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Review

Global LNG Maritime Transportation Network: A Systematic Review of Progress and Trends

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Abstract

With the global energy system undergoing a transition toward green and low-carbon systems, the scale of liquefied natural gas (LNG) maritime transportation has expanded rapidly. Influenced by a combination of factors including the global economy, geopolitics, energy policies, and environmental conditions, the Liquefied Natural Gas Maritime Transportation Network (LMTN) exhibits a high degree of structural complexity and has gradually emerged as a prominent research focus in the field. This study provides a comprehensive review of the current research progress on LMTN. First, the concept of LMTN is introduced and the major stages of its research development are highlighted. Second, LMTN construction methods are systematically summarized with data sources, theoretical foundations, and application scenarios, thereby establishing a technical framework for global LMTN research. Subsequently, bibliometric analysis is also employed to extract representative publications and reveal the knowledge structure, historical evolution, and emerging research frontiers of the field. Finally, from three technical perspectives—methodology, data, and computational power—this study discusses existing limitations and challenges, and identifies future development trends of LMTN research driven by big data and artificial intelligence. Overall, this study aims to provide scientific guidance for future LMTN research and theoretical support for enhancing the security and resilience of global energy transportation systems.

Keywords: Liquefied Natural Gas Maritime Transportation Network (LMTN); complex network analysis; bibliometric analysis; big data; artificial intelligence

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1. Introduction

Shipping networks are complex systems in which ports function as nodes, shipping routes between ports constitute edges, and vessels act as transport carriers [1]. As a fundamental modeling framework, shipping networks are widely used to assess maritime connectivity, forecast cargo demand and flows, analyze patterns of trade competition, and evaluate supply chain risks. Consequently, research on shipping networks is of critical importance for ensuring the stability and efficient operation of global supply chains.

Systematic research on shipping networks emerged around the year 2000 and has since developed rapidly [2], giving rise to a comprehensive research framework encompassing trade relationship analysis, network topology characterization, network vulnerability

assessment, and network optimization and decision-making [3]. Over time, the research focus has gradually shifted from macro-scale connectivity patterns to fine-grained analyses of transportation networks associated with specific cargo types, including containerized goods, bulk commodities, energy resources, and passenger transport [4].

The Liquefied Natural Gas Maritime Transportation Network (LMTN) constitutes an important component of the global shipping network and serves as a fundamental basis for analyzing global LNG trade relationships. Compared with general shipping networks, such as container shipping networks, LMTN exhibits a profound degree of specialization, functioning as a low-elasticity and exceptionally risk-sensitive strategic energy network. It is deeply bound to point-to-point long-term contracts and highly specialized ship-port infrastructure, making its flexibility in route reconfiguration far inferior to that of container shipping networks. The network not only exhibits a pronounced core-periphery spatial structure, but is also extremely sensitive to geopolitical risks, maritime chokepoints, and dedicated terminals. Following the adoption of the Paris Agreement in 2015, the global energy system has increasingly transitioned toward a greener and low-carbon structure. As an energy source characterized by relatively low carbon intensity and reduced pollutant emissions, LNG has gained growing acceptance in energy markets, leading to increased academic and industrial attention to LMTN research. In recent years, driven by rapid advances in big data science and artificial intelligence, data-driven approaches integrated with machine-learning algorithms have emerged as a major research frontier in LMTN studies [5,6]. These research efforts have provided scientific decision support for optimizing the organization of global LNG maritime transportation, enabling intelligent risk management, and enhancing supply-chain resilience.

As shown in Table 1, the development of LMTN research can be broadly divided into the following five stages.

Table 1. Development stages of LMTN research.

Development Stages	Early Exploratory Stage	Initial Research Stage	Foundational Research Stage	Rapid Development Stage	Deepening Stage
Development period	Before 2010	2011–2015	2016–2020	2021–2024	2025–present
Representative methods	Maritime logistics optimization; ship routing; maritime supply chain management	Mathematical programming; heuristic algorithms; supply-chain optimization	Complex network theory; gravity model; community detection; topological analysis	AIS big-data analytics; complex network modeling; robustness analysis; intentional attack simulation; vulnerability assessment	Machine learning; deep learning; graph attention networks; SIR diffusion model; digital twin; deep reinforcement learning; low-carbon optimization
Main research focuses	Studies were mainly scattered across container shipping, crude oil tanker transportation, ship routing, and maritime logistics. No specific studies directly focused on LMTN [2,7].	Research began to focus on LNG maritime supply-chain optimization, ship scheduling, cargo supply–demand coordination, ship routing, and berth availability constraints [8,9].	Scholars began to construct trade networks at the macro scale, analyze import–export relationships, identify core countries, evaluate trade competition patterns, and reveal regional competitive relationships [10–12].	Studies shifted toward port-level LMTN construction, network dynamics, evolution of port nodes and maritime corridors, cascading failure, robustness under disruptions, vulnerability under geopolitical shocks, and structural optimization [13–17].	Research increasingly focuses on disturbance propagation, critical node identification, link prediction, risk early warning, potential trade relationship mining, carbon-emission-constrained network optimization, and intelligent scheduling [18–21].

Table 1. *Cont.*

Development Stages	Early Exploratory Stage	Initial Research Stage	Foundational Research Stage	Rapid Development Stage	Deepening Stage
Research characteristics	LMTN had not yet been explicitly conceptualized as a complex network composed of ports, routes, and trade flows. Existing shipping network studies provided theoretical and methodological foundations.	Studies were mainly conducted from economic, operational, and supply-chain perspectives. A systematic network-based analytical framework for LMTN had not yet been established.	Research mainly focused on country-level trade networks and macro-scale trade patterns. The specific maritime transportation attributes of LMTN were still insufficiently characterized.	LMTN research entered a data-driven and multi-scale stage. The focus evolved from static structural analysis to dynamic analysis.	The research paradigm is shifting from retrospective structural description to intelligent decision-making and digital-twin-based dynamic optimization.

Based on the statistical analysis of the literature, review studies on shipping networks remain relatively limited. Among these, the most representative is the comprehensive review of shipping networks published in 2021 by Álvarez et al. [22]. Other scholars have conducted review studies focusing primarily on container liner shipping networks [23–25]. The most recent review, by Ye et al. [26], examines the integration of complex network theory with the 21st Century Maritime Silk Road initiative. However, to date, no review has been specifically dedicated to LMTN.

According to International Group of Liquefied Natural Gas Importers (GIIGNL) global trade statistics, the global fleet of specialized LNG carriers comprises approximately 750 vessels, with an annual LNG trade volume of around 400 million tonnes [27]. Compared with other types of shipping networks, LMTN relies heavily on hub ports and critical maritime corridors and is strongly influenced by factors such as energy policies, competition with pipeline gas, geopolitical dynamics, and terminal infrastructure constraints. Consequently, LMTN combines the general complexity of shipping networks with distinctive attributes shaped by energy supply-chain constraints, making it a research subject of considerable academic and practical significance.

This study is positioned as a systematic review rather than an empirical study aimed at developing new algorithms, models, or optimization methods. Its primary objective is to synthesize the current body of LMTN research, identify emerging research hotspots, examine existing bottlenecks, and provide forward-looking insights into future research directions.

To the best of the authors' knowledge, this study represents the first systematic review of LMTN research. The main contributions of this study are summarized as follows:

- Establishing a systematic technical framework for LMTN research: It comprehensively synthesizes the network construction methods, multiple data sources, theoretical foundations, and distinct application scenarios of LMTN, thereby establishing a systematic technical framework for global LMTN research and modeling.
- Deciphering the knowledge domain topology: Utilizing advanced bibliometric and knowledge-mapping methods, it reveals the underlying knowledge structure, chronological development trajectories, and emerging research hotspots in this field.
- Categorizing methodological paradigms: It systematically categorizes the major research themes and methodological advances in LMTN studies, providing an in-depth analysis of complex LNG maritime network research, resilience and vulnerability assessments, big-data-driven network modeling, and intelligent methods.
- Charting strategic future directions: It evaluates and discusses the current research bottlenecks and limitations across the three dimensions of methodology, data, and

computational capacity, while outlining future development directions aligned with data-driven intelligence and low-carbon shipping development.

This review is organized as follows. Section 2 establishes a technical framework for LMTN studies and introduces network construction methods, data sources, and theoretical foundations. Section 3 develops a comprehensive knowledge map of LMTN research from multiple perspectives, including authors, countries, keyword clustering, and temporal evolution, to elucidate research progress and development trends. Section 4 discusses existing challenges and future research requirements from the perspectives of data, methodologies, and computational capacity. Section 5 concludes the review.

2. Methodology

2.1. Research Framework

Current research on LMTN has largely been built upon studies of complex shipping networks. Drawing on the research paradigms and technical methods developed for typical maritime networks, such as container liner shipping networks and crude oil transportation networks, this study further incorporates the supply–demand characteristics driven by LNG energy trade [28]. Specifically, multi-source big data, including AIS spatiotemporal data, global trade data, and port operation data, serves as the foundation. Complex network analysis constitutes the core analytical approach, while interdisciplinary methods from economics, systems science, and artificial intelligence are integrated to develop theoretical models. The aim is to support practical application scenarios, such as global maritime supply chain risk management, the enhancement of network structural resilience, low-carbon optimization, and intelligent decision-making. As shown in Figure 1, this study proposes a research framework for LMTN, providing a systematic paradigm and fundamental research logic for current LMTN studies.

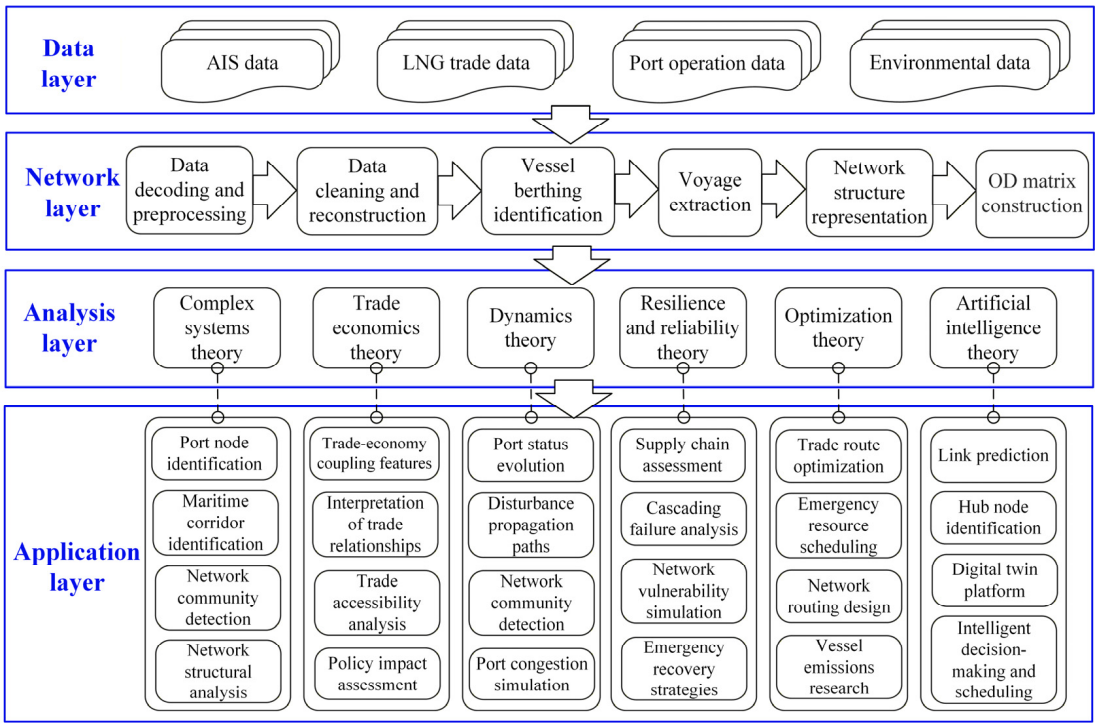


Figure 1. Framework of Current LMTN Research.

2.2. Data Resources and Analytical Support for LMTN Research

Research on global LMTN relies on multidimensional data resources, primarily including AIS trajectory data, LNG trade data, and environmental data. Table 2 presents the data types, detailed contents, and main sources of the data required for the LMTN research.

Table 2. Data Sources for LMTN research.

Data Category	Specific Data	Main Contents	Representative Data Sources	Function in LMTN Research
Vessel-related data	Static vessel attributes	Vessel type, ship size, capacity, flag state, ownership, technical specifications	https://www.marinetraffic.com (accessed on 6 June 2026); https://www.vesselfinder.com (accessed on 6 June 2026); https://www.hifleet.com (accessed on 6 June 2026)	Used to identify LNG carriers and characterize vessel heterogeneity
	Dynamic operational information	AIS trajectories, vessel positions, speed, heading, port calls, voyage records		Provides the fundamental basis for reconstructing vessel voyages, identifying OD relationships, and constructing port-level LMTN
	Vessel emissions data	Carbon emissions, energy efficiency, environmental performance indicators	https://rightship.com (accessed on 6 June 2026)	Supports low-carbon shipping analysis, emission assessment, and green route optimization
LNG trade data	Port characteristics	LNG terminals, terminal capacity, operating companies, infrastructure attributes	https://www.iea.org (accessed on 6 June 2026) https://www.giignl.org (accessed on 6 June 2026)	Used to identify LNG port nodes, terminal functions, and infrastructure capacity
	Import–export trade volumes	LNG importers, exporters, bilateral trade volumes, annual trade statistics	https://comtrade.un.org (accessed on 6 June 2026) https://www.cepii.fr (accessed on 6 June 2026) https://www.giignl.org (accessed on 6 June 2026)	Supports country-level trade network construction and macro-scale trade relationship analysis
	LNG logistics and cargo-flow data	Near-real-time LNG shipments, cargo flows, transaction-level data, shipping movements	https://www.spglobal.com/en (accessed on 6 June 2026) https://www.kpler.com (accessed on 6 June 2026)	Supports dynamic tracking of LNG flows and fine-grained maritime transportation analysis
Environmental and risk-related data	Meteorological and sea-state data	Wind, waves, sea surface conditions, visibility, route-related natural environment factors	https://www.remss.com (accessed on 6 June 2026)	Supports route safety assessment, navigation risk evaluation, and disruption scenario analysis
	Regional security information	Piracy, armed robbery, war, terrorist attacks, maritime threats	https://gisis.imo.org/public/default.aspx (accessed on 6 June 2026)	Used to assess maritime security risks and external threat exposure
	Global risk indicators	Environmental risks, social risks, economic risks	https://www.weforum.org/publications/global-risks-report-2026/ (accessed on 6 June 2026)	Provides macro-level risk background for LNG maritime transportation safety research
	Political stability indicators	Governance quality, political stability, regulatory environment of LNG trading countries	https://www.worldbank.org/en/publication/worldwide-governance-indicators (accessed on 6 June 2026)	Supports geopolitical risk analysis, country-level risk assessment, and supply-chain resilience studies

2.3. Construction Method of LMTN

LMTN construction can generally be approached from two perspectives. The first is a vessel-voyage-based perspective, in which the network is reconstructed from the spatiotemporal transportation behavior of vessels using large-scale vessel trajectory data. The second is a trade-statistics-based perspective, in which the network is constructed from import–export trade volumes reported by relevant trading countries. The choice of data source and modeling perspective should be consistent with the research scale and analytical objective. Specifically, when the objective is to construct a port-level network from the perspective of global port nodes and to reveal LNG maritime transportation connections at a finer spatial granularity, multi-source spatiotemporal vessel trajectory data and port information are required to identify and model vessel voyages, port-call behavior, and inter-port OD transportation relationships. When the objective is to analyze macro-level trade relationships among countries, national import–export trade volume data are more appropriate for constructing country-level trade networks. As shown in Table 3, the following is a comparison of the two perspectives.

Table 3. Comparison of two perspectives for LMTN construction.

Perspectives	Network Construction Based on LNG Carrier Transportation Behavior	Network Construction Driven by Trade Statistics
Data type	Multi-source spatiotemporal vessel trajectory data	Import–export trade data
Network scale	Spatial scale: can be refined to the level of ports, terminals, straits, canals, and even route segments. Temporal scale: dynamic networks can be constructed at temporal granularities ranging from daily to yearly [29].	Spatial scale: mainly at the national or regional scale. Temporal scale: mostly based on monthly or annual statistics, and is suitable for analyzing long-term trends and macro-scale patterns [11].
Node meaning	Ports, terminals, straits, canals, route nodes, etc.	Countries, regions, and economies.
Research questions	Identification of port importance, actual route structure, inter-port transportation connections, route congestion, rerouting, impacts of strait blockades, transportation network resilience [13,30].	National energy dependence, evolution of trade patterns [31].
Main advantages	Reflects actual vessel movement processes; suitable for port-level analysis; enables the identification of actual OD shipping routes; can capture rerouting, port calls, congestion, and voyage changes [32,33].	Has relatively standardized statistical definitions; suitable for long time-series analysis and cross-country comparisons [10].
Main limitations	Large data volume, complex data cleaning, and possible AIS data gaps [34].	Coarse spatial granularity, making it difficult to identify specific ports, shipping routes, and vessel behaviors; unable to directly reflect actual transportation paths and voyage processes [35].

For LMTN construction, raw data must be processed, extracted, and modeled, regardless of whether a vessel-voyage-based perspective or an import–export trade-statistics-based perspective is adopted. These two approaches share a broadly similar data-processing logic, generally involving data acquisition, data cleaning, data standardization, relationship identification, and network construction. However, compared with import–export trade statistics, AIS data are characterized by larger data volume, stronger spatiotemporal continuity, and more pronounced dynamic variation. Therefore, taking AIS spatiotempo-

ral trajectory big data as the primary data foundation, this study summarizes the main technical workflow for LMTN construction, as illustrated in Figure 2.

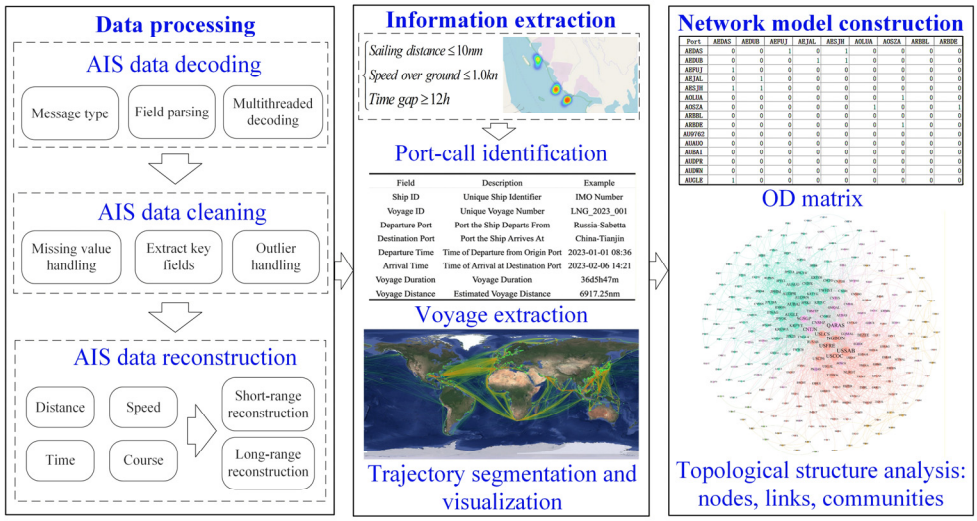


Figure 2. Technical workflow for LMTN construction.

2.3.1. AIS Data Decoding and Preprocessing

AIS data are classified, according to information type, into static and dynamic components. The data are encoded in a 6-bit ASCII format and consist of multiple fields. After preprocessing, AIS records are typically organized in the form <MMSI, IMO, NAME, Deadweight, Lon, Lat, Spd, Draught>, where MMSI represents the vessel's Maritime Mobile Service Identity and the IMO number denotes the vessel identification code [36]. By matching the IMO number or MMSI code with the vessel registry, spatiotemporal trajectory datasets of LNG carriers can be extracted from global AIS data.

2.3.2. AIS Data Cleaning and Reconstruction

Raw AIS data typically contain substantial amounts of invalid, redundant, or anomalous information. Therefore, AIS datasets must first undergo cleaning procedures, including the removal of duplicate records, treatment of missing values, and correction of abnormal data. Even after data cleaning, trajectory records may still exhibit data gaps and discontinuities. In such cases, AIS data reconstruction is required, usually by incorporating vessel navigation behavior and typical route patterns to enhance the completeness and accuracy of the reconstructed trajectories [37].

2.3.3. LNG Port-Call Identification

Based on a global port spatial database and the spatiotemporal trajectory data of LNG vessels, the geographic locations of ports in different countries are matched with LNG vessel arrival behaviors. In general, LNG vessel port-call identification adopts a combined rule based on spatial distance, time thresholds, and speed constraints to associate vessel movements with port locations, thereby identifying a sequence of LNG vessel port-call events [38].

2.3.4. Voyage Extraction

The core task of voyage extraction is to identify the complete sailing process of each LNG vessel from departure at one LNG port to arrival at another port, and to extract key attributes such as origin and destination ports, timing, and route characteristics. Voyage extraction takes the sequence of port-call events as input and constructs a time-ordered record of port arrivals. Each pair of adjacent valid port calls is then treated as the boundary

of a single voyage. By further imposing constraints such as minimum at-sea sailing time and voyage-segment integrity, a voyage dataset can be generated that includes attributes such as origin and destination ports, departure and arrival times, sailing distance, and voyage duration [39].

2.3.5. Network Construction

All voyages sharing the same origin and destination ports are aggregated and treated as a single route, based on which an origin–destination (OD) matrix of LNG carrier departures and arrivals is constructed. The resulting OD matrix can be undirected and unweighted when the analysis focuses on network connectivity, in which case the network is represented as G = (V, E). Alternatively, it can be directed and weighted when the objective is to characterize trade flows between ports, where edge directions point from loading ports to unloading ports. In this case, the network is represented as G = (V, E, W). Here, V denotes the set of port nodes, E represents the set of route edges, and W denotes the set of edge weights, corresponding to the cumulative LNG cargo volume transported along specific routes [40].

2.4. Research Theory and Methodology

LMTN is an open and evolving complex system shaped by interactions among energy trade, maritime transportation, port infrastructure, geopolitical risks, and environmental constraints. Accordingly, its analysis cannot rely on a single theoretical perspective. Existing studies have gradually formed an interdisciplinary methodological system that integrates trade economics, complex network theory, dynamics, optimization and operations research, resilience and reliability theory, and artificial intelligence. These approaches correspond to different analytical levels of LMTN research: trade economics explains macro-level supply–demand relations and trade-flow drivers [41–43]; complex network theory characterizes the topological structure and spatial organization of LNG maritime connections [3,16,44]; dynamics and resilience theories reveal disturbance propagation, vulnerability, and recovery mechanisms [45–47]; optimization and operations research support route selection, resource allocation, and scheduling decisions [48–50]; and artificial intelligence enables prediction, anomaly detection, risk early warning, and digital-twin-based decision support.

As summarized in Table 4, the theoretical basis of LMTN research has evolved from traditional trade and optimization models toward data-driven, dynamic, and intelligent analytical paradigms. This evolution reflects a shift in research focus from static descriptions of trade and network structure to dynamic modeling of "shock–propagation–adaptation–recovery" processes and forward-looking intelligent decision-making.

Table 4. Theoretical methods and applications in this research field.

Theoretical Methods	Algorithm Model	Application Scenario	Time of Application
Trade economics theory	Gravity model, Cost analysis, and trade-network Coupling analysis	Global LNG supply chain design, identification of trade–economic coupling characteristics, trade-flow interpretation, accessibility analysis, and assessment of trade policy shocks [51–53]	2010–present
Complex systems theory	Multilayer network model, Statistical physics methods, Centrality indicators, Community detection, K-core analysis, Percolation theory, and Network structural entropy	Identification of key nodes and corridors in LNG maritime transport, community detection in shipping networks, and network topological structure analysis [54–56]	2015–present

Table 4. *Cont.*

Theoretical Methods	Algorithm Model	Application Scenario	Time of Application
Dynamics theory	Vessel queueing model, Cascading failure model, SIR model, and System dynamics model	Disturbance propagation path identification, network state evolution, and port congestion simulation [57–59]	2016–present
Optimization and operations research theory	Multi-objective optimization, Mixed-integer linear programming (MILP), and Heuristic algorithms (GA, PSO, ALNS)	LNG trade route selection, emergency resource scheduling, network design and investment decision-making, and multi-objective balancing under carbon-emission constraints [60–62]	2016–present
Resilience and reliability theory	Resilience triangle, Markov model, Monte Carlo model, and Redundancy analysis	Complex network security assessment, simulation of network vulnerability and anti-disturbance capacity, and evaluation of network emergency recovery strategies [63,64]	2020–present
Artificial intelligence theory	Graph convolutional network, Graph attention network, Reinforcement learning, long short-term memory, Transformer, LLMs	Identification of critical network nodes, link prediction, prediction of network operational states, risk early warning, intelligent scheduling, and digital twins [65,66]	2020–present

3. Bibliometric Study of LMTN

This study employs bibliometric-based big data analytics to perform a multi-perspective quantitative analysis, encompassing publication trends, keyword clustering, and temporal evolution. The analysis aims to identify current research hotspots, influential authors, and the evolutionary pathways of research themes [67].

3.1. Data Collection

The bibliometric analysis in this study was conducted using CiteSpace 6.4.R1. Literature data were retrieved from Web of Science (WoS), with the search restricted to the Web of Science Core Collection. The selected citation indexes included the Science Citation Index Expanded (SCI-EXPANDED) and the Social Sciences Citation Index (SSCI).

The search query was defined as: (TS = "Liquefied Natural Gas" OR LNG) AND (TS = maritime OR marine OR shipping OR seaborne OR transport OR complex OR port) AND (TS = network* OR "supply chain"). The research areas were limited to Engineering, Operations Research & Management Science, Transportation, and Geography. Document types were restricted to Articles, Early Access papers, and Review Articles. Based on the developmental stages of this research field, the literature search covered the period from 2010 to 2026.

The literature screening process consisted of record identification, duplicate removal, and title-and-abstract screening. Initial records were retrieved from the Web of Science database, and irrelevant publications were excluded through manual screening. A total of 171 publications were retained for subsequent analysis.

As indicated by the annual publication statistics shown in Figure 3, research on LMTN has exhibited a clear upward trend, reflecting growing academic interest in this topic.

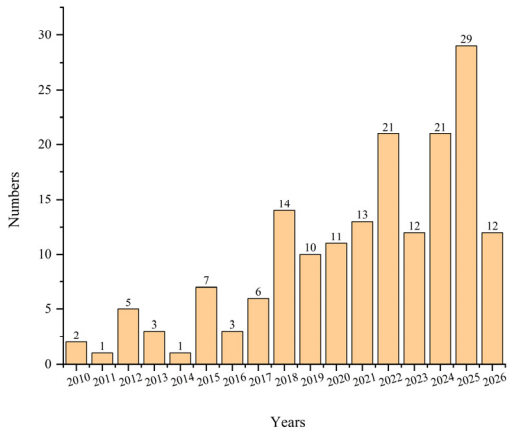


Figure 3. Annual publication statistics (the data for 2026 covers the first quarter).

3.2. Analysis of Leading Scholars and Research Orientations

Tables 5 and 6 list the top 10 scholars in this field ranked by publication output and citation counts, respectively, and report the average publication year and average citation year for each scholar. Among the top 10 scholars by publication output, nine have an average publication year later than 2018, indicating that research in this field has attracted increasing scholarly attention in recent years. Notably, the research teams led by Ducruet, C. and Peng, P. rank among the top in both publication output and citation counts.

Table 5. Top 10 scholars in this field by publication output.

No.	Counts	Authors	Year
1	7	Ducruet, C.	2012
2	4	Peng, P.	2018
3	4	Liu, W.	2022
4	4	Guo, J.	2022
5	4	Fang, Z.	2019
6	4	Chen, J.	2021
7	3	Zhao, P.	2025
8	3	Poo, M.	2024
9	3	Yang, Y.	2022
10	2	Mou, N.	2018

Table 6. Top 10 scholars in this field by citation count.

No.	Counts	Authors	Year
1	59	Ducruet, C.	2012
2	34	Peng, P.	2019
3	29	Wan, C.	2022
4	25	Calatayud, A.	2019
5	25	Xu, M.	2022
6	23	Mou, N.	2020
7	22	MEJ, N.	2012
8	20	Hu, Y.	2012
9	19	Guo, J.	2022
10	18	Bai, X.	2024

Research teams in this field have generally addressed maritime network-related issues from two analytical perspectives, which represent two important paradigms in maritime network studies. The first perspective, represented by the team of Ducruet, C., is mainly grounded in transport geography and spatial network analysis. Along this line of inquiry,

relevant studies have long focused on global maritime networks, port systems, port–city relationships, shipping networks, and the evolution of their spatial structures, emphasizing the interactions between maritime network configurations and regional development, urban systems, and the broader pattern of global economic geography. The second perspective, represented by the team of Peng, P., relies more strongly on big data analytics, GIS techniques, and complex network theory, with a focus on the topological structure, robustness, vulnerability, structural characteristics, and evolutionary mechanisms of global maritime networks.

3.3. Analysis of Country Distribution and Research Focus

As shown in Table 7, the major contributors to this research field are mainly countries with strong maritime capabilities, among which China, the United States, and the United Kingdom rank highest in terms of publication output. This distribution is closely associated with the strategic positions of these countries in the global LNG maritime trade system. For example, the United States and Australia are among the world's leading LNG exporters, while China is one of the largest LNG importers. Therefore, the intensity of research activity in the LMTN field is strongly related to a country's LNG trade scale, energy security concerns, and the structural complexity of its maritime transportation network.

Table 7. Top 10 countries in this research field.

No.	Country	Number of Publications	Main Start Time	LNG Trade Volumes (GIIGNL Statistics) [27]	LNG Maritime Trade Roles
1	China	91	2012	78.7 MT	World's largest LNG importer
2	USA	13	2012	85.8 MT	World's largest LNG exporter
3	UK	10	2013	7.9 MT	Major European LNG importer
4	France	9	2012	18.2 MT	Major European LNG importer
5	Australia	7	2013	79.2 MT	World's second-largest LNG exporter
6	Singapore	7	2012	6.1 MT	LNG hub and maritime service port
7	Germany	6	2010	4.6 MT	Major European LNG importer
8	Spain	6	2018	12.7 MT	Major European LNG importer
9	Finland	6	2022	1.6 MT	Emerging LNG market
10	Canada	5	2022	0.3 MT	Emerging LNG market

Furthermore, the research priorities of different countries exhibit a clear divergence shaped by their roles in the LNG trade system. Import-demand-driven countries tend to focus on supply security, port capacity, and network resilience under disruptive scenarios [68,69]. In contrast, export-supply-driven countries are more concerned with the spatial layout of export terminals, maritime routing, export market restructuring, and trade-flow reconfiguration under geopolitical shocks [70]. Meanwhile, emerging participants, such as Canada and Finland, have increasingly focused on FSRU deployment, Arctic navigation, and the development of new LNG transportation corridors [71].

3.4. Article Citation Analysis

Table 8 lists the top 10 articles in this field ranked by citation frequency, including one review article and nine research articles. These highly cited articles were published in 2015 or later, and their research contexts include the Russia–Ukraine conflict, Arctic routes, and other relevant scenarios. The most cited article in this field is "Application of risk analysis in the liquefied natural gas (LNG) sector: An overview", which is a review article that applies multiple risk analysis methods to examine LNG transportation safety. It can be observed that highly cited papers mainly focus on frontier directions and topical issues affecting the safety of LNG shipping. These research themes can be summarized as

follows: LNG maritime transportation safety risk analysis, identification of LNG trade and maritime transportation network structures, supply chain optimization, regional supply security, and network resilience and reconstruction under geopolitical shocks.

Table 8. Top 10 cited literature related to LMTN research.

No.	Citation Count	Article Title	Author and Year
1	97	Application of risk analysis in the liquefied natural gas (LNG) sector: An overview	Animah, I. (2020) [72]
2	72	Mapping the global liquefied natural gas trade network: A perspective of maritime transportation	Peng, P. (2021) [13]
3	62	Competition pattern of the global liquefied natural gas (LNG) trade by network analysis	Chen, Z. (2016) [10]
4	50	Decision-making on the process risk of Arctic route for LNG carriers via dynamic Bayesian network modeling	Li, Z. (2021) [73]
5	43	An MILP model for optimization of a small-scale LNG supply chain along a coastline	Jokinen, R. (2015) [74]
6	41	Using DBN and evidence-based reasoning to develop a risk performance model to improve ship navigation process safety in Arctic waters	Li, Z. (2022) [75]
7	34	Structure and resilience changes of global liquefied natural gas shipping network during the Russia–Ukraine conflict	Xiao, R. (2024) [76]
8	23	Assessing the stability of the LNG supply in the Asia Pacific region	Shaikh, F. (2016) [77]
9	17	Estimating global pattern of LNG supply chain: a port-based approach using the vessel movement database	Shibasaki, R. (2020) [78]
10	14	Turning the ships around: The Russia–Ukraine conflict reshapes the US LNG maritime transportation network	Zhang, S. (2024) [79]

3.5. Keyword Cluster Analysis

Keyword clustering analysis was conducted using CiteSpace to identify research hotspots in the LMTN field. By calculating the co-occurrence frequency of keywords within the same documents, the intellectual structure of this research domain was revealed. Latent Semantic Indexing (LSI) was used to extract semantic features, and the Log-Likelihood Ratio (LLR) algorithm was applied to generate representative cluster labels, thereby dividing the literature into several discrete thematic clusters. As shown in Figure 4, a total of 11 clusters were identified, labeled from "#0" to "#10," representing the core research themes of LMTN studies.

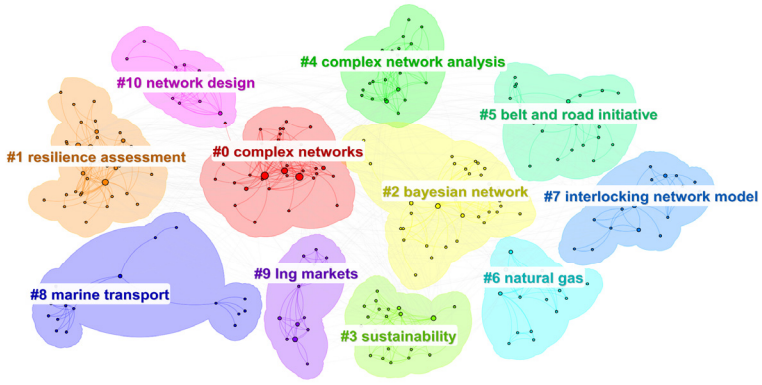


Figure 4. Keyword Cluster Map.

Cluster "#0" (complex network) reflects the characterization of LMTN as a complex system and forms the theoretical foundation of the field; Cluster "#1" (resilience assessment) represents a major recent research focus on network resilience under disruptions, including resilience measurement, cascading failure analysis, and disruption simulation; Cluster "#2" (Bayesian network) is a methodological cluster oriented toward risk analysis and network safety, commonly used to model and assess LNG accident probabilities and impacts; Cluster "#3" (sustainability) relates to emissions reduction, green shipping, and efficiency improvement, highlighting the trend toward low-carbon development; Cluster "#4" (complex network analysis) overlaps with "#0" and mainly involves studies on network topology and centrality indicators; Cluster "#5" (Belt and Road Initiative) reflects policy-driven maritime network research influenced by the Belt and Road strategy; Cluster "#6" (natural gas) captures research on natural gas energy transportation; Cluster "#7" (interlocking network model) focuses on multilayer and coupled network structures; Cluster "#8" (marine transport) represents the primary application context of LMTN research; Cluster "#9" (LNG markets) emphasizes LNG trade patterns and supply chains and, given its publication intensity, indicates a current research hotspot; and Cluster "#10" (network design) highlights studies on LMTN optimization, including facility layout, route planning, and network configuration.

3.6. Keyword Burst Analysis

Figure 5 presents the keyword burst analysis map generated by CiteSpace, which identifies 15 burst keywords in LMTN literature from 2010 to the present. The results reveal a clear evolutionary trajectory of research hotspots in this field. In the early stage, studies primarily focused on LNG maritime transportation management and trade market analysis, as reflected by keywords such as management, market, and international trade. Subsequently, the research emphasis shifted toward efficiency assessment and emission control in LNG transportation networks, with increasing attention to emissions and efficiency. After 2020, the focus further evolved toward port-related issues and network vulnerability, highlighted by keywords such as port, vulnerability, and evolution. In recent years, the research frontier has increasingly moved toward data-driven and intelligent approaches, represented by burst keywords such as data and machine learning, often in conjunction with application contexts such as the Maritime Silk Road. Notably, resilience has exhibited a strong burst intensity over the past three years, indicating that network resilience assessment has emerged as a dominant research hotspot in current LMTN studies.

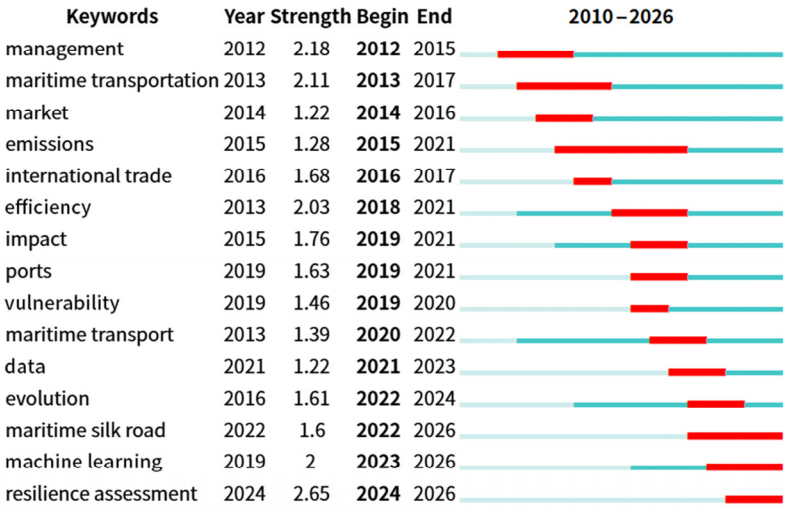


Figure 5. Keyword Burst Map.

Overall, the keyword clustering and burst results reveal several transitions in LMTN research:

- Shifting research scale: The research scale has gradually moved from macro-level trade relationship analysis to data-driven port-level maritime network analysis, enabling a more detailed understanding of LNG transportation connections and their spatial organization.
- Expanding research focus: The analytical focus has shifted from static structural description to vulnerability, resilience, and disruption propagation, reflecting growing scholarly attention to the dynamic response of LMTN under external disturbances.
- Upgrading research methods: Research methods have evolved from traditional statistical indicators and network metrics toward data-driven prediction, machine learning, and digital-twin-enabled decision support.

4. Discussions

4.1. Summary of Research Progress

Research on LMTN has exhibited a clear and progressive evolution in focus. Early studies (2011–2015) primarily concentrated on trade linkages and supply-chain configuration, followed by a phase (2016–2020) emphasizing complex network structures and competitive patterns. Since 2021, the field has entered a new stage characterized by big-data-driven, multiscale network modeling, dynamic structural evolution, micro-level interaction mechanisms, and dynamic resilience assessment [80,81]. Correspondingly, the analytical depth has gradually advanced from static topological descriptions to the dynamic characterization of disturbances from occurrence to propagation, with dynamic models such as the SIR framework increasingly applied to reveal patterns of risk diffusion.

From a knowledge-structure perspective, LMTN research exhibits a pronounced interdisciplinary trend [82]. As the research focus has gradually expanded from LNG supply-chain management and market-pattern analysis to network efficiency enhancement, carbon-emission mitigation, and system resilience assessment, related studies have increasingly integrated theories and methods from transportation systems, energy economics, complex network science, and maritime safety. Meanwhile, the strong burst trends observed in data-driven methods and machine learning techniques further indicate that the methodological framework of current LMTN research is gradually shifting from traditional indicator-based analysis toward digital-twin-enabled intelligent decision-making and dynamic prediction.

4.2. Challenges

Current LMTN research still requires further development in terms of data reliability, mechanism interpretation, and decision-making support. As summarized in Table 9, the main research bottlenecks are concentrated in three dimensions: methodology, data, and computational power. Methodological challenges mainly arise from the limited ability of traditional models to capture multi-source disturbances and from the insufficient interpretability of "black-box" intelligent algorithms. Data-related challenges include the difficulty of obtaining long-term high-quality datasets, the high cost of commercial data access, and the complexity of multi-source heterogeneous data integration. Computational power challenges are mainly reflected in the limited efficiency of single-machine serial processing, which is insufficient for real-time monitoring, rapid risk warning, and online decision-making based on massive maritime big data.

Table 9. Major challenges faced by LMTN research.

Dimension	Issue	Specific Manifestations	Solutions
Methodology	Limited capability of traditional network analysis	Existing studies mainly rely on topological indicators, but pay insufficient attention to geopolitical risks, energy policies, key maritime corridors, and port dependence [83].	Build a multidimensional evaluation framework integrating topology, trade flows, geopolitical risks, port capacity, and maritime corridor constraints [84].
	Limited interpretability of intelligent models	Deep learning methods have shown good performance in link prediction and risk identification. However, their "black-box" nature makes it difficult to explain decision-making bases.	Introduce explainable AI methods to improve model transparency and enhance interpretability using approaches such as SHAP, attention weight analysis, and feature contribution decomposition [85].
Data	Difficulty in obtaining long-term high-quality data	Network evolution and resilience studies require continuous multi-year data, but global AIS, trade, and port operation data are costly to obtain and store [86].	Establish long-term LMTN databases and validate data using AIS, trade statistics, and port throughput records [29].
	Limited access to commercial data	High-value data, such as global AIS, real-time LNG logistics, and vessel emissions data, are mostly controlled by commercial providers.	Promote open data sharing and build reproducible datasets using public AIS, UN Comtrade, GIIGNL, IEA, and other sources [35].
Computational power	Low efficiency in large-scale data processing	Single-machine CPU-based processing is inefficient for data cleaning, feature extraction, and model training.	Introduce parallel computing, distributed storage, and GPU acceleration [87].
	Immature application of high-performance computing	Parallel and edge computing remain limited by data-sharing barriers, inconsistent standards, and insufficient edge-side computing capacity [88].	Develop cloud–edge–terminal collaborative computing and standardize maritime data interfaces [89].

4.3. Future Development Trends

Data-driven approaches and artificial intelligence have become central themes in contemporary LMTN research. Future developments are expected to place greater emphasis on intelligent methods, including graph learning, deep reinforcement learning, explainable artificial intelligence, and spatiotemporal modeling, as well as digital-twin and simulation technologies. Recent studies have demonstrated the effectiveness of deep learning for large-scale spatiotemporal prediction tasks in maritime transportation systems, such as global shipping carbon-emission forecasting, highlighting the potential of AI-driven approaches for future LMTN monitoring, prediction, and decision support [90]. However, the effective application of these intelligent methods depends on the availability of high-quality labeled datasets, transparent model interpretation, standardized maritime data interfaces, and sufficient computational infrastructure.

As shown in Figure 6, multi-source data, including navigation data, global LNG trade data, port operation data, and environmental data, provide the fundamental data foundation for future LMTN studies. The integration of big data and advanced learning methods

is driving LMTN research beyond static structural characterization toward dynamic prediction and mechanism-oriented understanding. In parallel, digital-twin technologies are expected to strengthen the coupling between real-world maritime transportation systems and simulation models by enabling virtual–physical mapping, real-time synchronization, scenario simulation, and system state assessment. Such algorithm–simulation coupling can provide critical support for network risk early warning, disruption propagation analysis, resilience evaluation, and intelligent decision-making for LMTN [91].

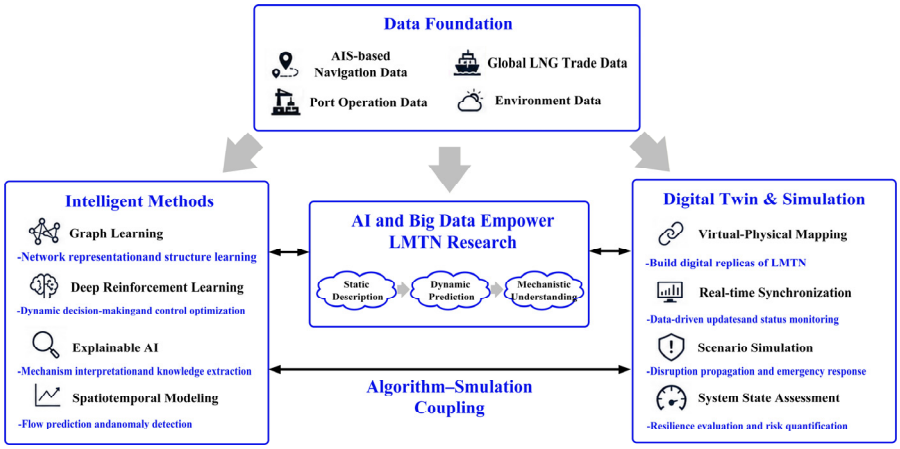


Figure 6. Future development trends in LMTN research.

5. Conclusions

This study provides a systematic review of progress in LMTN research. With the global energy system transitioning toward low-carbon development, LMTN—serving as a critical link in the energy supply chain—has gained substantial academic relevance and practical significance, particularly in studies of network complexity and resilience. Through a comprehensive literature review, the construction of a technical framework, and bibliometric analysis, the main conclusions are summarized as follows:

LMTN exhibits a high degree of specialization. Research on LMTN has evolved from an initial focus on supply-chain optimization to a foundational stage emphasizing macro-level trade pattern analysis, and subsequently to a rapid-development stage characterized by big-data-driven dynamic evolution analysis. It is now entering a deeper research phase dominated by artificial intelligence and digital-twin technologies, showing a clear and progressive evolutionary trajectory across research stages [92].

Bibliometric analysis reveals a clear shift in research hotspots. The focus has moved from early themes such as trade market analysis toward more intelligent and advanced directions, including resilience assessment, data-driven approaches, and machine learning. Overall, the field demonstrates a strong multidisciplinary orientation, integrating transportation, trade and logistics, maritime governance, energy and low-carbon studies, as well as safety and reliability research.

Significant methodological and computational challenges remain. Long-term historical data are difficult to obtain, traditional network indicators are insufficient to capture complex geopolitical influences and uncertainty factors, and intelligent algorithms such as deep learning still face the challenge of limited interpretability due to their "black-box" nature. In addition, existing serial-processing computing paradigms are unable to meet the growing demands for real-time monitoring and rapid early warning.

Future research directions are increasingly technology-driven. Advances in graph neural networks, deep reinforcement learning, and digital-twin technologies are expected to drive a paradigm shift from retrospective analysis toward real-time situational awareness

and forward-looking decision support [93]. At the same time, under the constraints of IMO carbon-reduction targets, network reconfiguration and low-carbon optimization will become major priorities for both research and industry practice.

Overall, LMTN research is expected to evolve toward greater intelligence, digitalization, and low-carbon development [94,95]. Future studies urgently need to overcome data silos and commercial barriers by promoting the establishment of open, shared global shipping databases and unified data standards [96]. In parallel, enhancements in computational power and infrastructure are required to improve the processing, modeling, and real-time inference capabilities for massive multi-source data. These efforts will provide critical foundational support for safeguarding global energy security, strengthening dynamic monitoring and risk early warning in the supply chain, and enhancing overall network resilience.

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References

1. Kaluza, P.; Kölzsch, A.; Gastner, M.T.; Blasius, B. The Complex Network of Global Cargo Ship Movements. *J. R. Soc. Interface* **2010**, *7*, 1093–1103. [CrossRef]
2. Notteboom, T.E. Container Shipping and Ports: An Overview. *Rev. Netw. Econ.* **2004**, *3*, 86–106. [CrossRef]
3. Hu, Y.; Zhu, D. Empirical Analysis of the Worldwide Maritime Transportation Network. *Phys. A Stat. Mech. Its Appl.* **2009**, *388*, 2061–2071. [CrossRef]
4. Wang, Z.; Fang, Z.; Yu, J.; Hu, X.; Gong, J. Red Sea Crisis Impacts on Maritime Shipping Networks. *Heliyon* **2024**, *10*, e40384. [CrossRef]
5. Mei, Q.; Li, Z.; Hu, Q.; Zhi, X.; Wang, P.; Yang, Y.; Liu, X. Spatio-Temporal Graph Neural Network Fused with Maritime Knowledge for Predicting Traffic Flows in Ports. *Reg. Stud. Mar. Sci.* **2025**, *85*, 104106. [CrossRef]
6. Yang, Y.; Liu, Y.; Li, G.; Zhang, Z.; Liu, Y. Harnessing the Power of Machine Learning for AIS Data-Driven Maritime Research: A Comprehensive Review. *Transp. Res. Part E Logist. Transp. Rev.* **2024**, *183*, 103426. [CrossRef]
7. Christiansen, M.; Fagerholt, K.; Ronen, D. Ship Routing and Scheduling: Status and Perspectives. *Transp. Sci.* **2004**, *38*, 1–18. [CrossRef]
8. Halvorsen-Weare, E.E.; Fagerholt, K. Routing and Scheduling in a Liquefied Natural Gas Shipping Problem with Inventory and Berth Constraints. *Ann. Oper. Res.* **2013**, *203*, 167–186. [CrossRef]
9. Christiansen, M.; Fagerholt, K.; Nygreen, B.; Ronen, D. Ship Routing and Scheduling in the New Millennium. *Eur. J. Oper. Res.* **2013**, *228*, 467–483. [CrossRef]
10. Chen, Z.; An, H.; Gao, X.; Li, H.; Hao, X. Competition Pattern of the Global Liquefied Natural Gas (LNG) Trade by Network Analysis. *J. Nat. Gas Sci. Eng.* **2016**, *33*, 769–776. [CrossRef]
11. Geng, J.-B.; Ji, Q.; Fan, Y. A Dynamic Analysis on Global Natural Gas Trade Network. *Appl. Energy* **2014**, *132*, 23–33. [CrossRef]
12. Zhang, H.-Y.; Xi, W.-W.; Ji, Q.; Zhang, Q. Exploring the Driving Factors of Global LNG Trade Flows Using Gravity Modelling. *J. Clean. Prod.* **2018**, *172*, 508–515. [CrossRef]

13. Peng, P.; Lu, F.; Cheng, S.; Yang, Y. Mapping the Global Liquefied Natural Gas Trade Network: A Perspective of Maritime Transportation. *J. Clean. Prod.* **2021**, *283*, 124640. [CrossRef]
14. Chen, S.; Xiao, Y.; Dai, Y.; Jinhong Mi, J. The Evolution of the Global Liquefied Natural Gas (LNG) Seaborne Trade Network: A Complex Network Analysis. *Procedia Comput. Sci.* **2024**, *242*, 396–403. [CrossRef]
15. Liu, M.; Liu, Y.; Wong, C.W.Y.; Lai, K.; Tu, E. The Impacts of Geopolitics on Global Liquefied Natural Gas (LNG) Shipping Network: Evidence from Two Geopolitical Events. *Ocean Coast. Manag.* **2025**, *267*, 107706. [CrossRef]
16. Xu, Y.; Peng, P.; Xie, X.; Lu, F. Structural Analysis and Robustness Assessment of Global LNG Transport Network from 2013 to 2023. *Ocean Coast. Manag.* **2025**, *263*, 107619. [CrossRef]
17. Mei, Q.; Qinyou, H.; Hu, Y.; Yang, Y.; Liu, X.; Huang, Z.; Wang, P. Structural Analysis and Vulnerability Assessment of the European LNG Maritime Supply Chain Network (2018–2020). *Ocean Coast. Manag.* **2024**, *253*, 107126. [CrossRef]
18. Xu, Y.; Peng, P.; Claramunt, C.; Qian, J.; Lu, F. Resilience of the Global Maritime LNG Network: From Static Bow-Tie to Dynamic SIR Modeling. *Reliab. Eng. Syst. Saf.* **2026**, *265*, 111605. [CrossRef]
19. Zhao, P.; Song, H.; Ling, G. Machine Learning Approaches for Predicting the Link of the Global Trade Network of Liquefied Natural Gas. *PLoS ONE* **2025**, *20*, e0326952. [CrossRef] [PubMed]
20. Yu, H.; Wu, W.; Zhang, X.; Fang, Z.; Fu, X.; Xu, L.; Liu, J. Optimization-Based Global Liquefied Natural Gas Shipping Network Management for Emission Reduction. *Ocean Eng.* **2025**, *321*, 120366. [CrossRef]
21. Hong, Y.H.; Wang, J.; Peng, C.; Zhao, J. A Risk-Aware LNG Terminal Scheduling Digital Twin Based on Deep Reinforcement Learning. *Comput. Chem. Eng.* **2026**, *206*, 109520. [CrossRef]
22. Álvarez, N.G.; Adenso-Díaz, B.; Calzada-Infante, L. Maritime Traffic as a Complex Network: A Systematic Review. *Netw. Spat. Econ.* **2021**, *21*, 387–417. [CrossRef]
23. Tovar, B.; Hernández, R.; Rodríguez-Déniz, H. Container Port Competitiveness and Connectivity: The Canary Islands Main Ports Case. *Transp. Policy* **2015**, *38*, 40–51. [CrossRef]
24. Ansorena, I.L. Bilateral Connectivity in the Liner Shipping Network: An Overview. *World Rev. Intermodal Transp. Res.* **2018**, *7*, 295–309. [CrossRef]
25. Wang, L.; Zhang, N.; Ye, F.; Lau, Y.; Ducruet, C. The Complex Network Analysis of Liner Shipping Networks: Lessons from the Merger between COSCO and CSCL. *Growth Change* **2020**, *51*, 1877–1893. [CrossRef]
26. Ye, J.; Huang, X.; Chen, W. Diffusion of Low-Carbon Shipping along the 21st Century Maritime Silk Road: From Complex Network Perspective. *Ocean Coast. Manag.* **2025**, *266*, 107662. [CrossRef]
27. International Group of Liquefied Natural Gas Importers (GIIGNL). *The LNG Industry: GIIGNL Annual Report 2025*; GIIGNL: Neuilly-sur-Seine, France, 2025.
28. Peng, P.; Yang, Y.; Cheng, S.; Lu, F.; Yuan, Z. Hub-and-Spoke Structure: Characterizing the Global Crude Oil Transport Network with Mass Vessel Trajectories. *Energy* **2019**, *168*, 966–974. [CrossRef]
29. Wang, Z.; Claramunt, C.; Wang, Y. Extracting Global Shipping Networks from Massive Historical Automatic Identification System Sensor Data: A Bottom-up Approach. *Sensors* **2019**, *19*, 3363. [CrossRef]
30. Zhang, D.; Tao, J.; Wan, C.; Huang, L.; Yang, M. Resilience Analysis of Maritime Transportation Networks: A Systematic Review. *Transp. Saf. Environ.* **2024**, *6*, tdae009. [CrossRef]
31. Hou, Z.; Niu, X.; Yu, Z.; Chen, W. Spatiotemporal Evolution and Market Dynamics of the International Liquefied Natural Gas Trade: A Multilevel Network Analysis. *Energies* **2024**, *17*, 228. [CrossRef]
32. Belcore, O.M.; Polimeni, A. Times of Ships in Container Ports: Automatic Identification System Data for Analyzing Traffic Conditions at a Maritime Terminal. *Front. Future Transp.* **2026**, *6*, 1735788. [CrossRef]
33. Savvakis, K.I.; Moschovou, T.P. European LNG Import Network Analysis and Investigation of Supply Security. *Energies* **2025**, *18*, 634. [CrossRef]
34. Guo, Z.; Qiang, H.; Xie, S.; Peng, X. Unsupervised Knowledge Discovery Framework: From AIS Data Processing to Maritime Traffic Networks Generating. *Appl. Ocean Res.* **2024**, *146*, 103924. [CrossRef]
35. Chen, C.; Jiang, Z.; Li, N.; Wang, H.; Wang, P.; Zhang, Z.; Zhang, C.; Ma, F.; Huang, Y.; Lu, X.; et al. Advancing UN Comtrade for Physical Trade Flow Analysis: Review of Data Quality Issues and Solutions. *Resour. Conserv. Recycl.* **2022**, *186*, 106526. [CrossRef]
36. Mei, Q.; Hu, Q.; Liu, X.; Zhao, R.; Yang, C.; Wang, P.; Qi, Y.; Yang, Y.; Yuan, Q. Research on the Evolution of Global LNG Maritime Transportation Network and Trade Condition of China. *J. Geo-Inf. Sci.* **2022**, *24*, 1701–1716.
37. Huang, I.-L.; Lee, M.-C.; Chang, L.; Huang, J.-C. Development and Application of an Advanced Automatic Identification System (AIS)-Based Ship Trajectory Extraction Framework for Maritime Traffic Analysis. *J. Mar. Sci. Eng.* **2024**, *12*, 1672. [CrossRef]
38. Iphar, C.; Le Berre, I.; Foulquier, É.; Napoli, A. Port Call Extraction from Vessel Location Data for Characterising Harbour Traffic. *Ocean Eng.* **2024**, *293*, 116771. [CrossRef]
39. Wijaya, W.M.; Nakamura, Y. Port Performance Indicators Construction Based on the AIS-Generated Trajectory Segmentation and Classification. *Int. J. Data Sci. Anal.* **2025**, *20*, 2473–2492. [CrossRef]

40. Peng, P.; Cheng, S.; Yang, Y.; Lu, F. Research on Characteristics and Evolution of Global LNG Transportation Network. *Geogr. Res.* **2021**, *40*, 373–386.
41. Barnes, R.; Bosworth, R. LNG Is Linking Regional Natural Gas Markets: Evidence from the Gravity Model. *Energy Econ.* **2015**, *47*, 11–17. [CrossRef]
42. Bittante, A.; Jokinen, R.; Krooks, J.; Pettersson, F.; Saxén, H. Optimal Design of a Small-Scale LNG Supply Chain Combining Sea and Land Transports. *Ind. Eng. Chem. Res.* **2017**, *56*, 13434–13443. [CrossRef]
43. Guo, J.; Liang, M. The Coupling Characteristics of the Shipping Network and Trade between China and the Countries along the 21st Century Maritime Silk Road. *Acta Geogr. Sin.* **2022**, *77*, 1531–1545.
44. Lin, J.; Ban, Y. Complex Network Topology of Transportation Systems. *Transp. Rev.* **2013**, *33*, 658–685. [CrossRef]
45. Cui, W.; Wu, D.; Huang, Q.; Yang, S. The Dynamic Evolution Mechanism of Liquefied Natural Gas Trade Dependency Networks: International Implications of the Russia-Ukraine Conflict. *Sustain. Futur.* **2025**, *9*, 100730. [CrossRef]
46. Hosseini, S.; Barker, K.; Ramirez-Marquez, J.E. A Review of Definitions and Measures of System Resilience. *Reliab. Eng. Syst. Saf.* **2016**, *145*, 47–61. [CrossRef]
47. Ke, R.; Wang, X.; Peng, P. Analysis of the Impact of the Russia–Ukraine Conflict on Global Liquefied Natural Gas Shipping Network. *J. Mar. Sci. Eng.* **2025**, *13*, 53. [CrossRef]
48. Bittante, A.; Pettersson, F.; Saxén, H. Optimization of a Small-Scale LNG Supply Chain. *Energy* **2018**, *148*, 79–89. [CrossRef]
49. Goel, V.; Slusky, M.; van Hoeve, W.-J.; Furman, K.C.; Shao, Y. Constraint Programming for LNG Ship Scheduling and Inventory Management. *Eur. J. Oper. Res.* **2015**, *241*, 662–673. [CrossRef]
50. Koza, D.F.; Ropke, S.; Boleda Molas, A. The Liquefied Natural Gas Infrastructure and Tanker Fleet Sizing Problem. *Transp. Res. Part E Logist. Transp. Rev.* **2017**, *99*, 96–114. [CrossRef]
51. Dieckhöner, C.; Lochner, S.; Lindenberger, D. European Natural Gas Infrastructure: The Impact of Market Developments on Gas Flows and Physical Market Integration. *Appl. Energy* **2013**, *102*, 994–1003. [CrossRef]
52. Eriksen, U.; Kristiansen, J.; Fagerholt, K.; Pantuso, G. Planning a Maritime Supply Chain for Liquefied Natural Gas under Uncertainty. *Marit. Transp. Res.* **2022**, *3*, 100061. [CrossRef]
53. Yu, H.; Fang, Z.; Lu, F.; Murray, A.T.; Zhang, H.; Peng, P.; Mei, Q.; Chen, J. Impact of Oil Price Fluctuations on Tanker Maritime Network Structure and Traffic Flow Changes. *Appl. Energy* **2019**, *237*, 390–403. [CrossRef]
54. Zhang, Q.; Li, M. A Betweenness Structural Entropy of Complex Networks. *Chaos Solitons Fractals* **2022**, *161*, 112264. [CrossRef]
55. Kitsak, M.; Gallos, L.K.; Havlin, S.; Liljeros, F.; Muchnik, L.; Stanley, H.E.; Makse, H.A. Identification of Influential Spreaders in Complex Networks. *Nat. Phys.* **2010**, *6*, 888–893. [CrossRef]
56. Xin, X.; Yang, Z. Resilience Assessment: Insights from Port Community Structures across the Global Container Shipping Network. *Reliab. Eng. Syst. Saf.* **2026**, *265*, 111489. [CrossRef]
57. Li, Y.; Tian, W.; Meng, B.; Zhang, J.; Zhou, R. A Simulation Model of the Influence of LNG Ships on Traffic Efficiency at Tianjin Port. *J. Mar. Sci. Eng.* **2024**, *12*, 405. [CrossRef]
58. Guo, S.; Wang, H.; Wang, S. Network Disruptions and Ripple Effects: Queueing Model, Simulation, and Data Analysis of Port Congestion. *J. Mar. Sci. Eng.* **2023**, *11*, 1745. [CrossRef]
59. Liu, Y.; Ma, X.; Qiao, W.; Ma, L.; Han, B. A Novel Methodology to Model Disruption Propagation for Resilient Maritime Transportation Systems–a Case Study of the Arctic Maritime Transportation System. *Reliab. Eng. Syst. Saf.* **2024**, *241*, 109620. [CrossRef]
60. Wen, X.; Chen, Q.; Yin, Y.-Q.; Lau, Y.; Dulebenets, M.A. Multi-Objective Optimization for Ship Scheduling with Port Congestion and Environmental Considerations. *J. Mar. Sci. Eng.* **2024**, *12*, 114. [CrossRef]
61. Dong, S.; Yang, G.; Liao, S.; Li, L. Optimizing Ship Traffic Scheduling in LNG Ports: An Enhanced Model Incorporating Navigation Characteristics and Night Sailing Risks. *Ocean Eng.* **2025**, *330*, 121117. [CrossRef]
62. Schach, M.; Madlener, R. Impacts of an Ice-Free Northeast Passage on LNG Markets and Geopolitics. *Energy Policy* **2018**, *122*, 438–448. [CrossRef]
63. Hu, W.; Shi, J.; Pang, C.; Chen, J.; Wan, Z.; Wang, Z. Assessment and Optimization of Shipping Network Resilience in the Maritime Silk Road Regions. *J. Transp. Geogr.* **2026**, *130*, 104454. [CrossRef]
64. Abioye, O.F.; Dulebenets, M.A.; Pasha, J.; Kavoosi, M. A Vessel Schedule Recovery Problem at the Liner Shipping Route with Emission Control Areas. *Energies* **2019**, *12*, 2380. [CrossRef]
65. Halvorsen-Weare, E.E.; Fagerholt, K.; Rönnqvist, M. Vessel Routing and Scheduling under Uncertainty in the Liquefied Natural Gas Business. *Comput. Ind. Eng.* **2013**, *64*, 290–301. [CrossRef]
66. Khan, R.U.; Yin, J.; Asad, M.; Alomayri, T.; Jameel, M. Predicting Seaport Disruptions from Natural Hazards Using Automated Machine Learning. *Mar. Pollut. Bull.* **2025**, *221*, 118477. [CrossRef]
67. Donthu, N.; Kumar, S.; Mukherjee, D.; Pandey, N.; Lim, W.M. How to Conduct a Bibliometric Analysis: An Overview and Guidelines. *J. Bus. Res.* **2021**, *133*, 285–296. [CrossRef]

68. Vivoda, V. LNG Import Diversification and Energy Security in Asia. *Energy Policy* **2019**, *129*, 967–974. [CrossRef]
69. Lambert, L.A.; Tayah, J.; Lee-Schmid, C.; Abdalla, M.; Abdallah, I.; Ali, A.H.M.; Esmail, S.; Ahmed, W. The EU's Natural Gas Cold War and Diversification Challenges. *Energy Strategy Rev.* **2022**, *43*, 100934. [CrossRef]
70. Wang, K.; Zhao, S.; Wang, Z. Global Liquefied Natural Gas Market Development and Future Outlook. *Nat. Gas Ind. B* **2025**, *12*, 636–646. [CrossRef]
71. Lehtonen, J.-M.; Aalto, M.; Hyytiäinen, M. Resilience to Russia's Energy Weapon: Natural Gas in Finland. *Contin. Resil. Rev.* **2025**, *8*, 38–53. [CrossRef]
72. Animah, I.; Shafiee, M. Application of Risk Analysis in the Liquefied Natural Gas (LNG) Sector: An Overview. *J. Loss Prev. Process Ind.* **2020**, *63*, 103980. [CrossRef]
73. Li, Z.; Hu, S.; Gao, G.; Yao, C.; Fu, S.; Xi, Y. Decision-Making on Process Risk of Arctic Route for LNG Carrier via Dynamic Bayesian Network Modeling. *J. Loss Prev. Process Ind.* **2021**, *71*, 104473. [CrossRef]
74. Jokinen, R.; Pettersson, F.; Saxen, H. An MILP Model for Optimization of a Small-Scale LNG Supply Chain along a Coastline. *Appl. Energy* **2015**, *138*, 423–431. [CrossRef]
75. Li, Z.; Hu, S.; Zhu, X.; Gao, G.; Yao, C.; Han, B. Using DBN and Evidence-Based Reasoning to Develop a Risk Performance Model to Interfere Ship Navigation Process Safety in Arctic Waters. *Process Saf. Environ. Prot.* **2022**, *162*, 357–372. [CrossRef]
76. Xiao, R.; Xiao, T.; Zhao, P.; Zhang, M.; Ma, T.; Qiu, S. Structure and Resilience Changes of Global Liquefied Natural Gas Shipping Network during the Russia-Ukraine Conflict. *Ocean Coast. Manag.* **2024**, *252*, 107102. [CrossRef]
77. Shaikh, F.; Ji, Q.; Fan, Y. Assessing the Stability of the LNG Supply in the Asia Pacific Region. *J. Nat. Gas Sci. Eng.* **2016**, *34*, 376–386. [CrossRef]
78. Shibasaki, R.; Kanamoto, K.; Suzuki, T. Estimating Global Pattern of LNG Supply Chain: A Port-Based Approach by Vessel Movement Database. *Marit. Policy Manag.* **2020**, *47*, 143–171. [CrossRef]
79. Zhang, S.; Wang, L.; Ng, A.K.Y. Turning the Ships around: The Russia-Ukraine Conflict Reshapes the US LNG Maritime Transportation Network. *Ocean Coast. Manag.* **2024**, *257*, 107351. [CrossRef]
80. Yang, H.; Liu, C.; Cao, Y.; Shu, Y.; Gan, L.; Liu, Z.; Yang, Z. Dynamic Resilience Assessment of Global Shipping Networks against Cascading Effects: An AIS Data-Driven Complex Network Analysis. *Sustain. Horiz.* **2026**, *18*, 100184. [CrossRef]
81. Fang, Z.; Yu, H.; Lu, F.; Feng, M.; Huang, M. Maritime Network Dynamics before and after International Events. *J. Geogr. Sci.* **2018**, *28*, 937–956. [CrossRef]
82. Xiao, G.; Wang, Y.; Wu, R.; Li, J.; Cai, Z. Sustainable Maritime Transport: A Review of Intelligent Shipping Technology and Green Port Construction Applications. *J. Mar. Sci. Eng.* **2024**, *12*, 1728. [CrossRef]
83. Lin, Y.; Li, X.; Yuen, K.F. Machine Learning Applications for Risk Assessment in Maritime Transport: Current Status and Future Directions. *Eng. Appl. Artif. Intell.* **2025**, *155*, 110959. [CrossRef]
84. Meza, A.; Ari, I.; Sada, M.A.; Koç, M. Disruption of Maritime Trade Chokepoints and the Global LNG Trade: An Agent-Based Modeling Approach. *Marit. Transp. Res.* **2022**, *3*, 100071. [CrossRef]
85. Wu, Z.; Wang, S.; Li, L.; Suo, Y. An Interpretable Ship Risk Model Based on Machine Learning and SHAP Interpretation Technique. *Ocean Eng.* **2025**, *335*, 121686. [CrossRef]
86. Zhao, L.; Shi, G.; Yang, J. Ship Trajectories Pre-Processing Based on AIS Data. *J. Navig.* **2018**, *71*, 1210–1230. [CrossRef]
87. Chen, H.; Wen, Y.; Huang, Y.; Xiao, C.; Sui, Z. Edge Computing Enabling Internet of Ships: A Survey on Architectures, Emerging Applications, and Challenges. *IEEE Internet Things J.* **2025**, *12*, 1509–1528. [CrossRef]
88. Raza, Z.; Woxenius, J.; Vural, C.A.; Lind, M. Digital Transformation of Maritime Logistics: Exploring Trends in the Liner Shipping Segment. *Comput. Ind.* **2023**, *145*, 103811. [CrossRef]
89. Xiu, S.; Zhang, Y.; Chen, H.; Wen, Y.; Xiao, C. Task-Driven Computing Offloading and Resource Allocation Scheme for Maritime Autonomous Surface Ships under Cloud–Shore–Ship Collaboration Framework. *J. Mar. Sci. Eng.* **2025**, *13*, 16. [CrossRef]
90. Yu, H.; Jiang, C.; Fang, Q.; Wei, T.; Xu, L. Deep Learning Driven Spatiotemporal Prediction of Global Carbon Emissions from Container Shipping. *Transp. Res. Part D Transp. Environ.* **2026**, *151*, 105169. [CrossRef]
91. Zhou, C.; Xu, J.; Miller-Hooks, E.; Zhou, W.; Chen, C.-H.; Lee, L.H.; Chew, E.P.; Li, H. Analytics with Digital-Twinning: A Decision Support System for Maintaining a Resilient Port. *Decis. Support Syst.* **2021**, *143*, 113496. [CrossRef]
92. Juan, N.P.; Valdecantos, V.N.; Troch, P. Advancing Artificial Intelligence in Ocean and Maritime Engineering: Trends, Progress, and Future Directions. *Ocean Eng.* **2025**, *339*, 122077. [CrossRef]
93. Neugebauer, J.; Heilig, L.; Voss, S. Digital Twins in the Context of Seaports and Terminal Facilities. *Flex. Serv. Manuf. J.* **2024**, *36*, 821–917. [CrossRef]
94. Robalo-Cabrera, I.; Alcayde, A.; Filgueira-Vizoso, A.; Castro-Santos, L.; García-Diez, A.I.; Manzano-Agugliaro, F. Shipping Sector Decarbonisation Measures: A Review. *Sustain. Energy Technol. Assess.* **2025**, *82*, 104549. [CrossRef]

95. Jovic, M.; Tijan, E.; Brcic, D.; Pucihar, A. Digitalization in Maritime Transport and Seaports: Bibliometric, Content and Thematic Analysis. *J. Mar. Sci. Eng.* **2022**, *10*, 486. [CrossRef]
96. Tijan, E.; Jovic, M.; Aksentijevic, S.; Pucihar, A. Digital Transformation in the Maritime Transport Sector. *Technol. Forecast. Soc. Change* **2021**, *170*, 120879. [CrossRef]

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