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A big data approach to oil cargo trade and its implications for the oil tanker ship charter market

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ABSTRAK

Analisis menggunakan big data, kecerdasan buatan, dan platform intelijen maritim mengubah perdagangan muatan minyak dan penyewaan kapal tanker. Artikel ini meninjau tiga perkembangan terkait, yaitu perubahan struktural pasar penyewaan tanker, penetapan tarif angkutan secara algoritmik, serta pemanfaatan intelijen maritim untuk keputusan operasional dan komersial. Berdasarkan dokumentasi platform, peraturan, kasus perusahaan yang dilaporkan, dan penelitian peramalan yang ditelaah sejawat, artikel ini berargumen bahwa arus data kini turut menentukan keputusan penyewaan selain arus muatan fisik. Sintesis bukti menunjukkan bahwa ukuran pasokan berbasis AIS dapat menjelaskan perkembangan tarif angkutan ketika indikator pasokan tradisional tidak mampu melakukannya, dan model peramalan hibrida telah menghasilkan nilai ekonomi terukur dalam portofolio penyewaan VLCC. Kajian ini merupakan sintesis bukti; tidak menyajikan estimasi kausal sendiri, dan angka yang dilaporkan perusahaan disampaikan sebagaimana adanya. Kontribusinya adalah mengorganisasikan bukti praktisi dan akademik yang tersebar ke dalam satu kerangka serta mengidentifikasi bagian yang didukung bukti kuat dan bagian yang masih terbatas.

Kata Kunci: big data; penyewaan tanker minyak; tarif angkutan algoritmik; intelijen maritim; AIS; dekarbonisasi.

ABSTRACT

Big data analytics, artificial intelligence, and maritime intelligence platforms are reshaping how oil cargo is traded and how tankers are chartered. This paper reviews three related developments: structural change in the tanker charter market, algorithmic freight pricing, and the use of maritime intelligence for operational and commercial decisions. Drawing on platform documentation, regulatory texts, reported company cases, and peer-reviewed forecasting studies, the paper argues that data flows now condition chartering decisions alongside physical cargo flows. The evidence synthesis shows that AIS-derived supply measures explain freight rate evolution where traditional supply indicators do not, and that hybrid forecasting models have produced measurable economic value in VLCC chartering portfolios. The paper is an evidence-synthesis review; it presents no causal estimates of its own, and company-reported figures are reported as stated. Its contribution is to organise fragmented practitioner and academic evidence into a single framework and to identify where the evidence is strong and where it remains thin.

Keywords: *big data; oil tanker chartering; algorithmic freight rates; maritime intelligence; AIS; decarbonisation*

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Introduction

Oil cargo trade and the shipping sectors that support it are undergoing significant changes due to digitalisation and data analytics. Geopolitical conflicts, environmental regulations, economic cycles, and technological developments have increased uncertainty in maritime trade routes [1]. In response, shipowners, charterers, and traders are adopting data-driven strategies to improve operational efficiency, resilience, and forecasting accuracy [2], [3]. This paper examines the role of big data analytics in oil cargo trade, focusing on structural changes in the tanker charter market, algorithmic freight pricing, and maritime intelligence for operations and forecasting.

This study adopts a narrative evidence synthesis approach based on peer-reviewed studies, publicly available platform documentation, company reports, and regulatory documents. Previous studies have examined tanker freight rate dynamics and the transmission of volatility between crude oil prices and tanker freight markets [9], [10], [11]. Other studies have investigated fleet capacity, freight forecasting during economic crises, the impact of the COVID-19 pandemic, and changes in tanker markets caused by sanctions and oil production policies [12], [13], [14], [15]. These studies provide a foundation for understanding the relationship between oil trade, market uncertainty, and tanker chartering decisions.

The development of forecasting methods has introduced new approaches to analysing tanker freight rates, including neural networks and chaos theory [16], [17]. Oil production indicators and freight rate relationships across tanker markets have also been investigated to understand market movements and associated risks [18], [19]. Meanwhile, the application of Automatic Identification System (AIS) data has expanded maritime research into trade patterns and vessel emissions [20], [21]. Further studies have examined the relationship between seaborne trade and freight rates, AIS-based carbon emission estimates, and the interaction between crude oil prices and shipping costs [22], [23], [24]. Together, these studies illustrate the potential of combining economic indicators, vessel movement data, and computational methods in maritime market analysis.

The application of AIS data also supports the estimation of crude oil export volumes and the analysis of global maritime oil trade networks [25], [26]. Understanding freight market behaviour requires consideration of non-linear rate dynamics, the influence of charterers and shipowners, and the characteristics of vessels and voyages [27], [28], [29]. Particular attention is given to two published studies, namely Regli and Nomikos (2019) [33] and the 2025 Transformer–Kalman study [7], which provide quantitative evidence of the potential economic value of AIS data and algorithmic forecasting in tanker chartering. The main contribution of this paper is to integrate these academic and industry perspectives into a coherent analytical framework. Accordingly, the review addresses three main questions concerning AIS-derived fleet measures in freight pricing, tanker freight forecasting, and the influence of operational intelligence and regulation on chartering decisions.

Quantitative findings are interpreted according to their original market conditions, sample periods, analytical models, and measured outcomes. Company claims are treated as illustrative evidence rather than independently verified findings. Differences in research settings and analytical methods are considered to distinguish empirical findings from proposed commercial applications. Since detailed search procedures, screening counts, and inclusion and exclusion criteria were not reported, this review is neither systematic nor exhaustive. Consequently, this study does not estimate pooled effects or establish causal relationships.

The remainder of this paper is organised into several interconnected sections. Sections 2–4 discuss technological foundations, structural changes in the tanker market, and algorithmic freight forecasting. Sections 5–8 examine maritime intelligence platforms, the Internet of Things (IoT), blockchain technology, and charter party modernisation. Sections 9–11 discuss regulatory developments, sustainability, and autonomous shipping. Finally, Section 12 presents the conclusions, research limitations, and directions for future research.

The Foundation: Big Data Analytics in Oil Cargo Trade

Scope of the transformation

Big data in oil cargo trade spans the oil and gas value chain, from upstream exploration through midstream logistics to downstream distribution. The global market for big data solutions in oil and gas was projected to reach USD 11.76 billion by 2029, growing at a 13.9 per cent compound annual growth rate [4]. Drivers include energy demand, expanding trade routes, supply imbalances, regulatory complexity, and demand for operational optimisation. Oil cargo trade generates structured and

unstructured data from tanker sensors, port logistics systems, chartering transactions, trading activity, weather services, satellite imagery, and Automatic Identification System (AIS) feeds [2]. Analytical tools use these datasets to support decision-making, supply chain risk management, asset utilisation, and compliance.

Key technologies and analytics tools

Table 1 summarises the main technologies and their applications in oil cargo trade. The list is illustrative rather than exhaustive; most commercial platforms combine several of these tools.

Table 1. Technologies and applications in oil cargo trade

Technology	Key functions	Application in oil cargo trade
Data management software	Cleansing, integration, governance	Centralised platform for end-to-end operations
AI and machine learning	Predictive maintenance, route and rate forecasting	Freight pricing, operational optimisation
IoT and sensors	Real-time capture (temperature, pressure, levels)	Cargo and engine monitoring, emissions
Edge computing	Low-latency processing close to source	Drilling rigs, vessel operations
Cloud computing	Scalable storage, advanced analytics	Trading and fleet platforms
Digital twin technology	Simulation and forecasting	Asset maintenance, voyage planning
Blockchain	Secure transactions, document management	Bills of lading, compliance, transparency
Visualisation tools	Dashboards, alerts, interactive reporting	Chartering, risk, sustainability
Big data platforms	Hadoop, Spark, cloud analytics stacks	ML pipelines, streaming analytics

Structural Disruption in the Tanker Charter Market

Big data changes market structure primarily by changing access to information and the speed of that access. It does not necessarily create entirely new information. The oil tanker charter market, including spot and time-charter arrangements, has historically been cyclical and shaped by supply–demand imbalances, fleet dynamics, and global oil flows. Big data is altering this market in five related ways.

Enhanced visibility and data integration

Granular tracking of vessels, cargoes, and port activity provides real-time insight into market inefficiencies. AIS data has become a primary source for this visibility. Regli and Nomikos (2019) used AIS data from MarineTraffic combined with Clarksons fixture records to construct a measure of short-term tanker capacity. They demonstrated that vessel employment status and geographical position carry information that traditional supply measures miss, and that this information adds to price discovery beyond what is already contained in forward freight agreement (FFA) prices.

Operational optimisation

Real-time analytics support fuel management and emissions control. Predictive models can also support proactive maintenance. Route and speed optimisation tools combine weather, vessel performance and market data. These tools have moved from experimental to routine use on many managed fleets.

Environmental regulation and digital compliance

The IMO Data Collection System (DCS) requires transparent data reporting. The Carbon Intensity Indicator (CII) also depends on digital documentation. These requirements interact with shipping's inclusion in the EU Emissions Trading System (MARPOL Annex VI, Regulations 27 and 28; Directive (EU) 2023/959). Compliance is no longer solely a back-office exercise because it can inform commercial negotiations and vessel employment decisions.

Fragmentation and bifurcation

Sanctions regimes, the growth of a shadow or dark fleet, and digital tracking have produced a divided market. One segment uses compliance and data-driven strategies. Another segment exploits opacity. Satellite imagery combined with AIS analysis has made this division more visible to market participants and regulators (Financial Times reporting on AIS spoofing, 2026; TankerTrackers and similar platforms).

New digital charter party agreements

The ASBATANKVOY 2025 revision, published jointly by BIMCO and ASBA, updates the principal independent tanker voyage charter party for the first time since 1977. The revision incorporates digital notification practices, cybersecurity and data-risk provisions, recognition of electronic bills of lading, and environmental compliance language [5]. Taken together, these changes are consistent with a leaner, more information-sensitive market, although the magnitude of the structural shift remains contested. Cyclical swings are now overlaid with algorithmic feedback loops as chartering decisions draw on predictive analytics and market signals derived from shipping and trade data.

Algorithmic Freight Dynamics

Freight rate determination has traditionally relied on human expertise and manual market signals. Contemporary models increasingly support this activity. They process operational, market and macroeconomic data in near real time. In some settings, parts of the freight rate determination process are therefore automated.

Predictive freight rate modelling

Machine learning models ingest historical freight rates, voyage durations, oil prices, bunker costs, vessel availability, and macroeconomic indicators to generate dynamic pricing signals. A systematic review of 28 studies published between 2012 and 2024 finds that neural-network architectures are the most common, although hybrid and specialised models often outperform standalone approaches; the literature remains heavily weighted toward dry bulk rather than tankers [6]. On the commercial side, Maersk Tankers reported a roughly 20 per cent average improvement in freight price forecast accuracy after integrating AI models with an extended historical dataset (2021.AI client case, Maersk Tankers).

Comparative synthesis of published studies

Table 2 compiles the two central verified studies discussed in this paper together with two additional forecasting studies that illustrate the wider methodological landscape. The table is the paper's original contribution: it organises fragmented forecasting evidence into a comparable framework. Error metrics are not directly comparable across studies because sample periods, vessel classes, and evaluation methods differ.

Table 2. Comparative synthesis of tanker and related freight forecasting studies

Study	Data and vessel class	Sample period	Model	Reported results
Regli & Nomikos (2019), Transp. Res. Part E	AIS (MarineTraffic) + VLCC fixtures (Clarksons)	Weekly VLCC market	AIS-based capacity measure (employment + position)	Capacity measure explains weekly freight evolution where traditional supply does not; 1 SD drop (≈14 vessels) → +$0.56/mt; +$151,200 gross revenue on 270,000 mt cargo. Adds to FFA price discovery.
Kim et al. (2025), J. Korean Soc. Ind. Syst. Eng.	VLCC TD3C; 4,267 daily samples; crude, fuel, margins, congestion, inventories, AIS activity	2014-02-01 to 2025-10-08	PyTorch Transformer + Monte Carlo Dropout + Kalman filter	Kalman-smoothed: MAE 4,326; MAPE 10.6%; R^2 0.83 (raw Transformer: MAE 5,259; MAPE 13.1%; R^2 0.74). Portfolio: $108.5M, 88.9% win rate, Sharpe 0.83 vs raw $32.9M / 0.24 and random ≈0.
ISTFIX XGBoost study (Turkish J. Marit. Mar. Sci., 2025)	Istanbul Freight Index (coaster / mini-bulk)	Weekly, Jan 2008–Mar 2025	XGBoost vs SARIMA and Prophet	XGBoost 1-month MAPE 5.47%; superior short-term accuracy relative to SARIMA and Prophet on a volatile regional index.
MEL systematic review (2025)	28 ML freight-rate studies (mostly dry bulk)	2012–2024 literature	NN, hybrid, specialised models	Neural networks most common; hybrids often outperform; literature remains dry-bulk dominant; RMSE/MAPE/MAE dominant metrics.

What the evidence shows

The two verified tanker-focused studies differ in method and purpose, but together they support two claims relevant to this paper. First, Regli and Nomikos (2019) demonstrate that AIS-derived capacity measures explain weekly freight rate evolution where traditional supply measures are uninformative, and that this information is additional to what FFA prices already contain. This is direct

evidence that big data—specifically AIS—has incremental information value for chartering decisions. Second, the Transformer–Kalman study [7] shows that algorithmic forecasting, when paired with uncertainty quantification and post-processing, can generate quantifiable economic value in real chartering portfolios: USD 108.5 million across 598 trades for 82 Korean VLCCs, with a Sharpe ratio of 0.83. Critically, the raw Transformer earned only USD 32.9 million with a Sharpe of 0.24, while random selection was near zero. The economic value came not from the model alone but from calibrating uncertainty and post-processing forecasts. This cautions against reading reported forecast accuracy as evidence of trading profitability.

Algorithmic trading and tanker deployment

Chartering platforms and digital pools allow near real-time assignment of tonnage based on price optimisation and anticipated demand swings. Floating storage decisions, once evaluated largely by hand, are now informed by real-time market analytics. FFAs, traded on digital exchanges, support algorithmic hedging and speculation. These models depend on data quality and remain vulnerable to structural breaks such as sanctions regimes or pandemics; the literature on model risk in freight forecasting is still thin.

Maritime Intelligence

Maritime intelligence platforms combine AIS, satellite imagery, port and weather data, regulatory feeds, and other datasets to deliver actionable insights. Signal Ocean integrates real-time vessel tracking, freight rate analytics, emissions monitoring, and congestion mapping for owners, charterers, and brokers (Signal Ocean platform documentation). TankerTrackers and similar services pair satellite imagery with AIS data to identify dark-fleet operations and sanctions-related behaviour. Commercial satellite and AI providers (Planet, Spire, and others) are used to detect tankers operating with AIS disabled or spoofed. Modern platforms interface with IMO DCS, CII ratings, EU ETS carbon pricing, and port incentive schemes. Claims of "unprecedented transparency" should be treated with caution; a more defensible formulation is that these platforms provide greater transparency than was previously available to commercial actors outside the largest integrated oil companies.

IoT and Sensor Data

IoT sensors on tankers monitor flow, pressure, temperature, position, bunkering levels, emissions and engine performance. Predictive maintenance algorithms aim to reduce unplanned downtime, while automated compliance modules alert operators to anomalies. Deployment claims by major operators, including Maersk entities and independent tanker owners, are reported in trade press and company materials. Independent verification of fleet-wide savings remains limited.

Blockchain

Smart contracts and permissioned blockchains, such as Hyperledger Fabric, are used in pilot and limited production settings. The applications aim to protect the integrity of trade documents, automate compliance checks and reduce document fraud. End-to-end supply chain visibility and ESG tracking are additional use cases. Adoption continues to confront interoperability problems and incomplete legal harmonisation across jurisdictions.

Charter Party Agreements

The 2025 revision of ASBATANKVOY reflects the shift toward digital market practices. The reported changes concern digital notices and documentation, cybersecurity and data-risk clauses, ESG and sustainability provisions, and the arbitration framework [5]. The source identifies New York, London, Singapore and Hong Kong as arbitration venues, with New York as the default. Owners and charterers increasingly use data-driven negotiation platforms incorporating operational and market data, although the extent of fully algorithmic negotiation remains limited.

Regulatory Environment

The IMO DCS requires vessels of 5,000 GT and above to collect and report annual fuel oil consumption data. The CII, in force from January 2023, assigns an operational carbon intensity rating (A–E) that can affect commercial employment (MARPOL Annex VI, Regulations 27 and 28). Shipping's inclusion in the EU ETS, phased in from 2024 under Directive (EU) 2023/959, makes carbon

cost modelling important for charter party negotiations and voyage planning. The stringency and distributional effects of these measures remain subjects of debate among owners, charterers and policymakers.

Sustainability

AI- and ML-based route and speed optimisation can deliver measurable fuel and CO_2 reductions. Anglo-Eastern reported that systems underlying its Sustainability and Performance Services (SAPS) platform, tested across more than 800 vessels and nearly 46,000 voyages between 2023 and 2025, contributed to reductions of more than 700,000 mt of CO_2 and 225,000 mt of fuel, with estimated cost savings of approximately USD 135 million [8]. Alternative fuel transition planning and carbon pricing models increasingly inform real-time asset decisions. Broader consulting claims that leading AI adopters capture large shares of incremental EBIT are not independently verified for the tanker sector and are omitted here.

Future Trends

The Yara Birkeland, a fully electric container feeder designed for autonomous operation, has demonstrated the technical feasibility of crewless short-sea operations and remains an important reference case for algorithmically managed, zero-emission assets, even though full autonomy timelines have been extended relative to early announcements. Progressive oil and gas players and tanker operators continue to integrate predictive analytics across operational and commercial layers. Digital twins support lifecycle prediction and maintenance automation. The transformation also requires new digital talent and continuous upskilling of existing seagoing and shoreside staff.

Conclusion and Limitations

This narrative evidence synthesis indicates that AIS-derived capacity measures and forecasting models may provide information relevant to freight pricing and chartering in the settings studied. The economic evidence from the cited VLCC studies is context-specific; it does not establish equivalent gains across vessel classes or all charter portfolios. Commercial platform examples illustrate possible applications rather than independently measured comparative performance. No new empirical tanker-market estimates were produced in this review.

This review has limitations. It relies on public sources, which likely overstate benefits because firms publicise successes more readily than failures. Proprietary chartering data were not accessible, and the comparative table in Section 4 draws on studies with different sample periods, vessel classes, and error metrics, limiting direct comparison. Future work should test the claimed pricing and efficiency effects using transaction-level fixture data, and should examine whether AIS-derived capacity measures hold for Suezmax and Aframax vessels as they do for VLCCs. A reproducible follow-up should document databases, search dates, selection criteria and exclusions, extract market segment, sample period, forecast horizon, model and error/economic metrics, and assess the independence of each evidence source before drawing comparisons.

DECLARATIONS AND ADDITIONAL INFORMATION

ORIGINALITY AND EXCLUSIVE SUBMISSION

The authors are requested to confirm that the manuscript is original, has not been published and is not under consideration elsewhere.

AUTHOR CONTRIBUTIONS

Mehrdad Zamankhah Somehsaraei: conceptualization, methodology, formal analysis, writing – original draft. Nazi Ahmadi: investigation, validation and writing – review & editing.

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No competing interests have been reported.

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ETHICAL APPROVAL

This narrative review uses published sources and does not involve recruitment of human participants.

INFORMED CONSENT

DATA AVAILABILITY

The study draws on published literature, reports and publicly described maritime intelligence platforms. Access to underlying material should be requested from the corresponding author and is subject to confidentiality and applicable permissions.

USE OF ARTIFICIAL INTELLIGENCE

ChatGPT (OpenAI) assisted with language editing, consistency checks, structure and formatting. The authors remain responsible for the data, interpretation and scientific content.

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Generative AI tools were used for language editing and structuring of early drafts. The author reviewed, verified, and takes full responsibility for all content, citations, and claims.

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