 and includes Yantai, Fuzhou, Nanjing, Lianyungang, Fangchenggang, Shantou, Nantong, Wenzhou, Zhanjiang, Yingkou, and Qinhuangdao. These ports are mostly located in less developed areas, are relatively small, and have limited functions.

In the first group, Shanghai recorded a container throughput of 47.033 million TEU in 2021, ranking globally as the first major hub port for 12th consecutive years. With a comprehensive score of 0.897, Shanghai significantly surpasses Ningbo (0.599), which ranks second, possibly owing to its large throughput capacity and highly connected maritime routes. Ningbo completed its merger with Zhoushan Port



Table 6 Comprehensive ranking results of port performance based on entropy–TOPSIS

	Distance to the best solution (D+)	Distance to the worst solution (D-)	Comprehensive score	Ranking
Shanghai	0.1142565	0.9689792	0.8945230	1
Ningbo	0.5022173	0.6321551	0.5572730	2
Shenzhen	0.5235099	0.5953316	0.5320965	3
Guangzhou	0.6628156	0.4529797	0.4059703	4
Tianjin	0.7001924	0.3823913	0.3532210	5
Qingdao	0.7088714	0.3859741	0.3525375	6
Xiamen	0.7654445	0.3070370	0.2862866	7
Dalian	0.8003093	0.2775821	0.2575232	8
Yantai	0.8245403	0.2599313	0.2396847	9
Fuzhou	0.8431924	0.2307704	0.2148775	10
Nanjing	0.8496955	0.2127526	0.2002475	11
Lianyungang	0.9129056	0.2246912	0.1975139	12
Fangchenggang	0.9343735	0.2186211	0.1896116	13
Shantou	0.8805355	0.2009324	0.1857960	14
Nantong	0.8890286	0.1949375	0.1798373	15
Wenzhou	0.9126637	0.1627124	0.1513074	16
Zhanjiang	0.9232653	0.1594071	0.1472349	17
Yingkou	0.9273500	0.1322138	0.1247813	18
Qinhuangdao	0.9437048	0.1308487	0.1217703	19

in 2015, achieving integration in comprehensive port planning, in terms of infrastructure construction, development of key port areas, maritime shipping services, and port supervision. Ningbo has a high infrastructure score, making it a crucial hub for cargo transit in China. Shenzhen and Guangzhou, the two major container ports in the Pearl River Delta port cluster, are important for regional economic development and foreign trade. Shenzhen, located in the Guangdong Province, is one of the most important ports in the South China Sea region and is approximately 40 km from Hong Kong. The port is among the first ones opening to the outside world and one of China's largest foreign trade ports. Guangzhou is also an important transportation hub in the Pearl River Delta, approximately 120 km from Hong Kong, connecting South China with the central and western regions. Shenzhen's locational advantages are more pronounced because of its proximity to Hong Kong and the Pearl River Delta, enabling stronger connectivity between mainland China and global markets. Therefore, Shenzhen's connectivity is higher than Guangzhou's, whereas the latter has higher throughput and infrastructure levels.

The four ports in the second group are comparable. Qingdao has low berth capacity but high throughput, which may be attributed to its average channel depth of 12.3 m and berth depth of 15 m, making it a rare deep-water harbour in China and globally. Qingdao is the core hub of Shandong Port Group (Qingdao, Rizhao, Yantai, in the Bohai Bay Port Group). The 2023 HHI of the group is 0.3209, indicating moderate concentration. Qingdao is China's largest container, crude oil, iron ore, and coal port, as well as a bulk grain-handling terminal. Although it has fewer berths, their utilisation rate is high. Each port should focus on what it does best. Qingdao can build on its deep-water hub capabilities and efficient bulk cargo handling. Tianjin is well-



positioned to concentrate on comprehensive logistics and strong hinterland links. Dalian can leverage its location to grow international transshipment and regional connectivity in Northeast Asia. Xiamen is a natural fit for trade-oriented shipping and regional feeder services. With clear functional roles, these ports can operate more efficiently and better coordinate with others in their regions.

The overall comprehensive capacity and individual indicator scores of the third group are generally low, especially for Yingkou and Qinhuangdao, both of which belonging to the Bohai Bay Port Group. The top two ports in the comprehensive ranking are located in the Yangtze River Delta, the third and fourth in the Pearl River Delta, and the fifth and sixth in Bohai Bay. This indicates that Chinese port groups are ranked, in general, as the Yangtze River Delta port group, followed by the Pearl River Delta port group and the Bohai Rim port group. Their development requires targeted measures, such as regional network integration or niche market development, supported by specific policies.

4.3 Results analysis

This section analyzes port performance by comparing the dual perspectives of network connectivity and traditional competitiveness.

4.3.1 The primacy of connectivity

Spearman correlation analysis (Table 7) shows that port connectivity has the strongest positive correlation (0.911) with the overall TOPSIS ranking, exceeding correlations with infrastructure (0.895), economic environment (0.823), and productivity

Table 7 Comparison of primary and composite index rankings at each port

	Connectivity	Infrastructure	Productivity	Economic environment	TOPSIS ranking
Shanghai	1	1	1	1	1
Ningbo	3	2	2	7	2
Shenzhen	2	8	5	2	3
Guangzhou	7	3	4	3	4
Tianjin	5	5	6	4	5
Qingdao	4	9	3	6	6
Xiamen	6	7	9	8	7
Dalian	8	4	17	12	8
Yantai	12	6	10	11	9
Fuzhou	13	11	14	5	10
Nanjing	11	10	15	9	11
Lianyungang	15	13	7	19	12
Fangchenggang	10	19	8	15	13
Shantou	9	15	11	16	14
Nantong	18	12	12	13	15
Wenzhou	14	16	18	10	16
Zhanjiang	19	14	13	18	17
Yingkou	16	17	19	17	18
Qinhuangdao	17	18	16	14	19



(0.798). These findings indicate that a port’s position in the shipping network is a more decisive factor for overall performance than any single aspect of internal competitiveness. Ports with high connectivity can attract more vessels (Kang and Woo 2017). While productivity directly reflects operational effectiveness, if port connectivity is insufficient or infrastructure is lagging, sustaining performance improvement will be difficult, even if goods are attracted in the short term through price discounts.

4.3.2 Synergies and mismatches in performance

A comparison of dimensional rankings (Table 8) reveals distinct patterns in how connectivity interacts with competitiveness. Shanghai represents a case of full synergy, ranking first in both connectivity and all three competitiveness dimensions. Its top network position, evidenced by a degree centrality of 111, is matched by leading infrastructure, productivity, and economic environment (Table 8), creating a self-reinforcing cycle of high performance. In contrast, Shenzhen shows a significant mismatch. The port ranks second in connectivity but only eighth in infrastructure, particularly in berth numbers (Table 9). Thus, its strong network position may be constrained by physical capacity limitations, potentially explaining why its overall performance slightly trails that of Ningbo. Qingdao demonstrates how operational efficiency can compensate for scale. Despite a middling infrastructure ranking (ninth), it achieves high productivity (third), supported by solid connectivity (fourth). This is attributed to its deep-water advantages and high asset utilization. Lianyungang illustrates how regional ports can excel in specific areas. Although the port’s overall rank is 12th, it leads in cargo and container throughput growth rates (Table 9). This shows that ports can achieve strong performance in particular competitiveness metrics, such as growth, by effectively serving niche or local markets, even without central network connectivity.

4.4 Regression analysis: drivers of port performance

To quantitatively verify the driving forces of port connectivity and competitiveness on comprehensive performance, this section constructs a robust Ordinary Least Squares (OLS) regression model. The entropy-TOPSIS comprehensive score is used as the dependent variable, while the core explanatory variables include port connectivity and competitiveness. Control variables include the number of 10,000-ton-class

Table 8 Spearman correlation coefficients

	Connectivity	Infrastructure	Productivity	Economic environment	TOPSIS ranking
Connectivity	1	0.716	0.735	0.765	0.911
Infrastructure	0.716	1	0.600	0.719	0.895
Productivity	0.735	0.600	1	0.554	0.798
Economic environment	0.765	0.719	0.554	1	0.823
TOPSIS ranking	0.911	0.895	0.798	0.823	1



Table 9 Individual index rankings

	Degree	Closeness centrality	Between-ness centrality	Eigen-vector centrality	Num-ber of berths	Num-ber of productive berths	Number of 10,000-ton-class berths	Length of quay line	Length of productive-use quay line	Cargo throughput	Container throughput	Cargo throughput year-on-year	Container throughput year-on-year	City GDP	Contribution of the tertiary sector to city GDP	Total value of imports and exports
Shanghai	1	1	1	1	1	2	2	1	2	1	1	7	8	1	1	1
Ningbo	3	3	3	3	2	1	1	4	1	4	2	15	6	6	13	3
Shenzhen	2	2	2	2	11	11	9	7	7	9	3	12	7	2	3	2
Guangzhou	8	9	7	4	3	3	8	5	6	3	4	16	13	3	2	4
Tianjin	7	7	5	5	6	9	3	4	4	5	6	11	5	5	5	6
Qingdao	4	4	4	6	15	15	6	9	9	2	5	13	9	7	6	7
Xiamen	5	5	9	7	9	8	7	8	8	15	7	5	11	13	7	5
Dalian	6	6	6	8	4	4	5	3	3	8	10	19	19	11	12	9
Yantai	10	11	13	12	5	5	4	6	5	6	11	9	4	10	10	10
Fuzhou	13	16	8	14	8	6	14	13	12	11	13	8	15	4	4	8
Nanjing	11	10	10	11	12	10	10	11	10	10	12	10	17	8	8	11
Lianyungang	13	14	12	15	7	14	15	10	15	17	18	2	1	19	19	15
Fangchenggang	12	12	11	10	19	19	19	19	19	19	15	1	3	16	14	16
Shantou	9	8	14	9	16	16	11	15	14	12	9	3	12	14	17	14
Nantong	17	18	15	19	14	13	13	12	11	7	14	4	10	9	15	12
Wenzhou	16	13	16	13	10	7	18	18	18	18	17	14	16	12	9	13
Zhanjiang	19	19	16	18	13	12	16	14	13	13	16	6	2	15	18	17
Yingkou	13	15	16	16	18	17	12	16	16	14	8	18	18	18	16	18
Qinhuangdao	17	17	16	17	17	18	16	17	17	16	19	17	14	17	11	19



berths, trade openness, and years of port operations. These are included to account for external factors and reduce omitted variable bias.

4.4.1 Methodology and data

4.4.1.1 Data This section analyzes the impact of port connectivity and external competitiveness on port performance in 2021. The dependent variable is port performance, measured by the entropy-TOPSIS comprehensive score, calculated in Sect. 4.2. The first core explanatory variable is competitiveness, measured by a proxy index calculated as the arithmetic average of three indicators—length of the quay line, city GDP, and throughput growth rate. These indicators cover the port's infrastructure, economic environment, and productivity, making them suitable for constructing a proxy index of competitiveness. The second core explanatory variable is port connectivity, quantified by the Port Liner Shipping Connectivity Index (PLSCI) published by UNCTAD (Q1 2023 average = 100 as the benchmark). Using connectivity data from SNA in Sect. 4.1 would cause multicollinearity, whereas the UNCTAD PLSCI adopts an independent calculation, avoiding endogeneity and ensuring robustness. Following previous studies (Yap and Ho 2023; Yen et al. 2023; Kuo 2025), the selected control variables are: infrastructure scale (the number of 10,000-ton class berths), trade openness (ratio of total import and export volume to city GDP), and port operating years (2021 minus official opening year).

4.4.1.2 Research model We use OLS regression to analyze factors influencing port performance. Robust standard errors are introduced to address heteroscedasticity, ensuring that coefficient estimates and significance levels remain reliable. The model is:

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \gamma_1 C_{1i} + \gamma_2 C_{2i} + \gamma_3 C_{3i} + \epsilon_i \quad (1)$$

where:

Y_i : Dependent variable, entropy-TOPSIS score of port i .

X_{1i} : Core explanatory variable, competitiveness proxy index of port i .

X_{2i} : Core explanatory variable, UNCTAD PLSCI of port i .

C_{1i} , C_{2i} , C_{3i} : Control variables representing the number of 10,000-ton class berths, trade openness, and operating years.

α : Constant term. β_1 , β_2 , γ_1 , γ_2 , γ_3 : Regression coefficients.

ϵ_i : Random error term, assumed normally distributed with zero mean and constant variance.

4.4.2 Research results

Regression analysis showed that port connectivity and competitiveness significantly impact port performance (Table 10). The coefficients of C_{1i} , C_{2i} , and C_{3i} are posi-



Table 10 Regression analysis results

Variables	Port performance
Port competitiveness	0.481*** (0.0791)
Port connectivity	1.860*** (0.250)
Number of 10,000-ton-class berths	0.00539 (0.0178)
Trade openness	0.0128 (0.0437)
Port operating years	0.0260 (0.0159)
Constant	−0.0934 (0.0747)
Observations	19
R-squared	0.975

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ **Table 11** Results of the VIF, BP, and Hausman tests

Test methods	Result	Explanation
VIF test		
Port competitiveness	2.84	No collinearity
Port connectivity	4.23	
Number of 10,000-ton-class berths	2.72	
Trade openness	1.99	
Port operating years	1.89	
BP test	0.3197	No heteroscedasticity
Statistic	<i>P</i> -value	
Hausman test	0.17	No endogeneity

tive, consistent with theoretical premises, but not statistically significant ($p > 0.1$). This is because the 19 sample ports are major coastal hubs with small variation in infrastructure scale, trade openness, and operational maturity. Nonetheless, including these controls eliminates interference from external factors, ensuring unbiased estimates of the core explanatory variables.

4.4.3 Robustness and endogeneity tests

4.4.3.1 Collinearity, heteroskedasticity, and endogeneity tests Before conducting robustness tests, potential data issues were examined using Stata/MP 17.0. Table 11 shows VIF values below 5, indicating no significant multicollinearity. The heterosce-

Table 12 Results of robustness tests

Variables	IV	Bootstrap
Port competitiveness	0.578*** (0.221)	0.481*** (0.112)
Port connectivity	1.668*** (0.471)	1.860*** (0.342)
Number of 10,000-ton-class berths	0.00434 (0.0190)	0.00539 (0.0253)
Trade openness	0.0131 (0.0311)	0.0128 (0.0584)
Port operating years	0.0315 (0.0207)	0.0260 (0.0223)
Constant	−0.134 (0.117)	−0.0934 (0.0973)
Observations	19	19
R-squared	0.973	0.975

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, *

$p < 0.1$

dasticity p-value is greater than 0.05, indicating no heteroscedasticity. The Hausman test value is 0.6842, significantly above 0.1, suggesting no endogeneity problem.

4.4.3.2 Alternative regressions (1) Instrumental variable regression (IV).

Due to limited data, robustness tests involving variable substitution, individual changes, or time adjustments were not applicable. Instrumental variables (IV) regression was therefore chosen to verify robustness and the validity of causal inferences. The port connectivity data (UNCTAD) used in the OLS regression differs from the SNA data used to calculate port performance; yet, both describe port connectivity. IV regression enhanced the independence of the explanatory variables.

The 2020 UNCTAD connectivity data was used as the IV for the 2021 analysis. This data is strongly correlated with the explanatory variable but not with the dependent variable, making it suitable as an instrument. As shown in Table 12, the IV regression results are consistent with the OLS regression, confirming model robustness.

Due to our small sample (19 port cross-sectional observations), we also employed *bootstrap regression* to verify the robustness of the regression results. This method estimates the standard error through repeated sampling (1,000 iterations), helping to avoid bias in standard error estimation caused by small sample sizes. As shown in Table 12, the results are consistent with those of the initial OLS regression. Specifically, the impact of port connectivity and port competitiveness on port performance remains positive at the 1% significance level, and the coefficient estimates remain unchanged (as shown in Table 10). This indicates that the model results are highly robust. In addition, the standard errors re-estimated using the Bootstrap method are slightly higher than those obtained using the traditional OLS method, indicating that Bootstrap better reflects uncertainty under small-sample conditions.



5 Conclusions

In recent years, with China's rapid social and economic growth, Chinese ports have flourished and have booked historic successes. Major coastal ports have 2,207 berths of more than 10,000 tons. Of the top ten ports in the world in terms of cargo and container throughput, China accounts for 70%, with Ningbo-Zhoushan, Shanghai, Tangshan, Qingdao, and Guangzhou among the top five (Lloyd's List, 2023). In spite of this, Chinese port technologies and intelligence remain at variance from those of other developed countries.

This study comprehensively evaluated major ports from four aspects: connectivity, infrastructure, productivity, and the port's economic environment. Ports were grouped according to their score. Interestingly, mega hub ports such as Shanghai, do not rank first in all individual indicators (Table 9). The connectivity and infrastructure rankings of Shenzhen are poles apart. Relying on a single criterion for port evaluation can introduce bias. Compared with such one-dimensional assessments, this study has constructed a new evaluation system to comprehensively assess ports from a more holistic perspective, yielding more reliable conclusions.

The results indicate that Shanghai, Ningbo-Zhoushan, Shenzhen, and Guangzhou ports hold leading positions. These ports are all located in economically developed regions, implying that the outstanding performance of top-tier ports is more strongly determined by their integrated service capabilities and favourable external conditions. Ports with relatively low comprehensive scores, such as Qinhuangdao, Zhanjiang, and Shantou, are typically characterized by their location in less developed cities, relatively weak infrastructure, and singular functional profiles. This result underscores the need for differentiated management strategies. Therefore, policy support for such ports should ultimately aim to empower them to develop distinctive competitive strengths, thereby securing a sustainable and differentiated position within the port ecosystem.

We show that, for an in-depth analysis of the causes of performance disparities and the formulation of effective management insights, a single-dimensional evaluation has limitations. Compared with existing studies, our evaluation framework demonstrates greater systematicity and explanatory power. Existing research has often focused on a single dimension, emphasizing factors such as infrastructure and throughput (De Martino and Morvillo 2008; Yeo et al. 2008), or solely concentrating on network connectivity (Wang and Cullinane 2016; Lu et al. 2018). Even when employing the TOPSIS method, network attributes are rarely systematically integrated (Nguyen and Woo 2022), making it difficult to fully reveal the performance-driving mechanism.

This study has addressed this gap by integrating connectivity- and competitiveness-related indicators, applying the entropy method for objective weighting, combined with TOPSIS, for comprehensive ranking. Compared with studies that emphasize only infrastructure or throughput drivers (Kim 2016), this study quantifies the intensity of each factor's influence through regression analysis, yielding more precise conclusions. Compared with studies focusing solely on network connectivity (Wang and Cullinane 2016), we confirm the necessity of multi-factor synergistic effects, aligning more closely with the actual development context of Chinese ports. Therefore, based on our comprehensive framework and employing SNA, entropy–



TOPSIS comprehensive evaluation, and robust OLS regression, we move beyond simple ranking comparisons to explore the managerial implications of the data. We subsequently propose the following targeted policy and managerial insights.

From a performance drivers perspective, port connectivity and competitiveness jointly constitute the core factors for performance improvement, with competitiveness exerting a relatively stronger influence. This conclusion is quantitatively verified through regression analysis, providing empirical support for the dual-drive strategy. This implies that port management needs to abandon a single-expansion orientation and focus on the coordinated development of connectivity and competitiveness.

From a stage of development perspective, the statistical insignificance of the control variables suggests that China's core hub ports have moved beyond the phase of pure quantitative expansion, where the marginal impact of indicators such as the number of 10,000-ton berths and trade openness has become limited. Future management should focus on quality upgrading of core areas such as operational efficiency optimization, intelligent transformation, and low-carbon development to tap new growth potential.

Furthermore, by comparing connectivity and competitiveness, this study has clarified the complex drivers of port performance. While high connectivity underpins top ports and creates synergies, many ports experience mismatches between their network position and competitive capabilities. Some ports exhibit strong connectivity but limited infrastructure, whereas others rely on specific competitive strengths to offset a peripheral network location. Therefore, port managers should first diagnose their position within their maritime network. Major hubs should translate network advantages into broader competitiveness, while regional ports should cultivate specific strengths or seek alliances to access higher-value networks. The framework developed in this study aids such diagnosis and strategy development.

The contributions of this study are the following. First, a quantitative analysis of port connectivity was performed using an SNA model, with the results used as partial variables. The entropy–TOPSIS method was applied to rank ports' overall capacity, yielding results that are more objective and comprehensive. The study compensates for the limited use of port connectivity in analyzing port integration capacity in the existing literature on Chinese ports. Second, the study develops a new evaluation framework, grounded in port competitiveness and port shipping networks, to comprehensively assess the performance of China's major ports. In theoretical terms, this study bridges the evaluation gap in previous research which examined separately the internal and external aspects of ports. In practical terms, our results can help port managers accurately identify performance shortcomings. This can help avoid resource waste caused by indiscriminate infrastructure expansion, or the simple increase of shipping routes, and enable the research conclusions to guide port optimization decisions in practice.

However, the study has also limitations. First, owing to limited data availability, the research objective was reduced from 27 to 19 ports. The scope of this study could be further expanded with more comprehensive data support in the future. In the interest of healthy port development, a larger number of ports should be ranked according to their comprehensive capacity, so that they can define their positions more accurately. Second, because route data were collected only for 2021, they do not consti-



tute panel data for comparison along the same port time series. Additional data will be collected in future research to enable temporal and spatial comparisons of ports.

Appendix 1. Entropy–TOPSIS calculation procedures

Step 1 Determine the original data matrix. Suppose a complex network has n nodes, and $V = \{V_1, V_2, \dots, V_n\}$ denotes the node set. Each node has m characteristic indicators, and $R = \{R_1, R_2, \dots, R_m\}$ denotes the indicator set. The j^{th} indicator for node i is expressed as $V_i(R_j)$, ($i = 1, 2, \dots, n; j = 1, 2, \dots, m$). Due to differences in indicator dimensions, the selected indicators are normalized to facilitate comparison. The normalised decision matrix is denoted as $X = (x_{ij})_{n \times m}$.

Step 2 Determine the weight of each indicator. The entropy weight method is used to obtain the weights of the indicators in Step 1. The entropy weight w_j of indicator j is calculated as.

$$w_j = \frac{1 - H_j}{m - \sum_{j=1}^m H_j}, \quad j = 1, 2, \dots, m \quad (2)$$

The information entropy value of indicator j is

$$H_j = -k \sum_{i=1}^n x_{ij} \ln x_{ij}, \quad j = 1, 2, \dots, m \quad (3)$$

Step 3 Based on the normalised decision matrix X , the positive ideal solution X^+ is $\{\max(x_{i1}, \dots, x_{im})\}$ and negative ideal solution X^- is $\{\min(x_{i1}, \dots, x_{im})\}$.

Step 4 The distances from each scheme to the positive and negative ideal solutions are calculated using the Euclidean distance:

$$D^+ = \sqrt{\sum_{j=1}^m \{x_{ij} - x_{jmax}\}^2} \quad (4)$$

$$D^- = \sqrt{\sum_{j=1}^m \{x_{ij} - x_{jmin}\}^2} \quad (5)$$

Step 5 Calculate the closeness coefficient, $0 \leq Z_i \leq 1$, and rank the schemes accordingly. Nodes with larger Z_i values indicate greater importance in the network:

$$Z_i = \frac{D^-}{D^+ + D^-} \quad (6)$$



Appendix 2. Detailed explanations of SNA centrality indicators for shipping networks

1. Degree centrality

Degree centrality is based on proximity analysis of nodes and reflects the degree to which one node in a network is directly related to all other nodes. The more neighbouring nodes a node has, the higher its degree centrality (Bonacich 1972). In shipping networks, degree centrality refers to the number of direct connections between port nodes and other port nodes; that is, the number of direct traffic routes between two port nodes. In-degree refers to the number of routes from other ports to this port, while out-degree refers to the number of routes from this port to other ports. This indicates that port accessibility is reflected in degree centrality. The higher the degree centrality of a port node, the more non-stop routes exist between that port and other ports, and the more connected the shipping traffic.

2. Closeness centrality

Closeness centrality is the average distance between a node and all other nodes in a network, eliminating interference from extreme values. Closeness centrality reflects the degree of proximity between two nodes; that is, the closer a node is to others, the higher its closeness centrality.

3. Betweenness centrality

Betweenness centrality is based on the shortest path and reflects the importance of a node by calculating its passing frequency. The more frequently a node appears on shortest paths, the higher its centrality value (Freeman 1978). In shipping networks, betweenness centrality refers to the number of times a port node appears on a network route; that is, the frequency with which the port is selected for transit. The higher a port node's betweenness centrality, the more frequently it is selected for transit.

4. Eigenvector centrality

Eigenvector centrality is based on the eigenvector value of a node, which measures the degree of a node's centrality in the network. The influence of local network characteristics is reduced by including connecting nodes in the calculation (Wasserman and Faust 1994). The eigenvector centrality index considers not only the number of neighbouring nodes but also the influence of the quality of neighbouring nodes on their importance. In a shipping network, eigenvector centrality refers to the amount of traffic between ports and other hub ports. Thus, eigenvector centrality reflects the relational characteristics of the port. Through connections with hub ports, ports indirectly improve their network position by benefiting from the competitiveness of the hub ports with which they operate.



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Declarations

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