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# Smart investment strategies in maritime operations: leveraging digital monitoring for operational efficiency

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**ABSTRACT**

This study evaluates the operational and economic impact of digitalization in maritime transport, focusing on telemetry-enabled monitoring and fuel oil consumption as key indicators of fleet performance and cost efficiency. Using empirical analysis of high-frequency sensor data collected over a six-year period (2017–2022) from a fleet of bulk carriers operated by a leading shipping company, the study examines how the implementation of onboard digital monitoring systems influences fuel consumption under real commercial operating conditions. A before-after comparison of vessel performance is conducted to quantify the operational effects of telemetry adoption, while an investment payback analysis evaluates the financial viability of the digitalization strategy. The findings show a statistically significant reduction in fleet fuel consumption following the adoption of telemetry-enabled monitoring, corresponding to measurable operational improvements and an estimated investment payback period of approximately 5.54 years. These results provide empirical evidence that digital monitoring technologies can translate digitalization into tangible operational and economic benefits in commercial bulk shipping. The study contributes to the literature by linking telemetry-based digital monitoring with measurable performance outcomes using real fleet data, highlighting the strategic role of Internet of Things and telemetry systems in improving both operational efficiency and financial sustainability in maritime transport.

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**KEYWORDS**
Digitalization; telemetry; shipping performance; fuel oil consumption; operational efficiency; payback period

## 1. Introduction

Maritime transport is the backbone of global trade, with over 80% of goods moving by sea. This sector is also one of the largest consumers of fuel oil, making it a major source of transport-related emissions (Fan et al. 2022). Projections suggest that shipping emissions could increase by 90–130% by 2050 compared to 2008 levels, highlighting the urgency of addressing this challenge (Fan et al. 2022; Guo et al. 2022).

Policy responses vary widely, as authorities must balance economic growth with environmental goals. Over the past decade, fuel prices have risen by an average of 16% annually, making fuel the heaviest operating expense for most ship owners (Hu et al. 2022). This dual environmental and economic challenge has driven research into

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efficiency improvements, but the focus and scope of solutions differ substantially across the literature (Bassam et al. 2022; Farag and Ölçer 2020). Some studies prioritize technological retrofits and design innovations (Bassam et al. 2022), which demand high investment and long implementation periods. Others favor operational measures such as speed or trim optimization, offering quicker but limited gains (Sang et al. 2023; Wang et al. 2023). Few studies integrate technology, economics, and regulation into a single framework, underscoring the need for holistic, cost-effective strategies that align efficiency improvements with both cost management and emission reduction (Tay et al. 2021).

Reducing fuel oil consumption remains the most viable short- to medium-term strategy for increasing operational efficiency (Farag and Ölçer 2020). Conventional practices such as hull cleaning and propeller polishing or fixed maintenance schedules improve performance but often raise costs or damage protective coatings, sometimes leading to higher resistance and fuel consumption (Gupta, Rasheed, and Steen 2022). Such reactive practices show why modern crews rely increasingly on data-driven systems that respond to actual engine performance rather than fixed maintenance intervals.

Recent research identifies digitalization, Internet of Things (IoT) and telemetry systems as more integrated and responsive solutions. Unlike static rule-based optimization (Sang et al. 2023; Wang et al. 2023), digital frameworks combine real-time sensor, propulsion, and metocean data to enable predictive maintenance, performance tracking, and voyage optimization (Bonislawski et al. 2019; Nguyen et al. 2025). Telemetry provides the data backbone by transmitting key variables such as shaft power and fuel flow for real-time assessment (Bonislawski et al. 2019), while marine IoT platforms ensure connectivity and interoperability between onboard and shore-based systems (Kabanov and Kramar 2022). The convergence of these technologies creates a feedback loop that supports predictive analytics, real-time decision-making, and fleet-wide energy management (Tay et al. 2021).

Compared with hardware retrofits or alternative fuels requiring substantial capital and long implementation, digitalization offers a scalable and cost-efficient path to immediate improvements in fuel economy and emission compliance (Tay et al. 2021).

Based on this evidence, digitalization, anchored in IoT and telemetry integration, surpasses traditional and hardware-based measures in practicality and performance. This paper positions itself within the operational and managerial dimensions of maritime performance, using fuel oil consumption as the basis for assessing digitalization's contribution to real-time monitoring, predictive maintenance, and optimized operations. The study demonstrates that digital transformation delivers tangible operational, environmental, and financial benefits, providing an effective pathway to sustainable and economically viable shipping (Bonislawski et al. 2019; Cai et al. 2024; Kabanov and Kramar 2022; Luo et al. 2025; Nguyen et al. 2025; Tay et al. 2021).

### 1.1. Scope of the study

Following the position outlined in the introduction, this study turns to how digital technologies are being integrated into maritime operations and where significant gaps remain (Ichimura et al. 2022; Zheng et al. 2023). Although interest in intelligent and data-driven systems continues to grow, their practical adoption and

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coordination across the sector vary widely (Zhang et al. 2024). Sensors and onboard monitoring platforms now collect continuous operational data (Liang et al. 2024), yet many vessels still lack processes that translate these streams into meaningful decision support, such as optimized routing or port planning. Research indicates that combining onboard data with external factors, including weather and port activity, can strengthen predictive scheduling and reduce fuel consumption, although structured frameworks that enable this integration are still limited (Yan, Wang, and Peng 2021).

As discussed by Fragapane et al. (2023), staying competitive in a rapidly evolving global market requires more than simply adopting new technologies. It also demands embedding them within broader strategic approaches focused on flexibility and cost-efficiency, an integration that remains underexplored in the maritime domain.

Given this context, the study aims to investigate comprehensively the particular mechanisms by which and to what degree digital technologies may facilitate the monitoring of fuel oil consumption, thus leading to the formulation of the following hypotheses:

**H1:** The fuel oil consumption in the fleet is significantly lower after the implementation of onboard digitalization systems compared to before.

*Novelty:* Unlike previous research that discusses the potential of digitalization to enhance operational efficiency in conceptual terms, this study empirically measures the impact of digital tools on actual fuel oil consumption. By utilizing high-frequency real-time vessel data, this research provides robust evidence on how digital monitoring systems influence energy performance at fleet level, offering rare, data-based quantification of the economic and environmental benefits of digitalization.

**H2:** The adoption of onboard digitalization systems results in a payback period that justifies the digitalization investment when fuel oil consumption is used as the main evaluation criterion.

*Novelty:* While most existing studies emphasize the technical or environmental aspects of energy efficiency, this study contributes by incorporating a financial perspective, assessing whether fuel savings achieved through digitalization justify the capital and operational costs of system adoption. By combining operational and cost data, the study provides a more comprehensive understanding of the business case for maritime digitalization.

By addressing these hypotheses, the study aims to provide empirical evidence of the economic and environmental value of digital monitoring systems. It further contributes to the broader discussion on digital transformation in maritime transport by clarifying the role of digital technologies in supporting informed decision making and improving fuel related performance across vessels and fleets.

The structure of the paper is as follows: Section 2 provides a review of relevant literature and the theoretical framework. Section 3 outlines the methodology used. Section 4 reports and interprets the findings, leading to a broader discussion in

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Section 5. Section 6 presents the key conclusions, addresses the study's limitations and suggests potential directions for future research.

## 2. Literature

### 2.1. Digitalization definition

Understanding digitalization requires more than defining the term. It also means evaluating how different scholars conceptualize the idea and what practical implications these views carry. Gong and Ribiere (2021) point out that distinguishing between digital transformation and digital maturity is difficult, because the suffix '–ization' describes both a process and an outcome. Their outcome-oriented stance draws attention to the effects of digitalization on products, services, and relationships, prioritizing performance over definition. In contrast, other scholars, such as Gonzalez Chavez et al. (2023), approach the topic from a technical angle, emphasizing aspects like interoperability, data availability, and connectivity. Complementing these views, Ciarli et al. (2021) describe digitalization as a process that enhances data collection, optimization, and predictive capability, shifting attention from tools to measurable improvements in information flow and decision quality.

Further broadening the conversation, Bygstad et al. (2022) introduce the idea of 'dual digitalization,' focusing on how both systems and organizations undergo transformation. Although their work primarily centers on education, the underlying concept of parallel transformation can be adapted to maritime contexts. Similarly, Zheng et al. (2023) differentiate between 'internal' and 'external' digitalization, capturing the balance between operational efficiency and stakeholder engagement. Bansal et al. (2023) move the debate toward the human factor, highlighting the interaction between digital agents and employees and revealing how the human dimension remains underexplored in many sectors.

Across these perspectives, a pattern emerges. Gong and Ribiere (2021) stress outcomes, Gonzalez Chavez et al. (2023) focus on infrastructure, Bygstad et al. (2022) and Zheng et al. (2023) emphasize structural dualities, and Bansal et al. (2023) bring in the human element. Yet, most of these approaches remain either conceptually abstract or narrowly focused, offering limited guidance for assessing practical implementation in industries such as shipping, where digital transformation increasingly involves the integration of Industry 4.0 technologies that enable data-driven monitoring, automation, and advanced decision-support capabilities (Kumari, Rohit, and Pratap 2026).

More recent maritime studies have attempted to provide sector-specific interpretations of digitalization. Ichimura et al. (2022) define shipping digitalization as the transformation of maritime operations and business models through the integration of digital technologies and intelligent systems aimed at improving efficiency, safety, and competitiveness. Building on this perspective, Tsoulakos and Pantouvakis (2026) conceptualize maritime digitalization as the strategic integration of digital technologies such as sensors, data analytics, and automated monitoring systems to enhance operational efficiency, safety, regulatory compliance, and data-driven decision-making across the vessel lifecycle.

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For the purposes of this study, the definition proposed by Tsoulakos and Pantouvakis (2026) is adopted because it more explicitly links digital technologies with measurable operational outcomes in maritime operations. Within this framework, sensor and telemetry systems represent key enabling technologies of maritime digitalization, enabling continuous data collection and real-time monitoring of vessel performance.

### 2.2. Sensor data

Digital technologies are increasingly transforming industrial systems into smart, data-centric operations (Luo et al. 2023). Recent maritime studies further highlight how digital transformation strategies reshape coordination mechanisms across port and maritime supply chains through enhanced connectivity and stakeholder integration (Fu, Cai, and Sun 2025). Many studies agree that these technologies enhance productivity, innovation, and process control (Grybauskas, Stefanini, and Ghobakhloo 2022), although they explain performance gains in different ways. Luo et al. (2023) link these improvements with automation and interconnectivity, whereas Grybauskas, Stefanini, and Ghobakhloo (2022) emphasize human-technology interaction and decision autonomy. This variation suggests that although the value of digitalization is established, success depends on contextual and organizational conditions that remain underexplored in more fragmented sectors such as maritime transport.

Within maritime operations, digitalization has begun to reshape practices by enabling real-time vessel monitoring and advanced analytics (Bassam et al. 2022). However, adoption levels differ greatly between technologically advanced fleets and those reliant on traditional reporting (Bassam et al. 2022). Many ship operators depend on single-source or low-resolution data, such as noon reports, which limit insights to one data point per day, yielding sparse annual datasets that poorly represent a vessel's dynamic performance (Cai et al. 2024). Particularly for newly built or retrofitted vessels, limited operational history further constrains data availability and model accuracy (Cai et al. 2024).

Recent trends suggest a gradual transition, as maritime operators adopt digital telemetry systems and machine learning for performance prediction and decision support (Bonislawski et al. 2019; Tay et al. 2021). However, these advances have revealed another layer of complexity. Predictive accuracy in such systems depends heavily on the volume, quality, and resolution of available data (Luo et al. 2025). Compared with manufacturing, where standardized datasets and validation frameworks are common, the maritime sector still lacks consistent protocols for data collection, integration, and benchmarking (Cai et al. 2024). Efforts to merge operational, environmental, and maintenance data streams are increasing, yet the absence of unified data governance remains a limiting factor (Cai et al. 2024).

As shipping remains in transition toward real-time, data-driven operations (Bassam et al. 2022; Luo et al. 2023), the present study focuses on the application of sensor and telemetry data within digitalization strategies as a pathway to improve fuel oil efficiency and enhance operational decision-making.

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### 2.3. Fuel oil consumption and cost

Within the ongoing digital transformation of maritime operations, fuel oil consumption has emerged as the most reliable indicator for quantifying the operational and financial outcomes of digitalization (Bassam et al. 2022; Fan et al. 2022). Unlike design-based or retrofit measures that demand substantial capital and long implementation periods, fuel-based performance monitoring provides immediate, quantifiable results through existing vessel systems (Nguyen et al. 2025). Across the literature, tracking and optimizing fuel consumption links digital innovation to measurable improvements in efficiency, cost control, and environmental compliance (Bassam et al. 2022; Fan et al. 2022). This dual relevance makes fuel consumption both a technical and economic performance proxy, aligning digital decision-making with profitability and operational efficiency targets (Altarriba et al. 2025; Fan et al. 2022; Nguyen et al. 2025).

Although scholars broadly agree on its relevance, their methodological approaches diverge, particularly between traditional modelling frameworks and more recent data-driven approaches aimed at improving prediction accuracy and operational decision support (Dun, Dang, and Yan 2025). While data-driven studies enhance predictive accuracy, many studies focus on improving algorithms rather than examining how different operational or environmental factors such as speed, trim, hull condition, or metocean parameters, affect performance (Sang et al. 2023). Traditional assessments often treat these factors independently, limiting their insights (Fan et al. 2022; Sang et al. 2023). In contrast, integrated digital frameworks combine multi-source sensor and telemetry data to model the interdependencies among variables dynamically, producing richer interpretability and operational precision (Gupta, Rasheed, and Steen 2022).

Since fuel expenses constitute more than 60% of total operating costs (Wang et al. 2023), optimizing fuel consumption directly enhances profitability and competitive positioning. Consequently, selecting fuel oil consumption as the core parameter for assessing digitalization provides a clear benchmark for evaluating the investment pay-back period and improving operational decision-making in shipping (Altarriba et al. 2025).

Evidence shows that IoT and telemetry-based performance monitoring systems can generate measurable economic returns by using existing onboard data infrastructure to enhance operational decision-making (Kim, Kim, and Jeon 2023; Tay et al. 2021). For instance, simplified performance monitoring frameworks for small and medium-sized vessels achieve cost-efficient implementation using readily available sensors and data channels, offering rapid payback and tangible savings without major retrofits (Dun, Dang, and Yan 2025; Kim, Kim, and Jeon 2023). Tay et al. (2021) further demonstrate that integrating telemetry with data analytics and machine learning reduces maintenance and fuel costs while minimizing unplanned downtime.

### 2.4. Human and digital factors in fuel efficiency

Recent studies agree that digitalization enhances operational control and analytical precision, but its effectiveness depends equally on human engagement (Yang and Lin 2025; Zoubir et al. 2025). In contrast with manufacturing or logistics sectors, where automation maturity and data standardization are more advanced, the maritime industry still relies heavily on

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human interpretation for translating digital insights into operational decisions (Bayrak and Muslu 2025; Theotokas, Lagoudis, and Raftopoulou 2024). As Theotokas, Lagoudis, and Raftopoulou (2024) note, this process requires continuous investment in seafarer training and digital competence. Bayrak and Muslu (2025) add that the cognitive demands of digital interfaces may induce technostress, affecting both decision quality and safety.

This interdependence becomes particularly visible in fuel-related decision-making. Although telemetry and sensor systems continuously generate high-resolution data, key operational choices, such as optimal routing, engine loading, or speed adjustment, still rely on human judgment. Zoubir et al. (2025) show that competing pressures, including workload, scheduling demands, and the need to balance autonomy with automation, shape how seafarers implement digital recommendations. Dewan and Godina (2024) further highlight that higher levels of digital literacy and situational awareness among crews correspond with more consistent fuel-saving outcomes. Fuel oil consumption functions not only as a technical performance indicator but also as a behavioral one, reflecting the degree to which human and digital systems operate in harmony.

From a managerial perspective, the financial and operational outcomes of digitalization materialize only when human readiness aligns with technological capacity. Training, clear procedures, and motivational frameworks are essential for converting digital insights into tangible reductions in fuel use and operating costs (Theotokas, Lagoudis, and Raftopoulou 2024). However, these gains are often moderated by competing imperatives: seafarers may prioritize safety margins or scheduling constraints over efficiency (Poulsen et al. 2022), highlighting the need for decision-support systems that reinforce balanced judgment under operational stress (Zoubir et al. 2025).

Overall, the literature points to a deep interconnection between digital capability and human adaptability. Unlike earlier efficiency measures focused solely on machinery or policy compliance, digitalization situates fuel oil consumption at the intersection of human behavior and technological precision (Bayrak and Muslu 2025; Nguyen et al. 2025; Theotokas, Lagoudis, and Raftopoulou 2024). Monitoring and optimizing fuel use therefore provides a direct means of evaluating how human and digital factors interact to shape operational and financial performance.

Despite the growing literature on digitalization, telemetry systems, and fuel performance modelling, empirical studies linking digital monitoring with measurable operational and economic outcomes in real commercial fleets remain limited. Much of the existing research focuses on predictive modelling or algorithmic optimization, while fewer studies examine how digitalization affects actual vessel performance under real commercial operating conditions. Furthermore, the techno-economic implications of telemetry adoption at the fleet level remain insufficiently explored. Addressing this gap, the present study investigates the impact of telemetry-enabled digitalization on fuel oil consumption and economic performance using empirical data from bulk carrier operations.

## 3. Methodology

### 3.1. Data acquisition

To test H1, the parameter 'fuel oil consumption,' measured in tonnes per nautical mile, was selected as the main variable of analysis. The historical data were derived from

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annual reports, noon reports, and high-frequency sensor data collected over a six-year period from a fleet of 51 bulk carriers operated by a leading shipping company. The vessels operate in tramp shipping markets, serving global trade routes including Asia-Europe, the Atlantic basin, China-Australia iron ore trades, South America-Asia grain trades and transoceanic bulk commodity trades. As typical for dry bulk operations, voyage patterns vary depending on charterers' demand and cargo availability.

Noon report data are recorded at 24-hour intervals, whereas high-frequency data are recorded every 60 seconds. Approximately 90% of the shipping company's fleet is equipped with telemetry and high-frequency data acquisition systems. At the outset, the analysis was conducted at the fleet vessel level, comparing data prior to and after the implementation of telemetry. This methodological approach enables researchers to derive new insights from operational data that are not readily available in existing databases.

As the installation period of the telemetry system differed for each vessel, we calculated the mean value of each measured parameter for the period before digitalization and compared it with the mean value for the period after digitalization. This approach allowed us to analyze the data at a fleet level more effectively. Then, we refined our dataset to include data from 31 bulk carriers within the fleet. Vessels without consistent telemetry installation periods during the observation window were excluded to ensure comparability between the pre- and post-digitalization periods. For the purposes of our study, we focused on this subset of 31 vessels outfitted with telemetry and high-frequency data collection systems, classifying them as digitally equipped. To ensure comparability across vessels, the analysis used equivalent observation periods before and after telemetry installation for each vessel. In addition, the within-vessel before-after design helps mitigate the influence of gradual aging effects, as each vessel is compared against its own operational baseline over time. As aging-related performance degradation is typically incremental, its impact is embedded in both pre- and post-digitalization periods and is therefore unlikely to bias the estimated effect of digitalization.

Regarding H2 and again focusing on the subset of 31 bulk carriers, we first compiled all costs associated with the implementation of digitalization at the vessel level. We then conducted a fleet-level analysis to compare fuel oil consumption costs before and after the adoption of telemetry. This comparison was based on equivalent time periods, measured in months, for each vessel, and the results were averaged across the fleet.

To ensure consistency, we normalized the prices of heavy fuel oil (HFO) and marine gas oil (MGO) by calculating the average price per vessel per year, using actual bunkering expense data. From these values, we derived a single average price for each fuel type, which was applied uniformly across the entire six-year period. This approach enabled a consistent comparison of HFO and MGO consumption costs before and after digitalization, based on the annual fuel consumption of each vessel.

The selection of a single shipping company for this empirical study was driven by the intention of concentrating on telemetry-related issues and excluding other factors that might affect the data, as common management practices are implemented across the entire fleet. All selected vessels were managed and operated by the same company, adhered to the same Safety Management System, followed a unified digital strategy, sailed under the same flag, and manned by crews with a common approach fostered by the company's crew department. Selecting vessels under a common management

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structure ensures a standardized operational environment, reducing the influence of confounding factors and strengthening the reliability and validity of the empirical findings.

### 3.2. Data description

The vessels were built between 2010 and 2021, with an average year built of 2015 (Standard Deviation (SD) = 3.21). Descriptive statistics for the fuel oil consumption parameter are presented in Table 1, where the average fuel oil consumption in tonnes per nautical mile prior telemetry (Median (Mdn) = 0.092) had a greater value compared to the fuel oil consumption in tonnes per nautical mile post telemetry (Mdn = 0.086).

## 4. Results

To test H1, the normality of the sample was examined in the first place using Shapiro-Wilk normality test with a significance level of $\alpha = 0.05$. The Shapiro-Wilk test is widely recommended (Monter-Pozos and Gonzalez Estrada 2024), as it allows the use of small sample sizes (<50 samples). The definition of normality assumption is based on the W statistic, which varies from zero to one, where a W value that is close to one indicates a normal distribution of the data. Oppositely, the closer the W value is to zero, the lower the probability that the data will meet a normal distribution (see Figure 1a,b) (De Souza et al. 2023).

The Shapiro-Wilk test on differences in the fuel oil consumption data before and after the implementation of telemetry indicated that we cannot reject the assumption that the data distribution is normal, test statistic W (31) = 0.9557 (which is in the 95% region of acceptance: [0.9321, 1]), *p*-value = 0.2231 ($P(x \leq 0.7616) = 0.7769$). As a result, based on the hypothesis that fuel oil consumption decreases after adopting digital tools, a left-tailed Paired Samples t-test (Langenberg et al. 2023) was applied to conduct the paired analysis of the two samples. In addition, Cohen's effect size (D = 0.333) was calculated. This indicates that the magnitude of the mean difference between the two samples is small.

In Table 2, the value of fuel oil consumption in tonnes per nautical mile was compared before and after the installation of telemetry using a left-tailed Paired Samples t-test, which indicated that fuel oil consumption significantly decreased after the implementation of digital tools as $t_{statistic} < t_{crit95\%}$ ($-1.856 < -1.697$) as well as $p_{value} < \alpha$ ($0.037 < 0.05$).

To identify any potential outliers, the Tukey Fence method, which uses the interquartile range (IQR), was applied (Dastjerdy, Saeidi, and Heidarzadeh 2023). This method allowed us to assess whether any of the 31 difference values (after—before) were extreme enough to potentially distort the results of the paired samples t-test. Using

**Table 1.** Descriptive statistics of fuel oil consumption.[1]

| | N | Mean | Median | SD | SE |
|---|---|---|---|---|---|
| Fuel Oil Consumption Prior Telemetry | 31 | 0.090 | 0.092 | 0.027 | 0.0048 |
| Fuel Oil Consumption Post Telemetry | 31 | 0.076 | 0.086 | 0.029 | 0.0052 |

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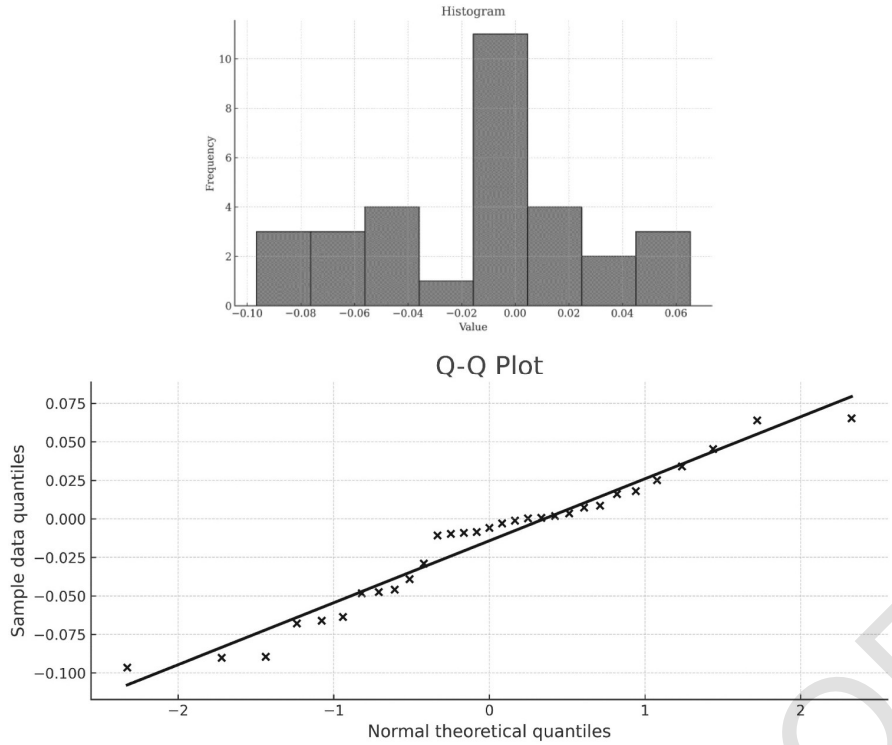


**Figure 1.** a. Histogram for fuel oil consumption differences prior and post telemetry. b. Q-Q plot for fuel oil consumption differences prior and post telemetry. Source: Authors.

**Table 2.** Left-tailed paired samples T-Test for fuel oil consumption.[2]

| | | | | | | | 95% Confidence Interval | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | t-crit95 % | t-statistic | p-value | Mean difference | SD difference | Lower | Upper | Test Power | Cohen's Effect Size |
| Fuel Oil Consumption Before Telemetry | Fuel Oil Consumption After Telemetry | −1.6970 | −1.856 | 0.037 | −0.0142 | 0.0426 | −0.1315 | 0.0926 | 0.8589 | 0.33 |

$H_a$: μ(After - Before) <0.

the standard threshold of k = 1.5 and considering that the minimum and maximum values in the dataset were –0.0965 and +0.0652 respectively, all data points fell within the calculated bounds: Lower fence = −0.1315 and Upper fence = 0.0926. Accordingly, no outliers were detected, supporting the assumption of no extreme outliers and confirming the appropriateness of the paired t-test for this analysis (see Figure 2a–c).

Fuel savings can also be expressed in physical units independent of bunker price fluctuations. Based on the operational dataset, the average sailing distance of the analysed fleet is approximately 53,807.6 nautical miles per vessel per year. Using the estimated reduction in fuel consumption following the implementation of telemetry systems, the

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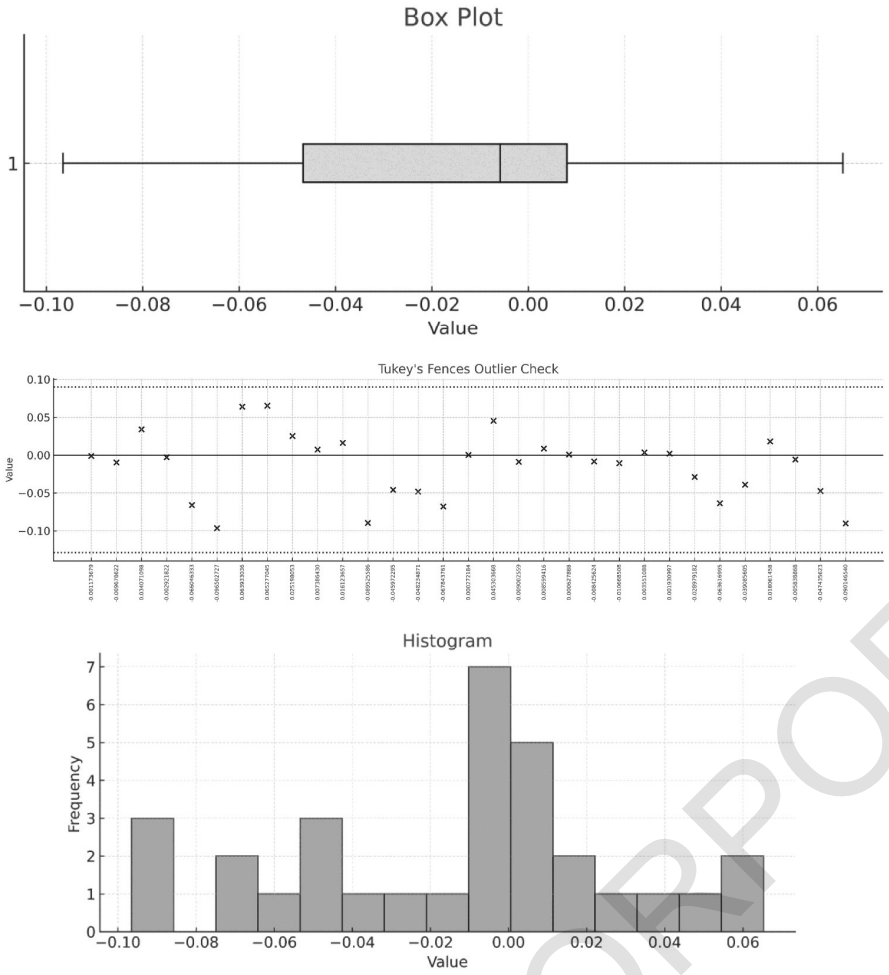


**Figure 2.** a. Box plot for outlier detection using tukey fence method. b. Scatter plot for outlier detection using tukey fence method. c. Histogram for outlier detection using Tukey Fence Method. Source: Authors. Source: Authors.

corresponding fuel savings were calculated for each vessel. The analysis shows that the average annual fuel saving per vessel is approximately 765 metric tons, while the total annual fuel saving across the 31 digitally equipped vessels reaches approximately 23,716 metric tons per year. Expressing savings in physical fuel quantities provides a price-independent indicator of the operational impact of telemetry systems on fleet energy efficiency.

These physical fuel savings form the basis for the subsequent economic evaluation, where the financial benefits of reduced fuel consumption are translated into annual cost savings and investment payback.

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**Table 3.** Descriptive statistics of cost of Bunkers and digitalization investment payback.[3]

| Description | Prior Digitalization Cost of Bunkers ($) | After Digitalization Cost of Bunkers ($) |
|---|---|---|
| Average Monthly Cost | $254,394.14 | $243,004.28 |
| Average Annual Cost | $3,052,729.69 | $2,916,051.31 |
| Annual Savings | $136,678.38 | |
| Digitalization Cost | $757,072.20 | |
| Payback period (years) | 5.54 | |

In Table 3, the descriptive statistics of bunker costs, in relation to the costs associated with digitalization, are presented. The analysis compares bunker costs before and after digitalization, focusing on the resulting financial impact and investment payback. These figures indicate a 4.48% reduction in annual bunker costs post-digitalization (see Figure 3), a notable improvement, especially for large fleets where fuel cost is a major OPEX factor. The bunker price values used in the economic analysis were derived from actual fleet bunkering records during the study period, covering multiple ports, fuel grades, and market conditions, thereby reflecting real operational fuel procurement costs rather than assumed benchmark prices. To ensure comparability across vessels and time periods, bunker prices were normalized by calculating representative average values based on actual fleet bunkering expenses, thereby reducing the influence of short-term regional and market price fluctuations.

$$Percentage\,Reduction = \frac{\text{Savings}}{\text{Prior Digitalization Cost of Bunkers}} \times 100 \quad (1)$$

Based on the annual savings of $136,678.38, the payback period is calculated as follows:

$$Payback\,Period = \frac{\text{Digitalization Cost}}{\text{Annual Savings}} \quad (2)$$

The investment performance in this study is evaluated using the payback period, expressed in years, which represents the time required for fuel savings to recover the initial digitalization investment. This indicates that the digitalization investment breaks even in just over 5.54 years, after which the company continues to benefit from ongoing cost savings.

Given the volatility of bunker fuel markets, the variation in annual savings presented in Table 4 is interpreted as representing alternative bunker price scenarios (pessimistic, base-case, and optimistic). Since the monetary value of fuel savings depends directly on bunker prices, lower annual savings correspond to a pessimistic fuel price environment, the base-case value represents the average bunker price observed during the study period, while higher savings correspond to an optimistic bunker price scenario associated with higher bunker prices. In this way, the sensitivity analysis captures the potential impact of bunker price fluctuations on the economic performance of telemetry-enabled digitalization investments.

To assess how variations in digitalization cost and annual savings influence the payback period, a one-way deterministic sensitivity analysis was conducted, following established approaches in techno-economic and energy investment evaluations (Bilal et al. 2025; McCabe et al. 2020; Vilaplana et al. 2025). This method evaluates

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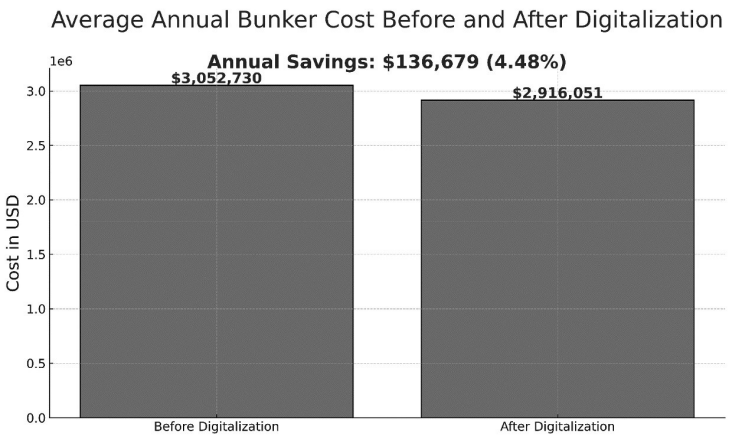


**Figure 3.** Visual comparison of the average annual bunker cost before and after digitalization. Source: Authors.

**Table 4.** Sensitivity analysis under alternative bunker price scenarios (left) and digitalization cost on investment payback (right).[4]

| Sensitivity Table of Annual Savings | | | Sensitivity Table for Digitalization Cost | |
|---|---|---|---|---|
| Scenario | Annual Savings | Payback Period (years) | Digitalization Cost ($) | Payback Period (years) |
| Pessimistic | $109,342.70 | 6.92 | $605,657.76 | 4.43 |
| Low-Intermediate | $123,010.54 | 6.15 | $681,364.98 | 4.99 |
| Base | $136,678.38 | 5.54 | $757,072.20 | 5.54 |
| High-Intermediate | $150,346.22 | 5.04 | $832,779.42 | 6.09 |
| Optimistic | $164,014.05 | 4.62 | $908,486.64 | 6.65 |

the effect of varying one parameter at a time while keeping the remaining parameters constant, allowing identification of the variables that most influence investment outcomes and ensuring the robustness of financial results. Each parameter was varied by ±20% around its base-case value, reflecting potential fluctuations in bunker fuel prices and investment costs commonly observed in maritime markets (Bilal et al. 2025; Vilaplana et al. 2025). This variation approximately reflects historical bunker price volatility observed in global markets during the study period and therefore provides a reasonable representation of potential market uncertainty affecting fuel savings.

In the sensitivity analysis results, the lowest values, indicating faster investment recovery, are highlighted with light grey, while the highest values, indicating slower recovery, are marked with dark grey (see Tables 4 and 5). As annual savings increase, the payback period decreases, meaning the investment is recovered more quickly. The estimated payback ranges from 6.92 years at the lowest savings level to 4.62 years at the highest, representing a variation of approximately 2.3 years across the ±20% range. Conversely, as digitalization cost increases, the recovery period becomes longer. Higher upfront investment increases the time required to recover the digitalization cost, with the

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**Table 5.** Estimated impact of annual savings and digitalization cost on investment payback.[5]

| Variable | Low Value | High Value | Base Value | Difference (High - Low) | Payback Period (Low) | Payback Period (High) | Net Change |
|---|---|---|---|---|---|---|---|
| Annual Savings | $109,342.70 | $164,014.05 | $136,678.38 | $54,671.35 | 6.92 | 4.62 | −2.30 |
| Digitalization Cost | $605,657.76 | $908,486.64 | $757,072.20 | $302,828.88 | 4.43 | 6.65 | 2.22 |

estimated payback ranging from 4.43 years at the lowest cost to 6.65 years at the highest, corresponding to a change of roughly 2.22 years.

The sensitivity analysis demonstrates that the economic viability of telemetry-enabled digitalization remains robust under different market conditions. Even under pessimistic assumptions corresponding to lower bunker price environments, the payback period remains below seven years. Under more favorable fuel price conditions, the payback period decreases to approximately 4.62 years. This relatively narrow range indicates that the investment outcome is not highly sensitive to moderate fluctuations in fuel prices or implementation costs. These findings suggest that telemetry-enabled digitalization remains economically viable across a range of plausible bunker market conditions.

Figure 4 illustrates the impact of annual savings and digitalization cost on the investment payback period.

The results highlight the strategic importance of telemetry-enabled digital monitoring in improving fuel efficiency and operational transparency in shipping. The integration of high-frequency performance monitoring supports data-driven decision-making and represents an important step toward more technologically advanced and energy-efficient maritime operations.

## 5. Discussion and implications

As highlighted in the literature, the effectiveness of digital tools ultimately depends on user engagement; however, this study focuses on the measurable technical and economic outcomes of digitalization. It compares vessel performance before and after the

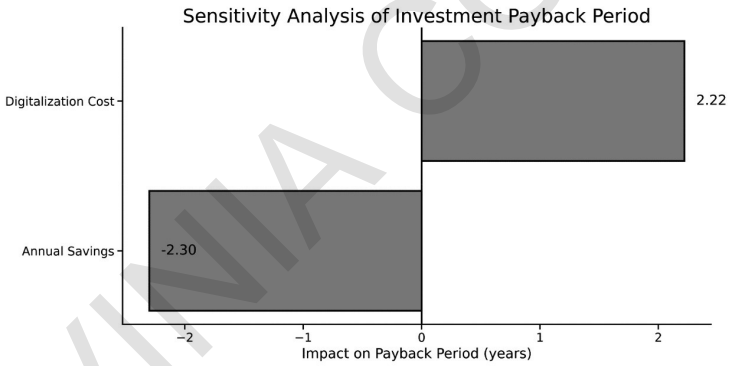


**Figure 4.** Impact of annual savings and digitalization cost on investment payback period (years). Source: Authors.

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implementation of telemetry systems, with particular emphasis on fuel oil consumption and its associated economic implications. The results demonstrate statistically significant reductions in fuel oil consumption following the adoption of onboard digital tools, thereby providing empirical support for the first research hypothesis (H1).

Telemetry systems improve fuel efficiency primarily by enhancing operational transparency and enabling data-driven decision support both onboard and ashore. Continuous monitoring of propulsion parameters such as engine load, shaft power, fuel flow, vessel speed, and environmental conditions allows operators to identify deviations from optimal operating states in near real time. For instance, telemetry data can reveal suboptimal engine loading ranges, unstable speed profiles, inefficient trim conditions, or abnormal increases in fuel consumption under comparable operating conditions. This enables both onboard crews and shore-based technical teams to implement timely corrective actions, including speed optimization, improved engine load management, trim adjustments, and early detection of performance degradation due to hull fouling or machinery inefficiencies.

In contrast to traditional noon reporting, which provides only a single daily observation of vessel performance, high-frequency telemetry enables continuous monitoring and establishes feedback loops between ship and shore. This enhanced visibility supports more informed operational decisions and facilitates the identification of inefficiencies that would otherwise remain undetected. These mechanisms collectively explain the statistically significant reductions in fuel consumption observed in the empirical analysis.

Fuel consumption in maritime transport is influenced by several operational factors, including vessel speed, weather conditions, and routing decisions. In tramp shipping markets such as dry bulk, voyage patterns are determined by charterers' demand and therefore vary across vessels and over time, exposing vessels to diverse environmental and operational conditions. Operational speed may also change depending on freight market dynamics and commercial requirements, such as slow steaming or faster sailing, which can significantly influence fuel consumption levels.

In the present study, these operational influences cannot be fully controlled, as the analysis is based on real commercial fleet operations. However, all vessels in the dataset were managed under the same Safety Management System and operational procedures, thereby reducing managerial and operational heterogeneity. Although detailed operational variables such as weather routing or speed profiles were not explicitly included in the statistical comparison, the before-after design applied to the same fleet ensures that each vessel serves as its own baseline. This allows the analysis to capture the overall operational impact of telemetry adoption while also reducing the influence of gradual aging effects, as such effects are inherently reflected in both pre- and post-digitalization periods. Consequently, the observed improvements in fuel performance should be interpreted as reflecting the contribution of telemetry-enabled monitoring within the context of normal commercial variability.

Furthermore, the techno-economic analysis indicates that the payback period, estimated at 5.5 years, is relatively fast considering that the typical lifecycle of a bulk carrier is around 25 years (Shimotsuura 2024). This finding suggests that investing onboard digitalization systems is economically justified when fuel oil consumption is used as

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the primary evaluation criterion, thereby supporting the second research hypothesis (H2).

In addition to fuel cost savings, improvements in fuel efficiency also have direct implications for exhaust emissions and environmental compliance costs (Fan et al. 2022; Nguyen et al. 2025). Since fuel consumption is closely linked to $CO_2$ emissions, reductions in fuel use translate into lower emission levels, a relationship frequently examined in studies assessing environmental and operational performance in maritime and port systems (Liu et al. 2025). This is particularly relevant in the context of recent regulatory developments such as the inclusion of maritime transport in the European Union Emissions Trading System (EU ETS), under which shipping companies operating in European waters must account for $CO_2$ emission allowances (Altarriba et al. 2025). In this regulatory environment, telemetry-enabled monitoring systems can provide additional value by supporting more precise tracking of fuel consumption and emissions performance, potentially reducing compliance costs associated with carbon pricing mechanisms.

The findings of this study contribute to the growing literature on maritime digitalization by providing empirical evidence linking telemetry-enabled digital monitoring with measurable operational and economic outcomes in commercial shipping. While previous research has largely focused on predictive modelling or algorithmic approaches to fuel consumption estimation, fewer studies have examined how digitalization influences actual vessel performance under real commercial operating conditions. By combining operational fleet data with a techno-economic evaluation of fuel savings and investment payback, this study provides rare empirical insight into how telemetry systems can translate digitalization into tangible efficiency gains and financial benefits in bulk carrier operations.

## 6. Conclusions and directions for future research

The findings of this study highlight the importance of digitalization in enhancing ship performance monitoring. The adoption of telemetry-enabled digital systems leads to measurable improvements in operational efficiency, reflected in reduced fuel consumption, lower emissions, and overall cost savings. These results confirm the strong value proposition of digital investments in maritime operations, demonstrating that data-driven monitoring can translate into tangible operational and economic benefits.

Future research could extend the present analysis by incorporating additional operational parameters such as weather conditions, vessel speed, revolutions per minute, and other main engine variables collected at high frequency. Integrating these factors would enable a more detailed examination of the interaction between operational conditions and performance outcomes, while also supporting a more comprehensive assessment of the economic benefits associated with telemetry-enabled digital monitoring.

As with all empirical research, this study has certain limitations. Vessel aging may influence fuel consumption due to machinery wear and gradual efficiency degradation over time. However, such effects are not necessarily linear or uniformly increasing, as vessel performance is also shaped by maintenance practices, dry-docking schedules, and operational management. In addition, the vessels included

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in the dataset were built between 2010 and 2021, which limits the magnitude of potential aging effects within the analysed period. Nevertheless, the within-vessel before-after design adopted in this study helps reduce the potential influence of such aging effects, as each vessel is evaluated against its own operational baseline over time.

Another limitation relates to the temporal scope of the dataset, which spans approximately six years and therefore constrains the ability to observe longer-term operational trends. Extending the data collection period in future studies would allow a more comprehensive assessment of performance dynamics over time. Furthermore, as the analysis focuses exclusively on bulk carriers, it does not capture the variability present across other vessel types. Expanding the dataset to include a wider range of ship categories would improve the generalizability of the findings.

In addition, some vessels installed their digitalization systems during 2022, which may affect the precision of the pre- and post-implementation comparison. Future research could refine the dataset by excluding such cases or by more precisely defining the observation windows around system installation.

Shipping operations and operating costs are also influenced by broader economic conditions, including fluctuations in bunker fuel prices across regions, fuel grades, and market cycles. Although the economic analysis in this study is based on actual fleet bunkering records, such market dynamics may affect the magnitude of the estimated financial savings and therefore represent an additional area for future investigation.

While this study focuses primarily on quantifiable operational and financial parameters, future research should incorporate behavioral and organizational dimensions to better capture the human-digital interface in maritime efficiency.

Finally, future studies could employ specific fuel oil consumption (SFOC), measured in grams of fuel per kilowatt-hour (g/kWh), as an alternative performance indicator. While fuel oil consumption reflects total fuel use over distance, SFOC provides a more precise measure of engine efficiency, offering additional insights into the performance implications of telemetry-enabled monitoring.

## Notes

1. Source: Authors.
2. Source: Authors.
3. Source: Authors.
4. Source: Authors.
5. Source: Authors.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

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