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Review

Review of intelligent maritime transportation systems facilitated by deep learning: A survey on safe navigation

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ABSTRACT: Intelligent maritime transportation systems (IMTSs) have become increasingly critical for enhancing navigational safety, improving operational efficiency, and supporting autonomous decision-making in maritime domains. With the growing volume and complexity of maritime operations, IMTSs have evolved rapidly through the integration of emerging technologies such as the internet of things (IoT), satellite communication, and artificial intelligence (AI). Among these, deep learning (DL) has shown particular promise, offering powerful capabilities to extract complex patterns from large-scale maritime data and enabling advancements in applications such as ship detection, trajectory prediction, collision avoidance, and traffic flow modeling. Despite these developments, a comprehensive review that critically assesses the strengths and weaknesses of these models, especially the DL-based models used in IMTSs, is lacking. As such, this study contributes to bridging this gap with a quantitative review of the technological evolution of IMTS and a systematic analysis of DL-based research within IMTSs, covering key domains such as risk assessment, autonomous navigation, situation awareness, and intelligent decision-making. Furthermore, this study highlights key challenges in recent research and identifies future research directions. This study not only provides a holistic understanding of how DL has transformed maritime intelligence but also offers practical insights for developing safe and more efficient IMTSs.

KEYWORDS: intelligent maritime transportation systems (IMTSs); deep learning (DL); autonomous navigation; maritime safety; artificial intelligence (AI); data-driven maritime systems

1 Introduction

Maritime transportation systems are the backbone of global trade, as more than 80% of the global trade by volume is transported by international shipping (United Nations Conference on Trade and Development (UNCTAD), 2022). However, any disruptive event of the maritime system can have a profound impact on the whole maritime industry, such as threats to the environment and loss of life and property (Durlik et al., 2024). To ensure the safety, efficiency and sustainability of maritime transportation, much attention has been devoted to digitalizing maritime transportation systems with adequate intelligent support. By integrating artificial intelligence (AI), big data analytics, and internet of things (IoT) technologies, these efforts aim to optimize vessel operations, enhance navigational safety, and improve supply chain efficiency (Zhang et al., 2021).

Building upon these technological advancements, the concept of intelligent maritime transportation systems (IMTSs) has emerged as a comprehensive system that integrates digital and intelligent solutions into the maritime industry. Originating from the concept of “e-Navigation” proposed by the International Maritime Organization (IMO) and formally introduced at the 17th Intelligent Transportation Systems (ITS) World Congress in 2009 (IMO, 2009), IMTSs aim to innovate the intelligent operation and navigation-aid techniques of maritime transportation systems, especially to ensure navigation safety, improve logistics efficiency and reduce impacts on the environment. The evolution of e-Navigation into IMTS has integrated elements such as maritime logistics, vessel traffic management, and decision-support systems, thereby transforming it into a broader and more interconnected framework beyond navigation. The architecture of IMTS was further refined and discussed at the 18th ITS World Congress (IMO, 2018a), where experts explored its potential for enhancing efficiency, safety, and automation in global maritime transport. Due to the numerous benefits, governments and international organizations are increasingly recognizing the importance of IMTSs in fostering a more sustainable and efficient maritime sector. The EU-funded AUTOSHIP project advances autonomous shipping in inland and short sea routes (European Commission, 2019), while the United States Maritime Transportation System National Advisory (U.S. MTSNAC) promotes AI-based port modernization strategies (Maritime Administration of the United States, 2024). These initiatives illustrate the evolution of IMTS from a navigation-oriented concept into a strategic framework, as recent projects focus on applying emerging technologies across multiple maritime domains to advance the intelligence of IMTS.

As nations worldwide ramp up investments in smart port technologies and autonomous shipping, driven by a shared vision

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of sustainable and efficient maritime logistics, it is essential to explore the technological advancements underpinning the system. Traditionally, maritime transportation relied on human judgment. For example, crew members identify encounter situations and maneuver the ship based on their experience and regulations. However, human errors have been a major cause of maritime accidents, prompting the demand for automated solutions (Ramos et al., 2019). In response, modern data-driven approaches have been adopted to partially replace human intervention in predictive analysis and monitoring (Murray and Perera, 2022). To date, the adoption of machine learning (ML) and deep learning (DL) in maritime transportation have demonstrated superior performance in autonomous navigation and accident prevention. While ML typically relies on handcrafted features and statistical learning to analyze structured data, DL employs multilayer neural networks capable of automatically extracting hierarchical representations from raw inputs. In the maritime domain, ML algorithms have been widely applied to analyze historical data for identifying navigation risks and optimizing ship routing (Jimenez et al., 2022), whereas DL models—such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—capture complex spatial and temporal dependencies to enhance vessel identification, automated surveillance, and real-time decision-making (Qiao et al., 2021). Together, these approaches complement each other in improving maritime safety and advancing intelligent ship operations.

The evolution of technological innovations in IMTS keeps pace with the accessibility of data and information. The ability to collect, transmit, and process maritime information has significantly influenced the level of autonomy of the IMTS system. Early sea navigation relied on paper charts from the 16th and 17th centuries (Plummer, 2004), with subsequent enhancements by radar in the 1930s and 1940s that provided increased situational awareness at sea (Skolnik, 1962). Advances in the Global Positioning System (GPS) in the 1970s and 1980s revolutionized positioning precision, enabling better navigation and route optimization (Spilker et al., 1996). In the late 1990s, the use of the automatic identification system (AIS) made ship tracking and collision avoidance possible through real-time data exchange (IMO, 1998). More recently, since the 2010s, the use of IoT-based ship monitoring systems has further evolved maritime intelligence to make predictive maintenance, environmental monitoring, and fleet optimization possible (Ding et al., 2021a). These technological innovations, especially the recent use of IoT-based ship monitoring systems, offer abundant technological and data resources that support both the practical project development mentioned above and subsequent theoretical advancement.

As a highly integrated system, an IMTS has a variety of components to achieve autonomous operation apart from the mentioned components (Kyaw, 2024). Most recent efforts have been made to review specific topics of ITMSs in certain domains, for example, safety management (Luo and Shin., 2019; Xu et al., 2023b), situational awareness (Misas et al., 2024; Qiao et al., 2021), energy consumption (Qi et al., 2021; Xiao et al., 2023), autonomous ships (Chaal et al., 2023; Veitch and Alsos, 2022), and accident prevention (Chaal, 2023; Zhu et al., 2025). Among the existing review studies, most have adopted a qualitative approach, where they primarily focus on descriptive, conceptual, or thematic analyses without systematically quantifying the progression of IMTS. For instance, Ichimura et al. (2022) examined the strategic implications of shipping digitalization, analyzing industry shifts without statistical or bibliometric analysis. Similarly, Yang et al. (2019) provided a qualitative synthesis of AIS data applications to discuss their potential and challenges but without a data-driven assessment of their impact. Therefore, there remains a significant research gap in the systematic and quantitative assessment of IMTS evolution. A quantitative approach, such as statistical trend analysis, bibliometric mapping, and empirical evaluations, can provide a data-driven understanding of how IMTS has progressed over time.

Additionally, ML and DL are among the most powerful tools for revolutionizing research in IMTS (Du et al., 2022b; Filom et al., 2022; Li et al., 2023b; Yan et al., 2021). While ML has been widely used in assisting intelligent decision-making and improving the capability of handling large volumes of data, DL, as an advanced algorithm, has become a popular research hotspot because of its self-learning capacity with an "end-to-end" approach (Wang et al., 2024a). Previous literature has reviewed the application of AI algorithms in IMTS as a whole with little emphasis on DL applications (Haghighat et al., 2020; Munim et al., 2020; Zou et al., 2025). Meanwhile, individual studies have discussed specific DL-based applications such as trajectory prediction (Li et al., 2023b) and the control of autonomous surface ships (Ye et al., 2023). However, there is no in-depth review dedicated to DL's role in IMTS. A systematic exploration of DL techniques, their comparative performance against traditional methods, and their integration into real-world IMTS solutions remains an underexplored area.

Therefore, this survey aims to provide a comprehensive view of the research progress in IMTS and present the application of DL methods in the system. The scope of this survey is as follows:

1) A comprehensive review of the entire IMTS from the aspects of human, ship, and environment, mapping its evolution and identifying key technological milestones.

2) A comparative review of IMTS methodologies, examining traditional rule-based approaches, data-driven techniques, and AI-driven algorithms, assessing their contributions and transformative impact on IMTS development.

3) A systematic analysis of DL applications in IMTS, evaluating the advantages, limitations, and future potential of DL-driven maritime intelligence.

The remainder of this paper is structured as follows: Section 2 describes the data and methods used in the study. Section 3 briefly presents the visual analysis of the literature. Section 4 presents the use of data. Section 5 presents a systematic analysis of IMTS, examining key technologies, applications, and trends. Section 6 explores the role of DL in IMTS. A discussion of future research is provided in Section 7, while Section 8 summarizes and concludes the review.

2 Data and methods

2.1 Research methodology

The procedure and general methodology of this study follow a structured four-stage framework. In the first stage, data sample collection is conducted by systematically gathering relevant literature from major databases. The selection criteria for filtering and refining the dataset are detailed in Section 2.2, ensuring that only high-quality and relevant studies are included for further analysis. In stage 2, a quantitative analysis is conducted to examine the research landscape of IMTS. This stage uses bibliometric methods to assess scientific production, collaboration networks, and research developments in the field. To visualize the research trend, CiteSpace software (V 6.3. R1 64-bit)[1] is utilized for keyword co-occurrence analysis, clustering analysis, and chronological research trend analysis (Chen, 2006), providing an overview of the IMTS framework and emerging research directions. Then, a systematic analysis of IMTS and a comparative analysis of DL applications in IMTS is conducted using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology, as shown in Appendix A of the Electronic Supplementary Material (ESM). The systematic analysis focuses on key technological advancements in IMTS, while the comparative analysis of DL applications in IMTS is conducted to bridge the gap mentioned in Section 1. Finally, future research directions in IMTS are discussed.

2.2 Data preparation

The Web of Science (WOS) Core Collection was selected as the primary database for the literature search (Falagas et al., 2008). This search focuses on safe navigation, especially on the coeffect between ships and other parts of the IMTS as well as the correlation between safe navigation and the IMTS. The search query "TS = (ship*) OR TS = (vessel*) OR TS = (autonomous surface vehicle*) OR TS = (unmanned surface vessel*) AND TS = (maritime transportation*) AND (TS = (maritime transportation system*) OR TS = (transportation system*))" is used. The search was conducted in April 2025 within the Web of Science Core Collection[2], limited to English-language journal articles, conference papers, and reviews, and yielded a total of 2400 records.

To ensure thematic consistency, a manual screening process is then conducted to exclude irrelevant papers. This filtering is based on a multicriteria review of titles, abstracts, and keywords, prioritizing papers that explicitly include terms such as navigation safety, safe operation, or risk assessment. Papers that are purely conceptual or theoretical are also excluded. In this stage, a total of 250 papers were selected for the final review. This multicriteria selection process ensures that the filtered papers are highly relevant to the research theme of enhancing navigation safety within the IMTS context.

Finally, the filtered papers are reviewed again for verification to ensure that the final dataset can meet the criteria, focusing on the presence of empirical or applied analysis, explicit discussion of navigation safety and clear linkage to IMTS. This verification step aims to further eliminate ambiguously relevant studies and to ensure the accuracy, reliability, and thematic consistency of the final dataset. The evaluation criteria are shown in Table 1.

3 Visualized analysis of the literature

To gain insight into the research landscape of IMTS, a bibliometric analysis is conducted using CiteSpace. This section provides an overview of publication trends and key research focuses to provide a structured understanding of the development of the field. Section 3.1 examines annual publication trends that reflect the growing research interest in IMTS over time. Section 3.2 conducts the research focus analysis, using keyword co-occurrence and clustering techniques to identify major research topics, methodologies and research directions. As shown in Fig. 1, the above analysis provides a comprehensive perspective on the development and trajectory of IMTS research.

3.1 Analysis of annual publication trends

The number of published papers partly reflects the developments of the research field. Fig. 1a shows the annual number of publications related to IMTS. The number of publications showed a steady upward trend over the years. Starting from a relatively low level in the early 2000s, research activity gradually increased, reflecting a growing academic interest in maritime digitalization and automation. A notable acceleration occurred after 2010, with the annual publication count more than doubling between 2010 and 2015. The most significant increase appeared after 2020, during which the number of publications grows at an average annual rate exceeding 15%. This continuous rise in publication volume highlighted the expanding recognition of IMTS as a critical field within transportation and engineering research. As this study was conducted in mid-2025, the number of papers published in 2025 is less than that of 2024.

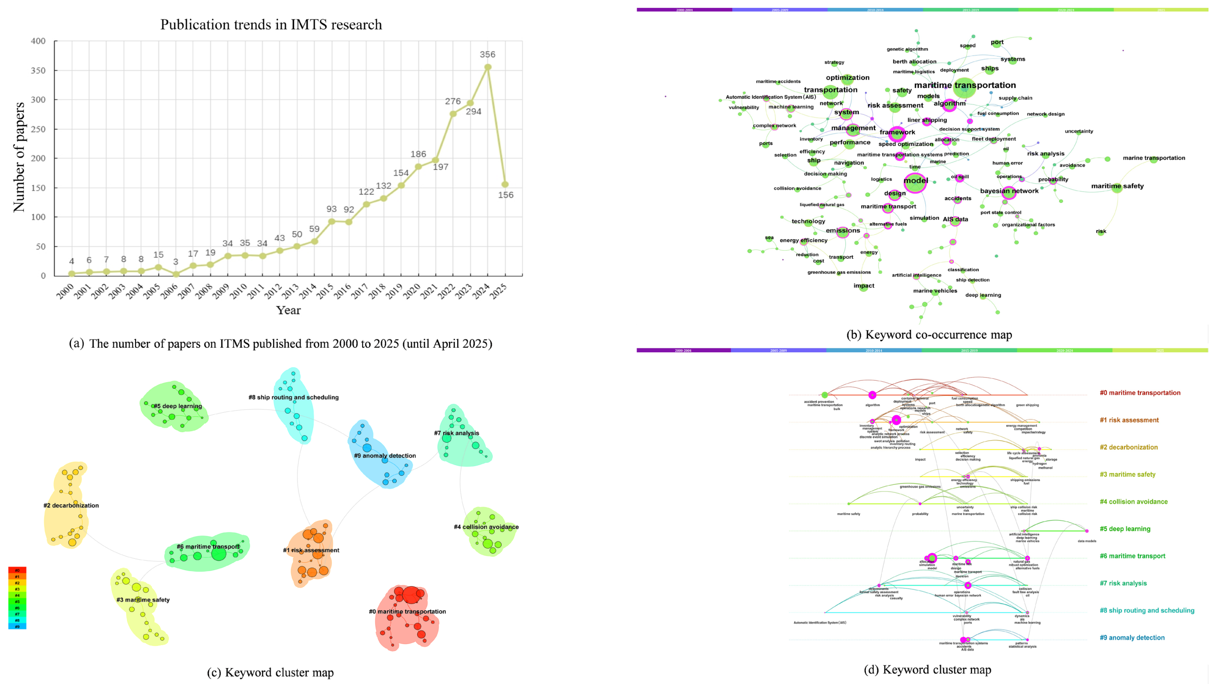
3.2 Research focus analysis in IMTS

As keywords carry important information about the collected papers, a keyword co-occurrence graph (from 2000 to 2025, time slice: 5 years) is generated using CiteSpace software, as shown in Fig. 1b, where the size of each node shows the frequency of keyword appearance, while the color represents the publication year. Table 2 lists the top ten most commonly used keywords, showing the hotspots in this research field. Maritime transportation and maritime transportation systems are the research scope of IMTS research. Therefore, they are the most frequent keywords. Additionally, methodologies such as Bayesian networks and model-based approaches are frequently used to enhance system reliability and navigation safety. AIS data are the most widely used data source in IMTS research studies. Furthermore, research efforts often emphasize optimization and management to improve operational efficiency and overall performance within IMTS.

The semantic clustering algorithm of CiteSpace is used to further analyze the collected papers' keywords to create the

Table 1 Categories of evaluation criteria

Criteria category	Research contents in IMTS
Safe navigation	Articles that focus on advancements in ensuring the safety of maritime navigation, including technologies and methodologies to prevent collisions, improve situational awareness, and navigate complex or congested waterways safely.
Navigation aid	Studies that contribute to the development of tools and systems for navigation support, such as route optimization, accurate position prediction, and the integration of navigation-aid devices.
Autonomous decision-making	Articles that explore the progress in autonomous systems and decision-making technologies, focusing on autonomous ships, adaptive control systems, and strategies for managing complex maritime scenarios.
Ship motion and trajectory prediction	Articles that address the advancement of ship motion, maneuverability pattern, and trajectory prediction techniques under dynamic environmental and traffic conditions, with the aim of providing real-time navigational safety support.
Navigation risk assessment	Articles that examine methodologies for identifying, analyzing, and mitigating navigation risks, including risk prediction models and probabilistic assessments of collision and grounding scenarios, are considered essential for improving maritime safety.



(a) The number of papers on ITMS published from 2000 to 2025 (until April 2025)

(b) Keyword co-occurrence map

(c) Keyword cluster map

(d) Keyword cluster map

Fig. 1 Results of the bibliometric analysis.

Table 2 High-frequency keywords in ITMS

Number	Frequency	Keyword
1	409	Maritime transportation
2	322	Maritime transportation systems
3	277	Model
4	129	Optimization
5	120	Management
6	110	Risk assessment
7	109	Maritime safety
8	99	Bayesian network
9	92	Emissions
10	87	AIS data

clustering diagram shown in Fig. 1c. Each cluster represents a major research focus in IMTS. The color of each cluster ranges from red to deep blue, indicating increasing cluster size. Lower cluster IDs indicate a larger number of associated keywords. The relevance of these clusters is visualized through linking edges, demonstrating how different research themes are interconnected. This clustering analysis highlights the key thematic structures and their constituent keywords that collectively shape the evolution of the field.

Based on these correlations, the temporal evolution of keywords is shown in Fig. 1d, which illustrates the evolution of research hotspots from 2020 to 2025. Fig. 1d illustrates how research themes have evolved over time, with clusters represented by different colors and arranged chronologically from left to right. The color-coded clusters correspond to different research areas, as indicated on the right side of Fig. 1d. The size of each node represents the frequency and significance of a keyword, while the curved linking lines indicate the relationships and co-occurrence trends between different research topics over time. Results indicate that maritime transportation represents a T0-level research hotspot, dating back to 2000. Its subsequent keywords, including container terminal, berth allocation problem, maritime logistics and berth allocation, are core topics to IMTS. The following keyword clusters include risk assessment, decarbonization, maritime safety and collision avoidance, which indicate the research focus of IMTS in recent years. The remaining clusters represent the latest developments in IMTS from different perspectives, such as DL. Table 3 lists significant keywords under each of the ten themes.

Table 3 Keyword clustering information

Number	Clustering theme	Specific keyword (irrelevant terms manually removed)
1	Maritime transportation	Maritime transportation; container terminal; berth allocation problem; maritime logistics; berth allocation
2	Risk assessment	Risk assessment; fuzzy topsis; framework; mixed-integer linear programming
3	Decarbonization	Methanol; ship emissions; emission reduction technologies; decarbonization; renewable energy sources;
4	Maritime safety	Maritime safety; sustainability; shipping; inventory management
5	Collision avoidance	Maritime safety; evidential reasoning; probability; human reliability
6	Deep learning	DL; marine vehicles; IOT; feature extraction; ship detection
7	Maritime transport	Maritime transport; multilevel hierarchical game; robust optimization; carrier interaction
8	Risk analysis	Bayesian network; risk analysis; fire and explosion; maritime accident
9	Ship routing and scheduling	Shipping network; AIS; complex network; maritime silk road; centrality
10	Anomaly detection	Anomaly detection; oil spill; ship collision; AIS data

4 Review of industry data sources and their role in IMTS

High-quality data are fundamental to the effectiveness of IMTS, supporting algorithm training, validation, and operational feedback. The development and advancement of IMTS heavily rely on diverse input data sources, which refer to industry-generated datasets—such as navigational regulations, sensor measurements, and operational records—that are directly used as inputs to ML/DL models for analysis and prediction, in contrast to the bibliometric data analyzed in Section 3. These data enable autonomous navigation, situational awareness, and safety monitoring. Broadly, the input data used in IMTS research can be categorized into three types: Text data, sensor data, and operational command and performance data. Text data primarily include regulatory documents, accident reports, and expert knowledge; sensor data comprise information collected from onboard and shore-based sensors; operational commands and performance metrics encompass human-commanded inputs and vessel operation records. Each data type plays an important role in different aspects of intelligent maritime operations, from risk assessment on a historical level and compliance with regulatory issues to real-time navigation and decision-making support. In the following subsections, the three major types of data—text data, sensor data, and operational command and performance data—are introduced in detail, highlighting their sources, characteristics, and roles in the development of IMTS.

4.1 Text data

Text data in the IMTS primarily include legal standards, investigative reports and expert judgment, as summarized in Table 4. Unlike sensor-based or operational data, which are primarily used for real-time or historical quantitative analysis, text data are often qualitative. They are commonly used as a basis for regulatory compliance, accident analysis, and decision model development.

One of the major sources of text data in IMTS is navigation regulations and laws. National and international authorities develop regulatory guidelines that set maritime operation standards and provide standardized safety procedures, environmental policies, and navigation regulations. Major guidelines, such as the International Regulations for Preventing Collisions at Sea (COLREGs) and the International Convention for the Safety of Life at Sea (SOLAS), establish fundamental safety standards for maritime operations (IMO, 2020). These legally binding guidelines not only influence ship operation, routing, and automatic decision-making but are also essential for developing AI-driven regulatory compliance to ensure that autonomous navigation systems adhere to internationally recognized norms.

In addition to regulatory guidelines, accident reports from well-respected organizations such as the IMO and national maritime authorities such as EMSA and NTSB are reliable sources of risk assessment and accident prevention. Accident reports comprise third-party examinations of past maritime incidents, which provide information about the human, mechanical, and environmental causes of incidents (EMSA, 2023; IMO, 2022; MAIB, 2021; NTSB, 2022). By systematically examining case studies, maritime safety authorities can develop predictive risk models, inform regulations, enhance crew training, optimize traffic management, and validate AI-based anomaly detection systems to prevent future accidents (Kristiansen, 2013; Montewka et al., 2014; Zhang et al., 2021).

Unlike regulatory documents and accident reports, which are objective and standardized, expert knowledge is commonly subjective text data for maritime decision-making. Maritime expertise, including experienced crew members, port authorities, and industry expertise, contributes through their subjective assessments, advisory documents and best-practice recommendations. The integration of expert knowledge into automatic decision-making models ensures that these models remain aligned with practical realities (Filom et al., 2022).

4.2 Sensor data

Sensor data are a key component of IMTS for real-time observation, predictive analysis, and autonomous decision-making. Sensing techniques in conjunction with IoT have transformed maritime navigation, safety, and decision-making by facilitating precise tracking of vessels, awareness of the environment, and autonomous navigation. Various types of sensors play different roles in IMTSs, as summarized in Appendix B1 of the ESM.

The most widely used sensor technologies in maritime operations are GPS, radar and light detection and ranging (LiDAR), which are used for ship positioning and navigation. The combination of these three sensor types was initially essential for human decision-making and minimizing accident risks in the early stage. Subsequently, AIS was introduced, which enables vessels to continuously transmit and receive data regarding their position, speed, and heading, facilitating real-time situational awareness among vessels and maritime authorities (International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA), 2016). The analysis of AIS data can significantly enhance navigational safety by providing early warnings of collisions, which can support traffic management in waterways.

In addition to tracking vessels, oceanographic and weather sensors also assist in improving maritime safety by monitoring sea currents and wind and wave conditions. These sensors, both onboard and shore-based, provide essential data for route optimization, traffic management, and risk prevention in extreme weather conditions (Du et al., 2022c; Filom et al., 2022; Zampeta et al., 2025).

To date, an increasing number of IoT devices are deployed onboard, which can collect and transmit operational data during navigation. The wide use of IoT devices assists in autonomous

Table 4 Summary of text data types in IMTS

Text data type	Main characteristic	Source
Regulatory guidelines	Legally binding, standards, ensuring compliance with applicable laws and regulations.	IMO (IMO, 2017), regional and national maritime authorities (European Commission, 2021)
Accident reports	Third-party investigations and accident analysis.	IMO (IMO, 2022), EMSA (EMSA, 2023), NTSB (NTSB, 2022), MAIB (MAIB, 2021), local port authorities (Port of Rotterdam Authority, 2021)
Expert knowledge	Experience-based data, providing insights and recommendations.	Experienced mariners (Kristiansen, 2013), port authorities (Baldauf and Rostek, 2024), maritime industry experts (Filom et al., 2022)

Note: EMSA, European Maritime Safety Agency; NTSB, United States National Transportation Safety Board; MAIB, Marine Accident Investigation Branch.

navigation and enables remote monitoring of shipboard systems (Zhang et al., 2021). Through the integration of IoT sensor data with AI models, IMTS can detect anomalies, assess fuel consumption patterns and optimize fleet management in real time.

4.3 Operational command and performance data

Unlike text data, which provide regulatory and historical information, or sensor data, which capture real-time environmental and navigational conditions, operational command data focus on human-issued and system-generated inputs. These inputs are used to remotely control vessels or provide decision-making support, while operational performance data document real-time vessel operation information and navigation status.

One primary source of operational command data is human-issued commands originating from vessel traffic services (VTSs) and shore control centers (SCCs). VTS systems, which are managed by shore-based maritime authorities, play an important role in coordinating vessels and issuing navigational advisories (IMO, 2021). Similarly, SCC monitors the navigation of autonomous and semiautonomous ships to ensure that AI-driven navigation commands adhere to regulations and avoid accidents (Ramos et al., 2019).

One vital source of operational performance data is vessel operation data during navigation, which includes noon reports and log data. Noon reports—also referred to as voyage reports—are submitted daily by crew members, which contain performance metrics of ships such as sailing speed, sailing distance, fuel consumption, engine status, weather conditions and voyage information (Li et al., 2022b; Xu et al., 2023a). Log data are recorded continuously by onboard monitoring systems, which provide information on vessel performance, equipment functionality, and deviations from scheduled routes (Gil et al., 2020). The analysis of these datasets enables fleet operators to detect inefficiencies, predict maintenance needs, and enhance fuel management strategies.

5 Systematic analysis of IMTS technologies for safe navigation

Building on the data foundation in Section 4, Section 5 analyzes the structure and functions of IMTS, which integrates advanced technologies such as AI, IoT and satellite communication technologies to enhance maritime safety, efficiency and sustainability. The research framework of IMTS is defined in Fig. 2.

From a human perspective, research in this area focuses on the development of systems that support human decision-making in navigation through risk assessment and intelligent navigation aids. Studies highlight predictive models for identifying potential risks and enhancing situational awareness. Navigation assistance systems integrate real-time data and advanced analytics, providing decision-makers with actionable insights to improve safety and operational efficiency.

From the ship perspective, autonomous ship technology and unmanned surface vessels (USVs) are at the forefront of maritime innovation. Research has explored the integration of autonomous control systems, AI-powered navigation, and collision avoidance mechanisms to improve ships' level of autonomy and ensure navigation safety. A key focus is on ensuring seamless communication between ships and remote-control centers via satellite and wireless networks, enabling real-time monitoring and decision-making for autonomous operations. Research in this domain can be broadly divided into two main categories: Technological development and economic performance evaluation.

With regard to the environmental perspective, studies in this domain emphasize the role of data-driven approaches in understanding and responding to environmental factors. Navigation environment awareness systems analyze data from sensors, satellites, and other sources to detect obstacles, monitor weather conditions, and map ocean currents. Traffic flow analysis research prioritizes optimizing vessel routes and reducing congestion in busy maritime corridors, contributing to efficient and sustainable shipping.

From a management perspective, research in management focuses on the integration of intelligent systems for traffic and operational coordination. This perspective can be divided into two main themes: Traffic management and ship operation management. Traffic management research explores algorithms and frameworks for optimizing port operations and vessel scheduling, ensuring smooth traffic flow and minimizing

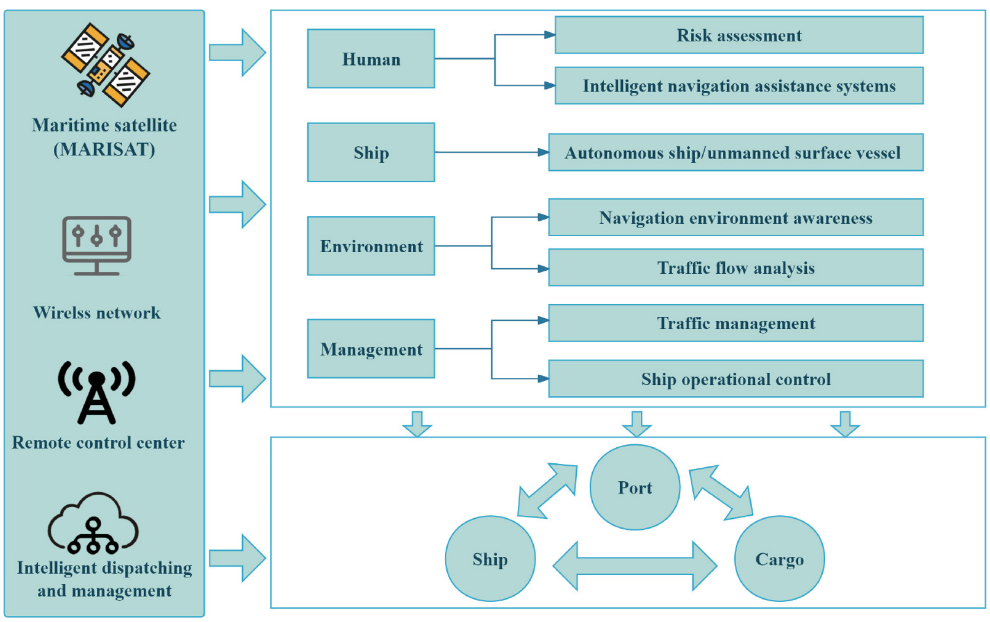


Fig. 2 Research framework of IMTS.

congestion. Meanwhile, ship operation management research emphasizes predictive maintenance, fleet performance monitoring, and fuel optimization. These studies aim to enhance operational reliability and reduce costs through data-driven decision-making and AI-driven maintenance strategies to achieve comprehensive optimization of maritime logistics.

The four perspectives—environmental, human, vessel, and management—are closely interconnected, reflecting the integrative nature of IMTS. Environmental conditions shape human perception and decision-making, which in turn guide ship operations, while management systems synthesize these dynamic interactions to promote the safety, efficiency, and sustainability of IMTS. Appendix B2 of the ESM summarizes how data sources discussed in Section 4 are utilized across different IMTS research domains. A detailed analysis of the selected papers is shown in Appendix C of the ESM.

5.1 Research trend in risk assessment in the IMTS

As IMTS continues to develop with ongoing technological developments, ensuring navigational safety remains a fundamental objective. Maritime operations are still exposed to numerous hazards due to the complexity and unpredictability of the marine environment. According to IMO, maritime risk is defined as a combination of the accident frequency and the severity of its consequences, and the types of accidents include collision, grounding, mechanical failure, pollution, and cyber issues (IMO, 2022). Understanding and categorizing these risks are essential for building a comprehensive risk assessment system to mitigate the impacts of risks in the IMTS.

The categorization of risk factors varies depending on specific research objectives. For example, Cao et al. (2023) conducted a comprehensive review of marine accident reports and safety literature, identifying five key categories of risk factors: ship-related, human-related, environmental, managerial, and accident-specific factors. When focusing on USVs, Fan et al. (2020) refined this classification into four categories: ship, human, environment, and technology, addressing the specific operational needs of autonomous systems and highlighting technological failures and AI-driven decision-making constraints as critical risk contributors. These different categorizations highlight the growing complexity of managing maritime risk.

As a complex system, the IMTS is susceptible to various uncertainties, which can lead to serious accidents and significant consequences. Safety assessments serve as the foundation for effective safety management, and numerous studies have been conducted in this area (Goerlandt and Kujala, 2011; IMO, 2018b; Kristiansen, 2013; Marino et al., 2023; Montewka et al., 2010). Current research on maritime safety assessments can be classified into two categories: Static risk assessment and real-time risk assessment. Their conceptual frameworks are shown in Fig. 3.

To provide a clear comparison between static and real-time risk assessment in maritime transportation, the main methodologies, representative models and research focuses are summarized in Table 5.

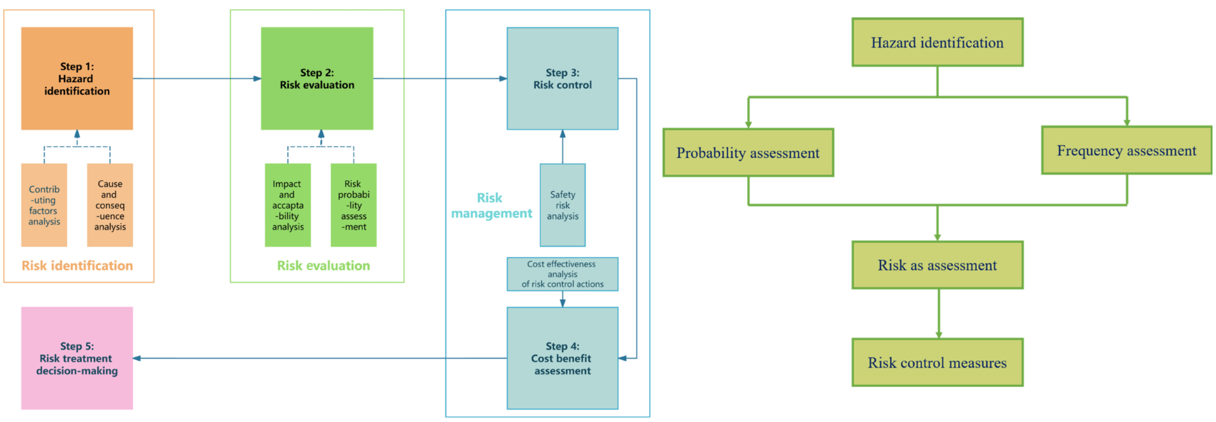
Although ML has gained increasing attention in maritime risk assessment, the application of DL remains relatively limited in this domain. There are two main reasons for this. First, most static and dynamic risk assessment frameworks rely on structured and low-volume datasets, such as historical accident records or ship logs, which are more compatible with traditional ML algorithms than data-intensive DL models. Second, real-time maritime applications require lightweight and computationally efficient models capable of rapid inference under constrained onboard environments, where the high complexity of DL architectures often makes them impractical. As a result, while DL has strong feature extraction and representation capabilities, ML-based and probabilistic models remain dominant in both static and real-time maritime risk assessments due to their interpretability, robustness, and operational feasibility.

5.2 Research trend in integrated navigation-aid systems (INASs)

The rapid advancement of information technology has transformed onboard operations from manual observation and decision-making to autonomous perception, diagnosis, prediction, and response. Modern INAS, defined by the IMO as a user-centered framework for situational awareness, navigation safety and human–machine interaction, typically comprises five modules: information acquisition, data fusion and processing, navigational environment awareness, decision-support and operational control, and cybersecurity (IMO, 2019b). Oruc et al. (2022) provided a review of recent INAS developments, structured around two key components: hardware and software. Among these, the integrated bridge system (IBS) remains the most widely used hardware component, while the software developed is commonly integrated into IBS to support crew decision-making or facilitate automatic operations such as collision avoidance and berthing.

5.2.1 Hardware components in INAS

From a physical perspective, the ship bridge serves as the central control hub, where maneuvering commands are issued, and navigation information is displayed. To fulfill this role, the first generation of Integrated IBS, known as the "data bridge", was



(a) Framework of FSA (b) Framework of dynamic risk assessment

Fig. 3 Conceptual framework of risk assessment.

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Table 5 Comparison between static and real-time risk assessment methods in IMTS

Aspect	Static risk assessment	Real-time risk assessment
Objective	Identify and quantify risk factors using historical data and expert judgment.	Detect and evaluate risks during navigation based on real-time data streams.
Data sources	Historical accident reports, expert surveys, regulatory documents, ship logs, etc.	AIS data, GPS signals, radar, sensors, and real-time vessel motion data, etc.
Representative models/methods	Fault tree analysis (FTA); Event tree analysis (ETA); Analytical hierarchy process (AHP); Bayesian networks (BNs); Fuzzy logic systems; Human factors analysis and classification system (CREAM) (Celik and Cebi, 2009; Chen et al., 2013; Goerlandt and Kujala, 2011; Karayalcin, 1982; Kuzu et al., 2019; Wang and Foinikis, 2001; Wang and Yang, 2018).	COLREG-based rule models (rules 13 –15); DCPA/TCPA models; Ship domain and collision diameter; Safe Boundary Approach; Markov chain and Monte Carlo simulations; BN for probabilistic reasoning (Fujii and Shiobara, 1971; García Maza and Argüelles., 2022; Kujala et al., 2009; Li et al., 2014; Montewka et al., 2014; Szłapczyńska and Szłapczyński, 2017; Xu and Wang, 2014).
Main period of development	1980s–2020s (transition from qualitative expert-based to AI-enhanced probabilistic approaches).	2000s–present (evolution from deterministic to probabilistic and dynamic prediction models).
Core contributions	Provide a structured framework for regulatory decision-making and long-term safety planning, as illustrated in Fig. 3a.	Support navigational decisions and collision-avoidance maneuvers in dynamic, uncertain maritime environments, as illustrated in Fig. 3b.
ML/DL applications	ML algorithms—such as Decision trees (DT), Random forests (RF), Support vector machines (SVM)—used for accident classification and failure prediction based on historical data (Fiskin et al., 2021; Medda et al., 2024; Zhu et al., 2023).	Limited DL use; Some ML integration with sensor data for real-time collision and motion prediction (Cademartori et al., 2023; Zhang et al., 2023b).

introduced in 1969 (Hadley, 1988). Over time, numerous systems have been integrated into IBS to extend its capabilities, including the electronic chart display and information system (ECDIS), positioning system, and autopilot control systems. These devices can be categorized into two functional groups: navigation-aided systems, which focus on situational awareness to support decision-making, and ship control systems, which assist with maneuvering operations. This categorization is illustrated in Fig. 4a (Perera and Soares, 2015). Research efforts on IBS have evolved across multiple dimensions, including human-machine interface optimization to improve usability and efficiency (Liu et al., 2022a; Man et al., 2023; Soper et al., 2023; Real, 2023), subsystem integration for USV applications illustrated in Fig. 4b (Xu et al., 2023b), and cybersecurity enhancements to ensure safe and reliable operation (Danielsen and Petersen, 2022; Melnyk et al., 2022).

5.2.2 Software components in INAS

From a software perspective, the embedded INAS functions as a decision support system. According to previous research, scholars have reviewed and developed decision support system frameworks according to their research scope (Power and Sharda, 2009), such as the targeted operational domain. Gil et al. (2020) conducted a systematic review of decision support systems, with a primary focus on accident prevention and technological readiness. Similarly, Gil et al. (2020) analyzed decision support systems addressing sustainability and management-related challenges in maritime transportation. Their findings highlight key research trends in INAS, including accident prevention, hull damage detection, path planning, cargo handling, and environmental awareness.

As this review concentrates on safe navigation, the most frequently cited studies emphasize automatic collision-avoidance systems as a central component of accident prevention (Liu et al., 2022b; Piccialli et al., 2020). A typical collision-avoidance system follows a multistep process, which includes risk assessment, ship motion prediction and ship trajectory prediction (He et al., 2024; Qiao et al., 2020; Zhu et al., 2025). The earlier sections summarize research trends in risk assessment and motion prediction. This section focuses specifically on trajectory prediction.

Ship trajectory prediction aims to infer a vessel's movement within a specified timeframe, ranging from seconds to several hours. In the context of collision avoidance, short-term trajectory prediction—typically within seconds to minutes—is the most relevant. These predictions rely heavily on AIS data and incorporate environmental conditions. Based on the modeling approach, trajectory prediction methods are commonly grouped into mathematical models, ML methods, and DL methods (Zhang et al., 2022d).

Mathematical models often utilize clustering-based algorithms, such as trajectory clustering, traffic route extraction, and velocity-based models. These methods analyze historical movement patterns to detect anomalies and forecast future trajectories (Wang et al., 2021; Zhang et al., 2023a). The advantages of mathematical models lie in their interpretability, low computational cost, and easy implementation in real-time systems (Li et al., 2023b).

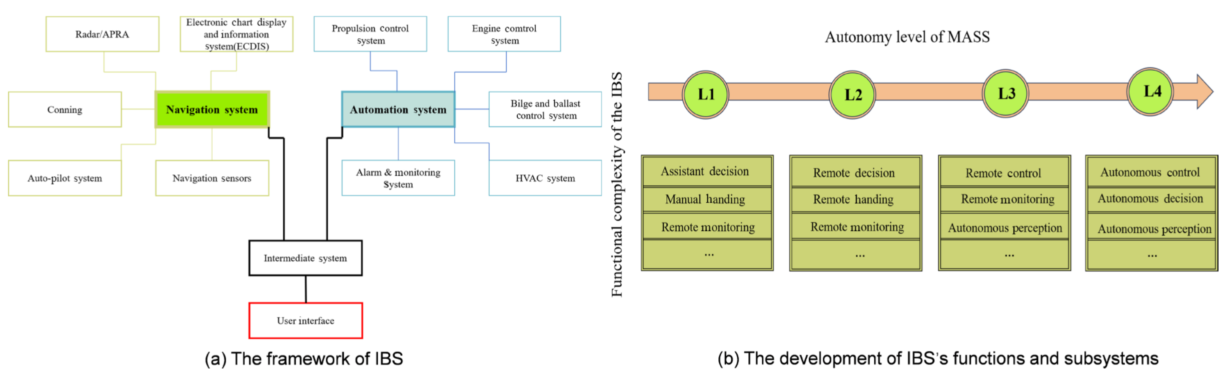

Fig. 4 Framework and development of IBS.

However, their low predictive applicability in dynamic sea environments limits their adaptation to real-time prediction.

ML methods—including reinforcement learning (Wang et al., 2024b) and K-nearest neighbors (KNNs) (Zhang et al., 2022a)—are used to extract features from ship trajectory data. The strengths of ML methods include their ability to model complex, nonlinear relationships and their flexibility in handling diverse data inputs. These methods often outperform traditional models when trained on large, high-quality datasets (Li and Yang, 2023). However, ML approaches are often constrained by data scarcity and overfitting risks.

To address such limitations, DL techniques are increasingly adopted. DL approaches commonly employ long short-term memory (LSTM) (Gao et al., 2021; Tang et al., 2022) and bidirectional LSTM (Bi-LSTM) models (Li et al., 2024a; Yang et al., 2022) to capture sequential dependencies in AIS data. More advanced architectures, such as gated recurrent units (GRUs) and Seq2Seq, are also integrated with DL models to overcome issues such as LSTM's inability to retain features from the early parts of long sequences (Li et al., 2023a). The advantages of DL methods include their capacity for automatic feature extraction, high predictive accuracy, and the ability to learn from long sequences of movement data. As a result, they are effective in complex navigation environments with nonlinear and continuous dynamics.

5.3 Research trends in autonomous ships

Human error, responsible for over 75% of maritime accidents, has driven technological efforts toward ship autonomy (Rothblum, 2000). To improve navigation safety, the concept of autonomous ships was proposed to minimize or remove human intervention during the voyage, with initiatives such as the MUMIN project supported by the European Commission in 2012 (Rødseth and Burmeister, 2012), the autonomous cargo carrier program in 2017 (Yara International ASA, 2017) and regulatory scoping exercises about the design and operation of maritime autonomous surface ships (MASSs) in 2018 (IMO, 2021). Since 2012, a growing number of papers on autonomous ships from operational, technical, management and economic aspects have been published.

5.3.1 Operational perspectives of autonomous ships

From an operational perspective, autonomy can be categorized into four degrees, as shown in Table B3 (IMO, 2021) in Appendix B of the ESM. Currently, common research focuses on short-sea operations monitored by a SCC, with the goal of reducing onboard crew requirements, representing an application scenario aligned with level 2 of autonomous ship automation (Ghaderi, 2019). The main challenge in recent autonomous ship operations lies in training SCC operators, as remote control demands higher levels of both maritime knowledge and technical competence than traditional ship maneuvering due to their reliance on limited sensor-based information (Kennard et al., 2022; Li and Yuen, 2024).

5.3.2 Technical perspectives of autonomous ships

From a technical perspective, research on autonomous ship operations centers on AI-driven developments in key functions such as risk detection, situational awareness, collision avoidance, autonomous docking, and berthing operations (Choi et al., 2023; Ding et al., 2021b; IMO, 2019a; Li et al., 2020; Wang et al., 2024c). Current studies primarily target short-sea navigation with Shore Control Centers (SCC) to reduce onboard crewing requirements, as shown in Fig. 5 based on the coordination framework discussed by Akdağ et al. (2022), often focusing on single-task performance optimization such as berthing, where multiagent coordination systems and berth allocation algorithms are employed to improve operational efficiency and handle uncertainty (Chen et al., 2023; Du et al., 2021; Felski and Zwolak, 2020). Despite these advances, navigation systems still rely on human-machine collaboration, and a key technical challenge remains the training of SCC operators who must compensate for limited sensor-based perception with higher levels of maritime knowledge and technical competence (Baldauf and Rostek, 2024; Sasha, 2023). Consequently, recent studies highlight the importance of human-machine interaction frameworks that integrate SCC, vessel traffic services (VTSs), and autonomous ships into a unified intelligent navigation ecosystem (Gil et al., 2020; Madsen et al., 2023).

5.3.3 Management perspectives of autonomous ship operations

From a management standpoint, key challenges lie primarily in regulatory adaptation and the modernization of navigational infrastructures. Existing conventions such as COLREGs and STCW need to be revised rather than replaced to accommodate mixed traffic scenarios where manned and unmanned ships coexist (Ringbom, 2019). At the same time, traditional

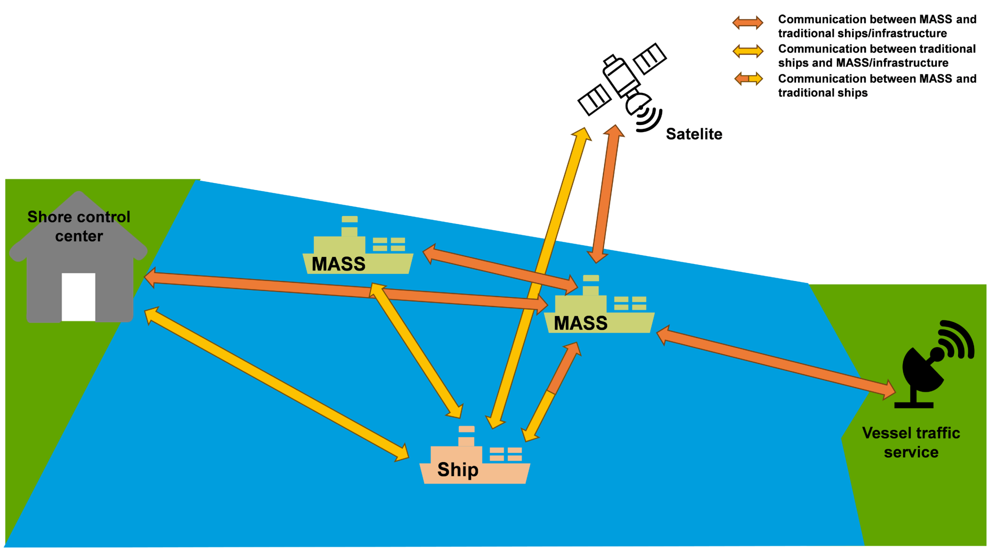

Fig. 5 Coordination system of the IMTS.

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navigational aid facilities—including buoys, lights, and port signaling systems—must be redesigned to remain interpretable for conventional vessels while being digitally detectable and machine-readable for autonomous ships (Nzengu et al., 2021; Ol'khovik et al., 2023).

5.3.4 *Economic perspectives on autonomous ship operations*

From an economic perspective, most studies draw on the MUNIN project, which establishes a cost framework for autonomous shipping encompassing capital, operational, and voyage-related expenditures (Kretschmann et al., 2017). The project results reveal that although fuel accounts for more than 50% of total expenses, these costs are offset by reductions in crew-related expenditures, deckhouse infrastructure, and air resistance (Ziajka-Poznańska and Montewka, 2021). To further enhance cost efficiency, researchers have proposed linear shipping networks and intelligent scheduling models to minimize voyage expenses (Zhang and Wang, 2020). Nevertheless, traditional economic models often neglect costs unique to autonomous operations—such as cybersecurity, remote monitoring systems, and emergency handling—thereby underscoring the need for updated cost-assessment frameworks (Kim et al., 2020).

5.4 Research trend in navigation environment awareness

As the level of autonomy in IMTS continues to rise, situational awareness of the surrounding environment has become a central component in ensuring navigational safety and enabling intelligent decision-making. IMTS relies not only on accurate positioning technologies but also on comprehensive perception and interpretation of environmental elements, including sea conditions, navigational surroundings, hydrological features, and traffic environments. Therefore, it is essential to identify and analyze the key factors that define the maritime navigation environment and to review the development and challenges of environment modeling approaches.

5.4.1 *Navigation environment factors*

According to Zhang et al. (2024a), the navigation environment can be categorized into four primary domains: hydrological, meteorological, topographical, and traffic flow. Their detailed descriptions can be seen in Table 6.

These environmental factors collectively influence essential tasks such as course-keeping, collision avoidance, and watch-keeping. Navigation data are acquired in multiple formats—visual (surveillance systems), acoustic (VTS, intercom), and textual (AIS, radar, ARPA)—and are integrated through the IBS (Thombre et al., 2022). The architecture of the autonomous navigation system (ANS) used in the MUMIN project is shown in Fig. B4 in Appendix B of the ESM.

5.4.2 *Navigation environment modeling*

As the complexity and variability of environmental factors increase, accurate navigation environment modeling becomes crucial. The models aim to simulate environmental interactions and provide support for risk prediction, path planning, and energy optimization. However, the inherently stochastic nature of the marine environment presents significant challenges.

Early approaches—primarily developed in the early 2010s—focused on physical and statistical models. For instance, Czaplewski and Zwolan (2012) developed hydrodynamic models for wave and current predictions. However, such models require extensive calibration and lack generalizability across different environments.

Recent studies adopt AI and DL methods to address these limitations. Qiao et al. (2021) demonstrated that DL algorithms significantly improve navigation environment interpretation. For example, Ma et al. (2020) used CNNs for visual-based obstacle detection in low-visibility conditions. Karst et al. (2025) employed DNNs to enhance acoustic signal processing for sound-based situational awareness.

To further improve environmental perception, recent multimodal fusion studies have combined visual, radar, and AIS data for situational awareness, which provides a solid foundation for collision avoidance and maritime traffic analysis (Guo et al., 2023; Qiao et al., 2021; Xin et al., 2025a, 2025b). Despite these advances, many models still struggle with multimodal data fusion and real-time responsiveness, indicating that navigation environment modeling remains a dynamic and evolving research frontier.

5.5 Research trend in traffic flow analysis

Understanding maritime traffic flow is essential for ensuring navigational safety and efficiency. Maritime traffic flow encompasses key parameters such as vessel density, flow direction, speed distributions, and interaction complexity and plays an critical role in traffic prediction, route planning, and collision avoidance (Mou et al., 2010; Silveira et al., 2013). As maritime operations grow in complexity, the analysis of traffic flow in specific regions is important for both port authorities and crew members. This section reviews improvements from statistical modeling to road-network-inspired microscopic, mesoscopic and macroscopic models and recent developments in complexity-based methods and AI-driven predictive traffic flow management.

Early maritime traffic modeling—particularly in the 2000s—mainly relied on statistical approaches using metrics such as average speed, flow density, and spatial distribution to describe long-term navigational patterns (Balmat et al., 2009; Mou et al., 2010; Pachakis and Kiremidjian, 2003). However, these models, constrained by historical data, lacked the capacity to capture real-time variations and vessel interactions, prompting the adoption of microscopic, mesoscopic, and macroscopic frameworks inspired by road traffic modeling, as shown in Table 7. However, adapting these methods to maritime contexts remains challenging due to differences in operational modes and environmental influences

Table 6 Environmental factors in maritime navigation

Environmental factor	Information included	Impacts on navigation	Ref.
Hydrological factor	Water currents, tides and sea depth	Affects ship maneuvering, course-keeping, and energy consumption	Yang et al. (2020); Zhang et al. (2023b);
Meteorological factor	Wind, waves, fog and precipitation	Influences navigation safety and efficiency; forecast limitations require real-time data	Heij and Knapp (2015);
Topographical factor	Coastlines, islands, reefs and seabed structures	Static obstacles in digital charts; updates for temporary obstructions are challenging	Chen et al. (2013); Xue et al. (2019)
Traffic flow factor	Vessel movements and congestion levels	Critical for collision avoidance, especially in narrow waterways and port approaches	Mou et al. (2010); Zhang et al. (2022b)

Table 7 Commonly used road traffic flow modeling approaches

Model type	Underlying principle	Advantage	Limitations if applied in maritime study	Ref.
Microscopic models	Simulate individual vehicle behavior, including interactions such as safe distances and responses to maneuvers	Suitable for constrained environments like port approaches or narrow channels	Requires highly detailed data and calibration; Difficult to model continuous environmental effects like waves and currents	Gipps (1981) Pachakis and Kiremidjian (2003)
Mesoscopic models	Model small groups of vehicles using probabilistic distributions of behavior like speed and headway	Balance between detail and computational efficiency; Suitable for analyzing local congestion	Limited granularity for capturing ship-to-ship interactions and varying navigational behaviors	Huang et al. (2019) Mahnke et al.(2005)
Macroscopic models	Treat traffic as a fluid continuum using aggregated metrics such as density and velocity	Effective for long-term planning and large-scale traffic trend analysis	Oversimplifies ship behavior and lacks adaptability to sudden changes in environmental conditions	Lebacque and Khoshyaran (2006) Wen et al. (2017b)

such as wind, currents, and waves. More recently, research has shifted toward complexity-based models—originating from air traffic control—to improve real-time monitoring and decision-making by integrating micro- and macrolevel factors (Prandini et al., 2011; Sridhar and Chatterji, 2001; Zhang et al., 2022b). This enables a more comprehensive understanding of navigational conditions. A key advancement is the use of traffic complexity maps, which visualize navigational conditions and help identify high-risk areas to enhance situational awareness and collision avoidance (Wen et al., 2017b; Zhang et al., 2022c).

As the marine domain tries to address increasing traffic density and environmental variability, AI and ML have emerged as powerful tools. Recent studies have applied various ML algorithms to process large-scale AIS datasets, extract traffic patterns, and predict vessel movements under complex conditions (Durlik et al., 2023; Li et al., 2018; Liang et al., 2022). These innovations improve the adaptability and responsiveness of traffic management systems, enabling predictive analytics and proactive interventions (Zhang et al., 2022b).

5.6 Research trends in ship routing and scheduling

Efficient ship routing and scheduling are fundamental to modern maritime logistics, directly affecting operational efficiency, cost optimization, and environmental sustainability. Although often interlinked, these two processes differ in focus and application. Routing involves determining the sequence of port calls and sailing paths to optimize traveling distance, cost, and/or time (Gelareh and Pisinger, 2011), while scheduling focuses on assigning precise arrival and departure times to avoid congestion and align with terminal and cargo constraints (Christiansen et al., 2013). Their detailed differences are summarized in Table 8.

5.6.1 Evolution of ship routing methods

Traditional ship routing methods evolved from deterministic and heuristic algorithms, such as dynamic programming and genetic algorithms, toward hybrid optimization frameworks addressing complex operational constraints, including port accessibility, weather conditions, and emissions (Christiansen et al., 2004; Fagerholt et al., 2010; Meng et al., 2015; Wen et al., 2017a). While these models effectively minimize voyage distance or cost, they are limited in adapting to dynamic marine conditions and real-time decision requirements (Hemmati et al., 2015; Ma et al., 2023; Meng et al., 2015; Wen et al., 2017a).

A key development in this area is the incorporation of weather-routing techniques into emission-optimized path planning, as illustrated in Fig. B5a in Appendix B of the ESM. Rather than selecting the shortest or fastest route, these models dynamically adapt voyage paths based on oceanographic conditions such as wave height and wind direction to reduce fuel consumption and associated emissions (Borén Altés, 2023). Furthermore, real-time data sources—such as IoT sensors and satellite tracking—are now widely employed to dynamically adjust routes based on live weather, port congestion, and cargo status (Borén et al., 2022; Li et al., 2022a).

Building on these foundations, recent studies increasingly integrate ML and DL to enhance energy efficiency and adaptability. ML models proposed by Wang et al. (2016) and Li et al. (2024b) improve energy optimization and speed planning with high interpretability but limited flexibility for nonlinear and unseen scenarios. In contrast, DL models are superior in capturing complex spatiotemporal patterns from weather and navigation data, improving prediction accuracy but requiring large datasets and higher computation (El Mekkaoui et al., 2023; Wu et al., 2023; Yoo and Kim, 2023). Overall, ML provides explainable efficiency, DL enables adaptive learning, and their integration supports intelligent, data-driven, and sustainable maritime routing systems.

5.6.2 Evolution of ship scheduling methods

Ship scheduling has evolved from static, deterministic models to adaptive frameworks that account for stochastic disruptions such

Table 8 Differences between ship routing and scheduling

	Ship routing	Ship scheduling
Focus	Determining the sequence of ports to be visited and selecting the sailing path to minimize voyage distance and cost	Scheduling the arrival and departure time of ships at each port to meet time windows and resource constraints
Decision variables	Port visiting sequence, sailing path selection	Arrival times, departure times, and berthing duration
Main objective	Minimizing sailing distance, fuel consumption, or travel time	Avoiding port congestion, ensuring on-time arrival, optimizing berth utilization
Planning horizon	Medium- to long-term planning; typically at the strategic- or tactical-level	Short-term, real-time or near-real-time; mainly at the operational level
Application	Strategic- and tactical-level route design, such as determining the optimal shipping network	Operational level scheduling, such as generating detailed shipping timetables

as port congestion, cargo delay, and weather uncertainty, as shown in Fig. B5b in Appendix B of the ESM (Christiansen et al., 2004, 2013; Meng et al., 2013; Psaraftis and Kontovas, 2014; Wen et al., 2024). Conventional approaches often focus on mathematical programming and heuristic algorithms to minimize cost or delay but struggle to incorporate real-time data and predictive intelligence.

Recent work increasingly emphasizes robust scheduling frameworks that leverage ML/DL to enhance adaptability under operational uncertainty. Kolley et al. (2023) applied machine learning to predict vessel arrival times and improve berth scheduling robustness, while Albloushi (2025) also demonstrated the use of ML for arrival-time prediction to optimize berth allocation. In the liner shipping context, Du et al. (2022a) combined machine learning with reinforcement learning to design more adaptive liner schedules that address stochastic delays and improving schedule reliability. Beyond port operations, deep reinforcement learning has been explored for ship energy and power scheduling. Hasanvand et al. (2020) proposed a multi-objective DRL approach for emission-free ship power scheduling, and Xiao et al. (2023) introduced a DQN-CE framework integrating bidirectional LSTM and attention mechanisms for ship energy scheduling. Together, these approaches illustrate how predictive analytics and intelligent scheduling models can strengthen resilience against extreme weather, port congestion, and unexpected disruptions.

At the same time, sustainability remains a central concern in scheduling research (Abioye et al., 2021; Elmi et al., 2023). Intelligent scheduling algorithms now increasingly incorporate energy efficiency and low-carbon objectives, extending beyond traditional cost and delay minimization (Qi and Song, 2012). For example, ML- and DL-driven energy scheduling models enable the integration of fuel-saving strategies, emission reduction targets, and alternative energy sources directly into vessel scheduling frameworks (Hasanvand et al., 2020; Xia et al., 2021; Zhang et al., 2024b). By integrating decarbonization requirements into operational planning, these methods ensure that shipping schedules remain not only economically viable but also aligned with global sustainability and regulatory goals, thereby supporting the transition toward greener maritime logistics.

5.7 Research trend in ship operational control

As discussed in Section 5.3, USVs are becoming increasingly involved in maritime transportation systems. Unlike traditional ships that rely heavily on onboard crew judgment, USVs rely on remote control from the SCC and onboard decision-making support systems to ensure safe and efficient navigation. This shift in operational control introduces new challenges in integrating real-time data processing, reliable communication, and adaptive human-AI collaboration.

5.7.1 SCC's role in USV operations

The SCC is the central hub for USV operations. It performs real-time monitoring, provides operational coordination, intervenes in emergencies, and optimizes fleet operations (Wang et al., 2023; Zhou et al., 2021). The interaction between SCC and USV is shown in Fig. 6, enabling shore-based operators to monitor navigation status, issue remote commands, and manage performance.

However, several critical challenges remain in SCC deployment. One major issue is ensuring reliable communication between SCCs and USVs, especially in remote or congested areas. Additionally, the high computational demands for real-time data processing, coupled with the increased cognitive workload on shore-based operators, significantly constrain the broader application of USVs in busy waterways (Kari and Steinert, 2021). Regarding the interaction between traditional ships and USVs, regulatory inconsistencies and a lack of guidance for mixed transportation modes pose threats to navigation safety (Kim et al., 2022; Orzechowski et al., 2024).

5.7.2 Human roles in USV operation

Despite increasing levels of automation, operators are essential for managing safety-critical situations, environmental protection, and ensuring system reliability. Research has classified human roles in MASS systems into three main categories: Active, backup, and passive (Veitch and Alsos, 2022). "Active" roles involve continuous monitoring and real-time decision-making, often required in busy or complex traffic conditions. "Backup" roles are characterized by supervisory control—humans intervene when automation fails to manage situations independently, such as unexpected environmental changes or system malfunctions

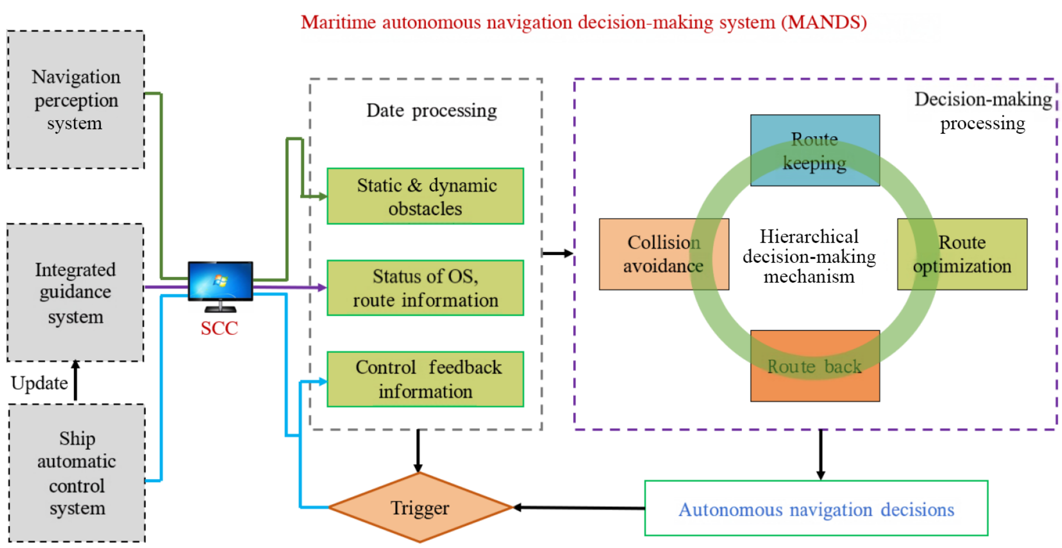


Fig. 6 Interaction between SCC and USV (Wang et al., 2023).

(Ramos et al., 2020). "Passive" roles represent minimal interaction, where operators primarily observe system outputs and maintain readiness to intervene. Each role may vary depending on system design and operational complexity.

The ability for one operator to remotely monitor multiple vessels opens up new dimensions in crew management strategies, emphasizing coordination, prioritization, and alarm management. Human responsibilities also include voyage planning, logistics oversight, and emergency intervention. In addition, studies such as Diaper (2004) and Bačkalov (2020) highlight the operator's responsibility in diagnosing faults and handling system-level disruptions. This growing complexity requires a careful allocation of cognitive and supervisory responsibilities, making human–machine collaboration in SCC a sociotechnical challenge rather than just a technological upgrade.

6 Role of DL in IMTS: Applications

To provide a comprehensive overview of the state-of-the-art DL applications in IMTS, 38 papers under this topic were selected for a further review from a methodological perspective in this section. Research on DL began in 2020, when the first DL-related publications in this domain emerged as identified through the search strategy detailed in Section 2 (Hong et al., 2020). A detailed analysis of the 38 papers is shown in Appendix E of the ESM. The publication trend of DL applications in IMTS shows a general upward trend from 2020 to 2024, as shown in Fig. 7a. The number of publications steadily increases, with a notable rise in 2022, reflecting growing research interest in this field. Although the number of papers in 2025 is lower than that in previous years, this is because the data for 2025 only include studies published up to April.

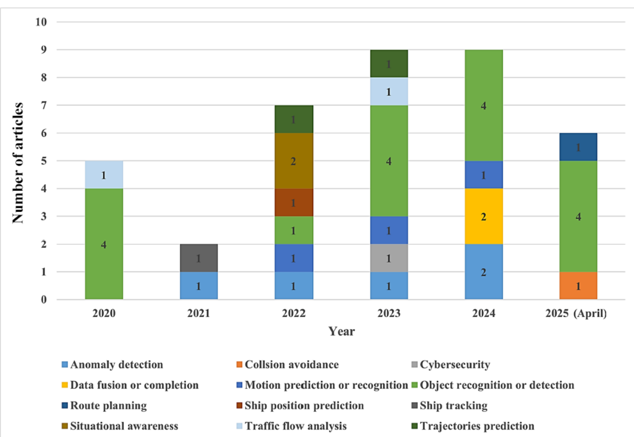
In terms of research purposes, as shown in Fig. 7b, most studies focus on object recognition or detection, followed by ship position prediction and behavior analysis, indicating a strong emphasis on situational awareness and autonomous decision-making in maritime environments. DL applications in IMTS can be divided into four categories and thirteen aspects based on the reviewed articles: Foundation (data fusion and completion), detection (anomaly detection and recognition, object detection and recognition, situational awareness, cybersecurity and image recognition), prediction (ship position prediction, motion prediction, trajectory prediction and maritime traffic flow prediction) and decision-making (collision avoidance and ship tracking).

The application of DL models in IMTS shows a diverse patterns in the use of specific models used for different research purposes, as shown in Fig. 8. Among all tasks, CNNs are the most frequently used, largely due to their strong capability in extracting spatial features from structured grid-like data such as images, heatmaps, and spatially encoded sensor data. Introduced into maritime research around 2020 (Shin et al., 2020), CNNs excel at spatial feature extraction from image-based data, which makes them highly effective in tasks such as object detection (Cheng et al., 2023; Huang et al., 2025), anomaly detection (Ergasheva et al., 2024), situational awareness (Lin et al., 2022), and data fusion (Kalliovaara et al., 2024). However, CNNs are limited in capturing temporal dependencies inherent in sequential data streams such as AIS logs.

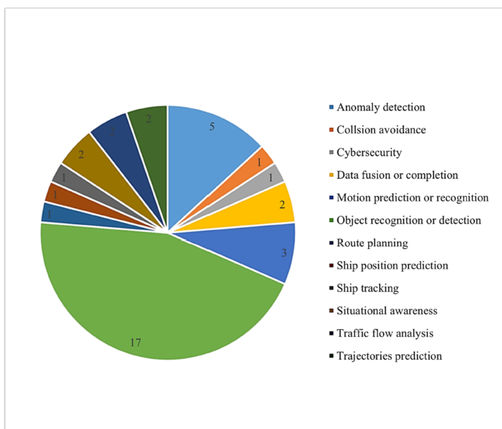
To overcome this limitation, researchers increasingly use hybrid models such as CNN-LSTM structures. These models combine the spatial capabilities of CNNs with the temporal modeling strengths of LSTM networks, which are designed to capture long-range dependencies in sequential data. Since around 2021, CNN-LSTM architectures have been applied in scenarios such as the anomaly detection of vessel behavior (Theodoropoulos et al., 2021), enabling integrated spatiotemporal analysis. In the cybersecurity domain, such hybrid frameworks have also been used for intelligent threat detection in IoT-enabled maritime systems, where identifying abnormal patterns over time is critical (Kumar et al., 2023). These applications demonstrate the versatility of CNN-LSTM models in handling complex maritime datasets that exhibit both spatial structure and temporal dynamics.

For prediction tasks, LSTM and bidirectional LSTM (BiLSTM) models have become prominent choices, especially from 2022 onward. These models process sequences of AIS data to predict ship positions, trajectories, or traffic flow. Zhou et al. (2020), for instance, used a BDLSTM-CNN hybrid model to analyze and forecast maritime traffic flows, demonstrating the effectiveness of combining time- and space-sensitive architectures.

Object detection also benefits from more recent models such as CenterNet, which was introduced by researchers into maritime studies around 2023. CenterNet uses key point estimation to perform anchor-free, end-to-end object detection and proves particularly efficient for real-time ship identification (Jiang et al., 2023). Despite its computational efficiency, it may face challenges in detecting objects in dense or cluttered marine scenes. Similarly, You Only Look Once (YOLO) and Single Shot Detector (SSD), known for their real-time processing capabilities, have been



(a) The number of papers (DL applications in IMTS) published per year



(b) Research topic distribution of DL applications in IMTS

Fig. 7 Publication trend of DL applications in IMTS. Note: The observed growth in DL-related IMTS publications may be driven by policy shifts toward autonomous navigation, advances computing infrastructure, and increased industry interest following major port automation and maritime AI trials.

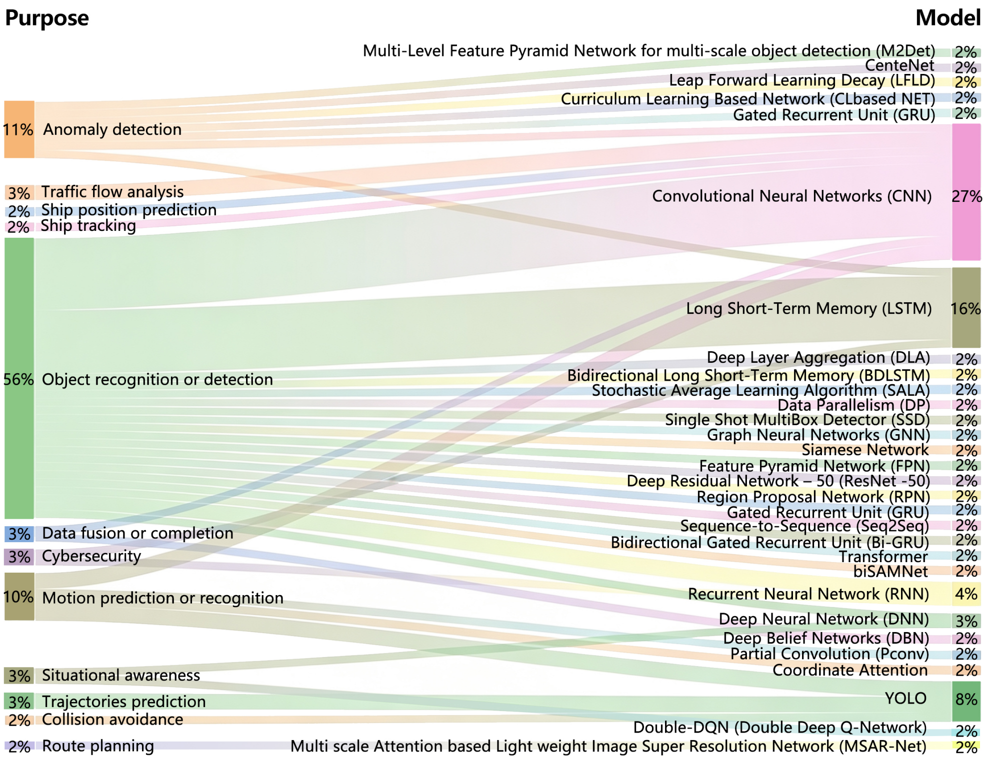


Fig. 8 Mapping DL models to research purposes in IMTS.

increasingly used since 2022 in ship recognition and maritime monitoring, although their performance on small or occluded vessels remains a concern.

Additionally, lightweight CNNs appear around 2022 and 2023 to support applications on embedded or edge devices. These models reduce computational complexity while maintaining acceptable accuracy, as shown by Raj et al. (2022), who designed a lightweight CNN for ship detection in synthetic aperture radar (SAR) images to optimize computational resource efficiency.

From a temporal perspective, the evolution of DL models in IMTS research reflects a progression toward higher performance, lower latency, and greater adaptability. The early dominance of CNNs around 2020 gave way to more advanced temporal and hybrid models such as LSTM and CNN-LSTM around 2022, followed by the integration of detection frameworks such as YOLO and CenterNet from 2023 onward. This shift illustrates the field's increasing emphasis on real-time situational awareness, spatiotemporal reasoning, and deployment efficiency in dynamic maritime environments.

In summary, different DL architectures demonstrate complementary advantages and limitations in IMTS applications. CNNs excel in visual perception tasks such as ship detection and scene recognition but are limited in capturing temporal dynamics. LSTM and BiLSTM models effectively model time-dependent behaviors such as trajectory prediction, although they require extensive sequential data and careful parameter tuning. Hybrid CNN-LSTM frameworks integrate spatial and temporal learning to improve adaptability in complex environments but face higher computational costs. Object detection frameworks such as YOLO and CenterNet enable real-time processing, yet their accuracy decreases in dense or cluttered maritime scenes. Transformer-based models show strong potential for multimodal fusion and long-sequence understanding but remain underexplored due to the lack of large-scale labeled maritime datasets and the high computational demand of training. Table D1 in Appendix D of the ESM summarizes the comparative features of representative DL models commonly used in IMTS based on the previous analysis.

7 Discussion

As discussed in Sections 5 and 6, the advancement of IMTS has significantly transformed maritime operations. However, several challenges, including data availability and quality, environmental complexity, integration with existing maritime systems, trust in automation and human-AI collaboration, and cybersecurity and system vulnerabilities, still hinder its effectiveness and widespread adoption. This section offers a critical synthesis of those issues and proposes targeted strategies to address them, guiding future development in maritime intelligence.

7.1 Data availability and quality

One of the major concerns is the limited availability of consistent and complete data sources, such as AIS data and onboard sensor data. As discussed in Sections 5.1 and 5.2, both risk assessments and trajectory prediction models rely heavily on these data inputs. Their assessment precision and prediction precision strongly correlate with the data accuracy. Similarly, traffic flow modeling (Section 5.5) and route optimization (Section 5.6) are also affected by data loss, especially in congested waterways that require continuous data for simulation. These data deficiencies reduce the accuracy and responsiveness of prediction algorithms and further weaken their effectiveness in safety-critical decision making.

While existing fusion algorithms such as Kalman filters, sensor-level fusion, and decision-level fusion are widely used, their adaptability to the dynamic, real-time, and large-scale data characteristics of IMTS remains a challenge and requires further investigation. This limitation is also reflected in the restricted application of transformer-based models discussed in Section 6, where the lack of large-scale datasets and the inconsistency across maritime data sources hinder model training and generalization.

To address this issue, it is important to develop standardized and open-access maritime datasets with unified data standards. This will not only improve the integration of data collected from various sources, such as ships, SCCs and authorities but also encourage global collaboration. From a technological perspective, advanced interpolation methods, outlier detection algorithms and signal reconstruction techniques should be used in data processing to improve the data input quality. These improvements will not only increase the reliability of prediction models but also enable the effective utilization of real-time analytics in autonomous ship operations and SCC-based supervision systems.

7.2 Environmental complexity

Environmental complexity poses a persistent challenge to the development of IMTS. As discussed in Section 5.4, the navigation environment is subject to a range of dynamic factors, including changing weather conditions, sea states, ocean currents, and visibility changes. These conditions introduce uncertainty into sensor readings and complicate the perception task, making it difficult for AI models to provide recommendations to the decision-making system. In addition, the traffic flow models discussed in Section 5.5 (especially those adapted from the road traffic paradigm) typically assume relatively stable and predictable conditions. This assumption does not hold in the navigation environment where natural forces fluctuate rapidly, resulting in inaccurate congestion predictions and estimates of traffic complexity. Real-time detection and avoidance strategies used in collision avoidance systems and risk assessments are also highly susceptible to interference from harsh and changing environments, which limits the widespread application of AI-based models.

To improve the robustness of IMTS under complex sea conditions, hybrid models that combine physics-based modeling with data-driven DL methods are increasingly needed. These models take advantage of the predictability of physical models while benefiting from the adaptability and learning capabilities of AI models. In addition, multimodal sensor fusion techniques, such as the integration of radar and LiDAR for obstacle detection in fog or low-visibility conditions and the fusion of satellite imagery with AIS data for wide-area traffic monitoring, can significantly enhance environmental perception. By combining complementary data sources, including radar, LiDAR and satellite imagery, systems are better able to filter noise, resolve ambiguity and maintain performance under adverse conditions. This data fusion helps develop more general models that can operate effectively in diverse and dynamic marine environments, thereby improving navigation safety and operational efficiency.

7.3 Integration of MASS with existing maritime systems

The integration of MASS into existing maritime infrastructure remains hindered by regulatory and operational uncertainties. As discussed in Section 5.3, the technological development of MASS has progressed rapidly, particularly in areas such as short-sea autonomous navigation. However, the widespread application of MASS is constrained by the lack of relevant legal and regulatory frameworks. In particular, existing rules such as COLREGs Rule 8 require action to be taken by a 'master' or 'responsible person', raising legal and operational concerns as to whether unmanned vessels can meet such requirements, including timely identification of their role in encounter situations. The transition from conventional ship operations to mixed or fully autonomous modes requires a relegislation of international maritime law, including COLREGs, STCW, and SOLAS. Without specific rules, issues related to liability, operating rules and human oversight in mixed-traffic scenarios remain unresolved.

The way forward requires continued collaboration between AI developers, maritime stakeholders and authorities such as the national maritime administrations or port state control agencies. Standardized regulatory guidance is needed to clarify the roles of AI systems, human operators and SCCs in mixed traffic environments. In addition, a global framework of liability for AI-related maritime accidents needs to be developed, which can refer to similar efforts in the fields of autonomous driving and aviation sectors. Such institutional coordination will not only accelerate the application of MASS but also ensure safety, legal liability, and system interoperability across jurisdictions.

7.4 Trust in AI and human-AI collaboration

A significant barrier to the adoption of AI-driven systems in maritime operations lies in the trust gap between human operators and intelligent automation. As highlighted in Section 5.7, SCCs currently act as the decision-making hubs for USV supervision, with human operators required to monitor, validate and occasionally override AI decisions based on their own judgment. While AI is good at processing vast sensor inputs and providing optimized route planning or collision-avoidance strategies, operators often struggle with overreliance or mistrust, especially in complex scenarios. Poorly designed human–machine interfaces further exacerbate these issues.

To strengthen human-AI collaboration, emphasis needs to be placed on designing intuitive, explainable, and context-aware interfaces that clearly communicate AI reasoning and provide operators with meaningful control. This includes integrating real-time visualizations, alert prioritization systems and adaptive feedback mechanisms according to operational demands. Additionally, training programs and simulation-based drills are needed to help maritime professionals gain confidence in AI-enabled systems.

7.5 Cybersecurity and system vulnerabilities

With the increasing integration of AI, IoT devices and remote-control devices into maritime systems, cybersecurity has emerged as a critical concern. As mentioned in Section 5.7, SCC operations, vessel control networks, and sensor systems all rely on stable and secure communication infrastructures. However, these systems are susceptible to cyberattacks such as data spoofing, signal jamming, malware infiltration, and denial-of-service attacks. Given the high stakes in maritime operations—ranging from navigation safety to cargo security—the consequences of cyber vulnerabilities can be catastrophic.

To safeguard the stable operation of an IMTS, a multilayered cybersecurity strategy is essential. First, AI-based anomaly detection mechanisms can be embedded within control networks to identify suspicious activity patterns, unauthorized access attempts or system behavior anomalies. These algorithms can operate in real time to isolate compromised modules and initiate containment protocols. Second, regular safety procedures such as regular audits, system penetration testing and fail-safe redundancies need to be performed to ensure the robustness of onboard and shore-based systems. As the maritime domain becomes more digitized, prioritizing cybersecurity is not just a technical imperative but a foundational requirement for sustainable and safe global maritime operations.

8 Conclusions

This study presents a dual-perspective analysis encompassing the technological architecture and DL applications in IMTS. Through bibliometric mapping and structured review, it establishes a datafunction-application framework that connects core research domains with real-world operational challenges. By classifying IMTS research along four functional dimensions—human, ship, environment, and management—the study offers a comprehensive understanding of how data-driven technologies support maritime intelligence, navigation safety, and system coordination.

The integration of emerging technologies such as DL, sensor fusion, and autonomous systems has significantly advanced the intelligence level of IMTS and contributed to safer navigation in increasingly complex navigation environments. In particular, DL models have shown great promise in applications such as ship trajectory prediction, situational awareness, and risk classification. However, two major categories of limitations remain. First, existing studies face technical constraints due to data incompleteness and lack of standardized open-access databases, which restrict model generalization and deployment. Second, the adoption of new technologies introduces broader systemic challenges, including gaps in international regulatory frameworks, insufficient training of maritime personnel and unresolved cybersecurity risks that may undermine autonomous operations.

Future research should prioritize the standardization of data formats, enhancement of maritime data-sharing mechanisms and alignment of emerging technologies with evolving legal frameworks in the short term. In the medium term, attempts such as launching cross-border MASS long-range navigation and developing governance protocols for mixed-traffic environments where autonomous and conventional vessels coexist can be made. Long-term directions point to fully autonomous port docking, intelligent fleet scheduling and collaboration, and intelligent ship formation, enabling integrated and adaptive control across global maritime transportation systems.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Electronic supplementary material

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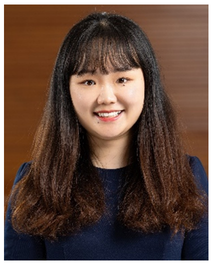

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