Multimodal Maritime Foundation Models: Challenges and Opportunities

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***Abstract*—Existing modeling approaches for global maritime traffic are fragmented across narrowly scoped tasks and fail to provide unified representations spanning strategic, tactical, and operational planning layers while accounting for safety and efficiency. This vision paper outlines the foundations of a general-purpose multimodal model for the maritime domain, enabling predictive, analytical, and optimization-driven intelligence. By leveraging diverse maritime data, the model captures recurring mobility patterns and connects operational signals with sector-level dynamics. We contextualize such models within maritime analytics by identifying the planning layers they must represent. We examine challenges and opportunities in multimodal integration and representation learning, including key resources and design considerations, and relate these to downstream tasks. The paper proposes a blueprint aligned with domain requirements and provides an extended bibliography.**

I. Introduction

The strategic importance of the shipping industry, combined with the unique characteristics of maritime mobility, has generated significant demand for domain-specific tools, spanning transportation risk monitoring, voyage optimization, and higher-level analytical tasks concerning operations and market behavior [1], [2]. Underlying these applications, a variety of data mining and machine learning solutions have been developed to leverage the growing abundance of sensor measurements from vessel traffic and port operations [3], [4], [5], addressing the underlying analytical tasks that enable real-world GIS functionality [6]. Modern architectures, including deep neural networks, have been widely employed on maritime datasets to construct faithful and informative models capable of capturing complex patterns in vessel operations [7], [8], [9], [10]. Nevertheless, existing models are typically task-specific and optimized for a single problem or application [9], [11], [12]. In practice, maritime systems often need to address multiple tasks that are correlated through shared context and data [13], [14], [15], such as destination prediction and weather routing or anomaly detection and collision avoidance. Although task-specific models can sometimes be adapted for related tasks, doing so is effort-intensive, and multi-task modeling remains relatively uncommon. To fully harness available contextual data and improve efficiency across tasks, unified models can serve as the backbone of maritime systems, reducing the need to maintain multiple versions [16].

¶ Both authors contributed equally to this research.

The limitations of task-specific models are not unique to maritime analytics; similar fragmentation in other domains has driven the transition toward unified modeling paradigms [16], [17]. Building on advances in attention mechanisms, particularly the Transformer architecture [18], a large number of general-purpose models have been developed. Originating in the language domain, foundation models (FMs) emerged as a practical framework for constructing such general-purpose systems [19], [20], typically trained via self-supervised learning on enormous and often highly diverse datasets. Moving beyond text, domain-specific FMs have since been proposed across several areas [21], [22], including healthcare [23], computer vision [24], and finance [25], [26].

Toward a Multimodal Maritime Foundation Model. We envision a general-purpose multimodal FM for the maritime domain. The proposed FM would leverage heterogeneous data describing vessel traffic as well as strategic market relationships, supporting tasks ranging from navigation and planning to sector-level analytics, while capturing the unique dynamics of maritime mobility. To our knowledge, no existing model for maritime operations integrates multiple data sources while addressing all three primary classes of tasks: navigation and planning; traffic data mining; and market-related analytics.

This

vision paper establishes three foundational pillars: (1) we conceptualize the role of FMs in the maritime domain and position them within the current state of the art; (2) we define the key operational layers such a FM should support; and (3) we identify crucial resources and opportunities, linking them to relevant downstream tasks and applications. Taken together, these pillars provide a structured perspective on existing knowledge and domain requirements, incorporate an extended bibliography on related topics (see Table I), and establish a blueprint to guide future developments in multimodal maritime foundation models.

II. Background and Current Landscape

Transportation Foundation Models. Leveraging primarily large collections of trajectory data, these models try to capture the interactions between spatial and temporal dimensions, including regional patterns and seasonal variations [27], [28], [29], [30]. Drawing a parallel between language and mobility, it has been suggested that BERT-style architectures, including suitable tokenization schemes, could provide a potential route toward unified trajectory modeling [31]. Nevertheless, the nature of mobility data introduces challenges that are often not encountered in natural language processing (NLP). For instance, trajectory data often exhibit irregular sampling even within the same dataset, while noise is ubiquitous, frequently resulting in faulty positions or significant temporal gaps [30], [32]. Moreover, mobility patterns learned in a specific region are often difficult to transfer directly to contexts with different constraints, requiring model adaptation to ensure reliable generalization [33]. In addition, constructing complete mobility representations requires integrating information from complementary data sources, such as map features or environmental sensor records, which necessitates specialized fusion techniques and adds further complexity to the learned representations [33], [32]. Overcoming these and related challenges is essential for enabling robust and effective Intelligent Transportation Systems (ITS) [34], [35].

Acknowledging the distinct characteristics of each mobility setting, domain-specific FM variants can better capture movement patterns, leading to more accurate mobility representations. This approach allows for the seamless integration of the respective constraints or regulations [22], the identification of unique relationships between features (e.g., correlations between speed and intent), and the avoidance of the overhead associated with modeling trajectories across highly diverse schemas. Hence, separate FMs have been proposed to tackle the distinct challenges of highly dense urban mobility [36], [37], intent-oriented human mobility [38], [39], and four-dimensional flight trajectories [40].

Current Approaches in the Maritime Domain. Despite the growing adoption of Transformer-based architectures for vessel trajectory prediction and behavior detection [41], only a limited number of works mention general-purpose maritime models. Based on a large dataset of vessel positions from the Automatic Identification System (AIS), [42] presents a framework capable of performing multiple tasks, including trajectory prediction, anomaly detection, and collision risk assessment. The system encodes AIS sequences using both a time-series encoder and a text-based prompt encoder, aligns the resulting embeddings, and produces numerical predictions along with textual explanations for each task. Multiple tasks through comprehensive AIS data modeling are also addressed in another recent proposal [43], where modeling is performed via a Transformer-based denoising network. The resulting model demonstrates strong performance in trajectory prediction, imputation, and route planning across diverse data distributions.

Moreover, [44] explores the potential applications of LLMs as AI agents in maritime operations, highlighting use cases such as communication enhancement, education, and incident investigation, while also discussing associated privacy and ethical challenges. An example of adopting existing LLMs for vessel movement is presented in [45], where complex tasks are decomposed by a large LLM and a fine-tuned compact model generates navigation recommendations. Furthermore, [46] specifically investigates the use of existing LLMs as navigation assistants for Maritime Autonomous Surface Ships (MASS), evaluating their potential to support decision-making in real-time maritime operations. For the integration of maritime knowledge beyond trajectory records, Llamarine [47] is an open-source LLM trained on maritime navigation literature and operating through text prompts. As mentioned, the integration of multiple heterogeneous data sources into multimodal models enables a more holistic understanding of vessel behavior [48]. An example is presented in [49], where a large vision-language model integrates satellite imagery, AIS data, and semantic information, using Chain-of-Thought prompting for compliance reasoning.

TABLE I: Landscape of Key Literature Across Core Topics.

Maritime Mobility	
Analytics	[50], [51], [52], [53], [54], [3], [55], [56], [57], [58], [59], [60], [61], [6], [62], [63], [64], [65]
Deep Learning	[7], [66], [4], [67], [8], [68], [69], [9], [11], [12], [70], [41], [71], [72], [73], [74]
LLMs	[46], [42], [44], [45], [47], [48], [75], [76], [77], [78], [79], [80], [49]

Spatiotemporal Foundation Models	
General	[81], [33], [27], [82], [83], [84], [28]
Transportation	[31], [34], [30], [35], [36], [37], [32], [85], [86]

III. Maritime Operation Layers

Maritime transportation exhibits several unique characteristics, combining high operational variability, limited visibility, and a conservative industry structure, while remaining strongly influenced by external conditions [87], [88]. It remains a central component of global trade and supply chains, and together with social, economic, and political factors, shapes the movement and distribution of most goods [89], [90]. Hence, analyzing maritime mobility data requires tailored approaches that simultaneously address multiple decision layers, considering operational efficiency, strategic planning, and safety [91].

Maritime mobility is commonly structured across three planning layers [87]. *Strategic planning* addresses long-term, high-level decisions such as fleet deployment, contract allocation, and the design of multi-port service schedules. *Tactical planning* focuses on voyage-level decisions, including route design between ports while accounting for environmental, regulatory, and vessel-specific constraints. *Operational planning* concerns short-term, real-time actions taken during navigation, such as speed adjustments and collision avoidance. A unified maritime FM should bridge these layers, capturing the decision-making processes at each level. Modeling vessel movement at a global scale is a highly complex task shaped by numerous interacting factors. To better articulate this complexity, we examine it through the three planning layers, outlining the key challenges and contextual considerations at each stage.

TABLE II: Key Maritime Data Sources.

Information Domain	Availability	Modality	Update Frequency	Considerations
Vessel Mobility Data	Proprietary Networks	Spatiotemporal Sequence	2 sec – 10 min	Coverage Gaps; Spoofing
Vessel Particulars	International Registries	Tabular Attributes	Annual	Information Latency
Port Infrastructure	Global Databases	Tabular Attributes	Periodic	Structural Inconsistencies
Port and Area Geometries	EO Extraction	Vector Polygons	On-demand	Extraction Noise; Resolution
Hydrographic Constraints	Open access	Raster	Static	Vertical Accuracy; Grid Density
Weather Data	Open access	Raster	6 h (3h steps)	Forecast Bias; Grid Density
Financial Data	Open access	Time-series	Daily	External Volatility; Weak Coupling

Strategic Planning. At the strategic level, the global port network both shapes and reflects broader economic and geopolitical dynamics [92], [93]. For instance, the war in Ukraine disrupted regular grain exports from Ukrainian ports, which were later partially restored under the Black Sea Initiative, helping stabilize global markets [90]. Consequently, shipment selection decisions cannot rely solely on historical mobility patterns, as origin–destination flows are also shaped by supply and demand, profit margins, and the configuration of the port network and its operators [94], [95]. Vessel mobility analysis, however, reveals the hierarchical structure of the port network, distinguishing mega-ports, hubs, transshipment centers, and specialized terminals (e.g., bulk, LNG, and cruise ports).

Tactical Planning. In contrast to land transportation, maritime mobility is highly sensitive to numerous exogenous and operational factors, including meteorological conditions, regional regulations, and vessel-specific capabilities (e.g., ice-class constraints) [96], [97]. At the tactical level (medium-term), these conditions are incorporated to determine the most suitable route for each vessel, given its specifications like its type and dimensions [98]. For example, larger vessels tend to avoid constrained waters and stay offshore, while smaller vessels are generally more sensitive to adverse weather. Furthermore, distinct vessel types are affected differently by environmental forces; for example, tankers are particularly influenced by currents [99]. In addition to environmental factors, constraints such as port access rules and security risks like piracy [100], [101] can also influence route selection.

Operational Planning & Navigation. On the operational level, beyond pre-planning, underway navigation relies on situational awareness and may be adjusted in real time due to unexpected disruptions. Ship operators on the bridge constantly monitor the behavior of nearby vessels and take appropriate actions to avoid collisions [56], [61] in compliance with International Regulations for Preventing Collisions at Sea (COLREGs) [102] and applicable traffic separation schemes [103]. Furthermore, unexpected events or deviations from forecasted conditions, such as sudden weather changes, military operations [104], or incidents like the 2023 Suez Canal blockage [105], may require on-site adjustments to the original voyage plan. Such adjustments aim to limit additional costs and ensure crew and cargo safety.

IV. Challenges and Opportunities

To develop a unified model that coherently incorporates all aforementioned planning layers, diverse and heterogeneous data sources must be leveraged. However, each source presents distinct challenges in terms of availability, quality, and coverage. Moreover, aligning contextual information with vessel trajectories requires dedicated mechanisms to support the training process. Here, we outline the key data sources required for the FM, present a high-level training pipeline, and discuss the associated considerations and limitations.

A. Data Availability

The last few decades have seen technological advancements in shipping, the adoption of regulations, and growing demand for data-driven decision-making, which have significantly increased the availability of maritime data. Since this onset of large-scale digitalization, numerous GIS-based applications have been introduced [106], [6]. While some critical business-related information remains inaccessible, vessel tracking services and maritime reports now provide greater visibility into maritime operations. We review the main data sources supporting large-scale maritime analytics and summarize their key dimensions and characteristics, highlighting their potential for integration into a unified modeling framework (see Table II).

Vessel Mobility. Vessel tracking can be achieved through remote sensing or self-reporting systems [107]. While the former is widely used for area monitoring, large-scale mobility analytics rely on the latter due to its high temporal resolution and structured navigational reports. Most significantly, since its wide adoption nearly two decades ago, AIS has become the primary source of vessel trajectories, collected via terrestrial receivers or satellite constellations [52]. Originally designed under SOLAS to assist in collision avoidance and reinforced for larger vessels [108], AIS is now used by vessels of all types, from tankers to sailboats, constantly transmitting reports via onboard VHF transceivers. In addition to positional features, these reports include navigational information (e.g., speed, heading), voyage planning (e.g., destination port), and static vessel attributes such as identifier and dimensions. Leveraging the vast volumes of AIS data generated daily, systems can extract information such as activity patterns [109], [110], common routes [111], [112], or instances of anomalous or suspicious movement [113], [114] using big data mining algorithms. Alternatively, fusing vessel tracks with other sources, such as satellite imagery or port networks, enables more advanced aggregations [94], [115].

Vessel Registries. In order to obtain detailed specifications of a vessel's operational characteristics and capabilities beyond what AIS provides, vessel registries should be consulted. All commercial vessels are required to be registered with the International Maritime Organization (IMO), which assigns a unique identification number. Through this identifier, one can access vessel particulars such as gross tonnage, year of build, flag, and ownership. In addition, the IMO identifier enables queries to classification societies, such as Lloyd's [116], as well as to port authorities and governmental agencies (e.g., Equasis [117]) for supplementary technical and compliance-related information. When data are incomplete, vessel characteristics such as engine power or average deadweight tonnage (DWT) can be estimated from IMO GHG emissions [118].

Port and Area Specifics. Ports and surrounding regulated areas provide essential spatial and operational context for maritime planning. High-level port metadata are available from public sources such as the World Port Index [119], which provides structured information on services, characteristics, and regional organization. In contrast, detailed geometric representations of port layouts, berths, and terminal infrastructures are not available globally; approximate boundaries must be inferred from buffer zones, AIS clustering, satellite imagery, and nautical chart digitization [120], [121], [122].

Outside of individual port data, additional navigational sources define area-specific navigation constraints. Digital nautical charts provided by hydrographic offices [123], along with OpenStreetMap [124], capture traffic separation schemes, navigational lights, and other critical markers. MarineRegions [125] provides polygons for contextual areas, including Exclusive Economic Zones, territorial waters, fishing zones, and UNESCO heritage areas. Dynamic maritime safety information for specific regions is provided through NAVTEX messages, with temporary hazards such as severe weather or restricted areas due to military exercises reflected, complementing the static navigational layers [104].

Weather Forecasts and Hydrographic Constraints. Weather conditions are crucial for maritime safety and inform tactical and operational planning. Static and seasonal phenomena are captured in nautical charts, whereas dynamic open-sea conditions appear on forecasts from global and regional weather and sea-state models, including wind, currents, wave height and tides. Operated by NOAA [126] and Copernicus [127], forecasts are updated daily at 3–6 hour intervals on predefined spatial grids. Regional models generally have higher spatial resolution and localized calibration, making them more accurate than global models. GEBCO [128] provides a global gridded bathymetry dataset to support navigation.

Market Indicators and Commodity Dynamics. Maritime transportation planning is driven by private contracts and supply-demand fluctuations. Although contract-level data are not publicly accessible, several market indices and trading signals can be used to approximate freight rates, profit margins and sectoral trends. More specifically, national import and export statistics provide a high-level macroeconomic overview, while financial markets trading major dry and wet bulk commodities offer insight into price formation and expectations. Freight benchmarks such as the Baltic Dry Index (BDI) [129] for dry bulk and the Freightos Baltic Index (FBX) [130] for containers capture market momentum. Moreover, news sentiment analytics may further reflect market expectations and emerging incentives that influence routing and chartering.

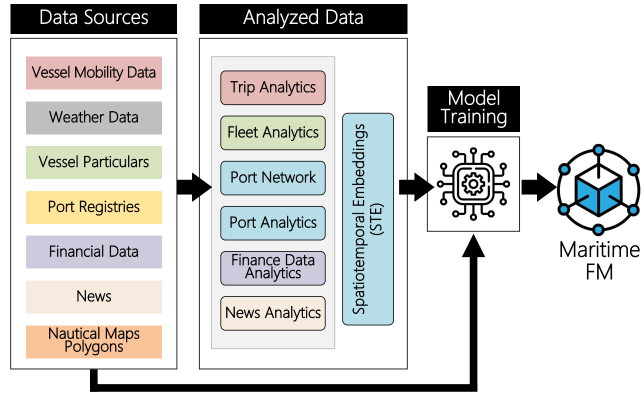

Fig. 1: STE-augmented Maritime FM Training Pipeline.

B. Spatiotemporal Embeddings and Training

Given these data sources, the FM development requires structuring them to capture spatial and temporal dependencies across all relevant planning layers and tasks. Following the placement of the model within maritime mobility analytics, vessel trajectory data should remain the central component of the training dataset and serve as a primary input for most downstream tasks [50], [51]. For effective training, extensive historical datasets spanning multiple years and diverse circumstances, such as seasonal weather patterns or economic fluctuations, should be compiled as the core, enabling the model to learn and differentiate patterns across varying scenarios.

To incorporate complementary information, each trajectory can be augmented with additional dimensions encoding environmental, operational, and regulatory signals. These enriched trajectories can then be structured into spatiotemporal embeddings (STEs) [131], [32], [132] for training the FM, enabling the joint handling of multiple data modalities. Initially, each data source is analyzed separately, as local analytics may require aggregations over large datasets, while area-level vectors could leverage vision-based models. In order to align the derived features (e.g., statistics), universal spatial projections can be used to create consistent area-level representations that are able to be combined with the raw trajectory data [133], [134]. Afterwards, these embeddings act as a first-level fusion mechanism, selectively retaining relevant features in each record before ingestion by the FM [135], [136]. As summarized in Table II, key contextual features include vessel particulars, deviations from regional trends, environmental conditions and operational constraints, related daily financial indicators, and overall trip labels (e.g., destination port). Although we assume numerical variables are mapped using a consistent projection, the resulting embeddings can differ across records, where features are missing (e.g., bathymetry) or irrelevant (e.g., trade values for passenger trips). These cases can be addressed through masking or neutral placeholders, ensuring that STE remains robust and informative. A high-level illustration of how different levels of analysis can be streamlined to train a maritime FM is shown in Fig. 1.

C. Limitations and Practical Considerations

Data Quality and Integration. Variations in data quality directly affect modeling reliability and predictive accuracy. The primary data source—AIS vessel tracks— often suffers from coverage gaps and GNSS interference (e.g., spoofing and jamming) [137], [65], [138]. In parallel, registries providing vessel particulars, ownership information, and sanction status are updated infrequently, leading to temporal inconsistencies that may affect modeling outcomes. Port-related information is highly fragmented, lacking standardized reporting formats and offering only limited metadata through official registries. Detailed port network dynamics and operational performance often require custom analytics and may shift abruptly during crises [139], [94]. Similarly, economic indicators often reflect aggregated supply–demand signals, while fine-grained business intelligence (e.g., cargo contracts, loading conditions, or segment-specific market analyses) is rarely publicly available and difficult to automate. Beyond operational data, environmental datasets introduce challenges, as sea-state estimation [140] depends on publicly available bathymetry and coastline data, which may be outdated or coarse. In near-shore regions, such datasets often fail to capture human-induced changes (e.g., dredging or coastal construction) potentially introducing systematic modeling inaccuracies.

For the fusion and alignment of contextual datasets with vessel trajectories, the highly variable spatial and temporal densities must be considered. AIS data are often sparse and unevenly distributed, while raster datasets (e.g., weather, bathymetry) are typically available on coarser grids [134]. Because update cycles are not always synchronized—such as daily market indicators versus real-time vessel positions—temporal alignment should account for the exact timestamps of AIS records to accurately represent the current state. Finally, forecasting accuracy decreases with increasing prediction horizon [141], suggesting that the FM should assign lower confidence to long-term predictions.

Dynamic Temporal Updating. Fleet-level maritime behavior is typically assessed annually [90], reflecting the long-term planning required for vessel and terminal development. However, the absence of a centralized network and the competitive, dynamic market means that localized disruptions (e.g., Suez Canal blockage) can propagate system-wide and significantly impact the market. Therefore, the adoption of architectures that allow partial or gradual retraining is essential to keep the model aligned with evolving maritime dynamics and maintain the performance of downstream tasks.

Explainable Decision-Making. In order for the resulting FM to be incorporated into real-world systems, its decision-making must be human-interpretable. Captains, operating companies, and port authorities remain responsible for operational decisions, so any recommendation (e.g., route divergence) must be understandable and actionable. Large models may produce statistically valid but counter-intuitive outputs, making robust explainable AI (XAI) mechanisms essential [71]. This is particularly important in remotely operated or autonomous systems [66], [72], where human cognitive capacity and the ability to intervene are inherently limited.

Data Privacy and Copyright. Although many data sources, such as AIS, are publicly accessible, combining them with proprietary market data can reveal sensitive commercial strategies. To prevent the learning process from revealing information about individuals or companies, and thus avoid unfair competitive advantages, techniques such as differential privacy [142] should be applied. Privacy considerations are particularly relevant for XAI systems, where the provided model behavior explanations may inadvertently reveal sensitive information, requiring appropriate filtering at inference [143]. In addition, proper attribution and adherence to licensing terms of each data provider must be ensured for all FM users and derivative works. FMs must also be compliant by design with maritime laws (e.g., COLREGs) [11] and compatible with AI regulations, such as the EU AI Act [144].

V. Downstream Tasks and Applications

After large-scale pretraining, the resulting FM can be adapted to support several use cases [145], raging from voyage optimization to market analysis. Such adaptations can take different forms [146], [147], depending on the target application or deployment environment. In instances where resources (either labeled data or computational capacity) are limited, adaptation can take the form of last-layer adaptation [148]. Here, the FM serves as a frozen backbone, and task-specific heads are trained on its embeddings, including simple linear layers (linear probing) as well as more flexible mappings (discriminative mapping). This is specifically applicable in industrial maritime settings, such as autonomous surface vehicles [73], [74], where models often need to handle a diverse set of tasks [149]. For higher accuracy requirements or for datasets that differ substantially from the pretraining distribution, full fine-tuning can be employed [150], with all FM parameters updated using task-specific data. In a maritime context, this approach is particularly justified for safety-critical applications [11], [151] or for exploration of unique areas such as ports [152]. As a middle ground, parameter-efficient fine-tuning (PEFT) [153], [154], [155], [156], [157] selectively updates only a small subset of parameters, largely retaining the pretrained FM backbone. Popular PEFT implementations that combine high accuracy and limited retraining include LoRA [158], [159], [160], adapters [161], [162], and prefix-tuning [163]. The resulted structures can be applied across several task families, categorized by their primary operational goal, even though applications may overlap in practice (Fig. 2).

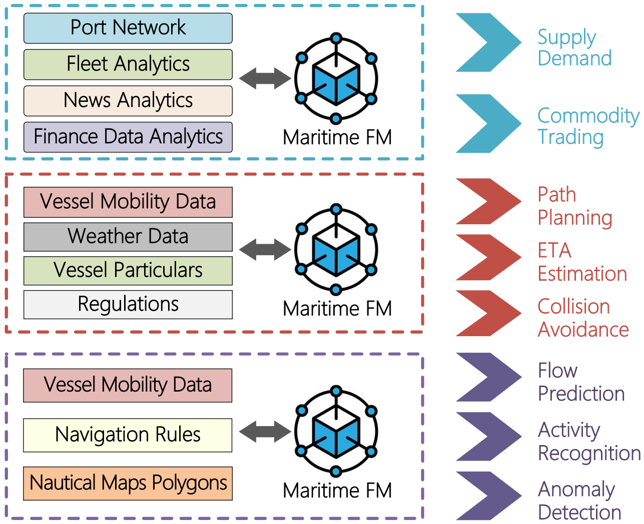

Fig. 2: Downstream Maritime FM Applications.

Optimized Navigation. For single-vessel operations, the adapted model enables multi-criteria path planning by integrating diverse data modalities, including past trajectories, environmental conditions, and vessel characteristics [164]. Such objectives may target the minimization of travel time [165], avoiding adverse weather conditions [53], [64], [166], reducing emissions [5], or balancing multiple criteria simultaneously [167]. At the local level, in dense areas or restricted waters, the model can support collision and grounding avoidance based on vessel-specific dimensions, maneuverability, and applicable navigation regulations [168], [54], [58], [169]. It can also be extended to multi-vessel cooperative operations by accounting for vessel interactions [70], [170]. Beyond planning and avoidance, the model can perform predictive analytics, including trajectory forecasting [57], [68] and arrival time estimation (ETA) [171], [62], [63]. For these predictions, the model would leverage the pretrained spatiotemporal embeddings of historical movement patterns [51], [172], [60], together with complementary information, such as current traffic and seasonal trends, through its contextualized embeddings.

Activity Monitoring. Beyond single-vessel navigation, the proposed model can be adapted to support large-scale monitoring of maritime traffic from an external perspective. For example, by capturing multiple vessel trajectories, the model can generate quantitative flow estimates and traffic predictions at different horizons [173], [174], [175], allowing prompt identification of port congestion events. Moreover, event detection can be carried out at the single-trajectory level using the model's representations of routine vessel behavior, encompassing both activity classification and the detection of irregular movements. For the former, representative applications include the identification of Search-and-Rescue (SAR) missions [109] and the classification of fishing behaviors (e.g., longlining) [176], [177], utilizing the normal movement patterns and vessel-specific features encoded in the model. Anomalous movements can similarly be identified by detecting vessels that deviate from main shipping lanes or travel at speeds inconsistent with their typical or seasonal movement patterns [55], [59], [69]. Since unregulated movements often coincide with sudden loss of AIS broadcasts [178], trajectory imputation [179], [79], [180] can provide a more complete view of maritime traffic. This task naturally fits the FM paradigm, resembling record reconstruction in Masked Language Modeling [181]. Moreover, the inclusion of both location-specific data and regulatory action records can generate more precise warnings about Illegal, Unreported, and Unregulated (IUU) fishing or sanction violations, and allows for enhanced monitoring of critical infrastructures [182], [183] and protected zones [71].

Shipping Intelligence. Moving to business-oriented applications, the model's implicit integration of trajectory data with market embeddings enables analytics that are aware of trading dynamics. Multi-hop trip planning to maximize profitability [184], accounting for delays [185] and potential cargo loss [186], can be informed by port-related statistics, commodity prices, and risk assessments handled by the model. Shipping efficiency depends not only on individual trips but also on the connectivity of ports within global and regional networks [187], [188]. Analyzing vessel trajectories and berthings, along with associated trade values, can reveal market trends, highlight evolving port relationships, and identify key port hubs [89], [94]. Aggregating historical data and processing new entries allows the model to monitor logistics chain network dynamics over time, including the influence of specific political factors [189], [190], [191], [192], [93].

VI. Conclusions

In this work, we envision a multimodal FM tailored to maritime mobility data. It leverages large-scale data, spanning vessel trajectories, market-related registries and environmental data, to learn context-aware representations that extend beyond the capabilities of task-specific models. To ground this vision in real-world maritime requirements, we highlight a holistic approach that addresses the multiple planning layers inherent in shipping activities. The envisioned FM serves as a decision support system across autonomous transportation, infrastructure monitoring, shipping analytics, and related maritime operations, providing actionable insights from multimodal data.

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