



Fuel Efficiency and Operational Excellence through Maritime Digitalization

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Abstract

Purpose

This study examines the impact of digitalization on maritime services, focusing on operational efficiency and return on investment (ROI) through the monitoring of fuel oil consumption.

Design/methodology/approach

An empirical analysis was conducted using high-frequency telemetry data from a fleet of 51 bulk carriers over a six-year period (2017–2022). The study utilizes advanced digital platforms to evaluate fuel consumption patterns and includes a ROI analysis to assess the financial viability of digitalization.

Findings

Results indicate that adopting digital platforms for real-time monitoring of fuel oil consumption enhances fleet efficiency and reduces operational costs. The ROI analysis shows that the digitalization investment breaks even in just over 5.54 years, confirming the economic sustainability of such initiatives.

Research limitations/implications

The findings are based on data from a single company, which may limit broader applicability. Future studies could expand to include multiple fleets or sectors for greater generalization.

Originality/value

This is one of the few studies to use real high-frequency data to empirically evaluate maritime digitalization. It provides evidence of both operational and economic benefits, offering practical insights for industry stakeholders considering digital investment.

Keywords: Digitalization, Shipping Performance, Fuel Oil Consumption, Operational Efficiency, OPEX reduction

1 Introduction

Over 80% of global trade is transported by ships, positioning the maritime sector as a major consumer of fuel oil within the transportation industry (Fan *et al.*, 2022). This

heavy reliance on fossil fuels not only highlights the sector's energy intensity but also its environmental impact. The combustion of these finite and non-renewable resources contributes significantly to greenhouse gas emissions and air pollution (Chizubem *et al.*, 2025). Maritime CO₂ emissions alone account for 3% of global emissions, a figure projected to increase by 90–130% by 2050 compared to 2008 levels (Fan *et al.*, 2022; Hu *et al.*, 2022), potentially resulting in 60,000 premature deaths annually due to related air pollutants (Guo *et al.*, 2022).

Beyond environmental concerns, the maritime sector also faces escalating economic pressures. The price of fuel oil has increased more than fourfold in the past decade, averaging a 16% annual rise, thus significantly raising operating costs for ship owners (Hu *et al.*, 2022). Since fuel accounts for a substantial portion of a vessel's OPEX (Zhou *et al.*, 2023), improving fuel efficiency has become not only an ecological imperative but also a financial necessity. Accordingly, a growing body of research has focused on enhancing operational performance to reduce both emissions and costs (Bassam *et al.*, 2022).

One of the most widely accepted short- to medium-term strategies is reducing fuel consumption through performance optimization (Frag *et al.*, 2020). A key driver of operational efficiency lies in minimizing marine fouling on the hull and propeller, which increases resistance and fuel use (Gupta *et al.*, 2022). Although regular cleaning mitigates this issue, it can be costly and may accelerate coating degradation, which in turn reduces efficiency. The current industry standard—scheduled maintenance—may not be the most effective approach, as it doesn't consider the actual performance condition of each vessel. More targeted and condition-based maintenance strategies could lead to better fuel efficiency if in-service performance could be accurately monitored.

This challenge opens the door to the transformative potential of digitalization in the maritime industry. Recent literature highlights how digital technologies are reshaping industrial practices by enabling real-time data analysis, automation, and predictive maintenance (Xu *et al.*, 2023; Dabbous *et al.*, 2023; Cirillo *et al.*, 2021). In the maritime context, smart shipping technologies—such as intelligent navigation, energy efficiency management, and hull monitoring—are increasingly being recognized for their role in optimizing performance and sustainability (Ichimura *et al.*, 2022; Zhang *et al.*, 2024). For example, telemetry and digital integration platforms can support continuous monitoring of hull and propeller condition, enabling data-driven decision-making and optimized cleaning intervals.

Rather than merely adopting a set of isolated digital tools, these developments signal a paradigm shift toward intelligent, adaptive ship management, where economic and environmental performance can be simultaneously improved. Yet, while promising, the adoption of such technologies requires careful consideration of implementation costs, data reliability, and integration into existing operational systems—factors which remain underexplored in current research.

This highlights the imperative need to investigate comprehensively the particular mechanisms by which and to what degree digital technologies may facilitate the monitoring of fuel oil consumption. In this respect, the study aims to shed light on the following research questions:

RQ1: Does the adoption of onboard digital tools lead to a statistically significant reduction in fuel oil consumption across a shipping company's fleet?

RQ2: Is it worth investing in an onboard digitalization system, considering fuel oil consumption as the main evaluation criterion?

The remainder of this paper is structured as follows: Section 2 presents a review of the existing literature to establish the theoretical framework. Section 3 outlines the

methodology used, while Section 4 presents the study's findings along with an analysis of their contribution to addressing the research questions. Section 5 discusses the results and their implications and lastly, Section 6 highlights the study's limitations and suggests potential directions for future research.

2 Literature

2.1 Digitalization Definition

Understanding the concept of digitalization requires attention to both its linguistic construction and practical implications. As Gong and Ribiere (2021) explain, the suffix “-ization” introduces ambiguity by denoting both the process of becoming digital and the state of having been digitalized. This dual interpretation often blurs the line between transformation and outcome. To resolve this ambiguity, they suggest shifting focus toward the results of adopting digital technologies—such as improved simplicity, efficiency, and competitiveness—rather than solely the transition process.

This outcome-oriented perspective is particularly relevant in industry contexts where digitalization does more than automate tasks—it also captures, stores, and analyzes data, creating a digital trace that enables continuous improvement and informed decision-making (Ciarli *et al.*, 2021). Rather than viewing digitalization as a static achievement, it is increasingly recognized as a dynamic enabler of operational intelligence, reshaping organizational structures and strategies.

In the maritime sector, this shift has profound implications. Ichimura *et al.* (2022) define digitalization in shipping as the transformation of traditional business models through the integration of Industry 4.0 technologies. These include real-time analytics, automation, and smart systems that collectively enhance efficiency and innovation. Crucially, this transformation is not merely technical—it is strategic, driving competitiveness and long-term resilience in a traditionally conservative industry.

2.2 Sensor Data

In recent years, advancements in digital technologies have significantly transformed a wide range of industries, including the maritime sector (Chizubem *et al.*, 2025). A broad consensus has emerged around the transformative potential of tools such as Artificial Intelligence (AI), Big Data Analytics (BDA), Machine Learning, Cloud Computing, and the Internet of Things (IoT). These technologies are not only reshaping traditional business operations but are also driving organizational adaptability, innovation, and resilience. Supporting technologies—such as Digital Twin Models, Advanced Simulation, and Digital Security—further enhance real-time decision-making and operational efficiency, while tools like Robotics, Augmented/Virtual Reality (AR/VR), and Additive Manufacturing contribute to dynamic responses to emerging challenges (Cheng *et al.*, 2023).

These digital systems are more than operational aids; they also play a pivotal role in knowledge management by enabling improved data acquisition, dissemination, and utilization across organizations. As Ning Tan *et al.* (2025) note, their implementation has been consistently linked to improved decision-making processes and overall efficiency. In the maritime domain specifically, advances in sensor technologies and digital infrastructure have enhanced the precision and reliability of vessel performance monitoring (Bassam *et al.*, 2022), while digital platforms have improved real-time communication and data analytics across stakeholders (Chizubem *et al.*, 2025).

Despite these benefits, the industry continues to face challenges. One major issue is the fragmented development of ship monitoring technologies, which has led to an over-

reliance on single-source data. Common limitations such as equipment failures, low-resolution inputs (e.g., daily noon reports), and transmission issues reduce data quality and quantity (Cai *et al.*, 2024). For instance, noon reports typically yield just one record per day, severely constraining the temporal resolution needed for accurate performance modeling. This problem is more acute for newbuilds or retrofitted vessels, where limited operational timeframes reduce data availability even further. As Luo *et al.* (2025) emphasize, such sparse datasets are insufficient to reflect true vessel behavior, making the use of high-frequency data essential for meaningful analysis.

To address these limitations, the industry is increasingly adopting digital telemetry systems capable of collecting large volumes of high-quality ship performance data. This evolution is accompanied by a shift toward applying machine learning techniques to develop robust, data-driven models for predicting fuel oil consumption (Cai *et al.*, 2024). These models integrate multiple variables—including ship-specific parameters, environmental conditions, and operational history (e.g., drydocking records)—to produce more accurate and actionable insights. However, their effectiveness still hinges on the availability of large, diverse, and high-quality datasets, highlighting the continued need for investment in data infrastructure and digital integration.

2.3 Fuel Oil Cost

The increasing integration of digital technologies and IoT in maritime operations underscores the strategic importance of fuel oil consumption as both an environmental and economic metric. These tools enable continuous performance monitoring, supporting regulatory compliance while simultaneously offering opportunities to reduce operational costs (Nguyen *et al.*, 2025). When paired with real-time data analytics, fuel oil consumption becomes a key indicator of economic efficiency and can inform predictive maintenance strategies and energy optimization models.

Literature on ship performance monitoring has largely converged around the modeling, prediction, and reduction of fuel oil consumption, reflecting mounting concerns about environmental impacts and escalating fuel costs (Bassam *et al.*, 2022; Fan *et al.*, 2022). These studies emphasize the value of advanced data processing techniques to extract actionable insights, identify operational inefficiencies, and establish correlations between variables influencing ship performance (Bassam *et al.*, 2022).

Modern vessels are increasingly outfitted with high-frequency sensors that capture a broad range of performance data, including variables that reflect a ship's hydrodynamic behavior (Gupta *et al.*, 2022). These sensors not only support fuel efficiency strategies but also enhance maritime safety by enabling real-time monitoring, early-warning systems, and predictive diagnostics (Chizubem *et al.*, 2025).

Reducing fuel oil consumption is therefore not merely a sustainability initiative, but a core component of maritime cost-control and performance management. With fuel expenses accounting for over 60% of a vessel's operating costs (Wang *et al.*, 2023), optimizing consumption plays a pivotal role in achieving financial viability, operational efficiency, and environmental responsibility. Implementing advanced fuel management systems can thus yield substantial economic returns while aligning global sustainability goals.

3 Methodology

3.1 Data Acquisition

To address the first research question of this study, the parameter “fuel oil consumption”, measured in tonnes per nautical mile, was selected for analysis. The historical

data were derived from 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.

During the data preprocessing phase, we removed minor missing values that had no significant impact on the analysis, corrected typographical errors, and excluded outliers deemed unrealistic. The dataset was then grouped by vessel and year, with the number of months before and after the installation of digitalization systems calculated accordingly.

Noon report data were recorded at 24-hour intervals, whereas high-frequency data were collected every 60 seconds. Notably, 90% of the shipping company's fleet is equipped with telemetry and high-frequency data acquisition systems.

The analysis initially focused on the vessel level, comparing operational performance before and after the introduction of telemetry. This methodological approach enabled us to derive insights that would not be accessible through conventional data sources.

Since the telemetry installation timeline varied across vessels, we computed the mean value of each measured parameter for the periods before and after digitalization. This facilitated a more effective fleet-level analysis. Ultimately, the dataset was refined to include 31 bulk carriers equipped with telemetry and high-frequency monitoring systems, which were classified as digitally equipped for the purposes of this study.

Regarding the second research question 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 (SMS), 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 structure ensures a standardized operational environment, reducing the risk of variables that could affect the study results which in turn strengthens 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 (SD = 3.23). The descriptives of fuel oil consumption parameter are presented in **Table 1**.

Table 1. Descriptive Statistics of Fuel Oil Consumption.

N	Mean	Median	SD	SE
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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

4 Empirical Analysis Results

For addressing the first research question of this study, 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 for using 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 (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: $[0.9321, 1]$), $p\text{-value} = 0.2231$ ($P(\chi \leq 0.7616) = 0.7769$). As a result, and basis 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, the effect size Cohen's was calculated $D=0.333$. This indicates that the magnitude of the difference between the average of the differences and the expected average of the differences is small.

As per **Table 1**, the average fuel oil consumption per nautical mile prior telemetry (Mdn = 0.092) had a greater value compared to the fuel oil consumption per nautical mile post telemetry (Mdn = 0.086). In **Table 2**, the value of fuel oil consumption per nautical mile was compared prior and post the installation of telemetry. A left-tailed Paired Samples T-Test indicated that fuel oil consumption significantly decreased after the implementation of digital tools as $t_{\text{statistic}} < t_{\text{crit}95\%}$ ($-1.856 < -1.697$) as well as $p_{\text{value}} < \alpha$ ($0.037 < 0.05$).

Table 2. Left-Tailed Paired Samples T-Test for Fuel Oil Consumption

		t-crit95%	t-statistic	p-value	Mean difference	SD difference	95% Confidence Interval		Test Power	Cohen's Effect Size
							Lower	Upper		
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

Note. $H_a \mu_{\text{Measure After}} - \mu_{\text{Measure Before}} \neq 0$

In addition, to identify any potential outliers, the Tukey Fence method, which uses the interquartile range (IQR), was applied (Dastjerdy *et al.* 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 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 . Therefore, no outliers were detected, supporting the assumption of no extreme outliers and confirming the appropriateness of the paired t-test for this analysis.

In **Table 3**, the descriptive statistics of bunker costs, in relation to the costs associated with digitalization, are presented. The analysis of the data on bunker costs before and after digitalization, focusing on the financial impact and return on investment (ROI). These figures indicate a 4.48% reduction in annual bunker costs post-digitalization— a notable improvement, especially for large fleets where fuel cost is a major OPEX factor.

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

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

$$\text{ROI} = \frac{\text{Digitalization Cost}}{\text{Annual Savings}} \quad (2)$$

This suggests that the digitalization investment breaks even in just over 5.54 years, after which the company continues to benefit from ongoing cost savings.

Table 3. Descriptive Statistics of Cost of Bunkers and Digitalization.

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	
ROI (in years)	5,54	

To assess how variations in digitalization cost and annual savings influence ROI, a sensitivity analysis was conducted (Vilaplana *et al.*, 2025). As annual savings increase, ROI decreases, meaning the payback period shortens. This aligns with expectations: greater savings accelerate the return on investment. ROI ranges from 6.92 years at the lowest savings level to 4.62 years at the highest, showing a variation of approximately 2.3 years across the $\pm 20\%$ range. Conversely, as digitalization cost increases, ROI rises, resulting in a longer payback period. This is also expected: higher upfront investment delays returns. ROI shifts from 4.43 years at the lowest cost to 6.65 years at the highest, a difference of roughly 2.22 years.

Overall, ROI is sensitive to both variables but is slightly more responsive to changes in annual savings (see **Fig. 1**). It behaves inversely with both: a drop in savings or an increase in cost leads to a higher ROI—meaning slower payback.

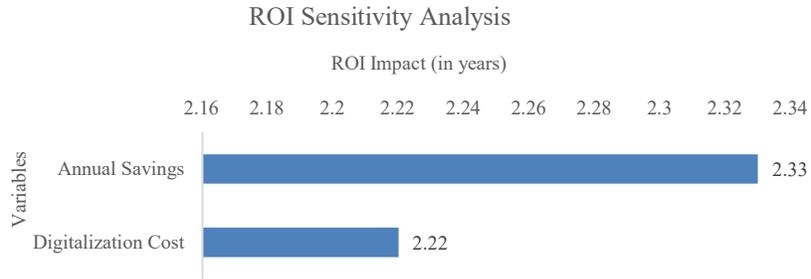


Fig. 1. Impact of Annual Savings and Digitalization Cost on ROI.

5 Discussions and implications

This study makes several contributions to literature. It presents a comparison of ship performance before and after the application of telemetry on the vessels of a shipping company, measuring the impact of various digitalization dimensions on fuel oil consumption while also taking economic data into account. The results show statistically significant differences in fuel oil consumption resulting from the adoption of onboard digital tools, addressing the first research question of this study.

Furthermore, a techno-economic analysis indicates that the return on investment, 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 in an onboard digitalization system is economically justified when fuel oil consumption is used as the primary evaluation criterion, thereby answering the second research question of this study.

The results presented in the previous section of this paper are considered new, particularly because existing literature lacks studies that directly link digitalization to ship performance and economic data. This gap is primarily due to shipping companies, driven by competitive pressures, being often reluctant to share such sensitive information. Integrating digitalization and telemetry highlights a remarkable technological shift adopting digital tools in shipping, optimizing fuel oil consumption monitoring, enhancing ship performance, improving operational efficiency, and enabling data-driven decision-making. This achievement lays the groundwork for future innovations, marking the increasing role of technology in maritime operations, unlocking new opportunities for enhanced ship performance, efficiency, and sustainability in the maritime sector.

6 Limitations and directions for future research

As with academic research, our study has also certain limitations. The primary limitation lies in the fact that our analysis is limited to a dataset that spans merely a six-year timeframe, thereby constraining the temporal scope of our analysis. This limitation affects the ability to identify long-term trends and variations in the data, potentially leading to an incomplete representation of the phenomenon under investigation. Additionally, by focusing solely on one vessel type—bulk carriers—our study does not capture the diversity and variability present across the broader maritime industry. Therefore, to

enhance the comprehensiveness of future research, extending the data collection period would allow for a more in-depth analysis of long-term trends. Additionally, incorporating data from various vessel types would better capture the industry's inherent diversity. This approach would provide researchers with a more holistic and robust understanding of the factors influencing maritime sector performance and dynamics.

Secondly, some vessels installed their digitalization system during 2022. For future research, refining the dataset—either by excluding these vessels or by more precisely defining the periods before and after digitalization implementation—could improve the accuracy of the results.

Finally, shipping operations are influenced by broader economic conditions (e.g., fuel price fluctuations, global trade volumes) that are not captured in this dataset. Ignoring these factors could lead to incomplete conclusions.

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