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OPTIMIZING MARITIME SUPPLY CHAINS USING ARTIFICIAL INTELLIGENCE AND BIG DATA

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Abstract: Maritime transport carries over 80% of global merchandise trade by volume, yet the sector faces mounting pressure from chokepoint disruptions, port congestion, freight rate volatility and decarbonization mandates. This paper examines how the convergence of artificial intelligence (AI) and big data analytics can optimize maritime supply chains across four operational layers: voyage and route optimization, port and terminal operations, predictive asset maintenance, and end-to-end visibility. Drawing on a structured review of recent peer-reviewed literature and industry evidence, the study synthesizes reported performance gains, including vessel estimated-time-of-arrival prediction errors in the range of roughly 0.25–5% depending on the dataset and method, container handling-time reductions of up to 25%, and idle-equipment reductions of 15–20% in digital-twin-enabled terminals. A four-layer conceptual framework is proposed that links Automatic Identification System (AIS) data streams, machine-learning models and digital twin simulations to measurable supply-chain key performance indicators. The framework is then mapped to the Port of Constanța, the largest port on the Black Sea, as an illustrative application from which a staged optimization roadmap is derived, building on the port's current Port Community System programme; a design for the empirical validation of the framework is also specified. The paper analyses the principal barriers to adoption, namely data quality and interoperability, cybersecurity exposure, infrastructure readiness and organizational capability, and outlines a phased implementation pathway for port authorities and shipping operators. The findings indicate that AI and big data are structural enablers of resilient, efficient and lower-emission maritime logistics rather than incremental tools.

Key words: artificial intelligence, big data, digital twin, maritime supply chain, Port of Constanța, predictive analytics.

1. INTRODUCTION

Maritime transport is the backbone of global commerce. According to the United Nations Conference on Trade and Development, around 80% of the volume of international trade in goods is carried by sea, and global maritime trade reached 12,720 million tons in 2024, up 2.2% from the previous year [1]. The sector, however, operates in an exceptionally demanding environment: geopolitical tensions and climate risks have placed strategic chokepoints under severe pressure, with Red Sea transits falling roughly 70% below 2023 averages as vessels reroute around the Cape of Good Hope, lengthening voyages, raising freight rates and increasing greenhouse gas emissions [1]. Maritime trade is forecast to slow to just 0.5% growth in 2025 amid this volatility [1]. These disruptions expose a structural vulnerability of contemporary supply chains: they are optimized for cost under stable conditions but are fragile when confronted with shocks.

In parallel, the maritime industry has entered an accelerated phase of digitalization. The Automatic Identification System (AIS), satellite connectivity, port sensor networks and terminal operating systems generate continuous, high-volume data streams describing vessel movements, cargo flows and asset conditions [2]. Reviews of emerging maritime technologies converge on one observation: the defining challenge is no longer data scarcity but the capacity to turn data into timely decisions [3]. Artificial intelligence (AI) and big data analytics provide exactly this capability, since big data technologies enable the storage and processing of vast, heterogeneous datasets, while AI methods derive predictive and prescriptive insights from them [2].

This paper examines how the convergence of AI and big data can optimize maritime supply chains. It pursues three objectives: first, to structure the application domain into clearly defined operational layers; second, to synthesize the quantitative evidence on performance improvements reported in recent literature; and third, to propose a conceptual framework and implementation pathway that connect data sources, analytical models and supply-chain key performance indicators (KPIs). Section 2 sets out the methodology and Section 3 the technological foundations. Section 4 presents the four-layer framework, Section 5 applies it to the Port of

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Constanța, and Section 6 specifies a validation design. Section 7 discusses adoption barriers and Section 8 concludes.

2. METHODOLOGY

This study combines a structured narrative review with conceptual synthesis. The aim is to organize a fragmented, rapidly evolving body of knowledge into a framework useful to researchers and practitioners rather than to perform a statistical meta-analysis.

The literature base was assembled through a structured search of four academic databases: Scopus, Web of Science Core Collection, IEEE Xplore and ScienceDirect, supplemented by Google Scholar queries capturing conference proceedings and recent preprints. The search was conducted between January and April 2026 and covered material published between January 2019 and March 2026, with a few seminal earlier works retained as canonical references. Search strings combined three concept blocks using Boolean operators: a maritime domain block ("maritime" OR "shipping" OR "port" OR "vessel" OR "container terminal"), a technology block ("artificial intelligence" OR "machine learning" OR "deep learning" OR "big data" OR "digital twin" OR "AIS"), and an application block ("supply chain" OR "optimization" OR "ETA prediction" OR "berth allocation" OR "predictive maintenance" OR "visibility"). Reference network expansion from the most recent bibliometric review of the field [4] was used to identify additional high-impact sources missed by keyword searches.

Screening proceeded in three stages. The initial queries returned approximately 380 records, reduced to 220 after duplicate removal and language filtering (English only). Title and abstract screening narrowed this to 71 candidates, of which 47 were retained after full-text reading. Inclusion required explicit relevance to maritime logistics, port operations or maritime supply-chain management; a clearly identified role for artificial intelligence, machine learning or big data analytics; empirical results, a validated prototype or a substantive conceptual contribution; publication in a peer-reviewed venue or issuance by a recognized body such as UNCTAD, the IMO or a national port authority; and availability of the full text. Sources addressing AI only in non-maritime modes, mentioning it in passing, lacking the methodological detail needed to interpret reported figures, or duplicating a more comprehensive source were excluded. Grey literature was included selectively, flagged as such, and used to corroborate deployment figures not yet documented academically. Empirical studies were assessed against a lightweight checklist covering dataset transparency, clarity of method description, presence of a baseline comparator and explicit reporting of evaluation metrics; those failing two or more criteria were retained for context only and not used as sources of quantitative claims.

The selected material was then analyzed thematically using an inductive coding approach. Each source was coded against three dimensions: data sources used, analytical method applied and reported performance indicator. The coded entries were grouped into the four operational layers that structure Section 4, and for each layer the dominant data sources, prevailing techniques and reported indicators were consolidated into the conceptual framework.

Two limitations follow from this design and are examined in Section 7.1: the reported performance metrics are highly heterogeneous, and a structured narrative review retains an element of analyst judgment. The search strings, databases and screening counts are reported above to make that judgment transparent and the procedure replicable.

To strengthen the framework beyond synthesis, two further components were added, both positioned as proposal-oriented rather than confirmatory. A single illustrative application, the Port of Constanța, was selected because it combines regional significance, documented exposure to disruption and a publicly reported digitalization programme; it is examined using port-authority statistics, official communications, regulator and industry reporting, and Eurostat data. In addition, a validation design is specified to test the framework empirically rather than accept it on conceptual grounds alone. Both are presented as a research agenda for subsequent work, and claims about benefits in Section 5 are formulated as expected returns drawn from the reviewed literature rather than as outcomes already realized at Constanța.

3. TECHNOLOGICAL FOUNDATIONS

Optimizing maritime supply chains with AI rests on three interdependent pillars: the data layer, the analytics layer and the decision layer.

3.1 The maritime big data landscape

Maritime operations generate data with the classic characteristics of big data: high volume, high velocity and considerable variety. The Automatic Identification System is the single most important source, broadcasting vessel position, speed, course and identity at frequent intervals to terrestrial and satellite receivers that aggregate billions of such messages [5]. This is complemented by terminal operating system records, quay-crane and yard-equipment telemetry, gate transactions, meteorological and oceanographic feeds, and engine and sensor data from increasingly instrumented vessels [2]. Big data analytics enables maritime businesses to evaluate and forecast cargo

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flows, optimize routes and minimize superfluous voyages [6].

The central difficulty is integration. Data originates from many actors, including shipping lines, terminals, port authorities, customs and freight forwarders, in incompatible formats and with uneven quality. Bibliometric analysis of the field confirms that system and technology integration, alongside cyber-attack risk, is among the most frequently cited open problems in maritime big data research [4]. Without a coherent data foundation, advanced analytics cannot deliver reliable results.

3.2 Artificial intelligence and machine-learning methods

On the analytics layer, supervised machine-learning models, including random forests, gradient-boosting methods such as XGBoost and LightGBM, and deep neural networks, dominate predictive tasks such as estimated time of arrival (ETA) forecasting and demand prediction [7][8]. Sequence models, in particular long short-term memory networks, are well suited to the temporal structure of vessel-trajectory data [9]. Reinforcement learning is increasingly applied to sequential decision problems such as crane sequencing and yard allocation, where an agent learns policies that balance productivity against future congestion risk [10].

A complementary technology is the digital twin: a continuously updated virtual representation of a vessel, terminal or port. Combining historical data with live telemetry, it lets operators simulate alternative berth schedules, stacking strategies and equipment assignments before applying them live, shifting from reactive firefighting to proactive planning [10][11]. Together these methods form the decision layer, where predictive and prescriptive outputs become operational instructions.

4. A FOUR-LAYER FRAMEWORK FOR SUPPLY-CHAIN OPTIMIZATION

This section presents the core contribution: a framework organizing AI and big data applications into four operational layers of the maritime supply chain. Figure 1 illustrates it; Table 2 summarizes the data sources, methods and reported gains for each layer.

The framework is intentionally layered rather than monolithic. Each layer can be adopted incrementally and delivers value on its own, but the largest benefits arise when the layers share a common data foundation. Its logic follows the physical flow of a maritime supply chain, from the voyage at sea through the port interface to the assets that sustain operations, and finally to the informational layer that binds the chain together.

4.1 Voyage and route optimization

The first layer concerns the vessel in transit. Accurate prediction of vessel ETA is fundamental because port resource planning, berth allocation and downstream land-side logistics all depend on it; inaccurate ETAs propagate as a ripple effect, leading to schedule disruptions, congestion and reduced terminal effectiveness [12]. Machine-learning models trained on historical AIS data have substantially improved ETA accuracy. A study using AIS data from the Port of Houston reported a mean absolute percentage error of approximately 5% with an XGBoost model [7]. In comparison, a hybrid tree-based stacking ensemble applied to Baltic Sea traffic achieved a mean absolute percentage error of 0.25% [8]. The two figures are not directly comparable: they come from different datasets, regions, vessel populations and prediction horizons, and illustrate a range of plausible accuracy rather than a like-for-like benchmark.

Big data analytics also supports weather routing and speed optimization: analyzing meteorological and oceanographic data alongside vessel performance, AI systems recommend routes and speeds that cut fuel consumption and emissions [6][13]. Dynamic rerouting in response to predicted congestion helps vessels avoid costly waiting time, improving schedule reliability and just-in-time coordination across the wider chain [2].

Table 1 makes this heterogeneity explicit. Ensemble and deep-learning methods consistently outperform classical baselines, but reported accuracy is strongly conditioned by dataset, geographic scope and the definition of the prediction horizon, which is why the standardized benchmark discussed in Section 6 is needed before such figures can be treated as comparable.

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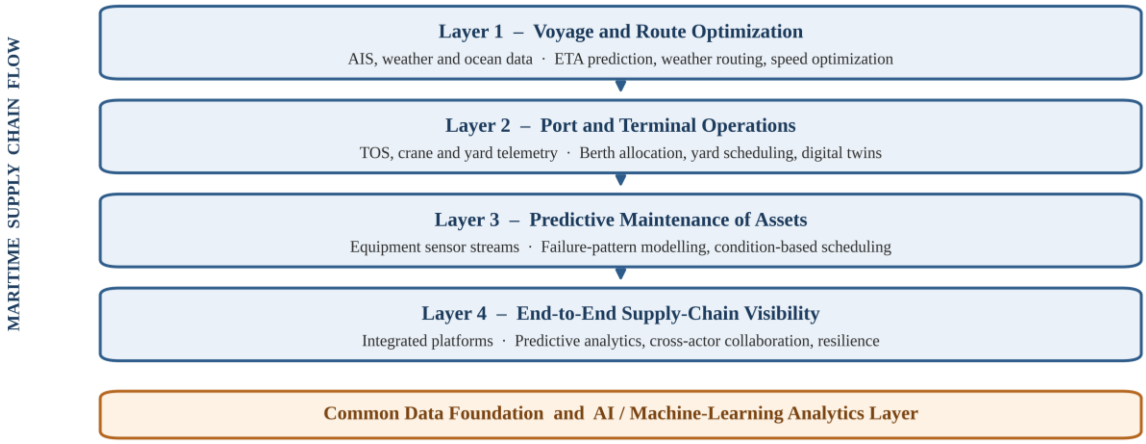

Figure 1 Conceptual four-layer framework for optimizing maritime supply chains with artificial intelligence and big data

Table 1. Comparison of representative machine-learning studies on vessel estimated-time-of-arrival (ETA) prediction

Study (reference)	Dataset / region	Method	Accuracy reported	Scope
Yu et al. 2024 [7]	Port of Houston, USA (2018–2020)	XGBoost with trajectory features	MAPE ≈ 5%	Narrow-waterway transit
Hossain et al. 2025 [8]	Baltic Sea AIS	Hybrid tree-based stacking ensemble	MAPE ≈ 0.25%	Seaport-bound vessels
El Mekkaoui et al. 2023 [9]	Bulk-port vessels, Mediterranean	LSTM / sequence models	Sequence models outperform baselines	Bulk-port arrivals
Xu et al. 2025 [14]	Container vessels, AIS	ML prediction coupled to the berth-allocation model	Reduced berth conflict	Berth scheduling

MAPE = mean absolute percentage error. Accuracy metrics are not directly comparable across studies because of differences in datasets, regions and prediction horizons; see Section 2.

4.2 Port and terminal operations

The second layer addresses the port-terminal interface, where the maritime and land-side chains meet and congestion costs are most acute. Accurate ETA predictions feed directly into berth allocation: integrating real-time AIS forecasts with berth scheduling models mitigates conflicts caused by arrival uncertainty and improves resource utilization [14]. Within the terminal, machine-learning models anticipate yard congestion and gate queues, supporting stacking, sequencing and truck-appointment decisions [15].

Digital twin technology amplifies these gains by enabling risk-free experimentation with yard layouts, crane allocations and berth schedules in a virtual environment before changes reach the quay [11][15]. Industry evidence and selected case-study reports indicate that integrated simulation and analytics can reduce idle equipment time by 15–20% and increase throughput by 10–12%, with some deployments reporting container-handling time reductions of up to 25% [15][16]. These figures are drawn from heterogeneous and partly vendor-reported sources and are conditioned on their baseline, so they indicate plausible upper bounds rather than guaranteed outcomes. With that caveat, the improvements they describe would shorten vessel turnaround and stabilize schedule reliability.

4.3 Predictive maintenance of assets

The third layer concerns the physical assets (vessels, quay cranes and yard equipment) whose availability determines supply-chain continuity. By monitoring telemetry and modeling wear and failure patterns, AI-driven predictive maintenance lets operators schedule repairs in low-impact windows rather than react to breakdowns [16]. This reduces emergency downtime, extends asset life and protects quay productivity during demand peaks.

4.4 End-to-end supply-chain visibility

The fourth layer is informational. It integrates maritime data with the broader supply-chain management systems used by shippers and logistics providers, creating a seamless, end-to-end view of operations [2]. Cloud-based platforms and collaboration tools let ports, shipping lines and logistics providers synchronize operations, making the system more agile [17]. Real-time visibility into vessel positions and arrival times improves coordination with land-side logistics, supports just-in-time delivery and reduces inventory holding costs [2].

This layer is also where AI most directly supports resilience. Predictive analytics across integrated data can give early warning of disruption and quantify its propagation, letting operators pre-position resources and reroute flows. Given the documented vulnerability of maritime chokepoints, this capability is strategic rather than merely operational [1].

Table 2. Summary of AI and big data applications across the four optimization layers of the maritime supply chain

Optimization layer	Primary data sources	Dominant AI / analytics methods	Reported performance gains
Voyage and route optimization	AIS, weather and ocean data, vessel performance	XGBoost, LightGBM, stacking ensembles, LSTM	ETA error 0.25–5% MAPE [7][8]
Port and terminal operations	Terminal operating system, crane and yard telemetry, gate logs	Berth-allocation optimization, digital twins, reinforcement learning	Idle time −15–20%; throughput +10–12% [15][16]
Predictive maintenance	Equipment sensor and telemetry streams	Anomaly detection, failure-pattern modeling	Reduced unplanned downtime [16]
End-to-end visibility	Integrated maritime and supply-chain platforms	Predictive analytics, cloud collaboration	Lower inventory and disruption cost [2][17]

Reported figures are indicative orders of magnitude drawn from heterogeneous studies and deployments; see Section 2.

5. CASE STUDY: APPLYING THE FRAMEWORK TO THE PORT OF CONSTANȚA

This section applies the framework to the Port of Constanța, the largest port on the Black Sea and the principal maritime gateway of Romania and its landlocked Central and Eastern European hinterland. It is an instructive case because it combines significant scale, acute exposure to disruption and an active but early-stage digitalization programme, precisely the conditions under which a layered approach is most relevant, and because the blue economy and Black Sea risk have become explicit regional policy priorities [18].

5.1 Operational profile and the case for optimization

Constanța is a port of call covering almost 3,926 hectares, offering depths of up to 18.5 meters and a direct link to the Danube via the Danube–Black Sea Canal [19]. Its recent traffic illustrates the volatility that motivates this study. In 2023 the port handled a record 92.7 million tonnes; in 2024 total tonnage fell by roughly 14% according to Eurostat, the steepest decline among major EU ports, as Ukrainian grain transit was redirected once Ukraine reopened its own export corridor [20]. Container traffic moved in the opposite direction: throughput reached 989,795 TEU in 2024, up from 884,598 TEU in 2023, and had surged by more than 30% between 2022 and 2024 as the port absorbed boxed cargo redirected from blockaded Ukrainian ports [21][22]. This divergence, contracting bulk tonnage alongside expanding container volumes, is itself an argument for the demand-uncertainty-aware optimization the framework provides. The port operates under a landlord model serving around 40 private operators, with the DP World-operated Constanța South Container Terminal as its main container facility [19][23].

This profile generates exactly the optimization problems the framework addresses. Volatile growth in container and grain volumes, the latter dependent on the Ukrainian export corridor, creates demand uncertainty that strains berth and yard planning [21]. Redirected Ukrainian containers caused congestion at terminal gates and at the entrance from the Danube Canal, a bottleneck the port has identified as a priority [22][23], and the berth-allocation and yard-scheduling gains summarized in Table 2 indicate the order of magnitude of potential improvement. The multiplicity of independent operators and public agencies (customs, border police, and veterinary and sanitary authorities) creates the fragmented information environment that Layer 4 is designed to integrate. Constanța thus offers a plausible, publicly documented setting for the framework, though the mapping is conceptual: it has not been validated against the port's operational data, and the benefits remain expected rather than measured.

5.2 Current digitalization baseline

Constanța is not starting from zero. The National Company Maritime Ports Administration S.A. Constanța has launched a digitalization programme centred on a Port Community System (PCS): a neutral, open platform serving as a one-stop shop for secure information exchange between public and private stakeholders [23]. The port joined the International Port Community Systems Association in 2020, and in 2024 a Romanian, German and Estonian consortium delivered the PCS specification; the system is designed to connect to the

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national Maritime Single Window [22][24]. A complementary truck appointment-booking application has also been developed to reduce congestion at the port gates [23].

Mapped onto the framework, this baseline corresponds principally to the foundational data layer and the early stages of Layer 4 (end-to-end visibility). The PCS standardizes and centralizes documentary and procedural data flows, a precondition for, but not equivalent to, analytical optimization. The predictive and prescriptive capabilities of Layers 1 to 3 are not yet part of the publicly documented programme. The case therefore illustrates a common situation: a port that has begun the digital groundwork but has not converted it into AI-driven decision support.

5.3 A staged optimization roadmap for Constanța

The framework translates this gap into a staged roadmap. In the near term, the PCS and the Maritime Single Window should be consolidated into a common data foundation, with explicit attention to data quality and interoperability, so that later analytics rest on reliable inputs. As an early-value step within Layer 1, AIS-based ETA prediction could be deployed for vessels approaching through the Bosphorus; Table 1 indicates such models are mature and that better berth planning and reduced waiting time are plausible, though the magnitude at Constanța would need a pilot calibrated to the port's own traffic.

In the medium term, the truck-appointment system provides a natural entry point for Layer 2: its booking data, combined with terminal-operating-system and gate records, could feed machine-learning models that anticipate gate and yard congestion, while a digital twin of the container terminal would allow berth and stacking strategies to be tested virtually before deployment. Layer 3 could be introduced in parallel by instrumenting quay cranes and yard equipment for condition-based maintenance. In the longer term, extending the PCS with predictive analytics across all operators and agencies would complete Layer 4, turning the platform into a decision-support system with early warning of disruption, which is of particular value given the exposure of Constanța to Black Sea geopolitical risk. Demonstrating realized benefits would require partnership with the port authority and access to operational data.

6. TOWARDS EMPIRICAL VALIDATION OF THE FRAMEWORK

A framework derived from a structured review must ultimately be tested against data. This section outlines a design through which the framework, and the Constanța roadmap in particular, could be validated. The aim is to specify a falsifiable evaluation rather than to report results.

6.1 Proposed methodology and data

The most tractable starting point is Layer 1. A validation study would assemble a historical AIS dataset of vessels arriving at Constanța over at least 12 months, enriched with meteorological and oceanographic data and actual berthing times from port records. Following the ETA literature, the data would be split by vessel route rather than at random, avoiding the optimistic bias that arises when trajectory segments from one voyage appear in both training and test sets [8]. Several model families (a regression baseline, gradient-boosting methods such as XGBoost and LightGBM, and a sequence model such as an LSTM) would be trained and compared, mirroring the studies summarized in Table 1.

For Layer 2, validation would take the form of a discrete-event simulation or digital twin of the container terminal, calibrated on historical terminal operating system and truck appointment data. It would compare a baseline reproducing current practice with scenarios in which berth allocation and yard stacking are driven by predictive models, isolating the marginal contribution of optimization under reproducible conditions.

6.2 Evaluation metrics and hypotheses

Validation requires metrics defined in advance. For Layer 1, the primary metric is the mean absolute percentage error of ETA prediction, with mean absolute error in hours as a more interpretable secondary measure. For Layer 2, the metrics are average vessel turnaround time, berth and quay-crane utilization, container dwell time and gate turnaround time, all of which connect to the KPIs identified in Section 4.

The study would test three hypotheses. First, that machine-learning models reduce ETA error relative to the schedule-based estimates currently used (H1). Second, that feeding these predictions into berth-allocation and yard-planning logic reduces turnaround time and raises equipment utilization against the baseline (H2). Third, that the largest gains arise when layers share a common data foundation rather than operate in isolation (H3), testing the central integration claim. Stating these hypotheses explicitly makes the framework falsifiable.

7. DISCUSSION: ADOPTION BARRIERS AND IMPLEMENTATION PATHWAY

The evidence reviewed above demonstrates substantial potential, yet adoption remains uneven, as the Constanța case illustrates. Four barriers recur. The first is data quality and interoperability: fragmented and sometimes incomplete data undermines model reliability, and the absence of common standards impedes the data sharing on which integrated optimization depends [4]. The second is cybersecurity: as operations become data-driven and interconnected the attack surface expands, and cyber risk is consistently identified as a leading concern [4][25]. The third is infrastructure readiness, particularly the uneven sensorization and connectivity of ports and fleets [26]. The fourth is organizational capability: realizing value from AI requires analytical skills, redesigned processes and cross-actor governance, a point underscored by practitioners on the Constanța PCS, who stress that digitalization is above all a change in working practices rather than a technical upgrade [24].

These barriers suggest a phased pathway, with the Constanța roadmap in Section 5.3 as a concrete instance. The first phase establishes the data foundation: instrumentation, data-quality management and interoperability standards, since every subsequent gain depends on it. The second deploys predictive analytics on a single high-value layer such as ETA prediction, where evidence of return is strongest and disruption least. The third introduces digital-twin simulation and prescriptive optimization for terminal operations. The fourth integrates the layers and extends visibility across actors, embedding cybersecurity and data governance throughout.

Two cross-cutting themes deserve emphasis. First, optimization and sustainability are complementary rather than competing: reductions in idle time, rerouting and superfluous voyages cut both cost and emissions, aligning AI adoption with the decarbonization agenda [6][13]. Second, benefits scale with integration; isolated pilots yield modest returns, whereas a shared data foundation across the four layers compounds them.

7.1 Limitations

Four limitations of the present study should be made explicit. First, the synthesis is a structured narrative review, not a PRISMA-compliant systematic review with independent dual screening; analyst judgment enters inclusion decisions, and the search strategy in Section 2 makes that judgment transparent rather than eliminating it. Second, the performance figures cited throughout come from heterogeneous studies and partly from vendor or industry sources, and should be read as indicative orders of magnitude rather than directly comparable benchmarks. Third, the Constanța case is an illustrative application rather than a completed empirical case study: it incorporates no primary field data, operator interviews or terminal-level operational records, so its findings are a mapping of the framework onto a real port rather than measured outcomes. Fourth, several sources in that analysis are online institutional and industry publications; while appropriate for documenting a live digitalization programme, they limit independent verification. The validation design in Section 6 is the planned response to the second and third of these limitations.

8. CONCLUSIONS

This paper has examined how the convergence of artificial intelligence and big data can optimize maritime supply chains. It proposed a four-layer framework covering voyage and route optimization, port and terminal operations, predictive maintenance and end-to-end visibility. The quantitative evidence for each layer was synthesized, with the heterogeneity of the underlying studies acknowledged throughout. The framework was then mapped to the Port of Constanța; the resulting staged roadmap shows how it can be operationalized at a specific port, while stopping short of demonstrating realized benefits, which would require validation against operational data.

The analysis supports three conclusions. First, the technological foundations are mature enough for operational deployment, but value depends decisively on the quality and interoperability of the underlying data. Second, the principal obstacles are organizational and infrastructural rather than algorithmic, which is why a phased pathway, instantiated here as the Constanța roadmap, is essential. Third, AI and big data are structural enablers of resilient, efficient and lower-emission maritime logistics in an era of chokepoint vulnerability and decarbonization pressure.

Future research should pursue the validation design of Section 6, beginning with AIS-based ETA prediction for Constanța and extending to digital twin simulation of its container terminal. Standardized benchmarks are needed to make cross-study results comparable, along with methods for secure multi-actor data sharing and longitudinal studies measuring realized rather than projected benefits. Testing the integration hypothesis empirically would be the most valuable single contribution of that work.

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