

Review

Exploring Recent Maritime Research on AIS-Based Ship Behavior Analysis and Modeling

Anila Duka ¹, Houxiang Zhang ¹, Pero Vidan ² and Guoyuan Li ^{1,*}¹ Department of Ocean Operations and Civil Engineering, Norwegian University of Science and Technology, Larsgaardsvegen 2, 6009 Aalesund, Norway; anilad@stud.ntnu.no (A.D.); hozh@ntnu.no (H.Z.)² Faculty of Maritime Studies, University of Split, Ruđera Boškovića 37, 21000 Split, Croatia; pvidan@pfst.hr

* Correspondence: guoyuan.li@ntnu.no

Abstract

Automatic Identification System (AIS) data provide valuable insights into ship behavior, supporting maritime safety, situational awareness, and operational efficiency capabilities that are increasingly required for autonomous ship functions and harbor maneuvering assistance. This review synthesizes recent research on AIS-based ship behavior analysis and modeling published between 2022 and 2024 using a structured literature search and screening process informed by PRISMA principles. The review presents a five-stage workflow, spanning data processing, data analysis, knowledge extraction, modeling, and runtime applications with emphasis on how these stages contribute to perception, prediction, and decision support in automated navigation. Four dimensions are considered in data analysis, including statistical analysis, safety indicators, situational awareness, and anomaly detection. The modeling approaches are categorized into classification, regression, and optimization, highlighting current limitations such as data quality, algorithmic transparency, and real-time performance, while also assessing runtime feasibility for onboard or edge deployment. Three runtime application directions are identified: autonomous vessel functions, remote monitoring and control operations, and onboard decision-support tools, with numerous studies focusing on constrained waterways and port-approach scenarios. Future directions suggest integrating multi-source data and advancing machine learning models to improve robustness in complex traffic and harbor environments. By linking theoretical insights with practical onboard needs, this study provides guidance for developing intelligent, adaptive, and safety-enhancing maritime systems.

Keywords: machine learning; decision-support system; autonomous ship; knowledge extraction; AIS-based ship behavior modeling

Academic Editors: Chungkuk Jin and
Sewon Kim

Received: 16 February 2026

Revised: 4 April 2026

Accepted: 10 April 2026

Published: 11 April 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Maritime transport is the backbone of global trade, accounting for over 80% of the world's merchandise by volume by sea [1]. Ensuring the safe and efficient operation of this vast network is critical. It supports economic stability, strengthens supply chain resilience, and advances environmental stewardship. However, maritime traffic is growing more complex. Rising vessel density, a diversity of ship types, and dynamic environmental conditions make monitoring and management more challenging than ever. The Automatic Identification System (AIS) is pivotal in maritime operations and addresses these challenges. The AIS is a shipborne communication system. It continuously transmits vessel identity, position, course, speed, and heading via VHF radio signals [2]. The International Maritime

Organization (IMO) mandates AIS for vessels over 300 gross tons. Initially, it was developed for vessel recognition, security, and Information Security and Privacy (ISP). The AIS has since evolved into a multifunctional data source that aids navigation, traffic regulation, maritime security, port logistics, and environmental monitoring.

AIS data are particularly valuable due to their global coverage, public accessibility, and high temporal resolution. These attributes have positioned AIS as a primary data source for international studies on maritime traffic patterns and vessel operations [3]. Beyond its operational utility, AIS enhances situational awareness for crews, supports regularity enforcement, and enables real-time coordination of port activities.

One of the most active research domains enabled by AIS is ship behavior analysis, which examines the interaction between a vessel, its operating environment, and human decision-making. Ship behavior is shaped by a complex interplay of factors, including vessel design (e.g., hull geometry and propulsion systems), environmental conditions (e.g., wind, currents, and bathymetry), and navigational choices (e.g., speed adjustments and maneuvering) [4]. Understanding this behavior is essential for improving maritime safety and operational efficiency.

Recent studies have leveraged AIS data to analyze and model ship behavior across various applications, including anomaly detection, risk assessment, traffic pattern analysis, and trajectory prediction [5,6]. Notable examples include AIS-based approaches for collision avoidance [7–9], behavior analysis [10], path planning [11,12], risk modeling [13,14], and deep learning-based trajectory prediction [15,16]. At a broader level, prior surveys have synthesized these directions from complementary perspectives: Tu et al. [17] organized AIS-enabled intelligent navigation into anomaly detection, route estimation, collision prediction, and path planning, while Xiao et al. [18] reviewed traffic-pattern mining and forecasting in maritime traffic service networks, emphasizing that traffic pattern knowledge is a foundation for forecasting and situation awareness. Collectively, these efforts demonstrate the potential of AIS to support safer, smarter, and more sustainable maritime operations.

Despite these advances, the existing literature remains fragmented across tasks and method families, often relying on different assumptions, datasets, and evaluation protocols, which limits comparability and hinders cumulative synthesis [19–21]. Although previous AIS surveys have provided valuable overviews of trajectory analysis, anomaly detection, traffic pattern mining, and related maritime applications, they have generally emphasized task-based categorization, algorithm inventories, or data characteristics rather than the interaction between methodological stages and deployment constraints. A focused review is therefore needed not only to consolidate the latest methodology, but also to provide a more integrative perspective that can inform the development of next-generation navigation and decision-support systems [22,23]. This paper addresses this need by providing a structured and comprehensive review of AIS-based methods for ship behavior analysis and modeling. It consolidates recent developments in the field, identifies key research challenges and gaps, and outlines future directions for advancing operationally feasible maritime analytics. Rather than proposing a new modeling method, this review contributes a workflow-based synthesis that links data processing, analysis, knowledge extraction, modeling, and runtime applications as interdependent stages. In addition, it proposes a modeling taxonomy that comparatively organizes major methodological paradigms in terms of their assumptions, outputs, and suitability under different data and operational conditions. In this way, this review aims not only to summarize the recent literature but also to provide a clearer conceptual structure for critical comparison, method selection, and interpretation.

The remainder of this paper is organized as follows: Section 2 presents the literature review methodology, informed by PRISMA principles, and outlines the general workflow

for AIS-based applications; Section 3 reviews data analysis approaches; Section 4 presents a taxonomy of modeling techniques; Section 5 discusses the main findings, limitations, and implications; and Section 6 concludes this paper.

2. Methodology

2.1. Literature Search Approach

This review adopted a structured literature search and screening process informed by PRISMA principles proposed by Moher et al. [24] in order to improve transparency in the identification, screening, and selection of relevant studies. Because the manuscript was not designed as a formal PRISMA 2020 systematic review, it is presented as a review of recent research rather than as a systematic review. The search targeted peer-reviewed journal articles and conference papers published between 2022 and 2024 that included the keyword "AIS" or "Automatic Identification System" in the title or abstract, combined with topic terms related to ship behavior (e.g., anomaly detection, collision risk, trajectory prediction, traffic monitoring, and decision support). Relevant studies were retrieved from three major bibliographic databases (Web of Science, Google Scholar, and IEEE Xplore) and complemented by two additional scholarly sources (ResearchGate and arXiv). The initial corpus was screened for relevance, language, publication type, and availability of full text. Studies examining the analysis, modeling, or decision-support applications using AIS data, as well as those providing methodological detail, were included. Materials such as theses, reports, workshop summaries, papers lacking experimental or analytical results, and non-English publications were excluded. After duplicate removal and excluding studies that used AIS only descriptively or where AIS played an incidental role, a total of 100 peer-reviewed journal articles and conference papers were retained for the final review. The process, illustrated in Figure 1, ensured a rigorous and transparent approach to identifying high-quality contributions in AIS-related research. Programming languages were not used as a screening criterion because the implementation language does not determine the scientific relevance, methodological soundness, or application domain of an AIS study. Using language as an inclusion or exclusion criterion could therefore introduce an artificial bias by filtering out otherwise relevant work based solely on technical implementation choices rather than on research contribution.

As with any literature review, the identified corpus may be influenced by database coverage and indexing practices, the choice of search terms, and language and publication bias. To mitigate these risks, searches were conducted across multiple sources, explicit inclusion/exclusion criteria were defined, and screening was performed in a structured and transparent manner. Nevertheless, relevant studies may remain underrepresented if they are not indexed in the searched sources or do not use standard AIS terminology in titles/abstracts.

To complement the literature screening process, author keywords from the final set of studies were analyzed using VOSviewer (version 1.6.20). A customized thesaurus was applied to merge synonymous or closely related terms, and a minimum occurrence threshold of two was used to highlight salient research themes. The resulting co-occurrence network, Figure 2, demonstrates the most frequently associated and conceptually interconnected keywords, providing insight into the dominant topics and methodological directions within recent AIS-based research. Node size represents keyword frequency, links indicate co-occurrence relationships (thicker = stronger), and colors denote thematic clusters.

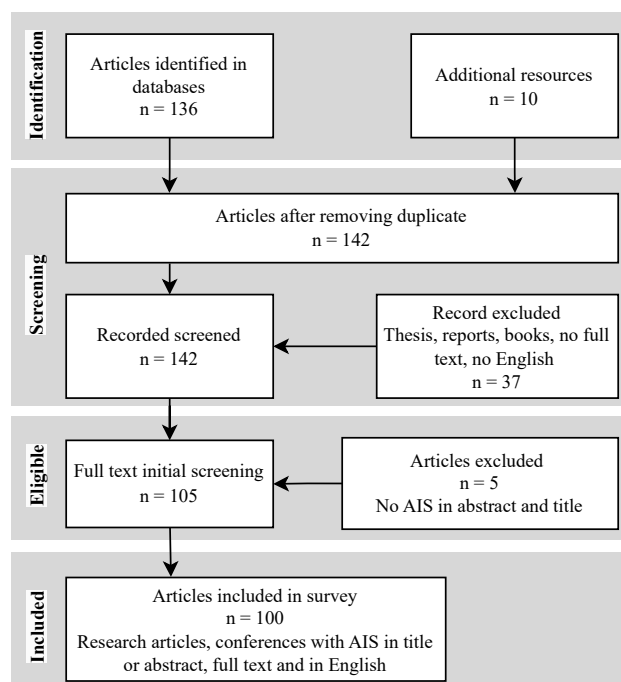


Figure 1. Structured study identification and screening process used for this review, informed by PRISMA principles.

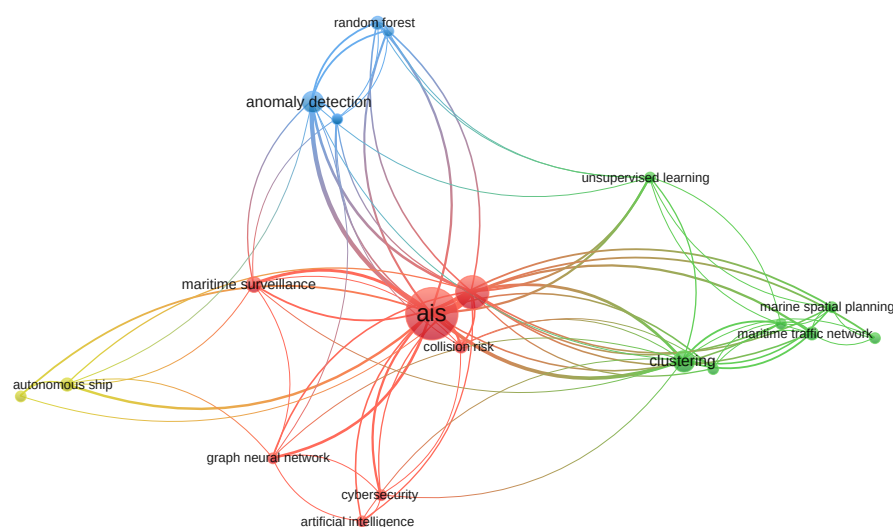


Figure 2. Keyword co-occurrence network of AIS-based ship-behavior studies (2022–2024) generated with VOSviewer using full counting and a minimum occurrence threshold of 2.

Table 1 summarizes the distribution of selected papers across journals and publishers. The corpus is dominated by contributions from Elsevier, MDPI, and IEEE journals, with Ocean Engineering and the Journal of Marine Science and Engineering, representing the most frequent publication venues. The geographical distribution of AIS-related research in Figure 3 shows that China has the highest publication output, contributing 23 studies independently and an additional 20 through international collaborations. Other countries with notable contributions and collaborations include South Korea, the United Kingdom, Norway, Portugal, Singapore, and Spain. This wide geographic spread highlights the global engagement in AIS-based research and reflects the shared importance of AIS data for advancing maritime safety, operational efficiency, and environmental sustainability across regions.

Table 2 distinguishes analysis-oriented works (indicator-based, interpretable AIS analytics) from modeling-oriented works (predictive/optimization). The categories encompass collision risk assessment, anomaly detection, trajectory prediction, maritime traffic monitoring and management, ship behavior analysis, environmental impact assessment, wildlife conservation, maritime spatial planning, maritime surveillance and security, traffic complexity analysis, vessel classification, port operations, autonomous navigation, and general maritime analytics. This broad range of application areas highlights the versatility of AIS data and its importance in supporting operational, analytical, and strategic decision-making across the maritime sector. Across applications, analysis approaches are typically more interpretable and data-light, whereas modeling approaches offer stronger predictive power but require robust validation and are more sensitive to domain shift and data quality.

Table 1. Distribution of AIS-related research papers across journals and publishers, with counts of publications.

Journal Name	Publisher	No. of Papers
Ocean Engineering	Elsevier	19
Journal of Marine Science and Eng.	MDPI	9
Expert System with Applications	Elsevier	7
IEEE Trans. on Intelligent Transportation Systems	IEEE	5
Sensors	MDPI	5
Applied Science	MDPI	4
IEEE Access	IEEE	4
Reliability Engineering & System Safety	Elsevier	3
Transportation Research Part E	Elsevier	3
Other journals (less than two papers per journal)	Elsevier, IEEE, MDPI, etc.,	25

Table 2. Classification of AIS applications based on methodological orientation, distinguishing between analysis, modeling, or combined approaches, with representative papers.

AIS Applications	Analysis	Modeling	Papers
Collision Risk Assessment	✓ ✓	✓ ✓	[25–32]. [33,34]. [26,35–39].
Anomaly Detection	✓ ✓	 ✓	[40,41]. [5,21,42–47].
Trajectory Prediction	 ✓	✓ ✓	[15,22,48–58]. [19,20,22,58–60].
Maritime Traffic Monitoring/Management	✓ ✓	✓ ✓	[61–71]. [57,72–74]. [75,76].
Ship Behavior Analysis	✓ ✓	✓ ✓	[20,43,64,65,77–82]. [10,30,77,83,84]. [10,85].
Environmental Impact, Wildlife Conservation	✓ ✓	 ✓	[63,69,75,86,87]. [88,89].
Maritime Spatial Planning/Optimization	✓ ✓	 ✓	[90]. [62,91,92].
Maritime Surveillance and Security	✓ ✓	 ✓ ✓	[45,93–95]. [96–98]. [5,21,42–44,47,67,99,100].

Table 2. Cont.

AIS Applications	Analysis	Modeling	Papers
Traffic Complexity, Pattern Recognition	✓	✓	[66,68,71,101–103]. [73,74]. [61,70,72,104–108].
Vessel Classification/Identification	✓	✓	[47,109,110].
Port Operation Analysis	✓	✓	[111]. [79].
Autonomous Navigation Support	✓	✓	[36,112]. [113].
Multipurpose/General Maritime Analytic	✓	✓	[76]. [114].

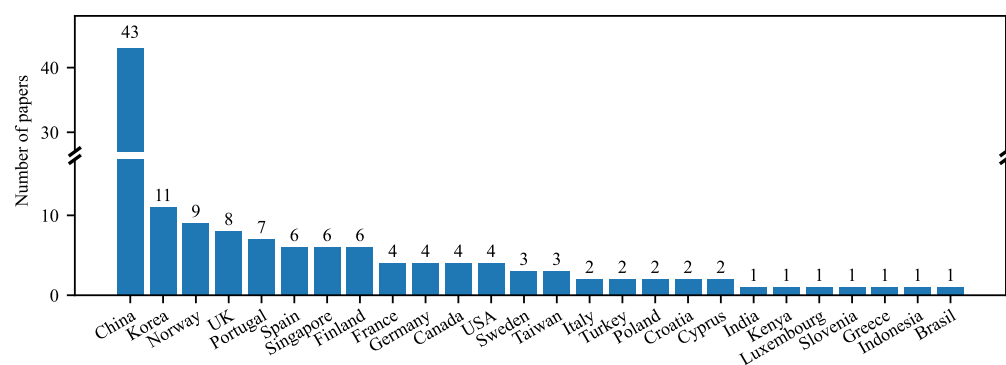


Figure 3. Country distribution of AIS publications, showing national outputs and collaborations.

2.2. General Workflow for AIS-Based Applications

The development of AIS-based applications typically follows a structured, multi-stage pipeline, summarized in Figure 4 and adapted from [76]. The first stage, data acquisition and preprocessing, focuses on collecting raw AIS messages and preparing them for reliable downstream use. AIS data are obtained primarily from two sources, terrestrial AIS (T-AIS) and satellite AIS (S-AIS), which differ substantially in coverage, reception frequency, message density, latency, and reliability. T-AIS typically provides denser, more continuous, and lower-latency observations in coastal waters, port areas, and nearshore traffic corridors, making it particularly suitable for fine-scale trajectory reconstruction, maneuver detection, port-call identification, and short-term behavioral analysis. In contrast, S-AIS offers much broader spatial coverage, especially in offshore and remote regions, but is more prone to sparse reception, message collision, irregular update intervals, and delayed availability, which can limit its suitability for resolving short-duration events or detailed vessel maneuvers. Instead, S-AIS is often more useful for large-scale traffic monitoring, route-pattern analysis, and broad characterization of vessel movement over wider geographic domains. Because these source characteristics directly shape the structure and continuity of the observations, preprocessing is a necessary methodological stage rather than a purely technical preliminary step. AIS data from both sources may be affected by missing transmissions, duplicated records, positional noise, message filtering, and irregular sampling intervals, so preprocessing commonly involves cleaning, filtering, interpolation, trajectory segmentation or reconstruction, and noise reduction before downstream analysis. These differences also imply that T-AIS and S-AIS should not be treated as interchangeable inputs, since the underlying acquisition mode influences the scale, reliability, and interpretability of subsequent modeling results. The second stage, data analysis, examines the processed data to identify fundamental navigational, spatial, and temporal patterns. Typical approaches

include clustering, density mapping, descriptive statistics, and exploratory spatiotemporal analysis, which help reveal movement behaviors, traffic flows, route structures, and operational characteristics of vessels in different maritime contexts. In the third stage, knowledge extraction [115], raw AIS trajectories are transformed into more informative and compact representations that are suitable for interpretation and modeling. This stage commonly includes trajectory compression, feature engineering, and the derivation of geometric, kinematic, and contextual descriptors, thereby converting raw vessel tracks into higher-level indicators of ship behavior and maritime activity. The fourth stage, modeling and inference, uses these extracted representations to build predictive, descriptive, or decision-oriented models. Classification, regression, probabilistic, and optimization-based approaches are employed to support a range of tasks, including anomaly detection, trajectory prediction, behavior recognition, and risk assessment [116,117]. At this stage, the objective is not only to characterize past and present vessel activity, but also to infer future states, detect abnormal situations, and support risk-aware maritime decision-making. The final stage, runtime application and operational use, integrates these models into practical maritime systems and decision-support environments. In this stage, analytical outputs are translated into actionable services such as real-time alerts, traffic monitoring dashboards, collision-risk warnings, adaptive navigation assistance, and other operational tools that enhance maritime safety, efficiency, and governance.

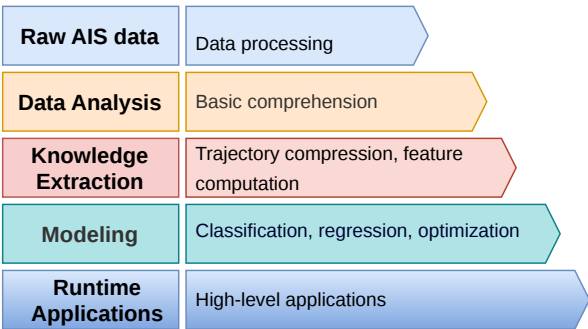


Figure 4. General workflow for AIS-based applications, comprising five stages from raw data to runtime applications.

3. AIS Data Analysis Overview

AIS data analysis can be viewed in four perspectives: statistical analysis, safety indicators, situational awareness, and anomaly detection. These domains are inherently interconnected: statistical patterns inform the construction of safety indicators; safety metrics contribute to situational awareness; and deviations from expected behavior support anomaly detection. Together, they form the analytical foundation for understanding the dynamics of maritime traffic and supporting data-driven ship behavior modeling.

3.1. Statistical Analysis

Statistical analysis provides the quantitative base for interpreting large-scale vessel movement patterns using AIS data. Beyond descriptive measures such as speed distributions and port arrival times, modern AIS analytics incorporate trajectory clustering, density estimation, and probabilistic sequence models (e.g., Hidden Markov Model (HMM)) to infer common navigational routes and behavioral states. Traffic density maps and time charts expose areas of high traffic concentration, and spatiotemporal heatmaps reveal congestion hotspots and peak movement periods, while temporal analysis supports the estimation of port activity cycles and navigational bottlenecks.

These statistical outputs often serve as inputs to higher-level safety assessment and decision-support frameworks. In this context, the integration occurs at the level of maritime traffic monitoring, where AIS-derived statistical features are combined with navigational risk indicators to provide a more comprehensive interpretation of vessel behavior. The main elements involved in this integration include statistical outputs such as deviations from typical route corridors, anomalous speed variations, traffic density distributions, and clustering-based outliers, together with safety metrics such as the Distance to the Closest Point of Approach (DCPA) and Time to Closest Point of Approach (TCPA). In some cases, course over ground, speed over ground, heading, and positional updates from AIS messages are further used to derive encounter patterns and local risk conditions. By combining these elements, the analysis helps identify hazardous areas, abnormal ship interactions, and emerging conflict situations, thereby informing proactive traffic management, operational planning, and risk-based maritime decision-support systems. Thus, statistical analysis not only characterizes traffic flows but also contributes to integrated safety evaluation in maritime systems.

3.2. Safety Indicator

Safety indicators play a central role in quantifying the risk of vessel interactions and supporting collision avoidance. Fundamental geometric descriptors such as distance and relative bearing provide essential insight into vessel proximity and motion dynamics. In AIS-based maritime research, the Closest Point of Approach (CPA) concept is widely used to evaluate the potential interaction risk between vessels based on their reported motion states. Using AIS-derived information such as vessel position, speed over ground, course over ground, and heading, researchers can estimate relative trajectories and determine the predicted point of minimum separation between two vessels under the assumed motion. In this context, DCPA and TCPA are the standard quantitative indicators derived from CPA. DCPA estimates the minimum predicted distance between two vessels if they maintain their current motion states, while TCPA estimates the time remaining until that minimum distance is reached. Because these indicators can be directly computed from AIS kinematic data, they are frequently employed in AIS-based publications for collision risk assessment, encounter analysis, anomaly detection, and maritime traffic safety evaluation. Together, they provide interpretable and operationally relevant metrics for evaluating encounter severity.

Safety assessments extend beyond pairwise interactions to incorporate a vessel's maneuvering safety margin, the effective space required to execute safe maneuvers under given operational and environmental conditions. This margin depends on vessel maneuverability, hydrodynamic characteristics, traffic density, visibility, environmental forces, and meteorological conditions, as well as COLREGs obligations. For example, geometric and shape-based features extracted from AIS data have been applied to classify vessel behavior and detect anomalies [47]. Behavioral classification also supports safety monitoring. Xin et al. [79] distinguish between underway, anchorage, and at-berth states, while Sturgis et al. [83] identify drifting and anchored modes that may indicate elevated risk if occurring in constrained areas. These indicators collectively support early danger awareness, collision risk assessment, and compliance monitoring, forming a critical component of maritime safety systems.

3.3. Situation Awareness

Situation awareness (SA) refers to the perception, comprehension, and projection of elements in the maritime environment [118]. It underpins safe navigation, especially in

dense and dynamic waterways. Figure 5 illustrates Endsley's three-level model adopted for AIS-based maritime traffic monitoring.

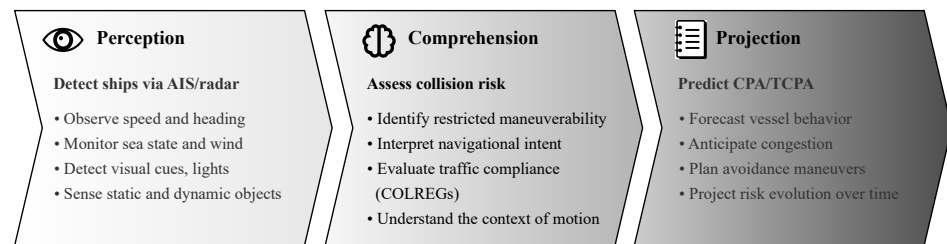


Figure 5. Application of Endsley's three levels of situational awareness to maritime navigation using AIS and radar data.

At the perception level, AIS and radar provide real-time information on vessel identities, positions, speeds, and headings. The comprehension level integrates these elements to assess encounter situations, evaluate risk, and interpret vessel intent. At the projection level, future states such as predicted CPA/TCPA or potential rule violations are inferred to support decision-making.

Traffic state indicators such as static and dynamic density, encounter geometry, traffic complexity, and collision risk further enhance SA [64]. Encounter analysis is particularly relevant, as it classifies navigational interactions (head-on, crossing, and overtaking) in accordance with COLREGs, providing interpretable descriptors for vessel behavior and facilitating automated rule compliance assessment [119]. Graph-theoretic and network-based approaches increasingly support multi-ship encounter understanding, enabling recognition of collective movement patterns and emergent risks.

Risk assessment models draw from geometric, probabilistic, and ML approaches. Bayesian networks capture dependencies among risk factors, ship domains, and velocity obstacle models that characterize spatial constraints, and ML models (e.g., RF, XGBoost, and NN) are widely used to classify risk levels and forecast collision likelihood. Hybrid methods that integrate deep learning with physical or probabilistic modeling have recently emerged as promising tools for improving prediction accuracy and robustness.

3.4. Anomaly Detection

Anomaly detection identifies deviations from expected vessel behavior and supports maritime surveillance, safety monitoring, and regulatory enforcement. Figure 6 illustrates the major categories of anomalies detectable from AIS data.

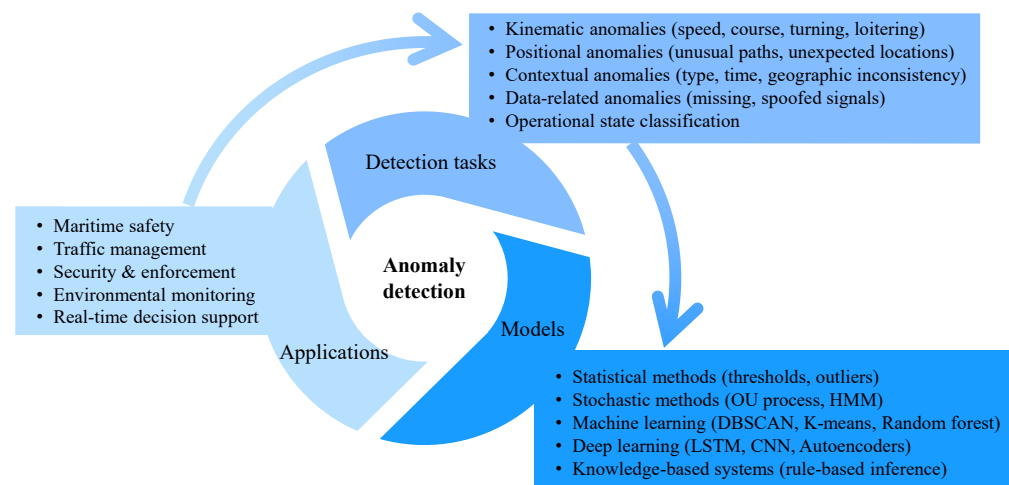


Figure 6. Overview of AIS-based anomaly detection, showing anomaly categories, associated detection tasks, and applications.

Anomalies may be kinematic, such as irregular speed, unexpected course changes, or extreme turning rates. They can be positional, including off-route deviations or unexpected geographic locations. Contextual anomalies arise when a vessel's behavior is inconsistent with its type, operational norms, or environmental constraints. Data-related anomalies include AIS gaps, transmission manipulations, and spoofing. Liu et al. [120] further refine kinematic anomalies into speed/course anomalies (SCAs), turning anomalies (TAs), and loitering anomalies (LAs), enabling more structured analysis of vessel behavior.

Anomaly detection methods range from descriptive statistics and rule-based systems [121] to probabilistic sequence models [23,40] and ML approaches such as DBSCAN, K-means, GMMs, and supervised classifiers. Knowledge-based systems incorporate maritime regulations and expert rules, while DL methods, including LSTM networks, autoencoders, and CNN models, capture complex temporal dependencies and subtle deviations [122]. Recent advances include online stochastic modeling approaches such as the Ornstein–Uhlenbeck process for real-time detection [44].

A persistent challenge is balancing detection sensitivity with false alarm reduction, especially in regions with highly variable traffic patterns. Effective preprocessing, including noise filtering, trajectory segmentation, normalization, and map matching, significantly improves model performance and reduces misclassifications in dense maritime environments.

4. Modeling Taxonomy

Modeling ship behavior involves constructing mathematical or algorithmic representations that capture how ships move, interact, and respond to environmental and navigational conditions. In AIS-based research, modeling serves multiple purposes, including behavior recognition, trajectory prediction, anomaly detection, encounter classification, and decision support for collision avoidance and routing. Since AIS observations encode both kinematic information and interaction cues, ship behavior modeling has progressed toward increasingly data-driven, context-aware, and multi-agent frameworks.

Ship behavior can be described from several perspectives, such as navigational status (e.g., underway, stopped, and anomalous), operational activities (e.g., docking, anchoring, and cargo handling), or interaction type (e.g., head-on, crossing, and overtaking) [78,117,123]. Additional taxonomies consider contextual factors (e.g., harbor vs. open sea), temporal variation, and behavioral scales ranging from individual vessels to multi-ship encounters. These perspectives highlight the need for a coherent modeling taxonomy capable of relating methodological choices to the specific characteristics of ship behavior problems.

To provide such a structure, this paper categorizes AIS-based modeling approaches into three foundational paradigms: classification, regression, and optimization. This taxonomy reflects the mathematical nature of behavior modeling tasks: assigning discrete behavior labels (classification), predicting continuous navigational states (regression), and computing optimal actions or routes under constraints (optimization). Table 3 compares these paradigms in terms of mathematical characteristics, strengths, limitations, and suitability for maritime applications. It is important to distinguish between modeling paradigms and algorithmic techniques. In this review, classification, regression, and optimization are treated as task-level paradigms, whereas methods such as DBSCAN, Random Forest, LSTM, GNNs, and DTW represent algorithmic techniques that may be incorporated within or across these paradigms depending on the target task.

Figure 7 presents the distribution of modeling techniques used in recent AIS-based ship behavior studies. DBSCAN and deep learning methods appear among the most frequently used approaches, together accounting for nearly 40% of the models represented in the reviewed studies. This distribution is analytically meaningful. The prominence of

DBSCAN suggests that a large part of the field still depends on unsupervised structure discovery, route extraction, and anomaly identification in settings where reliable behavioral labels remain scarce. The parallel rise of deep learning reflects the increasing importance of nonlinear temporal prediction, high-dimensional sequence modeling, and context-sensitive inference. Traditional machine learning approaches, such as Random Forest, K-Means, and hybrid ensemble models, form a robust middle tier, indicating that interpretability, moderate data requirements, and computational efficiency remain important practical considerations. Meanwhile, emerging techniques such as Graph Neural Networks (GNNs), self-supervised learning, and Dynamic Time Warping (DTW)-based models suggest a gradual shift toward relational, representation-learning, and sequence-alignment perspectives, although these approaches have not yet reached the same level of methodological consolidation as clustering- and prediction-oriented models. Overall, this diversity suggests that AIS-based ship behavior analysis is not converging on a single dominant modeling strategy; rather, methodological choice remains strongly dependent on whether the task is behavioral categorization, trajectory forecasting, anomaly detection, or operational decision support. Together, Table 3 and Figure 7 provide complementary evidence supporting a comparative analysis of modeling paradigms in AIS-based ship behavior research.

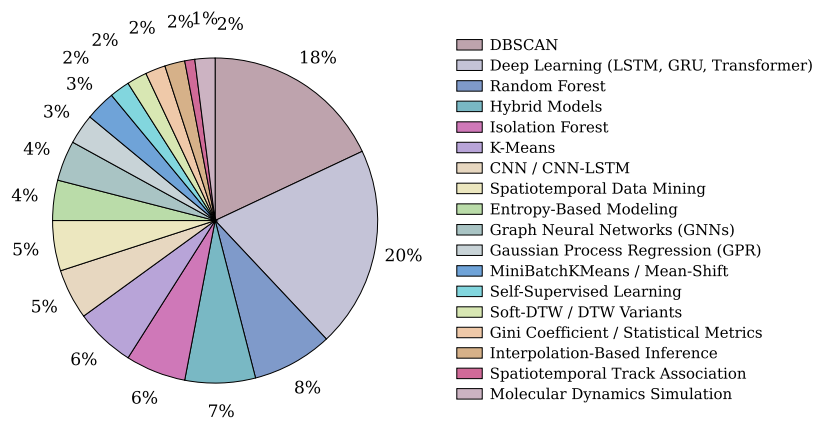


Figure 7. Distribution of modeling methods in AIS-based ship behavior studies (2022–2024).

Table 3. Modeling taxonomy for AIS-based ship behavior analysis.

Model Type	Mathematical Characteristics	Strengths	Limitations/Suitability
Classification	Maps input features to discrete categories. Typically based on decision boundaries, probability distributions, or similarity structures. Examples: $f(x) \rightarrow \{1, \dots, k\}$.	Effective for behavior recognition and anomaly detection. Handles heterogeneous AIS features well. Useful for maritime situational awareness.	Sensitive to noise, parameter tuning, and class imbalance. Not suitable for continuous prediction or long-horizon forecasting.
Regression	Learns continuous mappings from past states to future values. Based on time-series models, state-space models, or function approximation. Examples: $y_{t+h} = f(x_{t-h:t})$.	Best suited for trajectory prediction, ETA estimation, and risk forecasting. Can model nonlinear vessel dynamics. Deep models capture long-term temporal patterns.	Performance degrades with sparse or noisy AIS. Struggles with abrupt maneuvers. Requires careful generalization across regions.
Optimization	Solves constrained objectives of the form $\min f(x)$ subject to $g(x) \leq 0$. Includes deterministic and learning-based optimization.	Provides actionable navigation decisions (routing, collision avoidance). Directly relates to COLREGs and operational constraints.	Requires well-formulated constraints and accurate predictions. May be computationally heavy for real-time MASS. Less suitable for pure behavioral inference.

Taken together, these three paradigms address different analytical needs in AIS-based ship behavior research. Classification-oriented approaches are most suitable when the objective is to identify discrete behavioral states, operational categories, or anomalous events, but they are less effective for forecasting continuous vessel evolution. Regression-based models are more appropriate for trajectory prediction and risk estimation over time, although their performance is often sensitive to AIS sparsity, sampling irregularity, and abrupt maneuver changes. Optimization-based methods differ from the other two in that they are not primarily inferential, but prescriptive: they use predictions, constraints, and operational rules to generate actionable decisions such as route selection or collision-avoidance maneuvers. This distinction is important because it shows that AIS-based behavior modeling is not a single methodological problem, but a pipeline of related tasks spanning inference, prediction, and decision support.

Classification: Classification models assign vessels, trajectory segments, or encounter situations to discrete behavioral categories based on AIS-derived features. In AIS-based studies, this paradigm is interpreted broadly to include not only supervised category assignment but also unsupervised grouping methods used for behavior pattern discovery, route clustering, and anomaly identification. These methods are used for ship-type identification, encounter classification, anomaly detection, risk-level assessment, and intent inference. Classification relies on decision boundaries, similarity relationships, or probabilistic formulations to distinguish among behavioral states. Representative techniques include SVM, Logistic Regression, DBSCAN, HMM, Decision Trees, RF [85], CNN-based classifiers [13,38], and multiattention LSTM [119]. These models handle heterogeneous AIS features well, but face challenges such as class imbalance, ambiguous maneuver patterns, and hybrid behaviors not captured in training data.

Regression: Regression methods learn continuous relationships from historical AIS time-series to forecast speed, position, course, ETA, or associated risk metrics. Techniques include RF regression, SVM regression, LSTM, GRU, ARIMA, Kalman filtering, and other sequence learning architectures. Regression is fundamental for trajectory prediction and proactive traffic monitoring but requires clean data, consistent sampling, and careful calibration to avoid error amplification. Representative examples include route prediction using combined DP-DTW clustering and regression frameworks [50] and ship prediction using RF models [109].

Optimization: Optimization approaches formulate navigation and decision-making tasks such as route planning, speed control, collision avoidance, and berth scheduling as constrained optimization problems [124]. These techniques include Reinforcement Learning, Convex Optimization, Genetic Algorithms, A^* search, dynamic programming, and evolutionary strategies such as PSO-BP. Optimization is effective for generating COLREG-compliant trajectories and improving fuel efficiency, but often requires high-quality prediction inputs and can become computationally intensive, particularly in dense, multi-ship environments. Examples include quasi-intelligent route extraction from AIS data [92] and MPC-based path planning that integrates vessel dynamics and COLREGs for safe maneuvering [12]. Data-driven network inference from AIS trajectories has also been explored for large-scale digital shipping networks [62,91]. Overall, the proposed taxonomy highlights that AIS-based ship behavior modeling has evolved from an isolated method application toward a more differentiated analytical landscape in which discrete behavior recognition, continuous state prediction, and prescriptive navigation support are increasingly treated as distinct but interconnected problems. At the same time, the literature still reveals an important gap: although many studies report strong performance within individual tasks, fewer address how these paradigms can be integrated into coherent operational systems that

remain robust under noisy data conditions, cross-region variability, and constrained-water maneuvering contexts.

5. Discussion

This section synthesizes the 2022–2024 AIS-based ship behavior literature. Emphasis is placed on (i) positioning relative to prior AIS surveys, (ii) trends, methodological shifts, and persistent gaps, and (iii) implications for runtime deployment and operational decision support, with particular attention to relevance for autonomous navigation and maneuvering in constrained waters. The contribution of this review lies in conceptual integration rather than simple expansion of the method inventory.

5.1. Workflow-Based Synthesis and Modeling Taxonomy

Several influential AIS surveys (e.g., Tu et al. [17], Xiao et al. [18]) established systematic reviews of AIS-enabled maritime analytics by organizing core tasks such as trajectory analysis, anomaly detection, and traffic pattern mining, while emphasizing AIS data characteristics and largely offline modeling pipelines. Building on these foundations, this review focuses on the 2022-to-2024 literature, highlighting recent methodological developments and the growing shift toward real-time analytics and operational decision support. Rather than classifying studies solely by task, this review is organized using a five-stage workflow (data processing, data analysis, knowledge extraction, modeling, and runtime applications), linking methodological choices to data conditions, modeling assumptions, and deployment feasibility. In addition, a modeling taxonomy is proposed to synthesize classification, regression, and optimization paradigms comparatively, clarifying their typical assumptions, outputs, and suitability for operational tasks under real-world constraints. This positioning helps clarify what has changed most recently and why particular modeling choices are emerging in current AIS-based ship behavior research.

This perspective also clarifies that no single methodological family is universally optimal. Clustering approaches are often effective for exploratory analysis and for settings with limited labeled data, but they depend strongly on feature design, similarity measures, and the degree to which behavioral patterns form separable groups. Deep learning approaches are advantageous when large, relatively consistent datasets are available and when complex temporal or nonlinear dependencies must be captured. However, they are typically more data-intensive, computationally demanding, and less interpretable. Probabilistic models are particularly useful when uncertainty and state transitions must be represented explicitly, but their performance may depend on simplifying assumptions about latent structure and transition dynamics. Method selection should therefore be guided not only by predictive performance, but also by data quality, sampling regularity, trajectory completeness, interpretability, and operational constraints.

The workflow and taxonomy are also relevant from an application perspective. In port operations and constrained coastal environments, methods that perform well on dense nearshore AIS data and provide interpretable outputs are especially useful for congestion monitoring, berth allocation, port-call detection, and turnaround analysis. In autonomous navigation and maneuvering support, the emphasis shifts toward near-real-time processing, short-horizon trajectory prediction, and robust detection of rapid behavioral changes under uncertainty. At broader regional or global scales, such as maritime traffic monitoring, scalability and wide-area coverage become more important than fine-resolution maneuver detection, which increases the relevance of clustering, route extraction, and anomaly-screening approaches. This application-oriented view reinforces that methodological choices should be evaluated in relation to spatial scale, latency tolerance, uncertainty handling, and the characteristics of the available AIS data.

5.2. Trends, Methodological Shifts, and Persistent Gaps

Figure 2 shows AIS as the dominant hub in the keyword network, indicating that most studies continue to frame their contributions around AIS data itself rather than around narrower application labels. Three themes are particularly visible. The first is trajectory and pattern mining, reflected in terms such as trajectory mining, trajectory data mining, spatial clustering, spatial analysis, and maritime traffic network. This indicates continued interest in extracting structure from movement histories and traffic flows. The second is safety and monitoring, centered on anomaly detection and supported by relative motion and related traffic concepts, suggesting that detection-oriented analytics remain central to operational risk awareness. The third is autonomy-oriented research, where terms such as autonomous ship and intelligent navigation appear linked to the previous themes. This suggests a growing connection between AIS-based analytics and perception or decision pipelines for autonomous systems, although this area remains less central than surveillance and traffic-mining applications. Smaller terms such as cybersecurity, sentinel, and marine spatial planning point to diversification toward security and environmental or spatial-planning uses. Across the 2022–2024 literature, three methodological shifts stand out. First, there is a clear move toward machine-learning-based prediction and detection [42,44], including self-supervised and weakly supervised designs that reduce dependence on scarce labels [46]. Second, hybrid pipelines that combine rule-based maritime logic with learned models are increasingly used to balance interpretability, robustness, and predictive performance. Third, more studies now address deployment constraints directly, including streaming inputs, latency, and integration into operational workflows [76]. Compared with earlier reviews that emphasized AIS fundamentals and static modeling, recent work shows a stronger orientation toward real-time analytics and decision-support integration.

Despite this progress, several persistent limitations remain. AIS-based methods are inherently sensitive to signal loss, incomplete reception, irregular transmission intervals, positional noise, message filtering, and deliberate manipulation such as spoofing. These issues do not simply reduce data quality in a general sense. They can fragment trajectories, distort derived motion features, weaken anomaly detection, bias vessel profiling, and reduce sensitivity to rare or unusual behaviors. As a result, they directly affect downstream model outputs, uncertainty estimates, and the interpretation of inferred vessel activity.

Generalizability remains another major challenge. Many methodological components are broadly transferable, including preprocessing routines, common trajectory features, general modeling frameworks, and evaluation principles. However, their performance and interpretation often depend strongly on regional conditions such as traffic density, vessel composition, coastal and port geometry, local navigational practices, regulatory context, and AIS coverage or data quality. Models, thresholds, and behavioral labels developed in one region may therefore not transfer directly to another without recalibration or revalidation. In this sense, transferability applies more readily to analytical frameworks than to model calibration or behavioral interpretation.

A further gap concerns evaluation and benchmarking. Comparability across studies remains limited because datasets, preprocessing choices, behavioral definitions, validation strategies, and reported metrics often differ substantially. Progress toward more cumulative and reproducible research will require shared or clearly documented reference datasets, more consistent evaluation protocols, and task-appropriate performance measures. In particular, future evaluation should better account for temporal structure, class imbalance, missing data, and cross-region transferability. Without such standardization, it remains difficult to determine whether reported performance gains reflect genuine methodological advances or differences in experimental design.

Finally, transparency and explainability remain underdeveloped, especially in safety-critical applications where trust, accountability, and interpretability are essential for operational adoption [40]. This issue becomes even more important as AIS-based analytics move closer to real-time decision support and autonomous navigation.

5.3. Potential Runtime Applications of AIS-Based Models

Against this backdrop, three promising runtime application areas can be distinguished, each representing a different level of methodological maturity and operational readiness.

The first concerns autonomous ships, where AIS is increasingly combined with on-board sensors such as radar, sonar, and LiDAR (Light Detection and Ranging) to support situational awareness, collision avoidance, and route planning. Models based on unsupervised anomaly detection [42], online anomaly detection and behavior classification [44], and multi-stage traffic complexity assessment for probabilistic collision detection [31] illustrate plausible pathways for integration into MASS navigation modules. The keyword structure centered on traffic, prediction, and risk suggests that AIS analytics are currently most mature for autonomy functions related to encounter assessment and tactical decision support. By contrast, maneuvering-specific behaviors at low speed and close range remain less visible in the current literature.

The second application area is remote monitoring and traffic management. These settings increasingly rely on AIS-driven analytics for real-time fleet awareness and broader maritime domain awareness. Studies such as [40,41,43,45,46] show that unsupervised and learning-based methods can support large-scale anomaly detection and vessel surveillance. Entropy-based and quantitative risk models [25,27,28] extend this potential toward traffic risk evaluation and safety planning. Relative to autonomy-oriented applications, this domain aligns more closely with the present strengths of AIS data, especially wide-area coverage and continuous track-based monitoring. Even so, deployment remains constrained by false positives, regional sensitivity, and dependence on the completeness and reliability of AIS transmissions. Operational usefulness, therefore, depends not only on algorithmic performance but also on robustness, calibration, and the ability to support human operators without overwhelming them with uncertain alerts.

The third application area concerns onboard decision-support systems. In this context, AIS-based models are combined with collision-risk prediction, trajectory forecasting, and contextual information to recommend maneuvers, improve routing efficiency, and support safer navigation decisions [21,47,125]. Recent work on anchorage risk assessment [26] and berthing safety evaluation [30] further indicates that AIS-based analytics are beginning to address operationally relevant scenarios in ports and harbor approaches. However, compared with remote surveillance systems, onboard decision support places greater demands on timeliness, interpretability, and user trust. A model may perform well in retrospective evaluation yet still be difficult to operationalize if its recommendations are not transparent, context-sensitive, or compatible with bridge-level decision processes. This highlights the gap between predictive capability and actionable usability, which remains insufficiently addressed in much of the current literature.

Overall, the reviewed studies indicate a clear movement toward more operationally relevant AIS-based systems, driven by advances in machine learning, real-time analytics, and multi-sensor data fusion. However, runtime maturity differs substantially across application domains. Remote monitoring currently appears to be the most immediately deployable use case because it aligns well with the large-scale observational strengths of AIS data. By contrast, autonomous navigation and onboard decision support require a higher degree of contextual awareness, interpretability, and robustness under noisy real-world conditions. Wider deployment will therefore depend on progress in four areas:

resilience to imperfect AIS data, cross-region generalizability, transparent model behavior, and integration with existing maritime decision-support infrastructures. Future work should focus not only on improving predictive accuracy but also on developing evaluation frameworks that better reflect operational complexity and real-world usability.

6. Conclusions

By consolidating recent advances in AIS-based ship behavior modeling, this review provides a structured synthesis of studies published in English between 2022 and 2024. Through a structured literature review process informed by PRISMA principles, relevant studies were identified and categorized, highlighting how statistical, visualization, and ML techniques are applied to improve maritime safety, situational awareness, and operational efficiency. From this body of work, a modeling taxonomy is derived that organizes classification, regression, and optimization approaches according to operational tasks such as vessel type identification, trajectory prediction, and route optimization.

The analysis revealed persistent challenges at both the data and modeling levels. AIS datasets remain affected by noise, missing values, inconsistencies, and uneven coverage, while modeling approaches face issues of scalability, interpretability, and parameter sensitivity. Although DL methods capture complex spatial-temporal patterns, their generalizability across regions and vessel types is constrained by limited access to large, high-quality, real-time or simulated datasets. These limitations underscore the need for robust, explainable ML frameworks and onboard support tools that can operate under real-time constraints with reliability and transparency.

This review highlights three emerging runtime application domains for AIS-based models. Autonomous vessels are increasingly integrating live AIS streams into navigation and collision-avoidance pipelines, enabling dynamic route adaptation. Shore-based monitoring platforms employ anomaly detection and behavior analysis to support maintenance planning, incident investigation, and regulatory compliance. Integrated decision-support systems combine AIS with environmental and operational data, such as weather and ocean forecasts, to optimize routing, scheduling, and fleet-level decision-making. These applications demonstrate the growing operational relevance of adaptive maritime analytics and their potential to translate theoretical modeling into operational practice.

Future research should advance AIS-based maritime intelligence by focusing on three interconnected priorities. First, integrating heterogeneous data sources, including AIS, weather, radar, and camera feeds, into unified architectures will enable robust safety indicators, early anomaly detection, and richer situational awareness. Second, explainable AI approaches tailored to maritime operations are essential to ensure transparency, auditability, and trust as autonomy expands. Third, progress will depend on multidisciplinary collaboration across engineering, data science, and human factors, supported by evolving regulatory frameworks and explicit consideration of human oversight in monitoring and validation. Together, these directions provide a pathway toward intelligent maritime systems that are resilient, trustworthy, and operationally aligned.

A central finding of this review is that AIS-based ship behavior modeling is not converging toward a single dominant methodological solution. Instead, the field is evolving as a differentiated analytical landscape in which classification-, regression-, and optimization-based approaches address distinct but interconnected tasks of inference, prediction, and decision support. This insight shifts this review beyond a simple summary of existing studies and highlights the need to align methodological choices with operational objectives, data conditions, and maritime context.

In conclusion, synthesizing current methodologies, characterizing emerging applications, and identifying open challenges, this paper provides a structured road map for the

next generation of AIS-based ship behavior modeling. The insights presented here aim to guide researchers, system designers, and practitioners in developing maritime traffic systems that are efficient, transparent, and resilient to real-world demands. Overall, the value of this review lies in critically organizing a fragmented literature into a comparative framework that clarifies not only what methods exist but also where they are most applicable, where their limitations persist, and what is required for their operational use.

Author Contributions: Conceptualization, G.L. and H.Z.; methodology, A.D., G.L. and H.Z.; software, A.D.; validation, A.D. and G.L.; formal analysis, A.D.; investigation, A.D.; data curation, A.D.; writing original draft, A.D.; writing—review and editing, A.D., G.L. and H.Z., and P.V.; visualization, A.D.; supervision, G.L., H.Z. and P.V. All authors have read and agreed to the published version of the manuscript.

Funding: A.D. received support from the Ministry of Foreign Affairs of Norway through the Norwegian University of Science and Technology (NTNU), project number 987823100.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. UNCTAD. Review of Maritime Transport 2022. Available online: <https://unctad.org/rmt2022> (accessed on 24 September 2025).
2. Kjerstad, N. *Electronic and Acoustic Navigationsystems for Maritime Studies*; NTNU Norwegian University of Science and Technology: Trondheim, Norway, 2016.
3. Shepperson, J.L.; Hintzen, N.T.; Szostek, C.L.; Bell, E.; Murray, L.G.; Kaiser, M.J. A comparison of VMS and AIS data: The effect of data coverage and vessel position recording frequency on estimates of fishing footprints. *ICES J. Mar. Sci.* **2018**, *75*, 988–998. <https://doi.org/10.1093/icesjms/fsx230>.
4. Wu, B.; Yip, T.L.; Yan, X.; Soares, C.G. Review of techniques and challenges of human and organizational factors analysis in maritime transportation. *Reliab. Eng. Syst. Saf.* **2022**, *219*, 108249. <https://doi.org/10.1016/j.res.2021.108249>.
5. Rong, H.; Teixeira, A.; Soares, C.G. A framework for ship abnormal behaviour detection and classification using AIS data. *Reliab. Eng. Syst. Saf.* **2024**, *247*, 110105. <https://doi.org/10.1016/j.res.2024.110105>.
6. Jia, R.; Ma, C.; Kouw, W.M. Multiple Variational Kalman-GRU for Ship Trajectory Prediction With Uncertainty. *IEEE Trans. Aerosp. Electron. Syst.* **2024**, *61*, 3654–3667. <https://doi.org/10.1109/TAES.2024.3491053>.
7. Zhang, M.; Montewka, J.; Manderbacka, T.; Kujala, P.; Hirdaris, S. A big data analytics method for the evaluation of ship-ship collision risk reflecting hydrometeorological conditions. *Reliab. Eng. Syst. Saf.* **2021**, *213*, 107674. <https://doi.org/10.1016/j.res.2021.107674>.
8. Zhu, J.; Gao, M.; Zhang, A.; Hu, Y.; Zeng, X. Multi-ship encounter situation identification and analysis based on AIS data and graph complex network theory. *J. Mar. Sci. Eng.* **2022**, *10*, 1536. <https://doi.org/10.3390/jmse10101536>.
9. Jia, R.; Kouw, W.M.; Wu, W.; Xie, X. Bayesian Inference of Collision Avoidance Intent During Ship Encounters. *IEEE Trans. Autom. Sci. Eng.* **2024**, *22*, 17397–17410. <https://doi.org/10.1109/TASE.2024.3383819>.
10. Wang, C.; Li, G.; Han, P.; Osen, O.; Zhang, H. Impacts of COVID-19 on ship behaviours in port area: An AIS data-based pattern recognition approach. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 25127–25138. <https://doi.org/10.1109/TITS.2022.3147377>.
11. Zhang, H.; Li, G.; Hatledal, L.I.; Chu, Y.; Ellefsen, A.; Han, P.; Major, P.; Skulstad, R.; Wang, T.; Hildre, H.P. A digital twin of the research vessel Gunnerus for lifecycle services: Outlining key technologies. *IEEE Robot. Autom. Mag.* **2022**, *30*, 6–19. <https://doi.org/10.1109/MRA.2022.3217745>.
12. Zhu, M.; Tian, W.; Skulstad, R.; Zhang, H.; Li, G. Prediction-enabled path planning for multi-ship encounters in Oslofjord. *Ocean Eng.* **2024**, *294*, 116747. <https://doi.org/10.1016/j.oceaneng.2024.116747>.
13. Zhang, W.; Feng, X.; Goerlandt, F.; Liu, Q. Towards a Convolutional Neural Network model for classifying regional ship collision risk levels for waterway risk analysis. *Reliab. Eng. Syst. Saf.* **2020**, *204*, 107127. <https://doi.org/10.1016/j.res.2020.107127>.
14. Zhen, R.; Riveiro, M.; Jin, Y. A novel analytic framework of real-time multi-vessel collision risk assessment for maritime traffic surveillance. *Ocean Eng.* **2017**, *145*, 492–501. <https://doi.org/10.1016/j.oceaneng.2017.09.015>.
15. Wang, X.; Xiao, Y. A Deep Learning Model for Ship Trajectory Prediction Using Automatic Identification System (AIS) Data. *Information* **2023**, *14*, 212. <https://doi.org/10.3390/info14040212>.
16. Zhu, M.; Han, P.; Tian, W.; Skulstad, R.; Zhang, H.; Li, G. A Deep Generative Model for Multi-Ship Trajectory Forecasting With Interaction Modeling. *J. Offshore Mech. Arct. Eng.* **2025**, *147*, 031402. <https://doi.org/10.1115/1.4065866>.

17. Tu, E.; Zhang, G.; Rachmawati, L.; Rajabally, E.; Huang, G.B. Exploiting AIS Data for Intelligent Maritime Navigation: A Comprehensive Survey From Data to Methodology. *IEEE Trans. Intell. Transp. Syst.* **2017**, *19*, 1559–1582. <https://doi.org/10.1109/TITS.2017.2724551>.
18. Xiao, Z.; Fu, X.; Zhang, L.; Goh, R.S.M. Traffic Pattern Mining and Forecasting Technologies in Maritime Traffic Service Networks: A Comprehensive Survey. *IEEE Trans. Intell. Transp. Syst.* **2019**, *21*, 1796–1825. <https://doi.org/10.1109/TITS.2019.2908191>.
19. Liu, D.; Rong, H.; Soares, C.G. Shipping route modelling of AIS maritime traffic data at the approach to ports. *Ocean Eng.* **2023**, *289*, 115868. <https://doi.org/10.1016/j.oceaneng.2023.115868>.
20. Ma, H.; Zuo, Y.; Li, T. Vessel navigation behavior analysis and multiple-trajectory prediction model based on AIS data. *J. Adv. Transp.* **2022**, *2022*, 6622862. <https://doi.org/10.1155/2022/6622862>.
21. Shi, Y.; Long, C.; Yang, X.; Deng, M. Abnormal ship behavior detection based on AIS data. *Appl. Sci.* **2022**, *12*, 4635. <https://doi.org/10.3390/app12094635>.
22. Wang, W.; Bin, J.; Zaji, A.; Haldearn, R.; Guillaume, F.; Li, E.; Liu, Z. A multi-task learning-based framework for global maritime trajectory and destination prediction with AIS data. *Marit. Transp. Res.* **2022**, *3*, 100072. <https://doi.org/10.1016/j.martra.2022.100072>.
23. Forti, N.; d’Afflisio, E.; Braca, P.; Millefiori, L.M.; Carniel, S.; Willett, P. Next-gen intelligent situational awareness systems for maritime surveillance and autonomous navigation [Point of View]. *Proc. IEEE* **2022**, *110*, 1532–1537. <https://doi.org/10.1109/JPROC.2022.3194445>.
24. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G.; Group, P.; et al. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Int. J. Surg.* **2010**, *8*, 336–341. <https://doi.org/10.1016/j.ijsu.2010.02.007>.
25. Feng, H.; Grifoll, M.; Yang, Z.; Zheng, P. Collision risk assessment for ships’ routeing waters: An information entropy approach with Automatic Identification System (AIS) data. *Ocean Coast. Manag.* **2022**, *224*, 106184. <https://doi.org/10.1016/j.ocecoaman.2022.106184>.
26. Liu, Z.; Zhou, D.; Zheng, Z.; Wu, Z.; Gang, L. An analytic model for identifying real-time anchorage collision risk based on AIS data. *J. Mar. Sci. Eng.* **2023**, *11*, 1553. <https://doi.org/10.3390/jmse11081553>.
27. Liu, Z.; Zhang, B.; Zhang, M.; Wang, H.; Fu, X. A quantitative method for the analysis of ship collision risk using AIS data. *Ocean Eng.* **2023**, *272*, 113906. <https://doi.org/10.1016/j.oceaneng.2023.113906>.
28. Wang, B.; Tian, Q.; Wang, W. Risk analysis of ship collision in complex waterway system based on AIS data. In Proceedings of the 2022 3rd International Conference on Electronics, Communications and Information Technology (CECIT), Sanya, China, 23–25 December 2022; pp. 176–180. <https://doi.org/10.1109/CECIT58139.2022.00039>.
29. Zhang, L.; Chen, P.; Rong, H.; Mou, J.; Soares, C.G. A novel method for extracting near-misses from AIS data involving collision avoidance behaviour. *Ocean Eng.* **2024**, *301*, 117466. <https://doi.org/10.1016/j.oceaneng.2024.117466>.
30. Lin, B.; Zheng, M.; Chu, X.; Zhang, M.; Mao, W.; Wu, D. A novel method for the evaluation of ship berthing risk using AIS data. *Ocean Eng.* **2024**, *293*, 116595. <https://doi.org/10.1016/j.oceaneng.2023.116595>.
31. Xin, X.; Yang, Z.; Liu, K.; Zhang, J.; Wu, X. Multi-stage and multi-topology analysis of ship traffic complexity for probabilistic collision detection. *Expert Syst. Appl.* **2023**, *213*, 118890. <https://doi.org/10.1016/j.eswa.2022.118890>.
32. Oruc, M.F.; Altan, Y.C. Predicting the risky encounters without distance knowledge between the ships via machine learning algorithms. *Expert Syst. Appl.* **2023**, *221*, 119728. <https://doi.org/10.1016/j.eswa.2023.119728>.
33. Womersley, F.C.; Humphries, N.E.; Queiroz, N.; Vedor, M.; da Costa, I.; Furtado, M.; Tyminski, J.P.; Abrantes, K.; Araujo, G.; Bach, S.S.; et al. Global collision-risk hotspots of marine traffic and the world’s largest fish, the whale shark. *Proc. Natl. Acad. Sci. USA* **2022**, *119*, e2117440119. <https://doi.org/10.1073/pnas.2117440119>.
34. Li, D.; Wong, Y.D.; Tan, K.H.; Wang, N.; Yuen, K.F. Real-time prediction and detection of contacts between vessels and facilities based on AIS: A multivariate time-series classification approach. *Expert Syst. Appl.* **2024**, *257*, 125109. <https://doi.org/10.1016/j.eswa.2024.125109>.
35. Lin, Q.; Yin, B.; Zhang, X.; Grifoll, M.; Feng, H. Evaluation of ship collision risk in ships’ routeing waters: A Gini coefficient approach using AIS data. *Phys. A Stat. Mech. Its Appl.* **2023**, *624*, 128936. <https://doi.org/10.1016/j.physa.2023.128936>.
36. Zhu, F.; Zhou, Z.; Lu, H. Randomly testing an autonomous collision avoidance system with real-world ship encounter scenario from AIS data. *J. Mar. Sci. Eng.* **2022**, *10*, 1588. <https://doi.org/10.3390/jmse10111588>.
37. Kundakçı, B.; Nas, S.; Guçma, L. Prediction of ship domain on coastal waters by using AIS data. *Ocean Eng.* **2023**, *273*, 113921. <https://doi.org/10.1016/j.oceaneng.2023.113921>.
38. Zhu, M.; Tian, W.; Skulstad, R.; Zhang, H.; Li, G. Probability-Based Ship Encounter Classification Using AIS Data. In Proceedings of the Proceedings of the 3rd International Conference on Computer, Control and Robotics (ICCCR 2023), Shanghai, China, 24–26 March 2023; pp. 393–398. <https://doi.org/10.1109/ICCCR56747.2023.10193927>.
39. Silveira, P.; Teixeira, A.; Soares, C.G. A method to extract the Quaternion Ship Domain parameters from AIS data. *Ocean Eng.* **2022**, *257*, 111568. <https://doi.org/10.1016/j.oceaneng.2022.111568>.

40. Ribeiro, C.V.; Paes, A.; de Oliveira, D. AIS-based maritime anomaly traffic detection: A review. *Expert Syst. Appl.* **2023**, *231*, 120561. <https://doi.org/10.1016/j.eswa.2023.120561>.
41. Farahnakian, F.; Heikkonen, J.; Nevalainen, P. Abnormal Behaviour Detection by Using Machine Learning-Based Approaches in the Marine Environment: A Literature Survey. In Proceedings of the 2022 International Conference on Electrical, Computer and Energy Technologies (ICECET), Prague, Czech Republic, 20–22 July 2022; pp. 1–11. <https://doi.org/10.1109/ICECET55527.2022.9872905>.
42. Liang, M.; Weng, L.; Gao, R.; Li, Y.; Du, L. Unsupervised maritime anomaly detection for intelligent situational awareness using AIS data. *Knowl.-Based Syst.* **2024**, *284*, 111313. <https://doi.org/10.1016/j.knosys.2023.111313>.
43. Louart, M.; Szkolnik, J.J.; Boudraa, A.O.; Le Lann, J.C.; Le Roy, F. An approach to detect identity spoofing in AIS messages. *Expert Syst. Appl.* **2024**, *252*, 124257. <https://doi.org/https://doi.org/10.1016/j.eswa.2024.124257>.
44. Zaman, B.; Marijan, D.; Kholodna, T. Online Ornstein–Uhlenbeck based anomaly detection and behavior classification using AIS data in maritime. *Ocean Eng.* **2024**, *312*, 119057. <https://doi.org/10.1016/j.oceaneng.2024.119057>.
45. Wolsing, K.; Roepert, L.; Bauer, J.; Wehrle, K. Anomaly detection in maritime AIS tracks: A review of recent approaches. *J. Mar. Sci. Eng.* **2022**, *10*, 112. <https://doi.org/10.3390/jmse10010112>.
46. Bernabé, P.; Gotlieb, A.; Legeard, B.; Marijan, D.; Sem-Jacobsen, F.O.; Spieker, H. Detecting intentional AIS shutdown in open sea maritime surveillance using self-supervised deep learning. *IEEE Trans. Intell. Transp. Syst.* **2023**, *25*, 1166–1177. <https://doi.org/10.1109/TITS.2023.3322690>.
47. Yan, Z.; Song, X.; Zhong, H.; Yang, L.; Wang, Y. Ship Classification and Anomaly Detection Based on Spaceborne AIS Data Considering Behavior Characteristics. *Sensors* **2022**, *22*, 7713. <https://doi.org/10.3390/s220207713>.
48. Zhao, L.; Zuo, Y.; Li, T.; Chen, C.P. Application of an encoder–decoder model with attention mechanism for trajectory prediction based on AIS data: Case studies from the Yangtze River of China and the eastern coast of the US. *J. Mar. Sci. Eng.* **2023**, *11*, 1530. <https://doi.org/10.3390/jmse11081530>.
49. Liu, Z.; Qi, W.; Zhou, S.; Zhang, W.; Jiang, C.; Jie, Y.; Li, C.; Guo, Y.; Guo, J. Hybrid deep learning models for ship trajectory prediction in complex scenarios based on AIS data. *Appl. Ocean Res.* **2024**, *153*, 104231. <https://doi.org/10.1016/j.apor.2024.104231>.
50. Wang, C.; Han, P.; Zhu, M.; Osen, O.; Zhang, H.; Li, G. AIS Data-Based Hybrid Predictor for Short-Term Ship Trajectory Prediction Considering Uncertainties. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 20268–20279. <https://doi.org/10.1109/TITS.2024.3461210>.
51. Li, M.; Li, B.; Qi, Z.; Li, J.; Wu, J. Enhancing Maritime Navigational Safety: Ship Trajectory Prediction Using ACoAtt–LSTM and AIS Data. *ISPRS Int. J. -Geo-Inf.* **2024**, *13*, 85. <https://doi.org/10.3390/ijgi13030085>.
52. Yang, C.H.; Wu, C.H.; Shao, J.C.; Wang, Y.C.; Hsieh, C.M. AIS-based intelligent vessel trajectory prediction using bi-LSTM. *IEEE Access* **2022**, *10*, 24302–24315. <https://doi.org/10.1109/ACCESS.2022.3154812>.
53. Xiao, Y.; Li, X.; Yin, J.; Liang, W.; Hu, Y. Adaptive multi-source data fusion vessel trajectory prediction model for intelligent maritime traffic. *Knowl.-Based Syst.* **2023**, *277*, 110799. <https://doi.org/10.1016/j.knosys.2023.110799>.
54. Xiao, Y.; Li, X.; Yao, W.; Chen, J.; Hu, Y. Bidirectional Data-Driven Trajectory Prediction for Intelligent Maritime Traffic. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 1773–1785. <https://doi.org/10.1109/TITS.2022.3219998>.
55. Zaman, B.; Marijan, D.; Kholodna, T. Interpolation-Based Inference of Vessel Trajectory Waypoints from Sparse AIS Data in Maritime. *J. Mar. Sci. Eng.* **2023**, *11*, 615. <https://doi.org/10.3390/jmse11030615>.
56. Chen, J.; Chen, H.; Zhao, Y.; Li, X. FB-BiGRU: A deep learning model for AIS-based vessel trajectory curve fitting and analysis. *Ocean Eng.* **2022**, *266*, 112898. <https://doi.org/10.1016/j.oceaneng.2022.112898>.
57. Rong, H.; Teixeira, A.; Soares, C.G. Maritime traffic probabilistic prediction based on ship motion pattern extraction. *Reliab. Eng. Syst. Saf.* **2022**, *217*, 108061. <https://doi.org/10.1016/j.res.2021.108061>.
58. Chen, X.; Wei, C.; Zhou, G.; Wu, H.; Wang, Z.; Biancardo, S.A. Automatic identification system (AIS) data supported ship trajectory prediction and analysis via a deep learning model. *J. Mar. Sci. Eng.* **2022**, *10*, 1314. <https://doi.org/10.3390/jmse10091314>.
59. Li, H.; Jiao, H.; Yang, Z. AIS data-driven ship trajectory prediction modelling and analysis based on machine learning and deep learning methods. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *175*, 103152. <https://doi.org/10.1016/j.tre.2023.103152>.
60. Lee, W.; Cho, S.W. AIS trajectories simplification algorithm considering topographic information. *Sensors* **2022**, *22*, 7036. <https://doi.org/10.3390/s22187036>.
61. Zhang, M.; Zhang, D.; Fu, S.; Kujala, P.; Hirdaris, S. A predictive analytics method for maritime traffic flow complexity estimation in inland waterways. *Reliab. Eng. Syst. Saf.* **2022**, *220*, 108317. <https://doi.org/10.1016/j.res.2021.108317>.
62. Liu, Z.; Gao, H.; Zhang, M.; Yan, R.; Liu, J. A data mining method to extract traffic network for maritime transport management. *Ocean Coast. Manag.* **2023**, *239*, 106622. <https://doi.org/10.1016/j.ocecoaman.2023.106622>.
63. Lee, J.S.; Lee, M.S.; Cho, I.S. Changes in Maritime Traffic Patterns According to Installation of Floating LiDAR using Spatial Analysis. *IEEE Access* **2023**, *11*, 74784–74795. <https://doi.org/10.1109/ACCESS.2023.3296795>.
64. Sui, Z.; Wen, Y.; Zhou, C.; Huang, X.; Zhang, Q.; Liu, Z.; Piera, M.A. An improved approach for assessing marine traffic complexity based on Voronoi diagram and complex network. *Ocean Eng.* **2022**, *266*, 112884. <https://doi.org/10.1016/j.oceaneng.2022.112884>.

65. Wei, Z.; Gao, Y.; Zhang, X.; Li, X.; Han, Z. Adaptive marine traffic behaviour pattern recognition based on multidimensional dynamic time warping and DBSCAN algorithm. *Expert Syst. Appl.* **2024**, *238*, 122229. <https://doi.org/10.1016/j.eswa.2023.122229>.
66. Kim, H.S.; Lee, E.; Lee, E.J.; Hyun, J.W.; Gong, I.Y.; Kim, K.; Lee, Y.S. A Study on Grid-Cell-Type Maritime Traffic Distribution Analysis Based on AIS Data for Establishing a Coastal Maritime Transportation Network. *J. Mar. Sci. Eng.* **2023**, *11*, 354. <https://doi.org/10.3390/jmse11020354>.
67. Qu, J.; Liu, R.W.; Guo, Y.; Lu, Y.; Su, J.; Li, P. Improving maritime traffic surveillance in inland waterways using the robust fusion of AIS and visual data. *Ocean Eng.* **2023**, *275*, 114198. <https://doi.org/10.1016/j.oceaneng.2023.114198>.
68. Kim, Y.J.; Lee, J.S.; Pititto, A.; Falco, L.; Lee, M.S.; Yoon, K.K.; Cho, I.S. Maritime traffic evaluation using spatial-temporal density analysis based on big AIS data. *Appl. Sci.* **2022**, *12*, 11246. <https://doi.org/10.3390/app122111246>.
69. Madon, B.; Le Guyader, D.; Jung, J.L.; De Montgolfier, B.; Lopez, P.J.; Foulquier, E.; Bouveret, L.; Le Berre, I. Pairing AIS data and underwater topography to assess maritime traffic pressures on cetaceans: Case study in the Guadeloupean waters of the Agoa sanctuary. *Mar. Policy* **2022**, *143*, 105160. <https://doi.org/10.1016/j.marpol.2022.105160>.
70. Zhang, Y.; Li, W. Dynamic maritime traffic pattern recognition with online cleaning, compression, partition, and clustering of AIS data. *Sensors* **2022**, *22*, 6307. <https://doi.org/10.3390/s22166307>.
71. Chou, C.C.; Wang, C.N.; Hsu, H.P.; Ding, J.F.; Tseng, W.J.; Yeh, C.Y. Integrating AIS, GIS and E-chart to analyze the shipping traffic and marine accidents at the Kaohsiung Port. *J. Mar. Sci. Eng.* **2022**, *10*, 1543. <https://doi.org/10.3390/jmse10101543>.
72. Petković, M.; Vujović, I.; Kaštelan, N.; Šoda, J. Every Vessel Counts: Neural Network Based Maritime Traffic Counting System. *Sensors* **2023**, *23*, 6777. <https://doi.org/10.3390/s23156777>.
73. Eljabu, L.; Etemad, M.; Matwin, S. Spatial Clustering Method of Historical AIS Data for Maritime Traffic Routes Extraction. In Proceedings of the 2022 IEEE International Conference on Big Data (Big Data), Osaka, Japan, 17–20 December 2022; pp. 893–902. <https://doi.org/10.1109/BigData55660.2022.10020646>.
74. Liu, Z.; Wu, Z.; Zheng, Z.; Yu, X. A Molecular Dynamics Approach to Identify the Marine Traffic Complexity in a Waterway. *J. Mar. Sci. Eng.* **2022**, *10*, 1678. <https://doi.org/10.3390/jmse10111678>.
75. Bland, R.; Methion, S.; Sharp, S.P.; López, B.D. Assessing variability in marine traffic exposure between baleen whale species off the Galician Coast, Spain. *Mar. Pollut. Bull.* **2023**, *186*, 114439. <https://doi.org/10.1016/j.marpolbul.2022.114439>.
76. 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. <https://doi.org/10.1016/j.tre.2024.103426>.
77. Ma, J.; Zhou, Y.; Zhu, Z. Identification and analysis of ship waiting behavior outside the port based on AIS data. *Sci. Rep.* **2023**, *13*, 11267. <https://doi.org/10.1038/s41598-023-38080-2>.
78. Wang, W.; Huang, L.; Liu, K.; Zhou, Y.; Yuan, Z.; Xin, X.; Wu, X. Ship Behavior Pattern Analysis Based on Multiship Encounter Detection. *Asce-Asme J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.* **2024**, *10*, 04023045. <https://doi.org/10.1061/AJRUA6.RUENG-1145>.
79. Xin, X.; Liu, K.; Li, H.; Yang, Z. Maritime traffic partitioning: An adaptive semi-supervised spectral regularization approach for leveraging multi-graph evolutionary traffic interactions. *Transp. Res. Part C Emerg. Technol.* **2024**, *164*, 104670. <https://doi.org/10.1016/j.trc.2024.104670>.
80. Gu, K.; Song, J.; Ma, Z.; Sun, X.; Zhou, W.; Zhang, L. Understanding the Spatiotemporal Patterns of Cross Encounter Behaviour of Ships Based on Automatic Identification System Data. In Proceedings of the 2024 9th International Conference on Computer and Communication Systems (ICCCS) Xi'an, China, 19–22 April 2024; pp. 1210–1215. <https://doi.org/10.1109/ICCCS61882.2024.10602959>.
81. Murray, B.; Perera, L.P. Ship behavior prediction via trajectory extraction-based clustering for maritime situation awareness. *J. Ocean. Eng. Sci.* **2022**, *7*, 1–13. <https://doi.org/https://doi.org/10.1016/j.joes.2021.03.001>.
82. Ban, H.; Kim, H.J. Analysis and Visualization of Vessels' Relative MOtion (REMO). *ISPRS Int. J.-Geo-Inf.* **2023**, *12*, 115. <https://doi.org/10.3390/ijgi12030115>.
83. Sturgis, R.; Emiya, V.; Couëtoux, B.; Garreau, P. Beyond geofencing: Behavior detection using AIS. *Ocean Eng.* **2024**, *293*, 116630. <https://doi.org/10.1016/j.oceaneng.2023.116630>.
84. Yan, Z.; Cheng, L.; He, R.; Yang, H. Extracting ship stopping information from AIS data. *Ocean Eng.* **2022**, *250*, 111004. <https://doi.org/10.1016/j.oceaneng.2022.111004>.
85. Ma, L.; Guo, Z.; Shi, G. AIS Data Driven Ship Behavior Modeling in Fairways: A Random Forest Based Approach. *Appl. Sci.* **2024**, *14*, 8484. <https://doi.org/10.3390/app14188484>.
86. Woo, D.; Im, N. Estimation of the Efficiency of Vessel Speed Reduction to Mitigate Gas Emission in Busan Port Using the AIS Database. *J. Mar. Sci. Eng.* **2022**, *10*, 435. <https://doi.org/10.3390/jmse10030435>.
87. O'Hara, P.D.; Serra-Sogas, N.; McWhinnie, L.; Pearce, K.; Le Baron, N.; O'Hagan, G.; Nesdoly, A.; Marques, T.; Canessa, R. Automated identification system for ships data as a proxy for marine vessel related stressors. *Sci. Total Environ.* **2023**, *865*, 160987. <https://doi.org/10.1016/j.scitotenv.2022.160987>.

88. Rodriguez Valido, M.; Perez Marrero, J.; Mauro González, A.; Fabiani Bendicho, P.; Efrema Mora, C. Evaluation of the Potential of Sentinel-5P TROPOMI and AIS Marine Traffic Data for the Monitoring of Anthropogenic Activity and Maritime Transport NO_x-Emissions in Canary Islands Waters. *Sustainability* **2023**, *15*, 4632. <https://doi.org/10.3390/su15054632>.
89. Fink, L.; Karl, M.; Matthias, V.; Oppo, S.; Kranenburg, R.; Kuenen, J.; Moldanova, J.; Jutterström, S.; Jalkanen, J.P.; Majamäki, E. Potential impact of shipping on air pollution in the Mediterranean region—A multimodel evaluation: Comparison of photooxidants NO₂ and O₃. *Atmos. Chem. Phys.* **2023**, *23*, 1825–1862. <https://doi.org/10.5194/acp-23-1825-2023>.
90. Newaliya, N.; Agarwal, A.; Singh, Y. AIS data—enabler in marine spatial planning. In Proceedings of the OCEANS 2022—Chennai Chennai, India, 21–24 February 2022; pp. 1–9. <https://doi.org/10.1109/OCEANSChennai45887.2022.9775500>.
91. Liu, R.W.; Zhou, S.; Liang, M.; Gao, R.; Wang, H. From ports to routes: Extracting multi-scale shipping networks using massive AIS data. *Ocean Eng.* **2024**, *311*, 118969. <https://doi.org/10.1016/j.oceaneng.2024.118969>.
92. Onyango, S.O.; Owiredun, S.A.; Kim, K.I.; Yoo, S.L. A Quasi-Intelligent Maritime Route Extraction from AIS Data. *Sensors* **2022**, *22*, 8639. <https://doi.org/10.3390/s22228639>.
93. Khandker, S.; Turtiainen, H.; Costin, A.; Hämäläinen, T. Cybersecurity attacks on software logic and error handling within AIS implementations: A systematic testing of resilience. *IEEE Access* **2022**, *10*, 29493–29505. <https://doi.org/10.1109/ACCESS.2022.3158943>.
94. Farahnakian, F.; Nicolas, F.; Farahnakian, F.; Nevalainen, P.; Sheikh, J.; Heikkonen, J.; Raduly-Baka, C. A comprehensive study of clustering-based techniques for detecting abnormal vessel behavior. *Remote Sens.* **2023**, *15*, 1477. <https://doi.org/10.3390/rs15061477>.
95. Androjna, A.; Perkovic, M.; Pavic, I. Cyber Security Challenges for Safe Navigation at Sea. In Proceedings of the 14th Annual Baška GNSS Conference: Technologies, Techniques and Applications Across PNT and The 1st Workshop on Smart, Blue and Green Maritime Technologies, Baška, Krk Island, Croatia, 10–12 May 2021, pp. 47–61.
96. Yang, Y.; Yang, F.; Sun, L.; Xiang, T.; Lv, P. Multi-target association algorithm of AIS-radar tracks using graph matching-based deep neural network. *Ocean Eng.* **2022**, *266*, 112208. <https://doi.org/10.1016/j.oceaneng.2022.112208>.
97. Ahmed, I.; Jun, M.; Ding, Y. A Spatio-Temporal Track Association Algorithm Based on Marine Vessel Automatic Identification System Data. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 20783–20797. <https://doi.org/10.1109/TITS.2022.3187714>.
98. Xin, X.; Liu, K.; Loughney, S.; Wang, J.; Li, H.; Yang, Z. Graph-based ship traffic partitioning for intelligent maritime surveillance in complex port waters. *Expert Syst. Appl.* **2023**, *231*, 120825. <https://doi.org/10.1016/j.eswa.2023.120825>.
99. Harun-Al-Rashid, A.; Yang, C.S.; Shin, D.W. Detection of maritime traffic anomalies using Satellite-AIS and multisensory satellite imagery: Application to the 2021 Suez Canal obstruction. *J. Navig.* **2022**, *75*, 1082–1099. <https://doi.org/10.1017/S0373463322000364>.
100. Evmidis, N.; Odysseos, L.; Michaelides, M.P.; Herodotou, H. An intelligent framework for vessel traffic monitoring using AIS data. In Proceedings of the 2022 23rd IEEE International Conference on Mobile Data Management (MDM), Paphos, Cyprus, 6–9 June 2022; pp. 413–418. <https://doi.org/10.1109/MDM55031.2022.00091>.
101. Kaster, M.; Neugebauer, J.; el Moctar, B. Challenges of autonomous shipping: Traffic analysis of inland vessels on the Rhine River. In Proceedings of the 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC), Macau, China, 8–12 October 2022; pp. 2234–2239. <https://doi.org/10.1109/ITSC55140.2022.9922301>.
102. Troupiotis-Kapeliaris, A.; Spiliopoulos, G.; Vodas, M.; Zissis, D. Navigating through dense waters: A toolbox for creating maritime density maps. In Proceedings of the Proceedings of the 12th Hellenic Conference on Artificial Intelligence (SETN 2022), Corfu, Greece, 7–9 September 2022; pp. 1–4. <https://doi.org/10.1145/3549737.3549801>.
103. Monika, F.; Baiquni, M.; Hadi, M.P. Foreign vessels' mobility crossing the Archipelagic Sea Lanes in the Karimata Strait. *Aquac. Aquar. Conserv. Legis.* **2022**, *15*, 1712–1730.
104. Yang, J.; Bian, X.; Qi, Y.; Wang, X.; Yang, Z.; Liu, J. A spatial-temporal data mining method for the extraction of vessel traffic patterns using AIS data. *Ocean Eng.* **2024**, *293*, 116454. <https://doi.org/10.1016/j.oceaneng.2023.116454>.
105. Lee, J.S.; Lee, H.T.; Cho, I.S. Maritime traffic route detection framework based on statistical density analysis from AIS data using a clustering algorithm. *IEEE Access* **2022**, *10*, 23355–23366. <https://doi.org/10.1109/ACCESS.2022.3154363>.
106. Jain, R.P.; Brekke, E.F.; Rasheed, A. Unsupervised clustering of marine vessel trajectories in historical AIS database. In Proceedings of the 2022 25th International Conference on Information Fusion (FUSION), Linköping, Sweden, 4–7 July 2022; pp. 1–6. <https://doi.org/10.23919/FUSION49751.2022.9841274>.
107. Kang, M.J.; Zohoori, S.; Hamidi, M.; Wu, X. Study of narrow waterways congestion based on automatic identification system (AIS) data: A case study of Houston Ship Channel. *J. Ocean. Eng. Sci.* **2022**, *7*, 578–595. <https://doi.org/10.1016/j.joes.2021.10.010>.
108. Wei, Z.; Meng, X.; Li, X.; Zhang, X.; Gao, Y. Vessel manoeuvring hot zone recognition and traffic analysis with AIS data. *Ocean Eng.* **2022**, *266*, 112858. <https://doi.org/10.1016/j.oceaneng.2022.112858>.
109. Jeon, H.k.; Han, J.R. Random Forest Classifier-based Ship Type Prediction with Limited Ship Information of AIS and V-Pass. *Korean J. Remote Sens.* **2022**, *38*, 435–446. <https://doi.org/10.7780/kjrs.2022.38.4.10>.

110. Park, J.; Choi, M. A k-means clustering algorithm to determine representative operational profiles of a ship using AIS data. *J. Mar. Sci. Eng.* **2022**, *10*, 1245. <https://doi.org/10.3390/jmse10091245>.
111. Steenari, J.; Lwakatare, L.E.; Nurminen, J.; Talonen, J.; Manderbacka, T. Mining Port Operation Information from AIS Data. In *Proceedings of the Changing Tides: The New Role of Resilience and Sustainability in Logistics and Supply Chain Management — Innovative Approaches for the Shift to a New Era, Proceedings of the Hamburg International Conference of Logistics (HICL)*; Kersten, W., Jahn, C., Blecker, T., Ringle, C.M., Eds.; epubli GmbH: Berlin, Germany, 2022; Volume 33, pp. 657–678. <https://doi.org/10.15480/882.4705>.
112. Li, H.; Yang, Z. Incorporation of AIS data-based machine learning into unsupervised route planning for maritime autonomous surface ships. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *176*, 103171. <https://doi.org/10.1016/j.tre.2023.103171>.
113. He, Z.; Liu, C.; Chu, X.; Wu, W.; Zheng, M.; Zhang, D. Dynamic domain-based collision avoidance system for autonomous ships: Real experiments in coastal waters. *Expert Syst. Appl.* **2024**, *255*, 124805. <https://doi.org/10.1016/j.eswa.2024.124805>.
114. Li, Z.; Liu, T.; Peng, X.; Ren, J.; Liang, S. An AIS-based deep learning model for multi-task in the marine industry. *Ocean Eng.* **2024**, *293*, 116694. <https://doi.org/10.1016/j.oceaneng.2024.116694>.
115. Tian, W.; Zhu, M.; Han, P.; Kjerstad, Ø.K.; Li, G.; Zhang, H. Leveraging AIS data for maneuver detection and knowledge extraction during ship encounter. *Ocean Eng.* **2026**, *343*, 122973. <https://doi.org/10.1016/j.oceaneng.2025.122973>.
116. Murray, B.; Perera, L.P. An AIS-based deep learning framework for regional ship behavior prediction. *Reliab. Eng. Syst. Saf.* **2021**, *215*, 107819. <https://doi.org/10.1016/j.ress.2021.107819>.
117. Alese, M.E. Maritime Domain Awareness Through the Characterization of Ship Behavior with AIS Data. Master's Thesis, Naval Postgraduate School, Monterey, CA, USA, 2022.
118. Endsley, M.R. Toward a Theory of Situation Awareness in Dynamic Systems. *Hum. Factors J. Hum. Factors Ergon. Soc.* **1995**, *37*, 32–64. <https://doi.org/10.1518/001872095779049543>.
119. Tian, W.; Zhu, M.; Han, P.; Li, G.; Zhang, H. Pairwise ship encounter identification and classification for knowledge extraction. *Ocean Eng.* **2024**, *294*, 116752. <https://doi.org/10.1016/j.oceaneng.2024.116752>.
120. Liu, J.; Li, J.; Liu, C. AIS-based kinematic anomaly classification for maritime surveillance. *Ocean Eng.* **2024**, *305*, 118026. <https://doi.org/https://doi.org/10.1016/j.oceaneng.2024.118026>.
121. d'Afflisio, E. Maritime Anomaly Detection Based on Statistical Methodologies: Theory and Applications. PhD Thesis, Università degli Studi di Firenze, Florence, Italy, 2021.
122. Nguyen, D.; Vadaine, R.; Hajduch, G.; Garello, R.; Fablet, R. A Multi-Task Deep Learning Architecture for Maritime Surveillance Using AIS Data Streams. In *Proceedings of the 2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA)*, Turin, Italy, 1–3 October 2018; pp. 331–340. <https://doi.org/10.1109/DSAA.2018.00044>.
123. Cai, Z.; Fan, Q.; Li, L.; Yu, L.; Li, C. An efficient Meta-VSW method for ship behaviors recognition and application. *Ocean Eng.* **2024**, *311*, 118870. <https://doi.org/10.1016/j.oceaneng.2024.118870>.
124. Li, G.; Hildre, H.P.; Zhang, H. Toward time-optimal trajectory planning for autonomous ship maneuvering in close-range encounters. *IEEE J. Ocean. Eng.* **2019**, *45*, 1219–1234. <https://doi.org/10.1109/JOE.2019.2926822>.
125. Tian, W.; Sanguino, B.; Zhu, M.; Kjerstad, Ø.K.; Li, G.; Zhang, H. Knowledge extraction from decision-making data for maritime navigation support. *Ocean Eng.* **2025**, *331*, 121268. <https://doi.org/10.1016/j.oceaneng.2025.121268>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.