frontiers | Frontiers in Marine Science

TYPE Original Research
PUBLISHED 01 July 2025
DOI 10.3389/fmars.2025.1587019

OPEN ACCESS

EDITED BY
Junjie Wang,
Nanjing University of Aeronautics and Astronautics, China

REVIEWED BY
Mohamed Neffati,
Imam Muhammad ibn Saud Islamic University, Saudi Arabia
Yiying Jiang,
Dalian University, China
Xiaodong Nie,
Guangdong University of Technology, China

*CORRESPONDENCE
Weiteng Shen
shenweiteng@zwu.edu.cn

RECEIVED 03 March 2025
ACCEPTED 16 June 2025
PUBLISHED 01 July 2025

CITATION
Shen W, Zhong S and Yang X (2025) The effects of digitalization on the quality of marine economic development: evidence from a micro-level perspective.
Front. Mar. Sci. 12:1587019.
doi: 10.3389/fmars.2025.1587019

The effects of digitalization on the quality of marine economic development: evidence from a micro-level perspective

Weiteng Shen[1]*, Shunbin Zhong[2] and Xinhua Yang[3]

[1]School of Business, Zhejiang Wanli University, Ningbo, Zhejiang, China, [2]School of Business, Minnan Normal University, Zhangzhou, Fujian, China, [3]Environmental Assessment and Consulting Institute, Ningbo Research Institute of Ecological and Environmental Sciences, Ningbo, Zhejiang, China

Digitalization is transforming the marine economy at an accelerating pace, yet its effects on the Quality of Marine Economic Development (QMED) and the pathways driving these changes are underexplored. This study investigates these dynamics using an unbalanced panel of 168 A-share listed marine firms in China over the period 2003–2023. We apply a two-way fixed effects model to estimate the effect of digitalization on QMED and explore its mechanisms, complemented by heterogeneity analyses across firm sizes, industry types, government attention, and human capital levels. The results show that digitalization improves QMED, with a 0.01 rise in the digitalization index—about one-fifth of its mean—lifting Total Factor Productivity (TFP) of marine firms by roughly 0.599, or 6.85% of the average TFP. Digitalization boosts QMED by enhancing firms' resource allocation efficiency and spurring technological innovation. Larger firms benefit more than smaller ones, while labor-intensive industries outpace capital-intensive ones in QMED gains. Higher human capital levels weaken digitalization's positive effect on QMED. These findings suggest practical strategies for practitioners, such as adopting cost-effective digital tools like automation and big data analytics in labor-intensive sectors and providing subsidies or financing to support smaller firms' digitalization. These insights highlight digitalization's uneven effects and provide a foundation for targeted policy design to enhance marine economic development.

KEYWORDS

digitalization, marine economic development, total factor productivity, resource allocation efficiency, technological innovation

1 Introduction

As a nation endowed with extensive coastline and abundant marine resources, China views its marine economy as an indispensable pillar of national strategic development. The marine economy has increasingly emerged as a significant contributor to China's overall economic growth, with its contribution to GDP reaching 7.9% by 2023, reflecting a growth rate of 6.0% that surpasses numerous land-based industries (Meng et al., 2024). However, despite remarkable growth, the development pattern of China's marine economy has historically been characterized by extensive resource dependence, inefficient production practices, and significant environmental pressures, thereby raising critical concerns about long-term sustainability and growth quality.

The Chinese government has explicitly recognized these challenges, emphasizing a strategic pivot from extensive growth to high-quality development through advanced technologies, ecological preservation, and sustainable practices. The 13th Five-Year Plan for the National Marine Economy (2016–2020) and the subsequent 14th Five-Year Plan (2021–2025) underscore this transformation by advocating technological innovation, enhanced resource efficiency, and the establishment of green, sustainable marine industrial clusters (Commission, N.D.a.R and Administration, S.O, 2017; Wei et al., 2020). Nevertheless, achieving these ambitious objectives requires profound shifts in how marine enterprises operate, manage resources, and drive innovation.

Digitalization, characterized by the integration of digital technologies such as big data analytics, cloud computing, and artificial intelligence into traditional business processes, has emerged as a crucial transformative force across various sectors of the economy. In recent years, digitalization has demonstrated significant potential to revolutionize traditional industries by enhancing productivity, resource allocation efficiency, and innovation capabilities (Wu et al., 2022; Tian et al., 2023). However, despite the transformative impact digital technologies have demonstrated in terrestrial industries, scholarly attention regarding their implications specifically within marine sectors remains relatively sparse, particularly at micro-level perspective.

Current research largely addresses digitalization's influence on the marine economy from region or industry-wide perspectives (Hong Nham et al., 2023; Fang et al., 2024; Jin et al., 2024), exploring broad trends without capturing the nuanced, firm-level interactions and mechanisms. Yet, it is precisely at the micro-level, within individual marine enterprises, that digital technologies are adopted, integrated, and generate substantial performance improvements. Investigating how digitalization concretely affects marine enterprises, and thus the quality of marine economic development (QMED), is essential for comprehensively understanding its transformative potential. This research gap necessitates in-depth, empirical exploration to clarify whether and how digitalization translates into tangible gains in productivity, resource allocation efficiency, and technological innovation at the firm level.

This study addresses this gap by empirically examining the effects of digitalization on QMED using a detailed panel dataset of 168 A-share listed marine firms in China over the period 2003–2023. Through the application of the two-way fixed effects model, we not only quantify the impact of digitalization on firm-level TFP, but also unravel the underlying mechanisms driving these effects, including resource allocation efficiency and technological innovation. Additionally, this study explores critical dimensions of heterogeneity, such as firm size, industry characteristics, governmental attention, and human capital levels, thereby providing a nuanced understanding of the conditions under which digitalization most effectively promotes high-quality marine economic development.

The paper is structured as follows: Section 2 reviews the literature. Section 3 outlines the research methodology, including the data collection and analysis techniques used to explore the effect of digitalization on QMED. Section 4 presents the empirical results. Finally, Section 5 concludes the paper with policy recommendations and limitations.

2 Literature review

2.1 Digitalization and economic development

Digitalization refers to the widespread adoption and integration of digital technologies such as artificial intelligence (AI), big data analytics, cloud computing, and the Internet of Things (IoT). These technologies significantly enhance economic efficiency, foster innovation, and optimize resource allocation across various sectors (Zeng et al., 2022; Jiang and Li, 2024; Sun et al., 2024b). Existing research on the economic impacts of digitalization has primarily unfolded from two perspectives: macro-level and micro-level.

At the macro level, studies focus on national or city dimensions, investigating whether digitalization significantly promotes economic growth at these scales (Zhang et al., 2024; David et al., 2025). These studies generally find that digitalization drives economic growth. However, some research indicates that while digitalization fosters economic development, it may also exacerbate regional economic disparities (Liu et al., 2024). At the micro level, studies center on firms, examining the impact of digitalization on corporate financial metrics (Ribeiro-Navarrete et al., 2021) and productivity (Cheng et al., 2023). In most cases, integrating digital technologies into firm operations substantially enhances economic performance, though this integration tends to exhibit a stepwise progression (Horvat et al., 2019).

Despite this general acknowledgment of digitalization's economic benefits, research specifically investigating its impact on the marine economy remains relatively limited, necessitating focused studies to understand the unique context and specific outcomes in marine industries.

2.2 Marine economic development and quality concerns

The marine economy is increasingly recognized as a vital component of national economic strategies worldwide. China's marine economy, for instance, has experienced rapid expansion, contributing significantly to GDP and national employment (Jiang et al., 2014; Wang and Wang, 2019). However, this growth has primarily followed an extensive, resource-intensive trajectory characterized by inefficiencies and environmental degradation, raising critical sustainability concerns (Ren et al., 2018).

In response, recent literature advocates a transition from extensive growth to QMED. This transition emphasizes sustainable development, technological innovation, and efficient resource use (Sun et al., 2023a; Ji et al., 2024; Chen et al., 2025). QMED implies improvements not only in quantitative growth indicators but also in qualitative aspects such as resource allocation efficiency, technological innovation, environmental preservation, and overall productivity enhancement (Liu et al., 2021; Feng et al., 2024; Sun et al., 2024a).

Studies on the determinants of QMED have identified several key factors, including financial development (Meng et al., 2024), industrial structure upgrading (Li, 2023), and particularly technological innovation (Feng et al., 2024). These factors have varying degrees of positive impacts on the quality of marine economic development. With the accelerated adoption of digital technologies in the marine sector, a growing body of research has begun to explore their role in shaping QMED. These studies mainly explore the impact of digitalization on green and low-carbon development of the marine economy from a macro-level perspective (Yao et al., 2023; Jin et al., 2024). However, such research remains largely macro-oriented, leaving the micro-level mechanisms—such as how firm-level digital transformation enhances productivity or resource efficiency—relatively unexplored. This gap limits our ability to design targeted policies and fully understand the strategic value of digitalization in advancing QMED.

3 Theoretical analysis and hypotheses

Digitalization is reshaping the marine economy, from fisheries to offshore energy, by introducing technologies like big data analytics and automation that promise to enhance the QMED. The resource-based view (RBV) offers insight into this transformation, suggesting firms gain advantages through unique, hard-to-replicate resources (Kraaijenbrink et al., 2009). In marine sectors, digital tools—such as real-time analytics for optimizing shipping routes or IoT for monitoring fish stocks—act as strategic assets (Munim et al., 2020; Rowan, 2023), streamlining operations and boosting TFP. A fishing company, for instance, might use satellite data to target sustainable harvests, increasing output while preserving ecosystems (Fang et al., 2024). These digital resources, often requiring significant investment, enable firms to refine decision-making and achieve economic gains that competitors struggle to match, particularly in capital-intensive marine industries (Ed-Dafali et al., 2023). This dynamic suggests digitalization directly strengthens QMED by equipping firms with tools to maximize value from existing inputs. This leads to the first hypothesis:

H1: Digitalization significantly enhances the QMED.

Economic efficiency theory sheds light on another pathway, emphasizing how optimal resource use drives economic performance in resource-scarce marine environments. Digital technologies enable precise allocation, such as predictive maintenance in offshore wind farms to minimize downtime (Kou et al., 2022) or data-driven fishery management to prevent overexploitation (Leape et al., 2023). A shipping firm might use AI to optimize fuel consumption, cutting costs and emissions (Huang and Mao, 2024). By reducing waste and aligning resources with operational needs, digitalization enhances TFP, indirectly bolstering QMED. This efficiency is vital in labor-intensive sectors like fisheries, where small improvements yield significant returns. This leads to the second hypothesis:

H2: Digitalization enhances the QMED by improving resource allocation efficiency.

Technological innovation theory highlights digitalization's capacity to spur advancements that redefine marine economic growth. By enabling data-driven research, digital tools foster innovations like AI models for ecosystem forecasting or blockchain for transparent seafood supply chains (Rowan, 2023). A smart port, powered by analytics, might streamline logistics, boosting both trade and sustainability (Liu et al., 2025b). These innovations enhance competitiveness, improve product quality, and reduce environmental impact, contributing to QMED's long-term growth. While larger firms may lead in adopting such innovations, the benefits ripple across the sector. This perspective suggests digitalization drives QMED through new processes and opportunities. This leads to the third hypothesis:

H3: Digitalization enhances the QMED by promoting technological innovation.

4 Methodology and data

4.1 Methodology

To address potential endogeneity arising from omitted variables, this study employs a panel fixed-effects model to examine the impact of digitalization on QMED, utilizing firm-level panel data. The baseline regression model is specified as follows:

$$OceanEco_{it} = \alpha_0 + \beta_1 Digital_{it} + \sum_{j=2}^{7} \beta_j Control_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \quad (1)$$

Where $OceanEco_{it}$ represents the QMED for firm i in year t, measured by TFP. $Digital_{it}$ captures the digitalization level of firm i in year t. $Control_{it}$ is a set of control variables, including firm-level control variables such as firm size, debt level, return on assets, firm age, and equity concentration, as well as city-level control variables such as economic development level and industrial structure. To address omitted variable bias from unobserved heterogeneity, the model incorporates firm fixed effects μ_i to absorb time-invariant firm-specific traits (e.g., managerial practices, coastal proximity) and year fixed effects υ_t to control for macroeconomic shocks (e.g., national policy shifts, global trade fluctuations). The idiosyncratic error term ε_{it} captures residual variations. The coefficient β_1, which is the key focus of this research, is used to capture the impact of

10.3389/fmars.2025.1587019

digitalization on the high-quality development of the marine economy.

4.2 Variables

4.2.1 Dependent variable: QMED

Currently, the measurement of QMED mainly focuses on the sectoral and regional levels. The methods commonly used for this measurement include composite indicator systems based on indicator frameworks and non-parametric approaches based on Data Envelopment Analysis (DEA). Many studies adopt composite indicators to measure QMED. These indicators often consist of various factors such as economic growth rates, resource utilization, environmental sustainability, and social welfare (An et al., 2022; Sun et al., 2023a). These indicators are aggregated into a single composite index to provide an overall assessment of development quality. While this method is comprehensive, the selection of indicators and the weight assigned to each factor can be subjective, leading to potential bias in the results. DEA is widely used in marine economic research for assessing the relative efficiency of decision-making units, such as industries, firms, or regions. The DEA-Malmquist index has been frequently used to calculate TFP changes over time, based on input and output data (Charnes et al., 1978). This method is effective in evaluating the efficiency of marine industries or regional economies, particularly in cases where there are multiple inputs and outputs, such as labor, capital, and marine resources (Xu et al., 2023; Zou et al., 2023).

However, in the measurement of TFP at the enterprise level, semi-parametric methods are more prevalent. Among them, the Olley-Parkes semi-parametric estimation (OP) (Olley and Pakes, 1992) and the Levinsohn-Petrin semi-parametric estimation (LP) (Levinsohn and Petrin, 2003) are commonly used. The LP method builds on the OP method by replacing variables to address the issue of sample loss. Instead of using investment as a proxy variable, the LP method uses intermediate input as a proxy for TFP. As a result, there is less loss of sample size, and it can also effectively tackle the endogeneity problem to obtain consistent and valid estimates of input factors (Van Beveren, 2012). Additionally, since there are disputes regarding the depreciation rate used in the OP method to calculate investment, the investment calculated with different depreciation rates may also have some degree of bias. Following the existing practices for measuring the TFP of enterprises, this study utilizes the LP method to estimate the TFP of publicly listed marine companies. Specifically, the LP method estimates TFP by first specifying a production function using firm-level data like output, labor, capital, and intermediate inputs (like electricity or materials). Instead of using investment data, it uses intermediate inputs to control for unobserved productivity shocks. The method runs a two-step estimation: first to get labor's effect, then to estimate capital's role while accounting for the fact that firms make input decisions based on their own productivity. Finally, the part of output not explained by labor and capital is taken as TFP.

4.2.2 Independent variable: digitalization

Research on digitalization within the marine economy has traditionally emphasized macro-level analyses, often relying on broad proxies such as regional e-commerce transaction volumes (Hong Nham et al., 2023) or digital investment shares in marine equipment manufacturing (He et al., 2022). Studies using Chinese data have crafted composite indices—combining infrastructure spending, R&D intensity, and patent filings—to gauge regional digital maturity (Yao et al., 2023; Fang et al., 2024). In non-ocean economy research, scholars have applied text mining techniques to analyze annual reports of publicly listed companies, using the frequency of digitalization-related keywords to measure the extent of digitalization (Yu et al., 2023; Zhou et al., 2023).

Building on the word frequency analysis method, this study uses the Term Frequency-Inverse Document Frequency (TF-IDF) approach to construct an enterprise digitalization index. The methodology follows these steps:

- Data Collection: Annual reports of China's A-share listed firms were scraped from regulatory platforms. Text extraction utilized Python's PDFBox library to convert PDFs into analyzable formats while preserving structural elements like tables and footnotes.
- Lexicon Development: Drawing from policy documents such as the "14th Five-Year Plan and 2035 Vision Goals," the "Digital Transformation Index Report 2022," and the "Guide to Digital Transformation for SMEs," a corporate digitalization dictionary is developed. This dictionary includes both digital technologies and applications specific to digital business scenarios. The keywords in the dictionary are listed in Table 1.
- Text Processing: Based on the corporate digitalization dictionary, a Jiba Chinese word segmentation feature word library is constructed. Stop words in the annual reports are removed, and Python loop functions are used to extract and segment the text. The frequency of digitalization-related keywords for each company across different years is then calculated, resulting in a yearly dataset of digitalization keyword frequencies.
- TF-IDF Calculation: Following the methodology proposed by Hansen et al. (2018), the TF-IDF approach is applied to calculate the enterprise digitalization index. This method improves the ability to distinguish between keyword categories in text analysis, reducing the underestimation of keywords due to the presence of overly general terms.

4.2.3 Mechanism variables: resource allocation efficiency and technological innovation

For resource allocation efficiency, this study follows the method proposed by Richardson (2006), which has been widely adopted in the literature to identify firms' investment inefficiencies. Rather than using fixed asset investment directly as a proxy, we focus on

TABLE 1 Keywords of enterprise digitalization.

Category	Digitalization -related vocabulary
Artificial Intelligence-related technologies	Artificial Intelligence (AI), Business Intelligence, Image Understanding, Investment Decision Support Systems, Intelligent Data Analysis, Intelligent Robotics, Machine Learning, Deep Learning, Semantic Search, Biometric Technology, Facial Recognition, Voice Recognition, Identity Verification, Autonomous Driving, Natural Language Processing (NLP).
Big Data-related technologies	Big Data, Data Mining, Text Mining, Data Visualization, Heterogeneous Data, Credit Scoring, Augmented Reality, Mixed Reality, Virtual Reality.
Cloud Computing-related technologies	Cloud Computing, Stream Computing, Graph Computing, In-Memory Computing, Secure Multi-Party Computation, Brain-like Computing, Green Computing, Cognitive Computing, Converged Architecture, Mass Concurrency (100 million+), Exabyte (EB)-level Storage, Internet of Things (IoT), Cyber-Physical Systems (CPS).
Blockchain-related technologies	Blockchain, Digital Currency, Distributed Computing, Differential Privacy Technology, Smart Financial Contracts.
Digital technology applications	Mobile Internet, Industrial Internet, Mobile Connectivity, Internet Healthcare, E-commerce, Internet+, Internet Solutions, Mobile Payment, Third-Party Payment, NFC Payment, Smart Energy, B2B, B2C, C2B, C2C, O2O, Networked Services, Smart Wearables, Smart Agriculture, Smart Transportation, Smart Healthcare, Smart Customer Service, Smart Home, Robo-Advisor, Smart Tourism, Smart Environmental Protection, Smart Grid, Smart Marketing, Smart Warehousing, Smart Manufacturing, Smart Logistics, Smart Terminals, Integrated Solutions, Intelligent Equipment, Industrial Cloud, Factory of the Future, Intelligent Fault Diagnosis, Smart Technology, Digital Marketing, Unmanned Retail, Internet Finance, Digital Finance, Fintech, Financial Technology, Quantitative Finance, Open Banking.

the degree of deviation from expected investment behavior to infer potential misallocation of resources. Specifically, we first estimate a firm's expected investment level using Equation 2 and then compute overinvestment to measure firms' investment efficiency.

$$\begin{aligned} INVEST_{i,t} = {} & \beta_0 + \beta_1 GROWTH_{i,t-1} + \beta_2 LEV_{i,t-1} + \beta_3 ROA_{i,t-1} \\ & + \beta_4 AGE_{i,t-1} + \beta_5 SIZE_{i,t-1} + \beta_6 INVEST_{i,t-1} \\ & + \sum INDU + \sum YEAR + \varepsilon_{it} \end{aligned} \tag{2}$$

Where $INVEST_{i,t}$ represents fixed asset investment, calculated as the ratio of the original value of fixed assets to total assets at the beginning of the period. $GROWTH_{i,t-1}$, $LEV_{i,t-1}$, $ROA_{i,t-1}$, $AGE_{i,t-1}$, $SIZE_{i,t-1}$, and $INVEST_{i,t-1}$ correspond to the previous period's main business revenue growth rate, leverage ratio, return on assets, firm age, and total asset size, respectively. $\sum INDU$ and $\sum YEAR$ are industry and year dummy variables.

The residuals from this regression capture unexplained deviations in investment. A positive residual indicates overinvestment, interpreted as a sign of potential inefficiency or misallocation of capital. We define the overinvestment variable as the residual itself when it is positive and assign it a value of zero otherwise (to exclude underinvestment). Thus, higher values of the overinvestment variable indicate a lower degree of resource allocation efficiency. However, when the residual is less than zero (indicating underinvestment), we set the overinvestment variable to zero. This construction ensures that the variable strictly captures excessive investment behavior, which we use inversely to reflect resource allocation efficiency.

Technological innovation is measured using the natural logarithm of the number of patents granted to listed firms plus one.

4.2.4 Control variables

To minimize omitted variable bias, and drawing on related studies (Cheng et al., 2023; Nucci et al., 2023; Sun et al., 2023b; Wang et al., 2024), this research selects a set of control variables at the firm level, including firm size, leverage ratio, return on assets, age, ownership concentration, as well as economic development level and industrial structure at the city level. Firm size is measured by the natural logarithm of total assets. Leverage ratio is the proportion of total liabilities to total assets. Return on assets is represented by the return on equity. Age is calculated as the current year minus the year of firm registration, plus one. Ownership concentration is the proportion of shares held by the top ten shareholders. Economic development level is measured by the natural logarithm of GDP per capita. Industrial structure is represented by the share of the secondary sector in GDP.

4.3 Data sources

This study uses unbalanced panel data from 168 Chinese A-share listed companies engaged in marine economic activities, covering the period from 2003 to 2023. These 168 companies were selected by retaining only A-share listed firms from the sample list of companies included in the China Marine Economy Stock Price Index. The China Marine Economy Stock Price Index, developed under the guidance of the Ministry of Natural Resources and the China Securities Regulatory Commission, and with the support of the Shanghai Stock Exchange and the Shanghai Ocean Bureau, is the first comprehensive index in China to cover the entire market of Shanghai, Shenzhen, Beijing, and Hong Kong. The sample list of constituent companies was determined by the National Marine Information Center and includes 213 companies spanning 20 marine and related industries. The list was compiled from stocks of companies listed on the Shanghai Stock Exchange, Shenzhen Stock Exchange, Beijing Stock Exchange, and Hong Kong Stock Exchange, taking into account factors such as marine attributes, industry coverage, and financial performance, and selecting the highest-ranked stocks. Due to varying degrees of missing data across the sample companies during the study period, the final sample size used for analysis is 1,590.

The data used to measure the TFP of marine-related listed companies, as well as the data for the control variables, are sourced from the CSMAR Database in China. The annual reports of listed companies, which are used to assess digital transformation, are obtained from the Cninfo website. Per capita GDP and the share of the secondary industry in GDP are derived from the China Urban Statistical Yearbook. To ensure data quality, the following preprocessing steps are applied: (1) Exclusion of Financial Firms. Firms in the financial industry are removed from the sample to avoid structural differences that may affect the estimation results. (2) Elimination of Firms in ST and ST Status. Observations where firms are classified as ST (Special Treatment) or *ST in a given year are excluded, as these firms typically face financial distress or operational abnormalities. (3) Winsorization of Continuous Variables. To mitigate the influence of outliers, all continuous variables are winsorized at the 1% and 99% percentiles.

Descriptive statistics for all variables are presented in Table 2. According to Table 2, the actual sample size used in this study is 1,590. This is due to missing annual reports for some listed companies, as well as missing data required for TFP estimation.

5 Results

5.1 Main results

Table 3 presents the estimation results of the impact of digitalization on the quality of the marine economy. Columns (1) and (2) report the estimates without control variables. The results indicate that, regardless of whether year dummy variables are included, digitalization consistently exhibits a significant positive correlation with QMED. Column (3) introduces control variables based on Column (1), leading to a slight reduction in the estimated coefficient of DIGIPOWER, though it remains statistically significant. Column (4) further incorporates year fixed effects on top of Column (3), revealing that while the coefficient of DIGIPOWER remains largely unchanged, its statistical significance improves.

The results in Column (4) suggest that digitalization significantly enhances the quality of marine economic development. Specifically, a 0.01 increase in the digitalization index (approximately 19.31% of its mean) leads to an increase of about 0.599 in the TFP of listed marine enterprises, accounting for approximately 6.85% of the average TFP, demonstrating economic significance.

5.2 Robustness

Table 3 provides preliminary findings on the impact of digitalization on QMED, but further tests are needed to assess the robustness of these results. This study conducts robustness checks from multiple perspectives, with the findings presented in Tables 4, 5.

First, we control for time-varying industry-level factors. Since both the digitalization of listed companies and TFP are closely linked to industry trends, failing to account for this relationship may introduce endogeneity concerns. Column (1) of Table 4 reports the results after adding industry-year interaction fixed effects. The estimates indicate that the coefficient of DIGIPOWER and its statistical significance remain largely unchanged. Second, we consider potential lagged effects. In Column (4) of Table 3, the significant coefficient of contemporaneous DIGIPOWER may not necessarily reflect an immediate impact but could instead capture the influence of past digitalization levels. To examine this, Column (2) of Table 4 includes one-period and two-period lagged values of DIGIPOWER. The results show that while the coefficient of contemporaneous DIGIPOWER decreases slightly, it remains positive and statistically significant. Third, we modify the winsorization standard. To mitigate the influence of outliers, all variables were initially winsorized at the 1st and 99th percentiles before regression estimation. Here, we adjust the winsorization threshold to the 5th and 95th percentiles. The results in Column (3)

TABLE 2 Descriptive statistics.

Variable	Definition	N	Mean	SD	Min	Max
TFP_LP	The QMED measured by TFP	1590	8.7488	1.1454	6.4308	11.1637
DIGIPOWER	Digitalization	1590	0.0518	0.0866	0.0013	0.5307
INEFF	Resource allocation efficiency	1332	0.1574	0.1414	0.0021	0.7773
LNINNO	Technological innovation	1590	2.0761	1.5961	0.0000	5.2040
SIZE	Firm size	1590	23.1498	1.7764	20.1580	28.0356
LEV	Leverage ratio	1590	0.4938	0.1894	0.0787	0.8937
ROE	Return on net assets	1590	0.0645	0.1027	-0.4166	0.3291
FIRMAGE	Firm age	1590	2.8417	0.3850	1.6094	3.4657
TOP10	Ownership concentration	1590	0.6309	0.1603	0.2743	0.9614
LNPERGDP	The level of economic development in the prefecture-level city where the firm is located	1590	11.4295	0.5615	9.5940	12.2075
SECOND_GDP	The proportion of the secondary industry in GDP (%)	1590	38.1719	11.3799	14.9100	59.0300

TABLE 3 Effects of digitalization on QMED.

Variable	(1)	(2)	(3)	(4)
	QMED	QMED	QMED	QMED
DIGIPOWER	357.690***	149.798***	55.011**	59.918***
	(46.411)	(36.309)	(24.934)	(20.338)
SIZE			0.564***	0.557***
			(0.033)	(0.035)
LEV			0.164	0.190
			(0.151)	(0.149)
ROE			1.225***	1.202***
			(0.097)	(0.093)
FIRMAGE			0.063	-0.120
			(0.059)	(0.136)
TOP10			-0.516***	-0.519***
			(0.107)	(0.088)
LNPERGDP			0.021	-0.122**
			(0.044)	(0.052)
SECOND_GDP			0.001	0.003
			(0.003)	(0.003)
Constant	8.564***	7.314***	-4.626***	-2.869***
	(0.092)	(0.037)	(0.707)	(0.901)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
N	1590	1590	1590	1590
Within R-squared	0.087	0.430	0.715	0.727

** and *** denote the significance at the 10%, 5%, and 1% levels, respectively. Figures in () are Driscoll-Kraay standard errors, as proposed by Driscoll and Kraay (1998).

of Table 4 indicate that DIGIPOWER remains significantly positive. Fourth, we control for the level of digitalization in the prefecture-level city where the firm is located. The observed impact of firm-level digitalization on QMED may actually reflect the broader digitalization environment of the city. To account for this, we measure city-level digitalization using the artificial intelligence index of the firm's location and include it as a control variable. The results in Column (4) of Table 4 show that the coefficient and statistical significance of DIGIPOWER remain largely unchanged. Fifth, we modify the model specification. QMED across different years may exhibit serial correlation, meaning that current QMED could influence future values. To address this, we extend Equation 1 by including the lagged term of QMED on the right-hand side and employ a dynamic panel estimation approach. Column (5) of Table 4 reports the system GMM estimation results, which confirm that the coefficient of DIGIPOWER remains significantly positive. Sixth, endogeneity. There may be endogeneity concerns arising from bidirectional causality between digitalization and the quality of marine economic development. To address this, Column (6) in Table 4 presents two-stage least squares estimation results using lagged digitalization as an instrumental variable. The results indicate that the estimated coefficient for digitalization remains statistically significant and positive.

Seventh, we examine the nonlinear impact of digitalization on QMED. Existing studies suggest that digitalization may exhibit a nonlinear effect on TFP (Pan et al., 2022; Cheng et al., 2023; Liu et al., 2025a). Such a nonlinear relationship may also exist in the marine economy. To test this, we employ a panel threshold model to investigate whether digitalization exerts a nonlinear influence on the TFP of marine enterprises. The results of the single-threshold and double-threshold tests are reported in Columns (1) and (2) of Table 5, respectively. As shown, the p-values for both tests exceed 0.1, indicating that neither a single nor a double threshold effect is present. This suggests that digitalization does not exhibit a nonlinear impact on QMED within the examined context.

5.3 Mechanisms

To further explore the underlying mechanisms through which digitalization influences QMED, we conduct a series of mechanism tests. Specifically, we examine whether digitalization affects QMED through improvements in resource allocation efficiency and innovation capability.

5.3.1 Resource allocation mechanism

According to X-efficiency theory (Leibenstein, 1975), firms often experience suboptimal resource allocation due to incomplete information, poor managerial decision-making, and rigid operational structures. In traditional marine industries, inefficiencies arise due to: Delays in information flow, Inefficient capital utilization, and Labor misallocation. Digitalization addresses these inefficiencies by enhancing data-driven decision-making. Big data analytics improve firms' ability to predict demand, ensuring that resources are allocated more effectively (Zamani et al., 2023). AI-driven predictive maintenance minimizes equipment downtime, optimizing capital usage (Chen et al., 2021). Automated scheduling systems in ports and shipping logistics reduce idle time and labor redundancy (Muñuzuri et al., 2020). By reducing information asymmetry and managerial slack, digitalization closes the X-efficiency gap, leading to a negative relationship between digitalization and resource misallocation.

The empirical result in Column (1) of Table 6, which shows a significantly negative coefficient for DIGIPOWER, suggests that digitalization improves resource allocation efficiency in marine enterprises. This means that as firms undergo digital transformation, they reduce resource misallocation, thereby optimizing the deployment of labor, capital, and technology.

5.3.2 Innovation mechanism

One of the central tenets of Endogenous Growth Theory is that technological progress is driven by knowledge accumulation and

TABLE 4 Robustness checks.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	QMED	QMED	QMED	QMED	QMED	QMED
L_TFP_LP					0.8026***	
					(0.0498)	
L2_TFP_LP					-0.0814*	
					(0.0443)	
DIGIPOWER	68.3662**	32.3988*	70.2127**	59.1633***	16.5581**	91.5732***
	(31.2853)	(18.5659)	(32.5281)	(20.6452)	(7.5833)	(30.4013)
L1_DIGIPOWER		20.2056				
		(20.3504)				
L2_DIGIPOWER		-1.7750				
		(13.6776)				
AI				0.0378*		
				(0.0205)		
SIZE	0.5780***	0.5874***	0.5337***	0.5568***	0.5568***	0.5677***
	(0.0819)	(0.0361)	(0.0256)	(0.0354)	(0.0354)	(0.0199)
LEV	0.1228	-0.0725	0.0904	0.1888	0.1888	0.1151
	(0.1773)	(0.1250)	(0.1285)	(0.1491)	(0.1491)	(0.0860)
ROE	0.9173***	1.1279***	1.6718***	1.1950***	1.1950***	1.2105***
	(0.0951)	(0.1060)	(0.0832)	(0.0944)	(0.0944)	(0.0945)
FIRMAGE	-0.3259	-0.4259**	0.0048	-0.1168	-0.1168	-0.3060**
	(0.2915)	(0.1759)	(0.1223)	(0.1395)	(0.1395)	(0.1294)
TOP10	-0.5159***	-0.4092***	-0.5678***	-0.5255***	-0.5255***	-0.4805***
	(0.1752)	(0.1079)	(0.1006)	(0.0868)	(0.0868)	(0.1252)
LNPERGDP	-0.1265**	-0.2297***	-0.1025*	-0.1212**	-0.1212**	-0.1732**
	(0.0458)	(0.0692)	(0.0537)	(0.0494)	(0.0494)	(0.0704)
SECOND_GDP	0.0036	0.0021	0.0009	0.0031	0.0031	-0.0001
	(0.0040)	(0.0032)	(0.0022)	(0.0028)	(0.0028)	(0.0034)
Hansen p-value					0.836	
AR(1) p-value					0.000	
AR(2) p-value					0.272	
N	1560	1089	1590	1586	1089	1292

*, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively. Figures in () are robust standard errors clustered at firm level. Column (1) controls for firm fixed effects, year fixed effects, and the interaction of industry and year fixed effects. Columns (2)-(4) control for firm and year fixed effects, while the dynamic panel model estimation in Column (5) includes year dummy variables.

spillovers (Aghion et al., 1998). Digitalization enhances knowledge diffusion and collaborative innovation (Di Vaio et al., 2021), which are critical for marine enterprises engaged in cutting-edge fields such as marine biotechnology, offshore renewable energy, and smart maritime logistics. Marine enterprises leveraging AI-driven data analytics can quickly process vast amounts of research on marine resource utilization, enabling them to accelerate product development and technological breakthroughs (Gesami and Nunoo, 2024). Cloud computing and digital collaboration enable real-time knowledge sharing between firms, research institutions, and governments, reducing the time required to develop and commercialize innovations (Vance et al., 2019).

The finding in Column (2) of Table 6, which indicates a statistically significant positive coefficient for DIGIPOWER, suggests that digitalization significantly enhances the technological innovation capacity of marine enterprises.

TABLE 5 Estimated results using the threshold model.

Variable	(1)	(2)
	QMED	QMED
DIGIPOWER(DIGIPOWER ≤ 0.0471)	146.0346*** (34.0523)	326.1458***
		(97.6814)
DIGIPOWER(0.0471<DIGIPOWER ≤ 0.2944)		162.3430***
		(34.9474)
DIGIPOWER(DIGIPOWER>0.2944)	69.4542***	78.1656***
	(24.0236)	(24.3571)
SIZE	0.5068***	0.5113***
	(0.0359)	(0.0359)
LEV	0.1236	0.1171
	(0.1449)	(0.1445)
ROE	1.1198***	1.1194***
	(0.1330)	(0.1326)
FIRMAGE	0.6561***	0.6396***
	(0.1587)	(0.1585)
TOP10	-0.0424	-0.0450
	(0.1978)	(0.1972)
LNPERGDP	-0.2050*	-0.2129**
	(0.1064)	(0.1061)
SECOND_GDP	0.0015	0.0017
	(0.0042)	(0.0042)
Single threshold effect test (p-value)	0.1533	0.1533
Double threshold effect test (p-value)		0.8700

*, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively. Figures in () are standard errors.

TABLE 6 Mechanism test results.

Variable	(1)	(2)
	INEFF	LNINNO
DIGIPOWER	-0.131***	3.947***
	(0.039)	(1.179)
SIZE	0.045**	0.419***
	(0.021)	(0.045)
LEV	0.075***	-0.281
	(0.024)	(0.218)
ROE	0.107***	-0.545**
	(0.035)	(0.228)
FIRMAGE	0.048	-0.186
	(0.055)	(0.263)
TOP10	0.054	-0.557
	(0.052)	(0.424)
LNPERGDP	-0.061*	0.134
	(0.033)	(0.140)
SECOND_GDP	0.002*	-0.019***
	(0.001)	(0.005)
Constant	-0.432	-8.236***
	(0.276)	(1.862)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	1332	1590
Within R-squared	0.103	0.513

*, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively. Figures in () are Driscoll-Kraay standard errors.

5.4 Heterogeneity analysis

5.4.1 Firm size heterogeneity

Firm size plays a crucial role in shaping the relationship between digitalization and the quality development of the marine economy. The heterogeneity in firm size can lead to significant variations in how digital technologies are adopted, integrated, and leveraged for economic gains. Examining firm size heterogeneity provides deeper insights into the differential effects of digitalization across businesses with varying capacities, resources, and structural constraints.

To examine the heterogeneity of firm size, we classify all firms into large-scale and small-scale categories based on the median value of the natural logarithm of total assets. A firm size dummy variable is then constructed, and an interaction term between digitalization and firm size (DIGIPOWER*GROUP) is introduced into the model. Column (1) of Table 7 presents the corresponding estimation results. The results show that the estimated coefficient of DIGIPOWER*GROUP is significantly negative, indicating that, compared to small-scale firms, digitalization has a greater positive effect on QMED in large-scale firms.

This finding can be theoretically understood through the lens of absorptive capacity theory and scale-related digital complementarities. Larger firms typically possess more financial, technical, and human capital resources, enabling them to implement complex digital systems and align them with their strategic goals. They also benefit from economies of scale in digital investment, where the marginal cost of deploying digital tools decreases with firm size. Moreover, larger organizations often exhibit greater institutional readiness, including formal IT departments and digital governance frameworks, which support more efficient transformation processes. In contrast, small firms may face structural barriers—such as credit constraints and digital skill shortages—that limit the impact of digitalization on their productivity.

5.4.2 Industry heterogeneity

Industry heterogeneity plays a crucial role in determining how different sectors respond to digitalization. Industries within the marine economy vary significantly in terms of capital intensity, technological adoption rates, regulatory constraints, and market structures. Ignoring these differences could lead to misleading conclusions about the true impact of digitalization across various marine-related sectors.

To this end, this study classifies the industries of listed firms into capital-intensive and labor-intensive categories and constructs a dummy variable CAPIN, which takes the value of 1 if the firm belongs to a capital-intensive industry and 0 otherwise. Based on this, an interaction term between CAPIN and digitalization (DIGIPOWER*CAPIN) is introduced. The estimation results in Column (2) of Table 7 show that the coefficient of DIGIPOWER*CAPIN is statistically significant and negative,

TABLE 7 Heterogeneity test results.

Variable	(1)	(2)	(3)	(4)
	TFP_LP	TFP_LP	TFP_LP	TFP_LP
DIGIPOWER	0.203	1.078***	0.422	3.262***
	(0.156)	(0.236)	(0.310)	(0.421)
DIGIPOWER*GROUP	0.876***			
	(0.263)			
DIGIPOWER*CAPIN		-0.747***		
		(0.196)		
DIGIPOWER*INFRAFOCUS			38.930	
			(68.837)	
DIGIPOWER*HUMCAP				-0.034***
				(0.004)
SIZE	0.547***	0.577***	0.502***	0.532***
	(0.034)	(0.037)	(0.038)	(0.035)
LEV	0.223	0.092	0.248*	0.270*
	(0.152)	(0.155)	(0.140)	(0.128)
ROE	1.191***	1.174***	1.444***	1.161***
	(0.097)	(0.101)	(0.115)	(0.129)
FIRMAGE	-0.117	-0.156	-0.076	-0.238***
	(0.133)	(0.145)	(0.143)	(0.066)
TOP10	-0.536***	-0.558***	-0.297***	-0.505***
	(0.086)	(0.119)	(0.090)	(0.081)
LNPERGDP	-0.117**	-0.151**	-0.119***	-0.112*
	(0.053)	(0.056)	(0.038)	(0.061)
SECOND_GDP	0.003	0.003	0.000	-0.001
	(0.003)	(0.003)	(0.004)	(0.004)
Constant	-2.724***	-2.835***	-2.038**	-1.310***
	(0.863)	(0.789)	(0.833)	(0.365)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1590	1440	1047	1371
Within R-squared	0.728	0.728	0.759	0.688

*, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively. Figures in () are Driscoll-Kraay standard errors.

indicating that the digitalization benefits for firms in capital-intensive industries are lower than those for firms in labor-intensive industries. This appears counterintuitive, as capital-intensive firms are expected to have better conditions for digitalization compared to labor-intensive firms. However, this result is consistent with the idea of diminishing marginal returns to digital capital in sectors that are already technologically saturated. Capital-intensive industries often have well-established digital infrastructure (e.g., port automation, marine extraction technologies), and incremental investments in digital tools may generate only marginal efficiency gains. On the other hand, labor-intensive industries such as fisheries and logistics have higher transformation elasticity—meaning that even basic digital upgrades (e.g., mobile inventory systems, digital transactions) can lead to significant improvements in process efficiency and economic performance. This aligns with catch-up theory, where sectors with lower initial digital maturity gain more from marginal investments.

5.4.3 government attention heterogeneity

Different cities vary in digital infrastructure, economic development, policy incentives, industrial structure, and labor market conditions. These factors influence how effectively marine enterprises can integrate digital technologies, which in turn affects the extent to which digitalization improves economic quality. Ignoring these city-level differences could lead to overgeneralized conclusions that fail to capture the nuanced effects of digitalization across different urban environments. This section focuses on the heterogeneity in local government attention to digitalization in the regions where firms are located. This study measures local government attention to digitalization based on the proportion of digital infrastructure-related keywords in the government work reports of the prefecture-level cities where listed marine enterprises are located. The specific calculation process is as follows. First, government work reports from various years for the prefecture-level cities of listed marine companies are collected and digital infrastructure-related keywords are identified. Second, Python is used to segment the text of these reports, count the total number of words and the number of occurrences of digital infrastructure-related terms, and calculate their proportion in the reports. This proportion serves as an indicator of local government attention to digital infrastructure. Furthermore, an interaction term DIGIPOWER*INFRAFOCUS is constructed to examine the relationship between firm-level digitalization and government attention to digital infrastructure.

The results in Column (3) of Table 7 show that while the estimated coefficient of DIGIPOWER_INFRAFOCUS is positive, it is not statistically significant. This suggests that there is insufficient statistical evidence to conclude that the level of government attention to digitalization affects the benefits of digitalization. One possible theoretical explanation is that government attention alone does not guarantee effective policy implementation or firm-level digitalization. Institutional support must be accompanied by firm-level absorptive capacity, infrastructure quality, and local digital ecosystems to materialize into measurable performance gains. The result may also reflect policy-practice asymmetry—where high-level signals of support do not translate into operational or financial support that firms can access.

5.4.4 Human capital heterogeneity

Digitalization is not just about technology adoption—it requires a skilled workforce capable of adapting to new digital tools, optimizing processes, and driving innovation. Simply investing in AI, automation, blockchain, and IoT does not automatically lead to improved economic quality—firms need digitally literate employees who can leverage these technologies effectively. This section examines the heterogeneous impact of digitalization on QMED from the perspective of human capital. To measure human capital levels, we use the proportion of employees with an associate degree or higher and construct an interaction term between human capital and digitalization (DIGIPOWER*HUMCAP).

The results in Column (4) of Table 7 show that the estimated coefficient of DIGIPOWER*HUMCAP is statistically significant and negative, indicating that the higher the human capital level in marine enterprises, the weaker the positive effect of digitalization on QMED. This may appear counterintuitive, but it can be interpreted through the concepts of organizational inertia, skill redundancy, and adjustment costs. High human-capital firms are typically engaged in R&D, information services, or precision industries, where work processes are already knowledge-intensive and optimized. In such contexts, large-scale digital upgrades may disrupt existing systems, require significant retraining, and introduce coordination costs. Furthermore, when human capital is already high, the marginal utility of digital tools diminishes, as digital systems may not drastically improve workflows already operating near capacity. This aligns with skill-mismatch theory, where even highly educated employees may face misalignment when new technologies shift required competencies or workflows.

6 Conclusion and discussion

6.1 Conclusion

The rapid advancement of digitalization in the marine economy contrasts with the relatively limited research exploring its impact on QMED and underlying mechanisms. Utilizing an unbalanced panel dataset comprising 168 A-share listed marine enterprises in China from 2003 to 2023, this study employed a two-way fixed effects model to empirically examine digitalization's influence on QMED and its transmission mechanisms. Additionally, heterogeneity was analyzed from four perspectives: firm size, industry type, government attention, and human capital.

The results of this study indicate that digitalization significantly enhances QMED. Specifically, a 0.01 increase in the digitalization index (approximately 19.31% of its mean) leads to an increase of about 0.599 in the TFP of listed marine enterprises, accounting for approximately 6.85% of the average TFP, demonstrating economic significance. These findings remain robust after a series of robustness checks. The mechanism analysis further reveals that digitalization boosts QMED by enhancing firms' resource allocation efficiency and spurring technological innovation. Heterogeneity tests based on firm size suggest that digitalization in larger firms has a stronger positive effect on QMED compared to smaller firms. Industry-type heterogeneity indicates that digitalization in labor-intensive industries contributes more to QMED than in capital-intensive ones. Tests of government attention show that digitalization's effect on QMED does not vary with the level of government focus. Finally, heterogeneity analysis by human capital reveals that the positive impact of digitalization on QMED diminishes as human capital levels rise.

6.2 Theoretical implications

This research extends the theoretical understanding of digitalization's role in economic development by integrating insights from the resource-based view and technological innovation theory. It illustrates the specific channels—resource allocation and innovation capabilities—through which digitalization influences firm-level productivity and economic development, thus enriching the broader discourse on digital transformation in marine economies. Furthermore, this study contributes to institutional theory by highlighting the interplay between digitalization and firm-level institutional contexts, such as government attention and human capital, thus revealing nuanced conditions under which digital transformation yields varying outcomes. Additionally, the integration of heterogeneity analyses deepens our understanding of how firm-specific characteristics, including size and industry type, influence the magnitude of digitalization benefits. This broader theoretical synthesis helps build a more comprehensive framework for understanding digitalization's multifaceted impact in complex economic environments.

6.3 Practical implications

Despite focusing on listed enterprises, the findings hold valuable implications for smaller, non-listed marine companies in China. Policymakers should consider targeted incentives, such as subsidies and favorable financing options, to facilitate digital infrastructure adoption among smaller marine firms, thereby overcoming initial cost barriers and enhancing resource efficiency.

Given the pronounced benefits of digitalization in labor-intensive marine industries, targeted policies such as tax incentives and technical assistance for adopting digital tools (e.g., automation, big data analytics) should be prioritized in fisheries and traditional shipping sectors. Furthermore, since higher human capital levels correlate with diminishing returns from digitalization, policymakers must balance digital investments with continuous workforce training and skill development programs to sustain long-term productivity improvements.

This study also holds broader relevance for maritime economies beyond China, particularly in developing nations where digital infrastructure and human capital vary considerably. Developing maritime economies can benefit from China's experience by adopting tailored strategies aligned with their specific resource capacities and developmental stages. Countries at an early stage of digital adoption could initially focus on cost-effective digital tools, supported by international assistance and knowledge exchange initiatives. Over time, incremental investments in digital infrastructure coupled with human capital development could foster sustainable and resilient marine economic growth globally.

6.4 Limitations and future research

Nevertheless, this study has several limitations. First, due to data availability constraints, the analysis relies exclusively on A-share listed marine-related companies. While these firms represent a significant portion of the formal marine economy, they do not reflect the full diversity of the sector, particularly small and medium-sized enterprises or firms operating in informal or non-listed segments. As such, the generalizability of our findings may be limited. Future research should strive to include a broader range of marine enterprises to ensure more comprehensive and representative insights into how digitalization affects marine economic development.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://data.csmar.com/.

Author contributions

WS: Conceptualization, Formal Analysis, Methodology, Writing – original draft. SZ: Data curation, Software, Supervision, Writing – review & editing. XY: Resources, Validation, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was supported by the Soft Science Research Program of Zhejiang Province (Grant No. 2024C35085), the Fujian Provincial Social Science Foundation Project (FJ2025B029), and the Beilun District Philosophy and Social Sciences Planning Project (BLSK25-1-25).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Aghion, P., Howitt, P., Brant-Collett, M., and García-Peñalosa, C. (1998). *Endogenous growth theory.* (London, England: MIT press).

An, D., Shen, C., and Yang, L. (2022). Evaluation and temporal-spatial deconstruction for high-quality development of regional marine economy: A case study of China. *Front. Mar. Sci.* 9. doi: 10.3389/fmars.2022.916662

Charnes, A., Cooper, W. W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *Eur. J. Operational Res.* 2, 429–444. doi: 10.1016/0377-2217(78)90138-8

Chen, J., Lim, C. P., Tan, K. H., Govindan, K., and Kumar, A. (2021). Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments. *Ann. Operations Res.* 1-24. doi: 10.1007/s10479-021-04373-w

Chen, Y., Zhang, H., and Pei, L. (2025). The development trend of China's marine economy: a predictive analysis based on industry level. *Front. Mar. Sci.* 12. doi: 10.3389/fmars.2025.1544612

Cheng, Y., Zhou, X., and Li, Y. (2023). The effect of digital transformation on real economy enterprises' total factor productivity. *Int. Rev. Economics Finance* 85, 488–501. doi: 10.1016/j.iref.2023.02.007

Commission, N.D.a.R and Administration, S.O (2017). *13th five-year plan for the development of China's marine economy*, (ed.) S.C.o.t.P.s.R.o. China. Available online at: https://zfxxgk.ndrc.gov.cn/web/iteminfo.jsp?id=419.

David, L. K., Wang, J., Brooks, W., and Angel, V. (2025). Digital transformation and socio-economic development in emerging economies: A multinational analysis. *Technol. Soc.* 81, 102834. doi: 10.1016/j.techsoc.2025.102834

Di Vaio, A., Palladino, R., Pezzi, A., and Kalisz, D. E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. *J. Business Res.* 123, 220–231. doi: 10.1016/j.jbusres.2020.09.042

Driscoll, J. C., and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Rev. Economics Stat* 80, 549–560. doi: 10.1162/003465398557825

Ed-Dafali, S., Al-Azad, M. S., Mohiuddin, M., and Reza, M. N. H. (2023). Strategic orientations, organizational ambidexterity, and sustainable competitive advantage: Mediating role of industry 4.0 readiness in emerging markets. *J. Cleaner Production* 401, 136765. doi: 10.1016/j.jclepro.2023.136765

Fang, X., Zhang, Y., Yang, J., and Zhan, G. (2024). An evaluation of marine economy sustainable development and the ramifications of digital technologies in China coastal regions. *Economic Anal. Policy* 82, 554–570. doi: 10.1016/j.eap.2024.03.022

Feng, M., Guan, H., Wang, Y., and Liu, Y. (2024). Research on the impact mechanism of scientific and technological innovation on the high-quality development of the marine economy. *Front. Mar. Sci.* 11-2024. doi: 10.3389/fmars.2024.1341063

Gesami, B. K., and Nunoo, J. (2024). Artificial intelligence in marine ecosystem management: addressing climate threats to Kenya's blue economy. *Front. Mar. Sci.* 11. doi: 10.3389/fmars.2024.1404104

Hansen, S., McMahon, M., and Prat, A. (2018). Transparency and deliberation within the FOMC: A computational linguistics approach*. *Q. J. Economics* 133, 801–870. doi: 10.1093/qje/qjx045

He, X., Ping, Q., and Hu, W. (2022). Does digital technology promote the sustainable development of the marine equipment manufacturing industry in China? *Mar. Policy* 136, 104868. doi: 10.1016/j.marpol.2021.104868

Hong Nham, N. T., Mai Hoa, T. T., and Ha, L. T. (2023). Influences of digitalization on sustaining marine minerals: A path toward sustainable blue economy. *Ocean Coast. Manage.* 239, 106589. doi: 10.1016/j.ocecoaman.2023.106589

Horvat, D., Kroll, H., and Jäger, A. (2019). Researching the effects of automation and digitalization on manufacturing companies' Productivity in the early stage of industry 4.0. *Proc. Manufacturing* 39, 886–893. doi: 10.1016/j.promfg.2020.01.401

Huang, R., and Mao, S. (2024). Carbon footprint management in global supply chains: A data-driven approach utilizing artificial intelligence algorithms. *IEEE Access* 12, 89957–89967. doi: 10.1109/ACCESS.2024.3407839

Ji, J., Chi, Y., and Yin, X. (2024). Research on the driving effect of marine economy on the high-quality development of regional economy – Evidence from China's coastal areas. *Regional Stud. Mar. Sci.* 74, 103550. doi: 10.1016/j.rsma.2024.103550

Jiang, W., and Li, J. (2024). Digital transformation and its effect on resource allocation efficiency and productivity in Chinese corporations. *Technol. Soc.* 78, 102638. doi: 10.1016/j.techsoc.2024.102638

Jiang, X.-Z., Liu, T.-Y., and Su, C.-W. (2014). China's marine economy and regional development. *Mar. Policy* 50, 227–237. doi: 10.1016/j.marpol.2014.06.008

Jin, X., Li, M., and Lei, X. (2024). The impact of digitalization on the green development of the marine economy: evidence from China's coastal regions. *Front. Mar. Sci.* 11. doi: 10.3389/fmars.2024.1457678

Kou, L., Li, Y., Zhang, F., Gong, X., Hu, Y., Yuan, Q., et al. (2022). Review on monitoring, operation and maintenance of smart offshore wind farms. *Sensors* 22, 1-36. doi: 10.3390/s22082822

Kraaijenbrink, J., Spender, J. C., and Groen, A. J. (2009). The resource-based view: A review and assessment of its critiques. *J. Manage.* 36, 349–372. doi: 10.1177/0149206309350775

Leape, J., Abbott, M., Sakaguchi, H., Brett, A., Cao, L., Chand, K., et al. (2023). "Technology, data and new models for sustainably managing ocean resources," in *The Blue Compendium: From Knowledge to Action for a Sustainable Ocean Economy*. Eds. J. Lubchenco and P. M. Haugan (Springer International Publishing, Cham), 185–211.

Leibenstein, H. (1975). Aspects of the X-efficiency theory of the firm. *Bell J. Economics* 6, 580–606. doi: 10.2307/3003244

Levinsohn, J., and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Rev. Economic Stud.* 70, 317–341. doi: 10.1111/1467-937X.00246

Li, D. (2023). The impact of marine industrial structure rationalization on marine economic growth. *J. Sea Res.* 196, 102455. doi: 10.1016/j.seares.2023.102455

Liu, H., Wang, X., Wang, Z., and Cheng, Y. (2024). Does digitalization mitigate regional inequalities? Evidence from China. *Geogr. Sustainability* 5, 52–63. doi: 10.1016/j.geosus.2023.09.007

Liu, L., Xin, Y., Liu, B., Pang, Y., and Kong, W. (2025a). The panel threshold analysis of digitalization on manufacturing industry's green total factor productivity. *Sci. Rep.* 15, 4336. doi: 10.1038/s41598-025-86643-2

Liu, M., Lai, K.-h., Wong, C. W. Y., Xin, X., and Lun, V. Y. H. (2025b). Smart ports for sustainable shipping: concept and practices revisited through the case study of China's Tianjin port. *Maritime Economics Logistics* 27, 50–95. doi: 10.1057/s41278-024-00291-3

Liu, P., Zhu, B., and Yang, M. (2021). Has marine technology innovation promoted the high-quality development of the marine economy? –Evidence from coastal regions in China. *Ocean Coast. Manage.* 209, 105695. doi: 10.1016/j.ocecoaman.2021.105695

Meng, Z., Pang, M., Zhang, D., and Chen, W. (2024). Unlocking sustainable marine economic growth: the role of financial development, innovation, and capital investment in coastal China. *Front. Mar. Sci.* 11, 1463843. doi: 10.3389/fmars.2024.1463843

Munim, Z. H., Dushenko, M., Jimenez, V. J., Shakil, M. H., and Imset, M. (2020). Big data and artificial intelligence in the maritime industry: a bibliometric review and future research directions. *Maritime Policy Manage.* 47, 577–597. doi: 10.1080/03088839.2020.1788731

Muñuzuri, J., Onieva, L., Cortés, P., and Guadix, J. (2020). Using IoT data and applications to improve port-based intermodal supply chains. *Comput. Ind. Eng.* 139, 105668. doi: 10.1016/j.cie.2019.01.042

Nucci, F., Puccioni, C., and Ricchi, O. (2023). Digital technologies and productivity: A firm-level investigation. *Economic Model.* 128, 106524. doi: 10.1016/j.econmod.2023.106524

Olley, G. S., and Pakes, A. (1992). "The dynamics of productivity in the telecommunications equipment industry," in *National Bureau of Economic Research Working Paper Series.* Available online at: https://www.nber.org/papers/w3977

Pan, W., Xie, T., Wang, Z., and Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *J. Business Res.* 139, 303–311. doi: 10.1016/j.jbusres.2021.09.061

Ren, W., Ji, J., Chen, L., and Zhang, Y. (2018). Evaluation of China's marine economic efficiency under environmental constraints—an empirical analysis of China's eleven coastal regions. *J. Cleaner Production* 184, 806–814. doi: 10.1016/j.jclepro.2018.02.300

Ribeiro-Navarrete, S., Botella-Carrubi, D., Palacios-Marqués, D., and Orero-Blat, M. (2021). The effect of digitalization on business performance: An applied study of KIBS. *J. Business Res.* 126, 319–326. doi: 10.1016/j.jbusres.2020.12.065

Richardson, S. (2006). Over-investment of free cash flow. *Rev. Accounting Stud.* 11, 159–189. doi: 10.1007/s11142-006-9012-1

Rowan, N. J. (2023). The role of digital technologies in supporting and improving fishery and aquaculture across the supply chain – Quo Vadis? *Aquaculture Fisheries* 8, 365–374. doi: 10.1016/j.aaf.2022.06.003

Sun, C., Liang, Z., Zhai, X., and Wang, L. (2024a). Obstacles to the development of China's marine economy: Total factor productivity loss from resource mismatch. *Ocean Coast. Manage.* 249, 107009. doi: 10.1016/j.ocecoaman.2023.107009

Sun, C., Wang, L., Zou, W., and Zhai, X. (2023a). The high-quality development level assessment of marine economy in China based on a "2 + 6+4" framework. *Ocean Coast. Manage.* 244, 106822. doi: 10.1016/j.ocecoaman.2023.106822

Sun, C., Xu, M., and Wang, B. (2024b). Deep learning: Spatiotemporal impact of digital economy on energy productivity. *Renewable Sustain. Energy Rev.* 199, 114501. doi: 10.1016/j.rser.2024.114501

Sun, Z., Zhao, L., Kaur, P., Islam, N., and Dhir, A. (2023b). Theorizing the relationship between the digital economy and firm productivity: The idiosyncrasies of firm-specific contexts. *Technological Forecasting Soc. Change* 189, 122329. doi: 10.1016/j.techfore.2023.122329

Tian, M., Chen, Y., Tian, G., Huang, W., and Hu, C. (2023). The role of digital transformation practices in the operations improvement in manufacturing firms: A practice-based view. *Int. J. Production Economics* 262, 108929. doi: 10.1016/j.ijpe.2023.108929

Van Beveren, I. (2012). Total factor productivity estimation: a practical review. *J. Economic Surveys* 26, 98–128. doi: 10.1111/j.1467-6419.2010.00631.x

Vance, T. C., Wengren, M., Burger, E., Hernandez, D., Kearns, T., Medina-Lopez, E., et al. (2019). From the oceans to the cloud: opportunities and challenges for data, models, computation and workflows. *Front. Mar. Sci.* 6. doi: 10.3389/fmars.2019.00211

Wang, D., Liao, H., and Wang, X. (2024). The enabling effects of digital technology on the quality of firm development: Insights and implications. *Int. Rev. Financial Anal.* 96, 103555. doi: 10.1016/j.irfa.2024.103555

Wang, Y., and Wang, N. (2019). The role of the marine industry in China's national economy: An input–output analysis. *Mar. Policy* 99, 42–49. doi: 10.1016/j.marpol.2018.10.019

Wei, H., Nian, M., and Li, L. (2020). China's strategies and policies for regional development during the period of the 14th five-year plan. *Chin. J. Urban Environ. Stud.* 08, 2050008. doi: 10.1142/S2345748120500086

Wu, L., Sun, L., Chang, Q., Zhang, D., and Qi, P. (2022). How do digitalization capabilities enable open innovation in manufacturing enterprises? A multiple case study based on resource integration perspective. *Technological Forecasting Soc. Change* 184, 122019. doi: 10.1016/j.techfore.2022.122019

Xu, T., Dong, J., and Qiao, D. (2023). China's marine economic efficiency: A meta-analysis. *Ocean Coast. Manage.* 239, 106633. doi: 10.1016/j.ocecoaman.2023.106633

Yao, W., Zhang, W., and Li, W. (2023). Promoting the development of marine low carbon through the digital economy. *J. Innovation Knowledge* 8, 100285. doi: 10.1016/j.jik.2022.100285

Yu, F., Du, H., Li, X., and Cao, J. (2023). Enterprise digitalization, business strategy and subsidy allocation: Evidence of the signaling effect. *Technological Forecasting Soc. Change* 190, 122472. doi: 10.1016/j.techfore.2023.122472

Zamani, E. D., Smyth, C., Gupta, S., and Dennehy, D. (2023). Artificial intelligence and big data analytics for supply chain resilience: a systematic literature review. *Ann. Operations Res.* 327, 605–632. doi: 10.1007/s10479-022-04983-y

Zeng, H., Ran, H., Zhou, Q., Jin, Y., and Cheng, X. (2022). The financial effect of firm digitalization: Evidence from China. *Technological Forecasting Soc. Change* 183, 121951. doi: 10.1016/j.techfore.2022.121951

Zhang, Q., Wu, P., Li, R., and Chen, A. (2024). Digital transformation and economic growth Efficiency improvement in the Digital media era: Digitalization of industry or Digital industrialization? *Int. Rev. Economics Finance* 92, 667–677. doi: 10.1016/j.iref.2024.02.010

Zhou, M., Jiang, K., and Zhang, J. (2023). Environmental benefits of enterprise digitalization in China. *Resources Conserv. Recycling* 197, 107082. doi: 10.1016/j.resconrec.2023.107082

Zou, W., Yang, Y., Yang, M., Zhang, X., Lai, S., and Chen, H. (2023). Analyzing efficiency measurement and influencing factors of China's marine green economy: Based on a two-stage network DEA model. *Front. Mar. Sci.* 10. doi: 10.3389/fmars.2023.1020373