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Does Artificial Intelligence (AI) enhance green economy efficiency? The role of green finance, trade openness, and R&D investment

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Marine fisheries constitute a crucial component of global green development, where artificial intelligence (AI) plays an essential role in enhancing green economic efficiency associated with marine fisheries. This study utilizes panel data from 11 coastal provinces and municipalities in China from 2009 to 2020, employing the entropy method and the super-efficiency EBM model to calculate the AI index and the green economic efficiency of marine fisheries. Based on these calculations, we utilize fixed effects models, moderation effect models, and panel threshold models to examine the impact of AI on the green economic efficiency of marine fisheries. The study reveals that: (i) From 2009 to 2020, AI has significantly improved overall, while the green economic efficiency of marine fisheries has shown a fluctuating trend, with substantial regional disparities. (ii) AI significantly enhances the green economic efficiency of marine fisheries. (iii) Green finance, trade openness, and R&D investment act as crucial moderating variables, accelerating AI development and further improving the green economic efficiency of marine fisheries. (iv) The impact of AI on green economic efficiency varies across different intervals of green finance, trade openness, and R&D investment. These findings are crucial for understanding and advancing the informatization strategy of marine fisheries and hold significant implications for the sustainable development of global marine fisheries.

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Introduction

Since the early 21st century, the marine economy has become a pivotal force in driving global sustainable development (Winther et al. 2020). The oceans, absorbing ~23% of carbon emissions from human activities annually, play a crucial role in mitigating climate change (WMA, 2022). This phenomenon has elevated the exploitation of marine resources and the utilization of ocean carbon sinks as critical components in the maritime strategies of many coastal countries (Terhaar et al.,2024). Against this backdrop, the sustainable development of marine fisheries, an integral part of the marine economy, becomes paramount (Puszkarski and Śniadach, 2022). Despite this, the sector remains largely dependent on traditional fishing and aquaculture practices, which contribute to ocean pollution and ecological degradation, thus impeding sustainable progress (Suresh, 2023; Willis et al., 2022). For China, a nation with vast maritime domains and rich marine resources, there exists a critical challenge in harmonizing economic growth with marine ecological conservation. Despite various government efforts such as fishing bans and marine ranching, widespread issues of inefficiency and high energy consumption persist, attributed to the lack of sophisticated fishing technologies and management practices. In this context, green economic efficiency surfaces as a key measure for evaluating the sustainable progression of China's marine fisheries (Zheng et al. 2022). This metric comprehensively incorporates the constraints of limited fishery resources and environmental pollution, providing a more inclusive view of the economic state of marine fisheries (Cochrane, 2021). Consequently, improving the green economic efficiency of marine fisheries is crucial for sustaining and bolstering the health and prospects of the marine ecosystem.

Consistent with endogenous growth theory, artificial intelligence (AI), as a novel production factor, is increasingly acknowledged as an essential driver of sustainable development (Aghion et al., 1998; Nchofoung and Asongu, 2022). The adoption of machine learning algorithms, intelligent sensors, and deep learning technologies significantly enhances production efficiency, facilitating more rational resource management and environmental conservation (Alsaleh and Yang, 2023; Bhattacharya and Dash, 2021; Nthane et al., 2020). AI also assumes a critical role in improving the dissemination of fishery-related information, diminishing market asymmetries, and thus elevating transaction efficiency (Aura et al., 2019). The Chinese Ministry of Agriculture has emphasized the importance of AI in transitioning from conventional fishing methods to more sustainable, informative, and intelligent practices. Nevertheless, the development and deployment of AI technologies may lead to considerable fossil energy consumption, which could adversely affect the green economic efficiency of marine fisheries. Therefore, an in-depth examination of the application of AI in China's marine fisheries and its potential impact on green economic efficiency is crucial for balancing technological development with environmental protection and promoting sustainable development in fisheries.

The deployment of AI in marine fisheries faces multiple challenges, including technical difficulties, substantial investment requirements, and high-risk scenarios with the potential for significant returns. These issues highlight the critical roles of research and development (R&D) investment, green finance, and trade openness in fostering technological innovation and ensuring its successful integration within the fisheries sector (Mushtaq and Bruneau, 2019). Firstly, R&D investment acts as a fundamental catalyst for AI advancements, supporting activities from initial exploration through to development phases (Boeing et al. 2022). This involves not just funding but also the cultivation of talent and technological capabilities. Secondly, green finance offers a pathway to resolving funding challenges for AI applications in marine fisheries by supporting low-carbon technologies and sustainable projects, thereby reducing the risks associated with initial investments in AI (Zhou et al., 2022). Lastly, trade openness enhances market accessibility and diversifies funding sources for AI technologies, enabling international technological exchanges and collaborations that accelerate the adoption of AI-driven environmental solutions (Wang et al., 2024c). This enhances both the environmental and economic efficiencies of marine fisheries, enabling quicker adaptation to global market changes and environmental challenges. An in-depth exploration of these factors is crucial for propelling AI applications in marine fisheries and maximizing their contribution to green economic efficiency. This research not only offers strategic guidance for the informatization and intelligent transformation in the fisheries sector of China's coastal regions but also serves as a vital insight for the global efforts towards sustainable development in marine fisheries.

This study aims to investigate the relationship between AI and the green economic efficiency of marine fisheries in China's coastal regions. It addresses several pivotal questions for the first time: Can AI boost the green economic efficiency of marine fisheries? What role do green finance trade openness, and R&D investment play in this process? And how do these three moderating factors distinctly influence the outcome? To address these questions, the study utilizes panel data from 11 coastal provinces and cities in China covering the period from 2009 to 2020. The entropy method and the Super-EBM model are employed to calculate the AI index and green economic efficiency of marine fisheries, respectively. A two-way fixed effects model is then constructed to empirically assess the direct impact of AI on the green economic efficiency of marine fisheries. Furthermore, through a moderation effect model, the role of green finance, trade openness, and R&D investment as moderators in this relationship is explored. Finally, by implementing a panel threshold model, the study investigates how AI influences green economic efficiency across different threshold ranges of green finance, trade openness, and R&D investment, providing nuanced insights into the mechanisms at play.

The contributions of this study are threefold. Firstly, it integrates AI and the green economic efficiency of marine fisheries into a cohesive analytical framework, providing a novel perspective on their interrelationship. This approach not only enriches the field of AI and sustainable development in marine fisheries but also theoretically establishes the mechanism through which AI impacts green economic efficiency. Secondly, in terms of indicator construction, the Super-EBM model is employed to assess the green economic efficiency of marine fisheries. This model rigorously incorporates both slack and non-slack variables, enhancing the accuracy of efficiency evaluations. Furthermore, the study, starting from four dimensions—AI technology practices and research, fishery information services, talent training and development, and foundational information technology resources—employs the entropy method for a comprehensive evaluation of AI. This method addresses the limitations of previous research that relied on single-variable analyses. Finally, in the empirical analysis, the study employs a fixed effects model to investigate the linear impact of AI on the green economic efficiency of marine fisheries. Through the moderating effect model, this study highlights the influence of green finance, trade openness, and R&D investment in amplifying AI's role in fostering green economic efficiency in marine fisheries. Additionally, a panel threshold model is applied to reveal the nonlinear effects of AI across varying levels of green finance, trade openness, and R&D investment, deepening the understanding of how AI can foster green economic efficiency in marine fisheries.

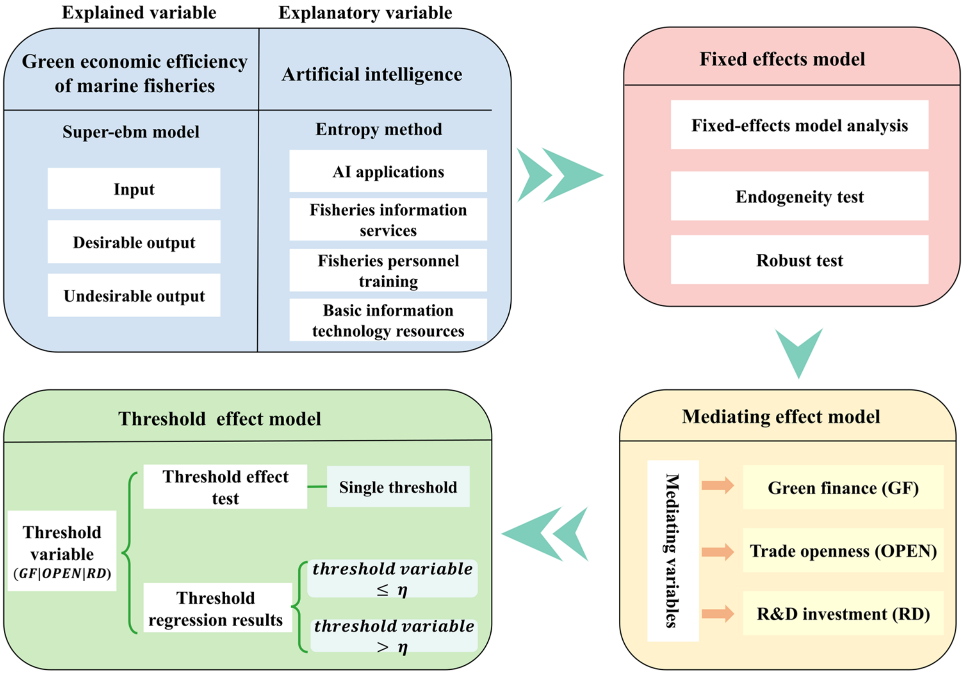

Fig. 1 The research framework. This figure outlines the conceptual and methodological framework of the study.

This article investigates the relationship between AI and the green development of marine fisheries, providing significant empirical evidence for emerging economies to improve marine resource management and environmental protection. It also offers new policy perspectives for promoting sustainable development in fisheries for coastal countries worldwide. Therefore, policymakers are urged to recognize the pivotal role of AI technology in the sustainable progression of marine fisheries and to develop policies that encourage technological innovation and its application. Moreover, the development of green finance should be encouraged to provide financial support for research and application of AI in marine fisheries. Additionally, through the optimization of trade policies, international exchange and cooperation in technology and knowledge should be promoted to jointly advance the green development of global marine fisheries.

The structure of this paper is organized as follows: section "Literature review" presents a comprehensive literature review. In the section "Theoretical analysis", we conduct a theoretical analysis. Section "Method and data" develops the models and provides a detailed description of the data sources utilized in our study. Section "Results and analysis" presents the econometric regression results. Section "Discussion" discusses the results. Finally, the section "Conclusions and recommendations" summarizes the key findings and policy recommendations. The research framework is illustrated in Fig. 1.

Literature review

Marine fisheries green economic efficiency. Marine fisheries green economic efficiency is a vital metric for evaluating the interplay between economic activities, resource utilization, and environmental impact within marine fisheries, serving as an impetus for sustainable development in the marine economy (Cochrane, 2021). Contemporary research primarily concentrates on its methodological calculation and influencing factors. Predominant calculation methodologies are categorized into two types: stochastic frontier analysis (SFA) (Li et al., 2021a; Xu et al., 2023b) and data envelopment analysis (DEA) (Li et al., 2022; Zou et al., 2023). SFA, suitable for single-output models and necessitating a predefined production function, encounters challenges related to subjectivity, which may lead to inconsistent outcomes (Lovell, 1996). In contrast, DEA offers greater flexibility as it does not depend on any specific functional form and can handle multiple inputs and outputs, making it ideal for assessing the efficiency of various decision-making units (Sarkar et al., 2024). Hence, this paper employs the DEA method to calculate the green economic efficiency of marine fisheries.

In the DEA framework, traditional models like CCR, BCC, and SBM exhibit certain limitations. Radial models such as CCR and BCC necessitate proportional changes in inputs and outputs, which may restrict their practical applicability (Charnes et al., 1978; Lee, 2022). The SBM model, while addressing non-radial slack variables, may distort the actual proportion of inputs to outputs, thus impacting the accuracy of assessments (Tone, 2001; Zheng et al., 2024). To overcome these challenges, Tone and Tsutsui (2010) introduced the EBM model, which incorporates non-radial slack variables while maintaining the input–output proportion, thereby enhancing assessment precision. However, the EBM model frequently results in a large number of efficient decision-making units (DMUs) scoring 1, making it difficult to differentiate among efficient units. To address this, our study employs the Super-EBM model to measure the green economic efficiency of marine fisheries. While this model is utilized in various sectors (Ding and Liu, 2024; Wang et al., 2023d; Wu et al., 2019), its application in examining the green economic efficiency of marine fisheries is relatively rare (Zhou et al., 2023). Existing studies applying these models to China's marine economy have yielded inconsistent conclusions (Guo et al., 2022; Zheng et al., 2022). For instance, Ren et al., (2018) identified a fluctuating trend in China's marine economic efficiency. Zou et al., (2023) employed a two-stage network DEA model and discovered that the green economic efficiency of China's marine economy exhibits a fluctuating declining trend, whereas Xu et al., (2023b) observed an overall upward trend. Given the critical role of marine fisheries in the marine economy, an in-depth examination of the green economic efficiency of China's marine fisheries, including its spatial–temporal development, is particularly important.

Regarding the factors influencing green economic efficiency in marine fisheries, research primarily focuses on technological advancements, environmental regulation, and economic factors. Firstly, technological progress is universally acknowledged as a pivotal driver of efficiency (Gao et al., 2024; Wang et al., 2024d). Xu et al., (2023b) detailed its positive effects on marine economic efficiency, particularly from the vantage points of marine science and industry structure. Additionally, Zhang et al., (2021b) emphasized the critical role of capital and technological investments. Secondly, the complexity of environmental regulation has attracted significant attention. Chen et al., (2023b) found that environmental regulation and economic development have a positive impact on marine ecological welfare, while Zheng et al., (2022) highlighted its beneficial moderating influence on the nexus between foreign direct investment (FDI) and marine green economic efficiency. Sun et al., (2023) discerned that different types of environmental regulations have nonlinear impacts on the marine green economy. Lastly, economic factors are crucial in affecting marine economic efficiency. Guo et al., (2022) applied the EBM model and a spatial Durbin model to analyze the positive correlation between economic development level, growth expectations, and openness with marine economic efficiency, accentuating the economic environment's influence. Zou et al., (2023) identified a positive effect of trade openness on ocean green economy efficiency, although they noted negative influences from the development of the ocean economy and industrial structure. Gao et al., (2022) investigated the implications of industry and employment structures, economic level, carbon sink capacity, and fisheries human capital from a macro perspective. Their findings reveal positive effects on efficiency, except for industry and employment structures, providing a comprehensive view of the determinants affecting carbon emission efficiency in marine fisheries.

AI and marine fisheries green economic efficiency. AI is increasingly recognized as a key driver of green economic efficiency (Hussain et al., 2023), primarily through optimizing resource allocation and enhancing information flow efficiency. Specifically, the application of AI can reduce waste and promote optimal resource utilization through deep learning and sophisticated algorithmic analysis (Zhu et al., 2023). Moreover, AI reduces production and transaction costs through digital platforms, thereby boosting overall production efficiency (Laddha et al., 2022). It also plays a crucial role in enhancing energy efficiency (Zhao et al., 2022b), through intelligent management systems (Wang et al., 2023b). Furthermore, AI supports environmental monitoring and pollution prevention, effectively reducing energy consumption and emissions, and thus mitigating environmental impacts (Saqib et al., 2024; Zhong et al., 2022). However, academic perspectives on the relationship between AI and green economic efficiency are diverse. Several studies (Bakker and Ritts, 2018) have highlighted AI's critical role in environmental improvement, enhancing energy efficiency, and fostering clean technology use. Conversely, others (Wang et al., 2022a) found that AI agglomeration has increased carbon emissions, as AI systems generally require substantial computational resources and energy. Furthermore, the interaction between AI and environmental quality demonstrates a nonlinear effect under the influence of various factors. For instance, Nchofoung and Asongu (2022) observed that globalization and the policy environment moderate the impact of AI on sustainable development. Similarly, Li and Wang (2022) discovered that the relationship between the digital economy and carbon emissions is influenced by resource endowment, city size, and innovation capacity, exhibiting complex threshold effects. Therefore, a unanimous agreement on AI's impact on green economic efficiency is yet to be established.

In the marine fishery sector, research on AI is currently in its nascent stages. A handful of scholars have explored the potential role of AI in fishery management, data sharing, and enhancing the sustainability of fisheries. Studies indicate that AI not only improves the operational efficiency of fisheries but also promotes the sustainable development of marine fisheries with accurate, precise data analysis and forecasting (Dash et al. 2023). Moreover, by processing extensive datasets on market and environmental conditions, AI tools play a significant role in overcoming market barriers and reducing information asymmetry. They exhibit considerable promise in providing aquaculture and market insights to fishermen, particularly by disseminating vital information effectively (Ntiri et al. 2022). Globally, some developed countries have already begun leveraging AI technology to promote the sustainability of fisheries (Alsaleh and Yang, 2023). For instance, AI's capabilities in analyzing and predicting fishery resources allow for more rational planning of fishing activities, thereby reducing overfishing risks and protecting marine ecosystems. In China, studies have indicated (Ji and Li, 2021) that the introduction of AI technologies, such as intelligent monitoring and analysis systems, can significantly enhance the economic efficiency and environmental sustainability of fisheries. In practical terms, AI has shown tremendous potential in various aspects of marine fisheries. With intelligent decision support and automated processing of fishery information and data, AI technologies assist practitioners in more effective resource management, augment production efficiency, and reduce environmental impacts, greatly promoting the sustainable development of marine fisheries (Huh, 2017; Saville et al. 2015; Teniwut et al. 2022). While existing research primarily analyzes AI in fisheries from a single-indicator perspective (Alsaleh and Yang, 2023), a more comprehensive understanding necessitates a multidimensional analysis. This study assesses different aspects of the AI development index, providing a more detailed view of its diverse impacts.

AI, green finance, and marine fisheries green economic efficiency. Green finance refers to financing activities that support environmental improvement, mitigate climate change, and promote the efficient and circular use of resources. By funding projects and offering incentives, green finance encourages companies to adopt environmentally friendly production methods and technologies. This approach not only expands the scale of investment and financing (Zhang et al. 2023a) and improves energy efficiency (Lee et al. 2023) but also effectively reduces carbon emissions (Liu et al. 2023). Consequently, green finance positively impacts corporate sustainable development and significantly contributes to global environmental protection and climate change mitigation.

Research indicates that since the implementation of the green finance pilot policy in 2017, companies have made significant progress in green innovation (Jia et al. 2023), providing robust support for the green transformation of the real economy (Hua et al. 2024). Green finance, through various financial instruments, has provided essential funding for the application of AI technology in marine fisheries (Qin et al. 2024). Additionally, green finance employs a series of risk mitigation and incentive mechanisms to reduce investment risks associated with AI technology in marine fisheries, thereby boosting investor confidence. Several studies have highlighted that AI technology, by optimizing resource allocation (Yu et al. 2020), addressing information asymmetry (Muganyi et al. 2021), and lowering production and transaction costs, has enhanced the effectiveness of green finance. This synergy between green finance and AI promotes sustainable economic growth, suggesting their integration as a key driver for sustainable development.

Although the literature exploring the interaction between green finance and AI in the marine fisheries sector is relatively limited, existing studies have begun to reveal the potential of green finance in promoting the application of AI technology (Liu et al. 2021b). Xu and Liu (2023) extend this discussion to the broader marine sector, indicating that green finance not only supports technological implementation but also facilitates the green transformation of the entire industry. Thompson (2022) offers an intriguing extension of this topic by exploring the role of blue bonds in financing marine projects that generate environmental and climate benefits, thereby providing a new perspective on sustainable development for the marine economy. However, the situation is not entirely optimistic. Vanderklift et al. (2019) raise concerns about the practical limitations of blue bonds, particularly the stringent conditions that may hinder sustainable development. Consequently, the effectiveness of green finance in accelerating AI's contribution to the green economic efficiency of marine fisheries remains unclear.

AI, trade openness, and marine fisheries green economic efficiency. Research generally suggests that trade openness facilitates technology transfer, market expansion, and resource optimization, thereby driving economic growth (Chen et al. 2022b; Hdom and Fuinhas, 2020). However, its impact on green economic efficiency remains contentious. On one hand, trade openness introduces advanced environmental technologies and management practices, optimizing industrial structures (Dou et al. 2021), and shifting resources from low-efficiency, low-value-added sectors to high-efficiency, high-value-added sectors, thereby enhancing green economic efficiency (Mealy and Teytelboym, 2022). For example, Qamri et al. (2022) analyzed data from 21 Asian countries between 1980 and 2018, finding that trade openness significantly improved environmental quality and promoted economic growth. Conversely, trade openness might lead to a "pollution haven" effect, where pollution-intensive industries relocate to developing countries with lower environmental standards, exacerbating pollution in these countries (Liu et al. 2022). Liu and Dong (2021), using a spatial econometric model, found that trade liberalization negatively impacted green economic efficiency in China. Additionally, Can et al. (2021) focused on the trade of environmentally friendly goods, discovering a trend of initial decline followed by an increase in environmental sustainability, supporting the environmental Kuznets curve hypothesis.

In the digital economy era, the continuous development of new-generation ICT technologies, such as AI and the Internet, has made digital trade a major form of trade (Cao et al. 2021; Danish et al. 2023). Evans and Mesagan (2022) emphasized that ICT trade, combined with effective government governance, can reduce environmental pollution. Moreover, AI significantly impacts carbon emissions and energy transitions under trade openness by enhancing industry efficiency, driving structural economic transformation, and promoting global cooperation (Wang et al. 2024c). Meanwhile, a number of studies have pointed out that AI technology also helps businesses identify and manage trade risks, increasing trade safety and stability, and providing crucial support for sustainable development (Feijóo et al. 2020; Horowitz et al. 2022).

However, in the marine fisheries sector, the effect of trade openness on accelerating AI-driven green economic efficiency remains unclear. This study aims to explore how the integration of trade openness and AI technology can accelerate green economic efficiency in the marine fisheries sector, using cases from China's coastal regions.

AI, R&D investment, and marine fisheries green economic efficiency. According to endogenous growth theory, R&D investment is a crucial endogenous variable driving economic growth, primarily through technological advancement that enhances productivity (Romer, 1990). Numerous studies have confirmed that R&D investment significantly positively impacts green economic efficiency (Liu and Dong, 2021; Song et al. 2019). These R&D activities not only foster the innovation and application of green technologies but also effectively reduce resource consumption and pollution emissions, thereby improving resource utilization efficiency (Shao and Chen, 2022). Specifically, research by Chen and Yang (2024) demonstrates that increased R&D investment in the renewable energy sector in China has significantly enhanced green economic efficiency. Furthermore, R&D investment promotes technological spillover effects, which, through knowledge sharing and technology transfer, elevate the overall technological level of society (Lei et al. 2024; Wang et al. 2024a). This, in turn, facilitates the upgrading and optimization of industrial structures, transitioning traditional industries towards environmentally friendly directions (Liu et al. 2024).

AI technology plays a crucial role in enhancing R&D processes, as evidenced by multiple studies. Liu et al. (2020) demonstrate that AI accelerates the R&D cycle and increases the success rate of research projects. Building on this, Kolluri et al. (2022) show that AI's capabilities in automation and prediction significantly shorten the R&D cycle and reduce costs, particularly in the development of new materials and pharmaceuticals. Similarly, Johnson et al. (2022) and Füller et al. (2022) highlight AI's contributions to enhancing the exploratory capabilities of research teams, accelerating development cycles, and improving decision-making accuracy. Moreover, Keding and Meissner (2021) illustrate how AI supports innovation management by structuring and streamlining decision-making processes in R&D investments. The synergy between R&D investment and AI not only drives the innovation of green technologies but also profoundly impacts sustainable development (Chen et al. 2022a). These technological innovations foster economic growth and enhance environmental sustainability by optimizing product design and production processes (Babina et al. 2024).

The current research primarily focuses on the measurement methods and influencing factors of green economic efficiency in marine fisheries, as well as the influence of AI on this efficiency. However, there are notable deficiencies: Firstly, although current research delves into the comprehensive impact of AI on green economic efficiency, the specific role of AI within the realm of marine fisheries frequently remains underexamined. Secondly, traditional DEA models, commonly used for efficiency assessment, may not fully address the importance of both slack and non-slack variables in inputs and outputs, possibly resulting in partial or imprecise evaluations. Thirdly, previous studies have primarily viewed AI from the perspective of individual industrial robots, lacking a comprehensive understanding of the impact of advanced AI technologies on the marine fishery sector as a whole. Finally, prior research has focused mainly on the direct effects of AI on green economic efficiency, overlooking its holistic impact in the marine domain as well as neglecting the crucial roles played by green finance, trade openness, and R&D investment.

Theoretical analysis

The direct impact of AI on the green economic efficiency of marine fisheries. AI, as an advanced information and communication technology (ICT), has profoundly influenced economic development, resource management, and environmental activities in the marine fisheries sector (Chen et al. 2023a). This impact is primarily achieved through optimizing resource allocation, reducing production costs, enhancing the efficiency of information flow, improving energy utilization, and promoting environmental protection.

Firstly, AI, with its robust data processing capabilities and pattern recognition, can analyze vast amounts of real-time ocean observation data (Sonnewald et al. 2021). Through deep learning and complex algorithms, AI accurately predicts the rich areas of marine biological resources and their changing trends (Lou et al. 2023). This enables AI to provide real-time recommendations on when and where to fish and guides how to adjust the location and size of aquaculture areas to achieve an efficient layout of fishery production, reducing overexploitation and waste of marine resources.

Secondly, AI plays a core role in the circulation of fishery information (Probst, 2019). Through automated and intelligent data collection and analysis, AI significantly improves the accuracy of market demand forecasting. This further optimizes supply chain management, including adjusting transportation routes and selecting the best logistics partners (Güven and Şimşir, 2020). These operations allow fisheries businesses to flexibly and efficiently respond to market changes, while reducing unnecessary transportation, enhancing logistics efficiency, and lowering the carbon emissions of fishery activities, thereby contributing to environmental protection.

Finally, AI plays a significant role in enhancing energy efficiency and environmental monitoring by reducing energy consumption through intelligent management systems and predictive maintenance (Saqib et al. 2024), and by using advanced monitoring technology for real-time monitoring of the marine environment, effectively preventing and reducing pollution emissions, thus protecting the marine ecological environment (Zhong et al. 2022).

Hypothesis 1: AI can improve the green economic efficiency of marine fisheries.

The potential impact of green finance on the relationship between AI and green economic efficiency of marine fisheries. Green finance enhances the availability and efficiency of funding (Ahmed et al. 2024), which further amplifies the positive impact of AI on the green economic efficiency of marine fisheries. Specifically, with the continuous development of green finance, sustainable fishery investments, and innovation activities in coastal areas have correspondingly increased. This financial support bolsters the technological innovation and transformation capabilities of AI within the fisheries sector (Qin et al. 2024). Guided and incentivized by green finance, fisheries enterprises are able to invest more effectively in AI technologies, thereby making significant progress in improving production efficiency and reducing damage to fishery systems, ultimately promoting the overall improvement of green economic efficiency in marine fisheries.

Research indicates that the impact of green finance may exhibit phase-specific characteristics (Song et al. 2024). Undoubtedly, green finance can exhibit conservatism and selectivity in its resource allocation strategies during its initial stages. Typically, it prioritizes support for industrial projects with apparent direct environmental benefits. This focus often leads to the neglect of investments in traditional sectors such as marine fisheries, especially concerning the infusion of AI technologies (Kantorowicz et al. 2024). Therefore, in a low-level green finance environment, the development of AI technology in coastal areas may face difficulties in funding acquisition and barriers to technology transformation, factors that collectively limit the potential of AI in enhancing green economic efficiency in marine fisheries. Under the drive for high levels of green finance, financial support provides ample funding for the innovation and application of AI technology (Xu et al. 2023a). This facilitates the progression of marine fisheries toward sustainable development (Abangan et al. 2023).

Hypothesis 2a: Green finance strengthens the promotional effect of AI on the green economic efficiency of marine fisheries.

Hypothesis 2b: The impact of green finance on the enhancement of green economic efficiency in marine fisheries by AI exhibits phase-specific characteristics.

The potential impact of trade openness on the relationship between AI and the green economic efficiency of marine fisheries. Trade openness enhances market access and opportunities for international cooperation, further strengthening the positive impact of AI on green economic efficiency in marine fisheries. With the continuous advancement of trade openness, investment and innovation activities in the fisheries sector of coastal regions have been bolstered, creating favorable conditions for the development and application of AI technology in fisheries. Trade openness allows fisheries enterprises to access advanced technologies and a broad international market, thereby motivating investments in AI technology (Chen et al. 2022b). These technologies have shown significant effects in optimizing production processes, improving resource utilization efficiency, and reducing impacts on ecosystems, ultimately driving marine fisheries toward a more sustainable and efficient direction.

Research indicates that the impact of trade openness may exhibit phase-specific characteristics (Murshed, 2020). A low level of trade openness leads to relative market closure and size limitations, resulting in marine fisheries products primarily satisfying local market demands, which are relatively limited (Dou et al. 2021). Such a limited market environment restricts the potential economic benefits of technological investments, causing fisheries enterprises to lack sufficient motivation to invest in AI technology. Meanwhile, the relative closure of trade not only weakens the circulation and availability of funds, reducing external investors' interest in the market but also restricts the introduction of external advanced technologies and knowledge (Kwan, 2020), which slows the improvement of local fisheries technology levels and constrains the space for AI technology innovation and application. Notably, in the early stages of trade openness, other countries may relocate polluting enterprises to the host country, not only potentially exacerbating the host country's environmental pollution issues but also affecting the potential of AI technology to improve green economic efficiency (Nejati and Taleghani, 2022). The advancement of trade openness, the expansion of market size, and the introduction of advanced technologies and capital have created favorable conditions for accelerating AI innovation. This has led to the optimization of production processes and improved resource utilization efficiency, further driving the fisheries sector towards more sustainable and environmentally friendly development.

Hypothesis 3a: Trade openness strengthens the promotional effect of AI on green economic efficiency in marine fisheries.

Hypothesis 3b: The impact of trade openness on the enhancement of green economic efficiency in marine fisheries by AI exhibits phase-specific characteristics.

The potential impact of R&D investment on the relationship between AI and the green economic efficiency of marine fisheries. R&D investment has the capacity to spark innovation and technological improvements, playing a significant role in propelling scientific and technological advancement (Boeing et al. 2022). Such investment has facilitated the deep integration and widespread application of AI in the marine fisheries sector (Wang et al. 2021). Moreover, the scale effects triggered by it have further enhanced R&D efficiency and the rate of outcome transformation (Aldieri et al. 2022). This not only attracts top talents to engage in the R&D of AI but also reduces the cost per unit of technology implementation through scale effects. Ultimately, these factors fundamentally contribute to the green economic development of marine fisheries. Consequently, this accelerates the pace of technological innovation, significantly boosting the overall green economic efficiency of marine fisheries and paving the way for sustainable development.

Research indicates that the impact of R&D investment may exhibit phase-specific characteristics (Arif Khan et al. 2020). In the context of limited R&D funding, the potential positive impacts of AI technology may not be fully realized. These scarce resources are often allocated to areas perceived as having more innovative potential or more urgent needs. This prioritization can place traditional industries, such as marine fisheries at a disadvantage in terms of resource allocation (Li et al. 2021c). Moreover, the marine fisheries sector tends to absorb and adapt to emerging technologies relatively slowly, making it difficult for AI to be effectively implemented (Gao et al. 2022). This not only hinders the application and promotion of the technology but may also lead to a decline in green economic efficiency in the initial stages. However, with increased R&D investment, fisheries enterprises can more effectively invest in advanced AI, not only enhancing the optimization and efficient management of the fisheries production process but also helping to reduce the adverse impact of fisheries activities on the marine ecosystem, ultimately driving overall growth in the green economic efficiency of marine fisheries.

Hypothesis 4a: R&D investment strengthens the promotional effect of AI on the green economic efficiency of marine fisheries.

Hypothesis 4b: The impact of R&D investment on enhancing the green economic efficiency of marine fisheries through AI exhibits phase-specific characteristics.

Method and data

This study utilizes panel data from 11 coastal provinces and cities in China, spanning from 2009 to 2020 (see Fig. 2). Initially, the study establishes a benchmark model, upon which a moderating effect model and a panel threshold model are constructed. These models are employed to examine the impact of AI, green finance, trade openness, and R&D investment on the green economic efficiency of marine fisheries. Additionally, the study meticulously outlines the composition indicators and measurement methodologies for each variable. Finally, this section provides the data source and descriptive analysis.

Model setting

Benchmark model. To more comprehensively measure the impact of AI on the green economic efficiency of marine fisheries, we have constructed a fixed-effects model with both temporal and individual dimensions, as illustrated in Eq. (1):

$$MFGEE_{it} = \alpha_0 + \alpha_1 AI_{it} + \sum_{j=1}^{n} \varphi_j X_{jit} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

In this model, $MFGEE_{it}$ serves as the dependent variable, representing the green economic efficiency of marine fisheries in province i during period t. AI_{it}, the explanatory variable, denotes AI in province i at time t. X_{it} encompasses a set of control variables. μ_i, δ_t, and ε_{it} represent individual-fixed effects, time-fixed effects, and the random error term, respectively.

Moderating effect model. In this study, we establish a moderating effect model to investigate the impact of three moderating variables—green finance, trade openness, and R&D investment—on the relationship between AI and the green economic efficiency of marine fisheries. We introduce an interaction term between AI and moderating variables in Eq. (2):

$$\begin{aligned} MFGEE_{it} = {} & \alpha_0 + \alpha_1 AI_{it} + \alpha_2 \mathrm{AI}_{it} \times GF_{it} + \alpha_3 GF_{it} \\ & + \sum_{j=1}^{n} \varphi_j X_{jit} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} MFGEE_{it} = {} & \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AI_{it} \times OPEN_{it} + \alpha_3 OPEN_{it} \\ & + \sum_{j=1}^{n} \varphi_j X_{jit} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} MFGEE_{it} = {} & \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AI_{it} \times \mathrm{RD}_{it} + \alpha_3 \mathrm{RD}_{it} \\ & + \sum_{j=1}^{n} \varphi_j X_{jit} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

In Eqs. (2)–(4), GF_{it} denotes green finance in province i at time t, OPEN_{it} represents the trade openness of province i at time t, and RD_{it} indicates the R&D investment of province i at time t. The interaction terms $\mathrm{AI}_{it} \times \mathrm{GF}_{it}$, $\mathrm{AI}_{it} \times \mathrm{OPEN}_{it}$ and $\mathrm{AI}_{it} \times \mathrm{RD}_{it}$ represent the interaction of AI with green finance, trade openness, and R&D investment, respectively, in region i at time t. In the moderation effect model, our primary focus is on the coefficient α_2. If the signs of coefficients α_1 and α_2 are consistent and α_2 are significant, it indicates that green finance, trade openness, and R&D investment have a moderating effect in the context of this study. The remaining variables are consistent with those in Eq. (1).

Panel threshold model. To evaluate the threshold effects, we employ a panel threshold model, in which green finance, trade openness, and R&D investment are designated as the threshold variable. The model is formulated as follows:

$$\begin{aligned} MFGEE_{it} = {} & \alpha_0 + \gamma_{11} AI_{it} \times I(q_{it} \le \eta) + \gamma_{12} AI_{it} \times I(q_{it} > \eta) \\ & + \sum_{j=1}^{n} \varphi_j X_{jit} + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

Equation (5) represents a single-threshold model describing the impact of AI on the green economic efficiency of marine fisheries. In this model, q_{it} signifies the threshold variable, specifically referring to green finance, trade openness, and R&D investment in this study. $I(\cdot)$ is the indicator function, taking values of either 1 or 0. η denotes the specific value of the single threshold. The remaining variables are consistent with those in the previously mentioned models.

Variable explanation

Explained variable. The marine fisheries green economic efficiency (MFGEE) serves as an integrative metric for evaluating the green economic development of marine fisheries, with a foundation in resource consumption and environmental pollution considerations. Reflecting on the characteristics of China's 11 coastal provinces and cities and the data availability, this study, building upon existing research (Ding et al. 2020; Li et al. 2021a; Wang et al. 2020), has integrated factors that affect this efficiency, including labor, capital, and resource inputs, pollutants, and economic outputs. In Table 1, the evaluation indicators of MFGEE are classified into three categories: inputs, desired outputs, and undesired outputs, thereby formulating an indicator system. To calculate the MFGEE, we employ the Super-EBM model, the formula for which is provided in Appendix A.

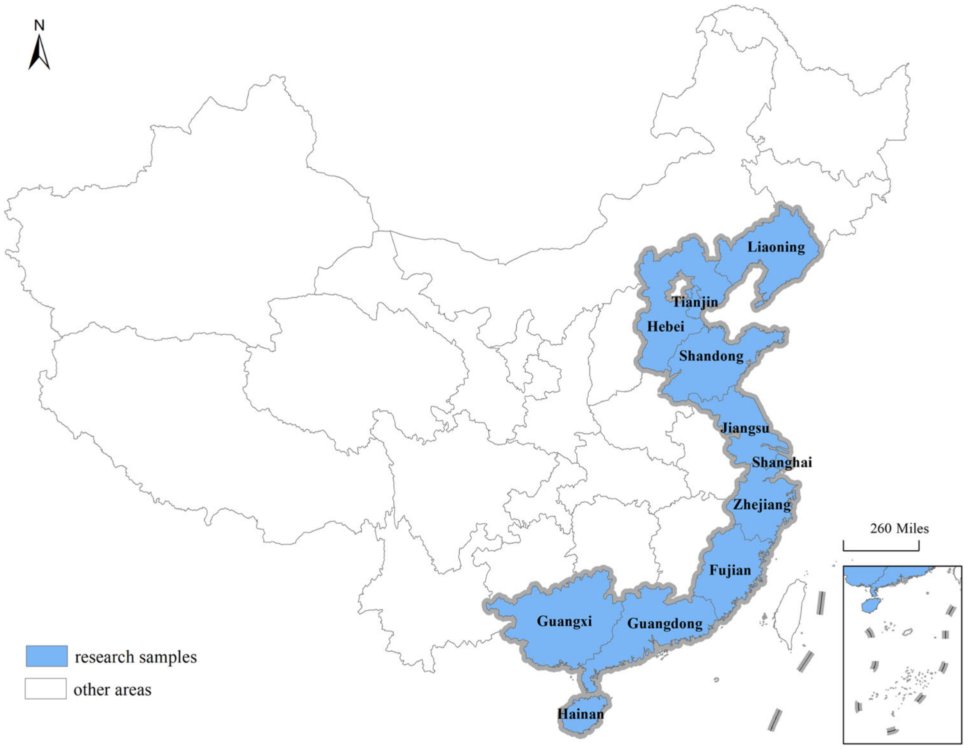

Fig. 2 Research sample of this article. This figure provides an overview of the research sample, focusing on the selected data from 11 coastal provinces of China.

Table 1 Selection indicators of green economic efficiency of marine fisheries.

Target	Category	Specific component	Indicator	Attribute
Green economic efficiency of marine fisheries	Input	Labor input	Marine fishery workers	+
		Capital input	ocean capital stock	+
		Resource input (entropy method)	Port production berths	+
			Total number of travel agencies	+
			Marine culture area	+
	Desirable Output	Economic benefits	Actual output value of marine fisheries (based on 2009)	+
	Undesirable output	Negative environmental impact (entropy method)	Marine fishery carbon emissions	−
			Direct discharge of pollution source into the sea—ammonia nitrogen	−
			Direct discharge of pollution source into the sea—chemical oxygen demand	−

We categorize MFGEE into five intervals: low (≤0.684), moderately low (0.684–0.891), medium (0.891–1.015), moderately high (1.015–1.109), and high (>1.109). As illustrated in the accompanying Fig. 3, the MFGEE of China's coastal areas displayed a fluctuating trend from 2009 to 2020. Generally speaking, in regions with rapid economic development and diversified industrial structures, such as Shanghai and Zhejiang, it is usually possible to allocate more resources and capabilities toward the sustainable development of fisheries and environmental protection, thereby maintaining higher levels of efficiency. Liaoning, Fujian, Tianjin, and Shandong have achieved significant improvements or stable growth in the green economic efficiency of marine fisheries by implementing detailed fisheries development plans, actively promoting environmentally friendly aquaculture technologies, and committing to the conservation of aquatic biological resources. Conversely, Hainan faces the negative impacts of activities such as overfishing and tourism development due to its unique environmental vulnerability and significant environmental pressures as an island, leading to a decline in fisheries efficiency compared to the highest levels. Hebei and Guangxi, despite making certain progress in fisheries development, still face issues such as the lack of leading enterprise examples, self-sufficiency in high-quality aquatic breeds, and weak safety guarantee capabilities. These issues limit their progress in fisheries technological innovation and the promotion of environmentally friendly aquaculture technologies. Guangdong and Jiangsu, as economically more developed regions, despite their abundant resources, face shortcomings in implementing fisheries management policies and environmental protection measures. Additionally, pressures from industrial pollution and sea area development may lead to the deterioration of the marine ecological environment, further impacting the quality and quantity of fisheries resources. These factors collectively contribute to a decline in fisheries efficiency.

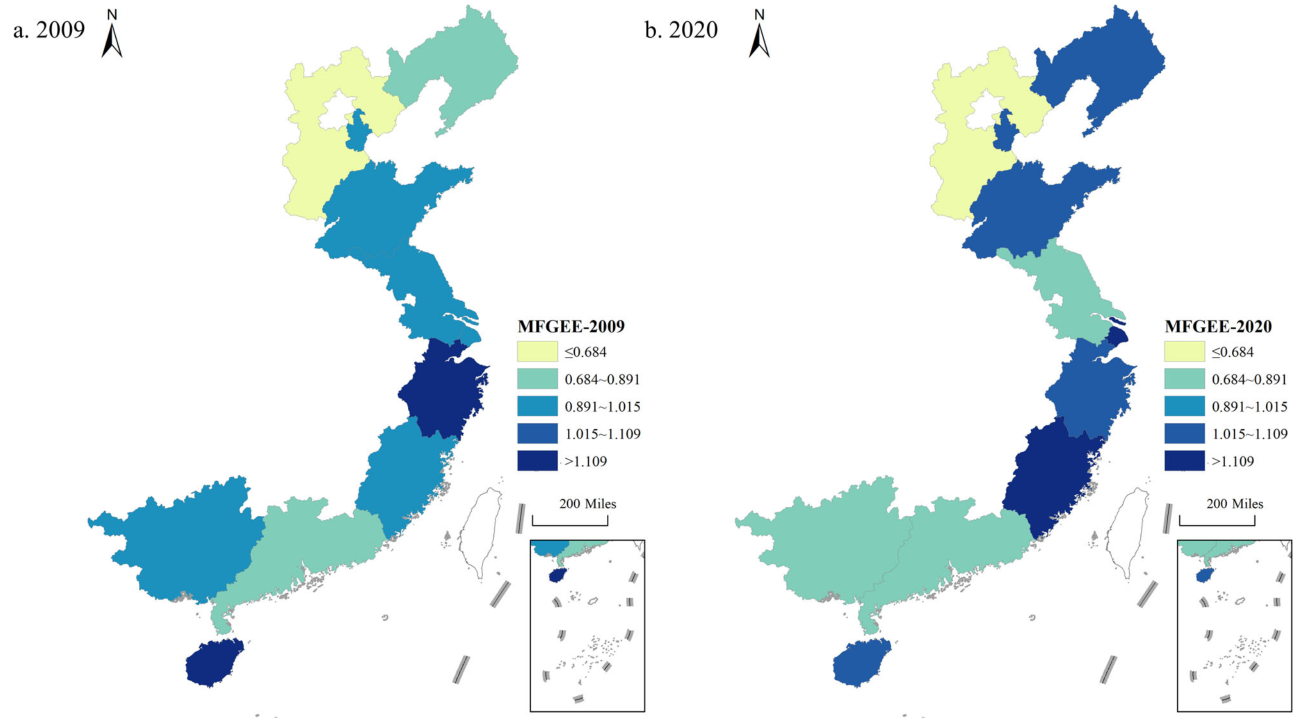

Fig. 3 Distribution of MFGEE in 11 coastal provinces of China in 2009 and 2020. This figure illustrates the spatial distribution of marine fisheries green economic efficiency (MFGEE) across China's 11 coastal provinces in 2009 and 2020. Among them, (**a**) represents the situation in 2009, while (**b**) represents the situation in 2020.

Explanatory variable. Artificial intelligence (AI) encompasses the application of advanced algorithms and computational models to simulate, enhance, and expand human decision-making capabilities, especially in addressing complex fisheries management and operational issues. To objectively analyze the development trends of AI and its impacts, quantification is essential. Drawing on Ji and Li (2021) and Alsaleh and Yang (2023), and considering the actual conditions of fisheries in China, this paper starts from four dimensions: AI application, fisheries information services, fisheries talent training, and foundational information technology resources. It selects 12 indicators to measure the application level of AI in fisheries, as shown in Table 2. Specifically, AI application covers the direct applications of AI technology in the fisheries sector and related research progress; the fisheries informatization services evaluate the ability to provide fisheries-related information services, offering necessary data support for the application of AI technology and fisheries management; fisheries talent training focuses on the acceptance of AI technology in the fisheries field and talent training, which constitutes the foundation for the widespread application of AI technology; the foundational information technology resources reflects the infrastructural conditions relied upon by fisheries informatization and AI applications. We use the entropy method to combine these indicators to calculate the AI technology in China's fisheries from 2009 to 2020.

We categorize AI into five intervals: low (≤0.080), moderately low (0.080–0.107), medium (0.107–0.132), moderately high (0.132–0.155), and high (>0.155). As depicted in Fig. 4, from 2009 to 2020, the overall trend of AI in China's coastal regions has been ascending, indicating significant growth in investment and development in AI. Most provinces have transitioned from a lower to a higher range in AI application levels, indicating increased attention and investment in AI technology in these areas. However, Fujian and Guangxi remain in the lower range, which may be due to deficiencies in these regions regarding investment in fisheries AI, the pace of technological updates, talent development, or policy support. This uneven development reflects the differences in AI investment and application across regions, while also highlighting the potential opportunities and challenges in enhancing AI application in fisheries in lower-level areas.

Moderating variable

Green finance (GF): It is increasingly recognized as an effective tool for fostering the healthy operation of economies and sustainable development (Saeed Meo and Karim, 2022). Numerous studies have examined green finance from various perspectives (Debrah et al. 2022; Hafner et al. 2020). To ensure the feasibility and operability of the indicators, this study aims to construct a comprehensive index of green finance development, encompassing four dimensions: green credit, green investment, green insurance, and governmental support, as detailed in Table 3. Specifically, as a core component of the green finance system, green credit directly affects the funding supply for sustainable projects; green investment not only reflects the financial market's support for green industries but is also an important indicator of the market's depth and breadth; green insurance aims to reduce environmental risks through insurance products and services, encouraging and supporting environmental protection activities; government policies and fiscal support play a crucial role in promoting the development of green finance. We employ the entropy value method to calculate GF in China's coastal provinces and cities from 2009 to 2020.

Consistent with the previous categorization approach, we have also divided green finance into five intervals. As shown in Fig. 5, from 2009 to 2020, the overall trend of green finance in China's coastal regions has been upward, indicating continuous growth and development in this sector. By 2020, the majority of the provinces had entered the high interval of green finance. This signifies significant progress in green finance across these coastal

Table 2 Selection indicators of AI in fisheries.

Target	Rule	Criteria	Indicator	Attribute
Artificial intelligence of fisheries	AI Application	AI technology practice	First industry industrial robot installation density	+
		Research on AI-related papers	Found AI-related papers used in the marine field from WOS	+
	Fisheries information service	Number of websites	Websites (number)	+
		Number of mobile platform users	Mobile platform (household)	+
		Number of telephone hotline services	Telephone hotline (number)	+
		Proportion of aquatic technology promotion funds	Aquatic technology promotion operating funds/total aquatic technology promotion expenses	+
	Fishery information talents	Ratio of trained fishermen	Number of trained fishermen/number of fishermen	+
		Frequency of training for extension personnel	Number of business training for extension personnel/number of people promoting aquaculture technology	+
	Fisheries Information Resources	Internet penetration rate	Number of Internet broadband access users/end-of-year resident population	+
		Landline penetration rate	Number of fixed-line telephone users/end-of-year resident population	+
		Mobile phone penetration rate	Number of mobile phone users/end-of-year resident population	+
		Total postal and telecommunications services per capita	Total postal and telecommunications services per capita	+

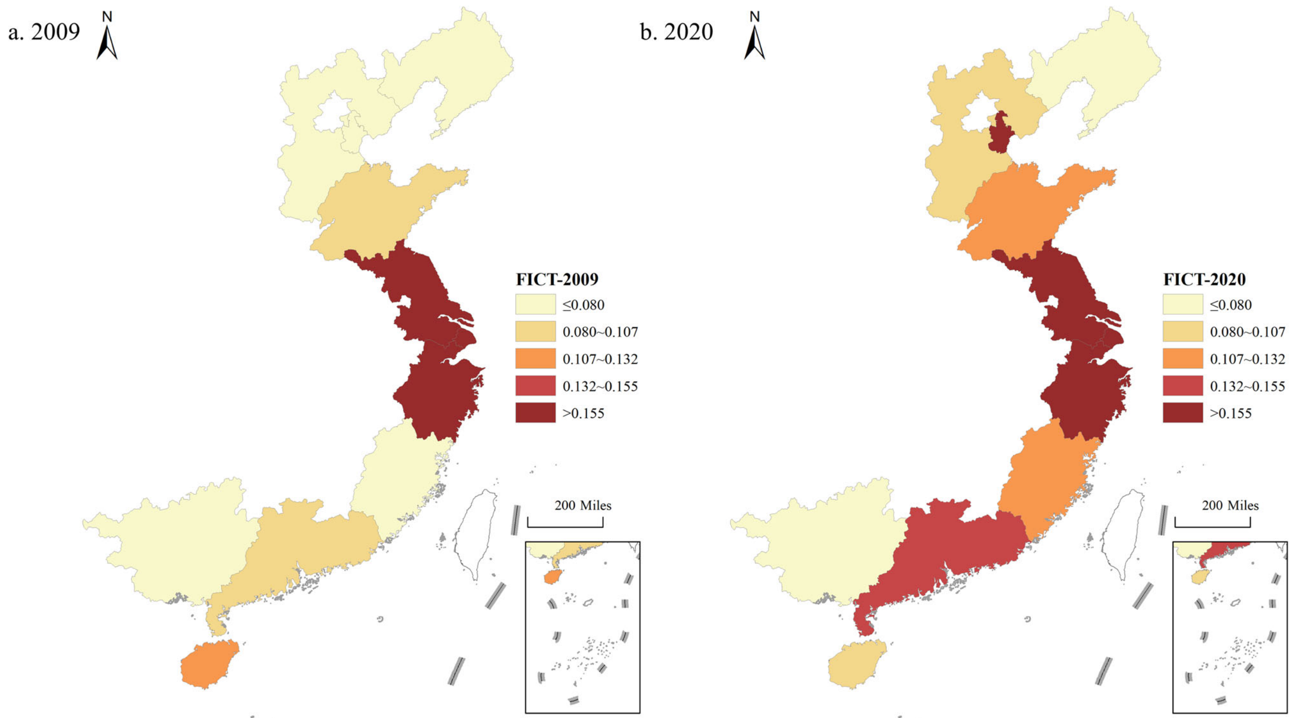

Fig. 4 Distribution of AI in 11 coastal provinces of China in 2009 and 2020. This figure shows the distribution of AI (Artificial Intelligence development levels) in 11 coastal provinces of China for the years 2009 and 2020, indicating temporal and regional variations. Among them, (**a**) represents the situation in 2009, while (**b**) represents the situation in 2020.

provinces over the past decade. The widespread transition into the high interval may be attributed to supportive green finance policies and a growing emphasis on environmental sustainability.

Trade openness (OPEN): This article uses the ratio of total imports and exports to GDP as a proxy variable to define trade openness. Trade openness is widely regarded as a key factor in driving economic growth and global integration (Wu, 2022). Trade openness brings advanced knowledge and technology to the host country, accelerates the efficient allocation of resources, and enhances industrial competitiveness. However, trade development also presents certain challenges, especially in host countries with more lenient environmental regulations, which may lead to the introduction of low-quality products, increase resource consumption and environmental pollution, and in turn, restrict the sustainable development of China's economy (Li et al. 2021b).

As illustrated in Fig. 6, from 2009 to 2020, trade openness in China's coastal regions did not show a continuous upward trend,

Table 3 Selection indicators of green finance.

Target	Rule	Criteria	Indicator	Attribute
Green finance development	Green credit	Proportion of interest expenses of high energy-consuming industries	Interest expenses of six major energy-consuming industrial industries/total industrial interest expenses	−
	Green investment	Environmental pollution control investment as a share of GDP	Environmental pollution control investment/GDP	+
	Green insurance	Agricultural insurance depth	Agricultural insurance income/gross agricultural output value	+
	Governmental support	Proportion of fiscal environmental protection expenditure	Fiscal environmental protection expenditure/fiscal general budget expenditure	−

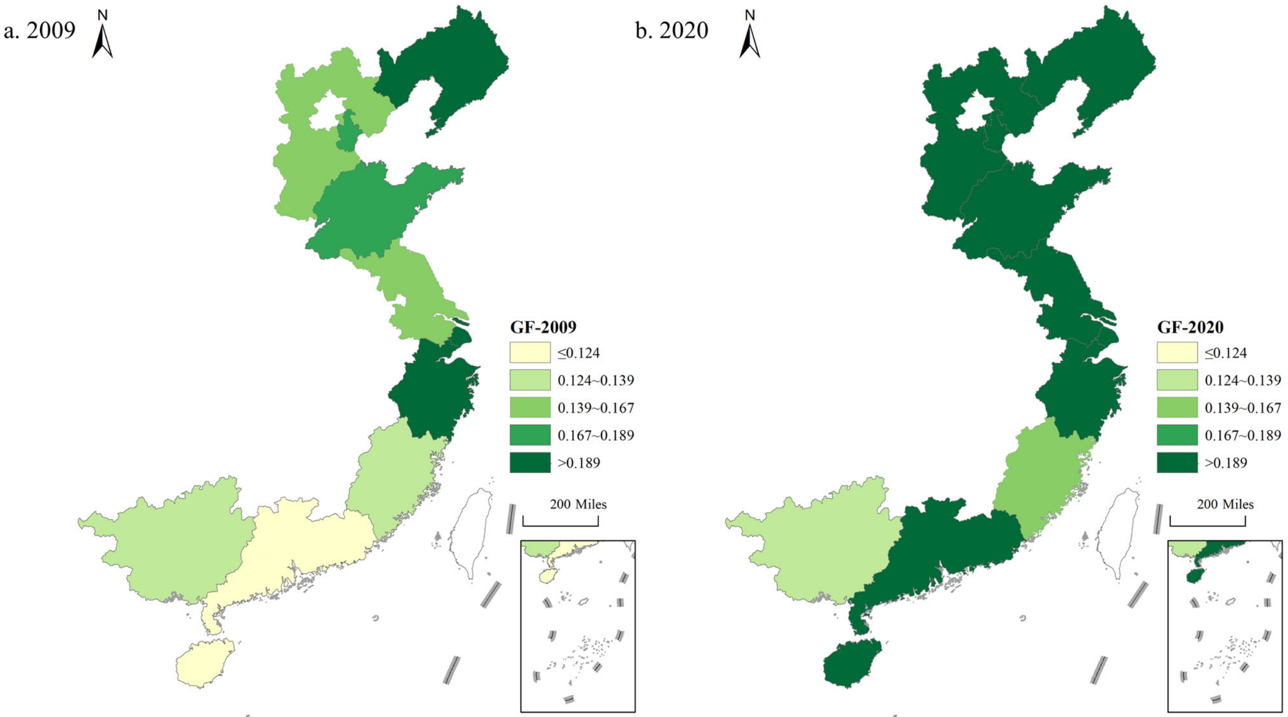

Fig. 5 Distribution of GF in China's 11 coastal provinces in 2009 and 2020. This figure presents the spatial distribution of Green Finance (GF) in the 11 coastal provinces of China for 2009 and 2020. Among them, (**a**) represents the situation in 2009, while (**b**) represents the situation in 2020.

and some provinces even experienced a decline. This fluctuation is directly related to the trade policy tightening and trade lockdown measures implemented by the United States, which significantly affected the foreign trade activities of China's coastal regions. Moreover, the outbreak of the COVID-19 pandemic at the beginning of 2020 caused unprecedented shocks to global economic activities and international trade. As the frontier of openness to the outside world, the trade openness of China's coastal regions was significantly affected. The pandemic-induced supply chain disruptions, reduction in trade flows, and shrinkage of international market demand further exacerbated the decline in the level of trade openness.

R&D investment (RD): To ensure the practicality and operability of the indicator, this paper uses "the natural logarithm of internal expenditures on R&D" as the proxy variable to measure R&D investment. Existing research has identified R&D investment as a key factor in improving green economic efficiency. According to Zhang et al. (2021a), a higher ratio of R&D investment not only promotes the development of new technologies and products but also helps improve production efficiency, reduce environmental pollution, and foster the development of a green economy. However, it is noteworthy that current R&D investments are often concentrated in high-end, high-tech industries, potentially neglecting support for R&D in traditional industries and environmental technologies, thus possibly limiting the green economic efficiency of marine fisheries (Chen et al. 2022b).

As shown in Fig. 7, from 2009 to 2020, R&D investment in China's coastal regions overall shows an upward trend, indicating that investment and efforts in R&D activities in coastal regions have been continuously strengthened. By 2020, most provinces saw a significant increase in R&D investment, reflecting the important progress made by coastal provinces over the past decade in intensifying scientific innovation. This continuous increase in R&D investment may benefit from policy support, the optimization of the innovation environment, and the strengthening of intellectual property protection.

Control variables

Marine technology innovation (MTI): Marine technology innovation is a key factor in driving the green economic efficiency of marine fisheries. This paper represents it as the ratio of the added

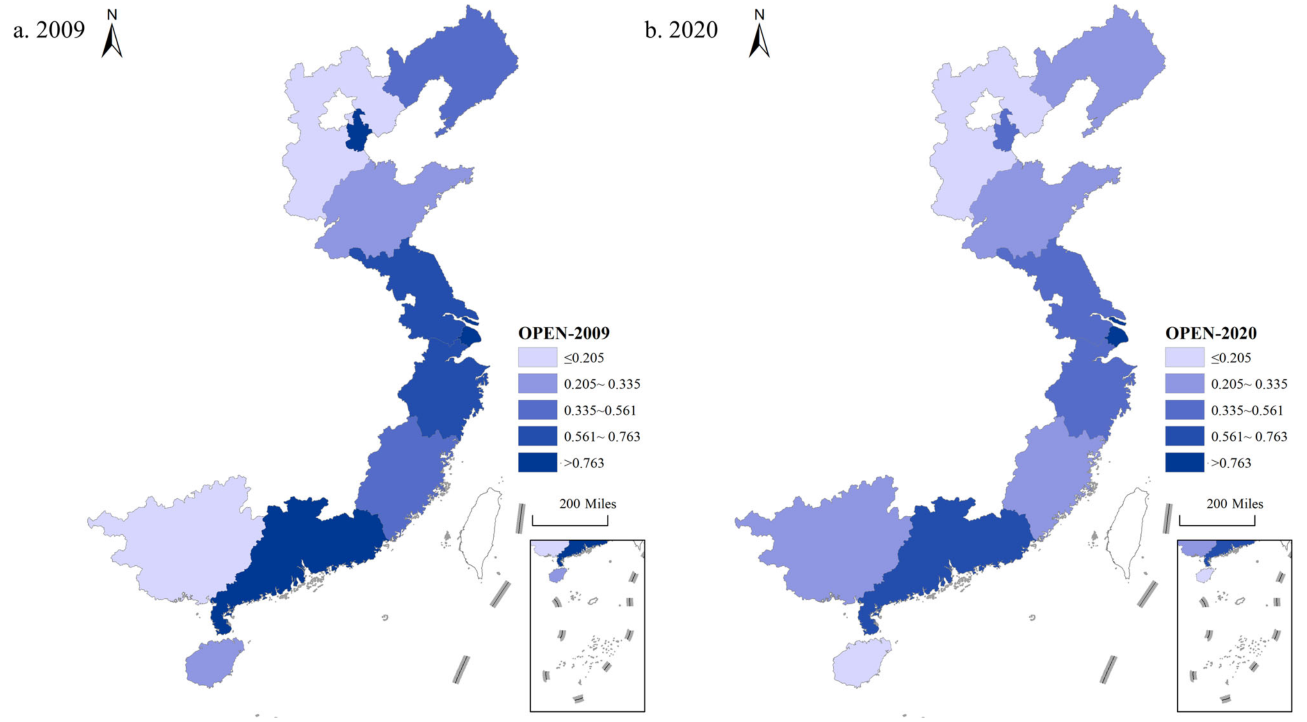

Fig. 6 Distribution of trade openness in China's 11 coastal provinces in 2009 and 2020. This figure displays the distribution of trade openness in 11 coastal provinces of China during 2009 and 2020. Among them, (**a**) represents the situation in 2009, while (**b**) represents the situation in 2020.

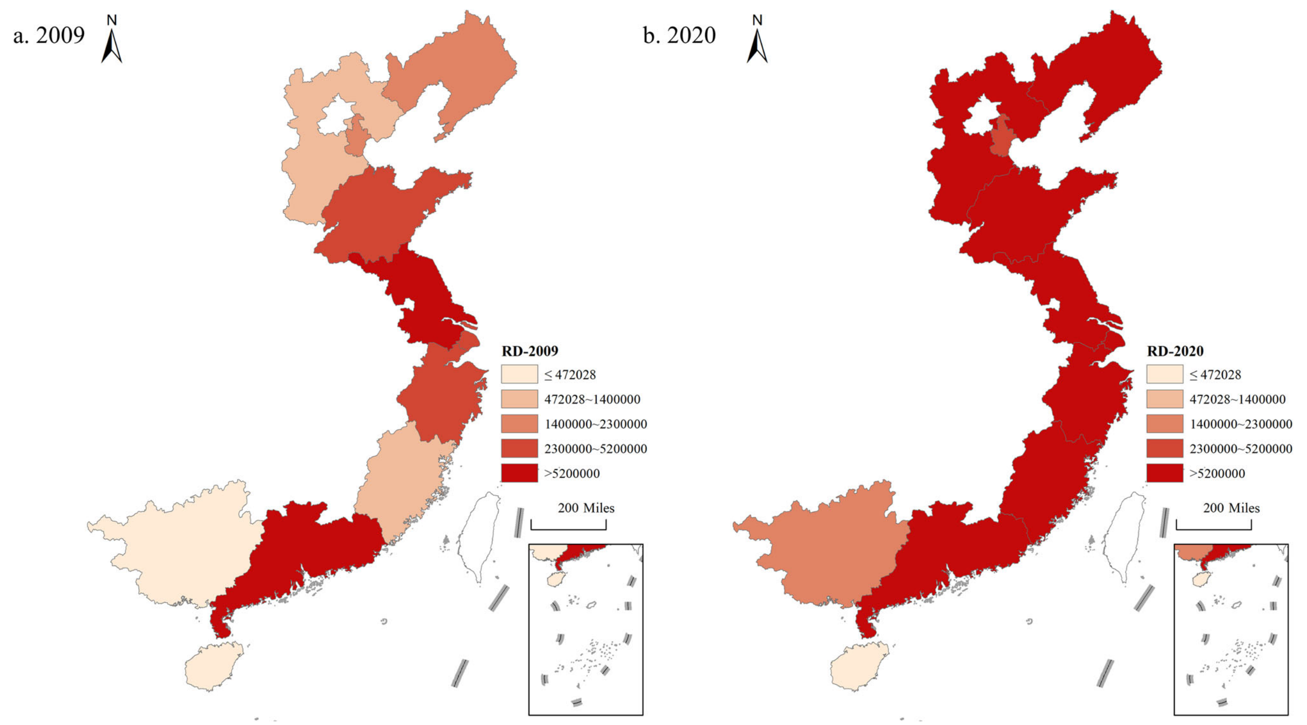

Fig. 7 Distribution of R&D investment in China's 11 coastal provinces in 2009 and 2020. This figure illustrates the distribution of Research and Development (R&D) investment across China's 11 coastal provinces in 2009 and 2020, emphasizing regional disparities and temporal trends. Among them, (**a**) represents the situation in 2009, while (**b**) represents the situation in 2020.

value of marine scientific research services to GOP. A higher ratio implies that the region has significant investment and achievements in marine technology innovation, positively affecting the enhancement of the green economic efficiency of marine fisheries (Liu et al. 2021a).

Energy intensity (ET): As an important indicator for measuring the energy efficiency of economic activities and environmental impacts, the role of energy intensity in the fisheries economy cannot be ignored (Bastardie et al. 2022). Low energy intensity means that energy is used more efficiently in the production of equivalent economic output, resulting in less environmental impact, which is conducive to achieving green and sustainable development in the fisheries economy (Li et al. 2024). This paper uses energy consumption per unit of GDP as the proxy variable for energy intensity.

Marketization (MAR): It is directly related to the efficiency of resource allocation and the freedom of economic activities (Zhang et al. 2023b). Regions with higher marketization indices possess more free and open market environments, which are conducive to promoting healthy economic development and can effectively enhance green economic efficiency (Zeng et al. 2021). This paper measures the degree of marketization using the marketization index.

Marine industry agglomeration (MIA): A higher location entropy value indicates a high degree of marine industry agglomeration in the region, suggesting that the region has comparative advantages and a high level of specialization in marine industry development, which may have a positive impact on promoting green economic development. Drawing on existing research, this paper measures marine industry agglomeration using location entropy. The formula is as follows:

$$LQ = \sum_j \frac{x_{ij}/\sum_j x_{ij}}{\sum_i x_{ij}/\sum_i \sum_j x_{ij}} \times \frac{1}{3} \tag{6}$$

Table 4 Descriptive statistics of variables.

Variable	Obs.	Mean	Std. dev.	Min	Max
MFGEE	132	−0.060	0.217	−0.766	0.165
AI	132	−2.284	0.610	−3.653	−0.907
GF	132	−1.563	0.392	−2.203	−0.256
RD	132	15.261	1.374	10.965	17.365
OPEN	132	−0.915	0.660	−2.217	0.345
MTI	132	0.177	0.085	0.044	0.457
ET	132	0.677	0.304	0.285	1.661
MAR	132	2.195	0.184	1.714	2.479
MIA	132	1.148	0.378	0.679	2.065

In the formula, x_{ij} represents the scale of industry j in region i, $\sum_j x_{ij}$ represents the total scale of all industries in region i, $\sum_i x_{ij}$ represents the total scale of industry j across all regions, and $\sum_i \sum_j x_{ij}$ represents the total scale of all industries across all regions.

Data source. The data sources include the China Statistical Yearbook, China Fisheries Statistical Yearbook, China Marine Statistical Yearbook, Marine Ecological Bulletins, National Provincial Marketization Index Report, China Energy Statistical Yearbook, provincial statistical yearbooks, and the National Bureau of Statistics of China. Certain variables were logarithmically transformed for analysis. Table 4 provides the descriptive statistics for these variables. Figure 8 shows the correlation coefficients. It can be observed that, apart from the correlation coefficient observed between marketization and R&D investment, the rest of the correlation coefficients are <0.8, indicating that there is no multicollinearity among the variables.

This paper sets 2009 as the base year, mainly based on the following considerations: First, 2009 was a global turning point when the attention to green economy and sustainable development significantly increased, especially with the convening of the Copenhagen United Nations Climate Change Conference and China's emphasis on high-quality development. Selecting this year as the starting point facilitates tracking and analyzing the subsequent development and improvements in the green economic efficiency of marine fisheries. Secondly, since this year, the application of AI technology in marine fisheries began to increase, making 2009 a suitable base year for the study to assess the impact of AI technology in this field. Furthermore, since 2009, relevant data on marine fisheries and the green economy have been complete and coherent, providing reliable data support for this research.

Results and analysis

Benchmark regression results

Variable test. Before proceeding with regression analysis, we first employed unit root tests to verify the stationarity of the selected variables. As indicated in Table 5, the unit root test results for the original variables indicate that some variables are stationary; after

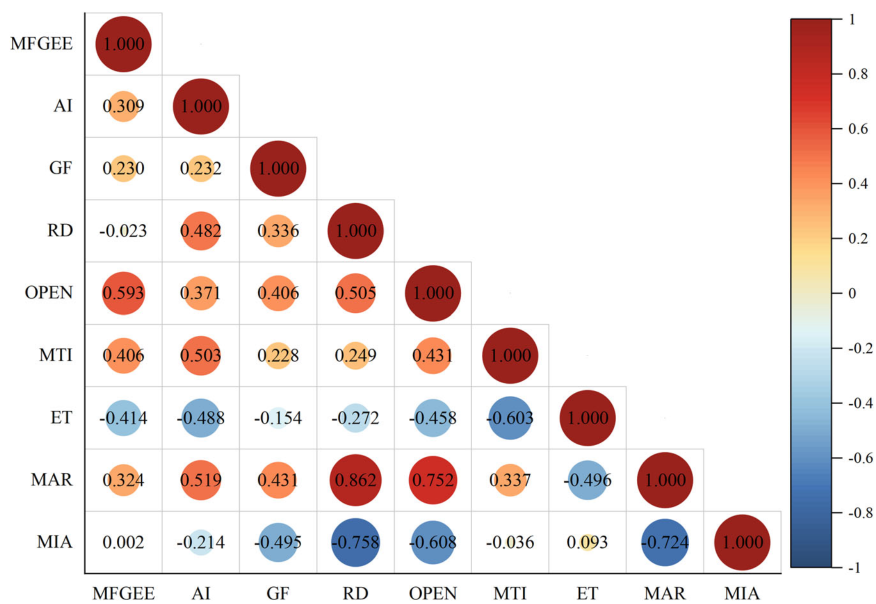

Fig. 8 Correlation coefficient diagram between variables. This figure shows the correlation coefficients among key variables used in the study.

Table 5 Unit root tests.

Unit root test	Variable	LLC	IPS	Fisher-ADF	Fisher-PP
Original	MFGEE	−1.479*	0.741	24.416	24.271
	AI	−0.886	−0.069	22.967	23.028
	GF	−7.327***	−4.429***	58.826***	39.240**
	RD	−8.523***	−4.688***	63.248***	87.866***
	OPEN	−2.867***	0.463	19.122	5.136
	MTI	4.428	6.602	2.180	2.455
	ET	−14.099***	−7.353***	88.206***	136.373***
	MAR	−2.086**	0.637	17.750	25.270
	MIA	−1.988**	0.063	26.110	17.040
First difference	MFGEE	−14.347***	−9.230***	94.402***	94.212***
	AI	−9.978***	−6.052***	73.515***	75.299***
	GF	−16.351***	−10.283***	113.990***	99.070***
	RD	−4.586***	−1.681**	30.738	32.721*
	OPEN	−7.508***	−5.346***	67.064***	87.721***
	MTI	−3.668***	−1.326*	31.524*	35.057**
	ET	−5.395***	−2.128**	39.727**	42.056***
	MAR	−10.907***	−6.646***	78.276***	93.408***
	MIA	−4.789***	−3.117***	45.474***	56.952***

***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

Table 6 Panel cointegration test.

	t-Statistic	Prob.
ADF	−3.2625	0.0006
Residual variance	0.0030	
HAC variance	0.0026	

applying the first differencing, all variables passed the LLC, IPS, Fisher-ADF, and Fisher-PP tests, indicating that the variables in this study are confirmed to be stationary. Following this, to ascertain the existence of long-term relationships among the variables, we applied the Kao cointegration tests. The results, as presented in Table 6, indicate that the Kao tests confirm the presence of long-term relationships among the variables. Therefore, the variables selected for this study can be used for subsequent regression analysis.

Fixed effects model result. To validate Hypothesis 1, we sequentially incorporated a series of control variables into the fixed effects model (1), including AI, marine technology innovations, energy intensity, marketization, and marine industry agglomeration. This procedure was undertaken to examine the impact of AI on the green economic efficiency of the marine fishery sector. The results are presented in columns (1)–(5) of Table 7. Particularly in column (5), the regression coefficient of AI is 0.033, which is significant at the 5% level. This indicates that AI deployment in coastal regions can indeed enhance the green economic efficiency of the marine fishery industry, thereby substantiating Hypothesis 1.

Endogeneity test. In analyzing the effect of AI on the green economic efficiency of marine fisheries, the baseline regression results may be subject to potential endogeneity issues such as reverse causality and omitted variable bias, which can distort the findings. To address potential endogeneity, this study employed an instrumental variable (IV) approach.

Drawing on the approach adopted by Wang et al. (2022b), this study selected the number of post offices per million people in 1988 as IV for AI. This choice is grounded in two primary considerations: Firstly, historical reliance on postal services for information transfer and communication, and the provision of early ICT technologies, such as landline telephones primarily by post offices, suggests that the number of post offices is a strong indicator of a region's information infrastructure level. This historical context satisfies the relevance criterion for an IV, as it significantly influenced the application of AI in the fishery field. Secondly, from a time-span perspective, the historical number of post offices is unlikely to be directly related to the current green economic efficiency of marine fisheries, thus meeting the exogeneity requirement. Additionally, the study adopts a refinement technique proposed by Nunn and Qian (2014) to further refine the IV approach, incorporating the interaction between the number of post offices per million people in 1988 and the lagged value of AI as the final IV to account for provincial variations over time.

The results, as presented in Table 8, demonstrate that the coefficient of IV is significantly positive in the first stage, indicating a positive correlation between the IV and AI. The statistical tests, including the Kleibergen–Paap rk LM statistic and the Kleibergen–Paap rk Wald F statistic, significantly reject the null hypothesis of the IV's inadequacy, validating the appropriateness of the chosen IV. In the second stage, the coefficient of AI remains significantly positive at the 1% level. This suggests that AI positively affects the green economic efficiency of marine fisheries, even after controlling for potential endogeneity issues. Therefore, the findings of this study are robust.

Robust test

Replacing the explained variable: To verify the robustness of our findings, this section employs the Super-SBM model to recalculate the green economic efficiency of marine fisheries and incorporates this into Model (1) for robustness testing. The results, as shown in column (1) of Table 9, reveal that the coefficient of AI is consistent with the baseline results, implying that AI enhances the green economic efficiency of marine fisheries, thereby affirming the robustness and reliability of our findings.

Adjusting the sample period: Considering the pioneering trial of the green finance information management system in Zhejiang in 2020 and the extensive impact of the COVID-19 pandemic, this study modifies the sample period from 2009–2020 to 2009–2019. This adjustment aims to mitigate potential confounding effects

Table 7 Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)
AI	0.026*	0.026*	0.034**	0.038**	0.033**
	(1.915)	(1.861)	(2.262)	(2.572)	(2.341)
MTI		−0.020	−0.179	−0.239	−0.202
		(−0.049)	(−0.416)	(−0.607)	(−0.529)
ET			0.261	0.263	0.242
			(1.567)	(1.563)	(1.471)
MAR				−0.418**	−0.397**
				(−2.586)	(−2.442)
MIA					−0.146
					(−1.208)
Constant	0.000	0.004	−0.128	0.808**	0.929**
	(0.006)	(0.046)	(−1.114)	(2.074)	(2.025)
Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
N	132	132	132	132	132
R^2	0.914	0.914	0.917	0.924	0.926

Robust standard errors in brackets; ** and * indicate significance at 5% and 10% levels, respectively.

Table 8 Endogeneity test.

Variables	2SLS-stage (1) AI	2SLS-stage (2) MFGEE
IV	0.012***	
	(5.953)	
AI		0.077***
		(2.659)
MTI	2.176	−0.547
	(1.571)	(−1.492)
ET	−1.975*	0.216
	(−1.663)	(1.498)
MAR	−0.050	−0.463***
	(−0.069)	(−3.001)
MIA	−0.094	−0.116
	(−0.230)	(−0.957)
Year FE	Yes	Yes
Province FE	Yes	Yes
N	121	121
R^2	0.749	0.156
Kleibergen-Paap rk LM	23.692 (0.000)	
Kleibergen-Paap rk Wald F	35.443(16.38)	

Robust standard errors in brackets; *** and * indicate significance at 1% and 10% levels, respectively.

Table 9 Robustness test regression results.

Variables	MFGEE (1)	MFGEE (2)	l. MFGEE (3)
AI	0.150***	0.034**	0.047***
	(4.935)	(2.370)	(3.047)
MTI	−0.087	−0.078	−0.117
	(−0.134)	(−0.184)	(−0.341)
ET	−0.158	0.260	0.164
	(−0.712)	(1.650)	(0.867)
MAR	−0.723**	−0.379**	−0.457***
	(−2.071)	(−2.044)	(−2.827)
MIA	0.311	−0.115	0.020
	(1.595)	(−0.910)	(0.181)
Constant	1.278	0.818	0.947**
	(1.505)	(1.593)	(2.296)
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
N	132	121	121
R^2	0.895	0.936	0.940

Robust standard errors in brackets; *** and ** indicate significance at 1% and 10% levels, respectively.

stemming from the initiation of the green finance information system and the outbreak of the pandemic. The results, displayed in column (2) of Table 9, demonstrate that AI remains significantly positive, further validating the robustness of the results to changes in the sample timeframe.

Lagging the explained variable: To further test robustness, the study lags the dependent variable by one period and then re-runs the regression. According to the results in column (3) of Table 9, the coefficient of AI continues to exhibit a directionally consistent impact with previous results. Overall, these tests collectively affirm the robustness of the regression results in this study.

Moderating effect results. To validate Hypothesis 2a, we established a moderation effect model (Eq. (2)) with green finance acting as the moderating variable. The regression outcomes, as displayed in column (1) of Table 10, demonstrate a significantly positive coefficient for the interaction term AI×GF. This suggests that green finance enhances the role of AI in improving the green economic efficiency of marine fisheries. Specifically, after applying Eq. (2), the marginal effect of AI is 0.095, whereas in column (5) of Table 7, without the moderating variable, the marginal effect of AI is 0.033. Therefore, the marginal moderating effect of green finance on the primary effect is 0.062, and this moderating effect is significant, thereby substantiating Hypothesis 2a.

To validate Hypothesis 3a, we constructed a moderation effect model (Eq. (3)), incorporating trade openness as the moderating variable. The regression results, as presented in column (2) of Table 10, reveal a significantly positive coefficient for the interaction term AI×OPEN. This outcome suggests that trade openness enhances the efficacy of AI in boosting the green economic efficiency of the marine fishery sector. Specifically, upon applying Eq. (3), the marginal effect of AI is found to be 0.088, as opposed to a marginal effect of 0.033 for AI without the inclusion of the moderating variable, as observed in column (5) of Table 7. Thus, the marginal moderating effect of trade openness on the primary effect is 0.055, and this moderating effect is statistically significant, thereby substantiating Hypothesis 3a.

To substantiate Hypothesis 4a, we formulated a moderation effect model (Eq. (4)), with R&D investment serving as the moderating variable. The regression findings, delineated in column (3) of Table 10, exhibit a significantly positive coefficient for the interaction term AI×RD. This result indicates that R&D investment can intensify the role of AI in augmenting the green economic efficiency of the marine fishery sector, thereby exerting a moderating effect. Consequently, Hypothesis 4a is affirmed.

Moreover, considering the launch of the green finance information management system in 2019, potential issues related to AI could emerge. Initially piloted in Huzhou City, Zhejiang Province, this system was subsequently expanded to other cities in Zhejiang in 2020. This regional pilot and implementation might endow the data from Zhejiang Province with a degree of specificity in the research. Therefore, to circumvent potential data biases, we adopted the approach of excluding all samples from Zhejiang Province, as illustrated in column (4) of Table 10. Through this robustness check, we ascertain that our research conclusions remain stable, further affirming the robustness and reliability of our study findings.

Threshold effect results. In accordance with Hypotheses 2b, 3b, and 4b, Changes in green finance, trade openness, and R&D investment may alter the impact of AI on the green economic efficiency of marine fisheries. In response to this possibility, we utilize a panel threshold model to analyze the trends in the efficacy of AI across different threshold intervals of green finance, trade openness, and R&D investment.

Table 10 Regression results of moderating effect model.

Variables	(1)	(2)	(3)	(4)
AI×GF	0.043*			0.046*
	(1.735)			(1.716)
AI×OPEN		0.065***		
		(3.191)		
AI×RD			0.035**	
			(2.211)	
AI	0.095***	0.088***	0.014	0.101***
	(2.807)	(4.652)	(0.994)	(2.698)
GF	0.066			0.078
	(0.961)			(1.008)
OPEN		0.153**		
		(2.227)		
RD			−0.193***	
			(−3.189)	
MTI	−0.275	−0.317	−0.445	−0.323
	(−0.690)	(−0.879)	(−1.324)	(−0.753)
ET	0.212	0.204	0.359**	0.186
	(1.298)	(1.169)	(2.421)	(1.047)
MAR	−0.399**	−0.361**	−0.353**	−0.411**
	(−2.493)	(−2.251)	(−2.558)	(−2.510)
MIA	−0.163	−0.162	−0.281***	−0.174
	(−1.390)	(−1.479)	(−3.038)	(−1.447)
Constant	1.075**	1.034**	3.841***	1.135**
	(2.306)	(2.320)	(4.457)	(2.240)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
N	132	132	132	120
R^2	0.927	0.933	0.940	0.924

Robust standard errors in brackets; ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.

Threshold effect test. In our analysis, we employed the bootstrap method, replicating the sample 300 times to determine the number and their specific values of thresholds. As indicated in Table 11, following the guidelines by Hansen (1999), we determined that green finance, trade openness, and R&D investment each exhibit a significant single-threshold characteristic. Their respective threshold values are −1.9505, −1.0935, and 13.3514.

Subsequently, we employed the likelihood ratio (LR) test to verify the accuracy of the single-threshold model. As illustrated in Fig. 9, there is a consistent match between the estimated threshold values and the actual data. Moreover, the LR statistic is notably less than the critical value of 7.35 (indicated by the dashed line). These results collectively affirm that the estimated threshold is accurate and effective. In summary, we constructed single-threshold regression models with the green economic efficiency of the marine fishery sector as the dependent variable, AI as the explanatory variable, and green finance, trade openness, and R&D investment as threshold variables.

Threshold regression results. Following the verification of a single threshold's presence, Eq. (5) is utilized to examine the varying impact of AI on the green economic efficiency of marine fisheries under different green finance, trade openness, and R&D investment. The results are presented in Table 12.

In column (1), we used green finance as the threshold variable to examine the nonlinear relationship between AI and the green economic efficiency of the marine fishery sector. Our results show that when green finance is within a low range ($GF \leq -1.9505$), the coefficient for AI is 0.008, which is statistically insignificant. This indicates that at lower levels of green finance, AI does not significantly impact the green economic efficiency of marine fisheries. Conversely, when green finance is at a higher range ($GF > -1.9505$), AI demonstrates a positive impact on green economic efficiency (0.037), achieving significance at the 5% level. This indicates that with the enhancement of green finance, AI plays a more pivotal role in improving the green economic efficiency of marine fisheries. Thus, Hypothesis 2b is validated.

In column (2), with trade openness serving as the threshold variable, the nonlinear relationship between AI and the green economic efficiency of the marine fishery sector was investigated. Specifically, when trade openness is within a low range ($OPEN \leq -1.0935$), the coefficient for AI is 0.012, which is not statistically significant. This indicates that at relatively lower levels of trade openness, AI fails to significantly enhance the green economic efficiency of the marine fishery sector. Conversely, when trade openness is at a higher range ($OPEN > -1.0935$), the coefficient for AI is significantly positive at 0.055, suggesting that as trade openness continues to expand, AI plays a more critical role in improving the green economic efficiency of marine fisheries. Therefore, Hypothesis 3b is corroborated.

Table 11 Threshold test.

Threshold variables	Threshold effect test	Threshold value	Confidence interval	*F*-stat	*P*-value	10%	5%	1%
GF	Single threshold	−1.9505	[−2.0115, −1.9257]	14.23	0.070	13.049	15.298	18.684
OPEN	Single threshold	−1.0935	[−1.1150, −1.0923]	18.98	0.040	14.935	17.883	22.294
RD	Single threshold	13.3514	[13.0648,13.6050]	38.56	0.003	19.130	23.152	29.453

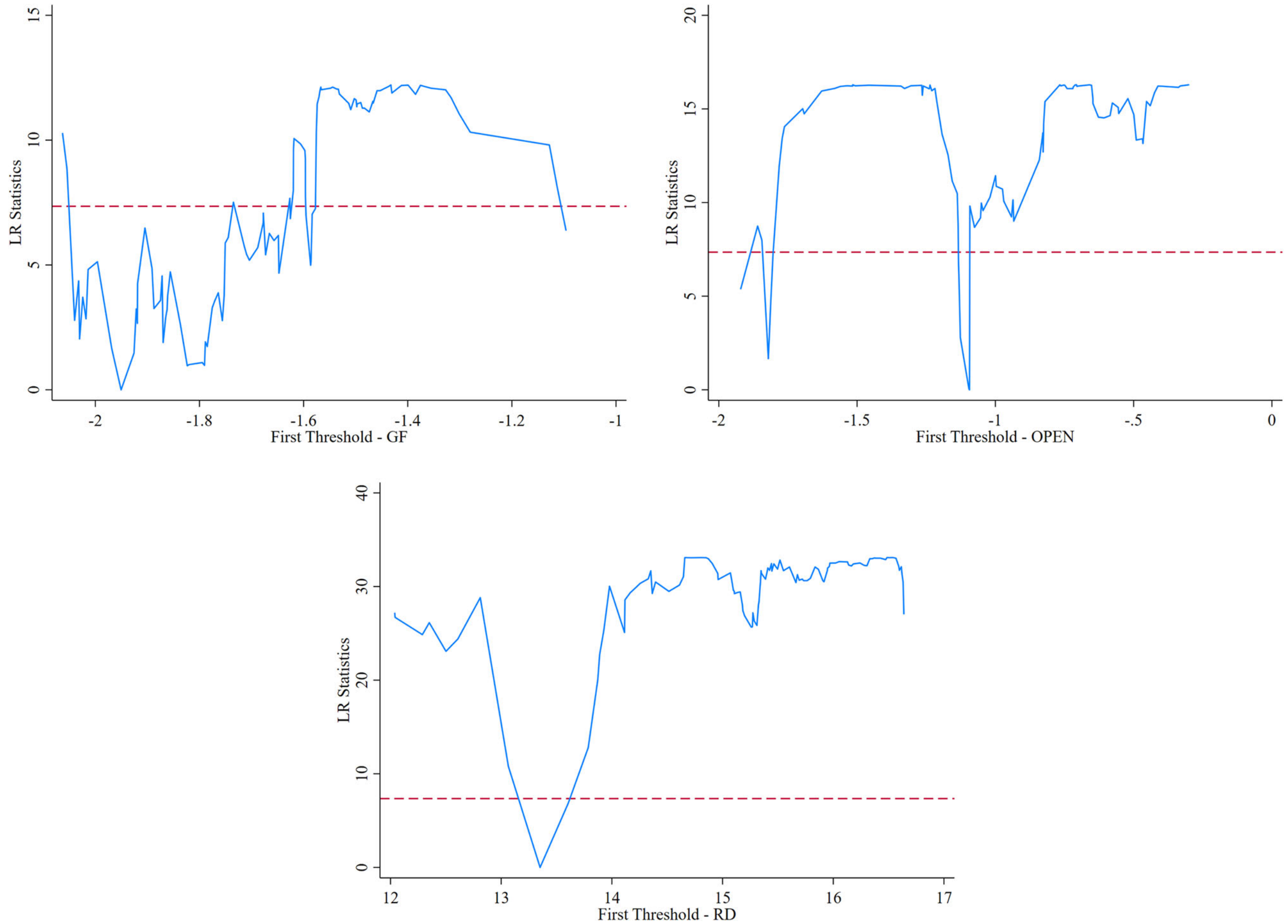

Fig. 9 LR test. This figure illustrates the LR diagram used to test the threshold value, highlighting the critical points where the threshold values change.

In column (3), using R&D investment as the threshold variable, the nonlinear relationship between AI and the green economic efficiency of the marine fishery sector was explored. When R&D investment is in a low range ($RD \leq 13.3514$), the coefficient for AI is -0.040, and it is significant at the 1% statistical level. This finding suggests that in the context of limited R&D funding, AI technology may not realize its potential positive effects. Conversely, when R&D investment is in a high range ($RD > 13.3514$), the coefficient for AI exhibits a positive impact on the green economic efficiency of the marine fishery sector (0.045), achieving significance at the 5% level. This indicates that with increased R&D investment, AI plays a positive role in enhancing the green economic efficiency of marine fisheries. Therefore, Hypothesis 4b is validated.

Discussion

Discussion of fixed effects model. Our initial research objective was to investigate the impact of AI on the green economic efficiency of the marine fishery sector. Building upon previous research by Zhao et al. (2022a), which highlighted AI's positive influence on green economic growth within China, this study specifically narrows its focus to the marine fisheries of China's coastal regions. It has been observed that the extensive application of AI in the fisheries sector has propelled traditional fisheries towards intelligent and automated transformations, injecting new vitality into enhancing green economic efficiency in coastal areas. Existing literature indicates that fisheries informatization can facilitate technological innovation and optimize the allocation of fishery resources, thereby enhancing the economic benefits of fisheries (Ji and Li, 2021), which is particularly vital for the sustainable development of fisheries (Alsaleh and Yang, 2023). As a more advanced form of ICT, AI intrinsically promotes the efficient utilization of fishery resources and environmental protection (Wang et al. 2023c) through the intelligent optimization of production technologies and processes. Leveraging machine learning and big data analysis, fishermen can precisely predict fish population dynamics, optimize fishing strategies, and improve resource utilization efficiency (Shreesha et al. 2023). Furthermore, the application of AI in monitoring and managing fishery resources helps prevent overfishing and reduce damage to the fishery ecosystem, thereby enhancing the green economic efficiency of marine fisheries.

Discussion of moderating effect model. The regression outcomes of the moderation effect model unveil a pivotal finding: the integration of AI with green finance, trade openness, and R&D investment significantly enhances the green economic efficiency of the marine fishery sector.

(1) This result resonates with the research of Goodell et al. (2021), which underscored the role of AI in enhancing the efficiency of financial transactions and decisions. Furthermore, with the increase in digital finance, the transformation of financial products and services through technological means has been confirmed to have a positive impact on China's green economic growth (Razzaq and Yang, 2023). Fin-tech, as a technology-driven financial innovation, when integrated with green finance, not only reduces environmental pollution but also promotes the enhancement of green economic efficiency (Muganyi et al. 2021;

Table 12 Threshold model regression results.

Variable	(1) q_{it}=GF	(2) q_{it}=OPEN	(3) q_{it}=RD
AI ($q_{it}\eta$)	0.008	0.012	−0.040***
	(0.457)	(0.585)	(−3.206)
AI ($q_{it}>\eta$)	0.037**	0.055***	0.045**
	(2.231)	(3.236)	(3.090)
MTI	−0.238	−0.258	−0.450
	(−0.402)	(−0.478)	(−0.845)
ET	0.259	0.358**	0.265
	(1.491)	(2.804)	(1.179)
MAR	−0.374	−0.380*	−0.437*
	(−1.669)	(−2.204)	(−2.202)
MIA	−0.211	−0.111	−0.245
	(−1.498)	(−0.902)	(−1.671)
Constant	0.849	0.698	1.063*
	(1.391)	(1.445)	(1.896)
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
N	132	132	132
R^2	0.353	0.375	0.452

Robust standard errors in brackets; ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.

Zhou et al. 2022). Unlike these studies, our focus, starting from the emerging technological means of AI, explores its interaction with green finance and its impact on the green economic efficiency of the marine fishery sector, thus filling a gap in the existing literature.

(2) Our research on trade openness aligns with previous scholars (Wang et al. 2024b), where AI, by promoting trade openness, further reduces carbon emissions and fosters energy transformation. Trade globalization has facilitated the inflow of advanced technologies (including green technologies and AI) (Ahmed and Le, 2021). Moreover, trade openness contributes to environmental improvement through enhanced management skills and technological innovation (Can et al. 2021; Wang et al. 2023a). However, this study utilized an integrated development index of AI, which was not employed in previous research.

(3) Consistent with the research of Babina et al. (2024), AI fosters economic growth through product innovation, a process inseparable from the crucial role of R&D investment. This further substantiates the significance of R&D investment in driving the advancement of environmentally friendly technologies and enhancing environmental protection capabilities.

Discussion of panel threshold model. The regression results of the panel threshold model confirm that the impact of AI on the green economic efficiency of the marine fishery sector is non-linear when green finance, trade openness, and R&D investment serve as threshold variables.

Specifically, when green finance is below a certain threshold, the impact of AI on the green economic efficiency of the marine fishery sector is not significant. Conversely, when green finance exceeds this threshold, the impact of AI on green economic efficiency becomes positively significant. Existing research indicates that when the development of green finance is not sufficiently mature, it may hinder the positive effects of AI (Ge et al. 2022). Insufficient green finance support implies a lack of adequate funding for the research and development of AI technologies (Muganyi et al. 2021), especially for projects that could directly promote the environmental sustainability of marine fisheries. Moreover, an immature green finance system might also result in a lack of necessary risk assessment and management tools (Wu, 2023), thereby affecting the confidence of investors and financial institutions in supporting the application of AI in marine fisheries.

When trade openness is below a threshold value, the impact of AI on the green economic efficiency of the marine fishery sector is not significant. In contrast, once trade openness exceeds this threshold, AI significantly promotes green economic efficiency. Research indicates that due to restrictive trade policies, as well as the lack of opportunities for transnational technological exchanges, countries with relatively closed trade may face significant challenges in harnessing the potential of AI (Wang et al. 2022c). Additionally, the closed nature of trade results in fisheries enterprises in these countries lacking opportunities to participate in international markets, diminishing their incentive to gain a competitive advantage through technological innovation (Hülsmann et al. 2008; Rosenthal and Strange, 2020).

When R&D investment is below a threshold value, AI exhibits a negative impact on the green economic efficiency of the marine fishery sector. However, once R&D investment exceeds this threshold, AI demonstrates a positive impact on green economic efficiency. We find that the positive influence of AI on the green economic efficiency of marine fisheries is significantly influenced by R&D investment, exhibiting distinct stage-like characteristics. This observation contrasts with the findings of Liu et al. (2020), who investigated AI applications in the manufacturing sector and noted that AI's influence on technological innovation was more pronounced in low-tech industrial sectors. Unlike their research scope, this study concentrates on the traditional and resource-intensive marine fishery sector, revealing the significance of R&D resources and the influence of industry characteristics on the success rate of AI applications.

Conclusions and recommendations

Conclusion. After thorough testing and analysis, this study robustly establishes the crucial role of AI in enhancing the green economic efficiency of marine fisheries in coastal regions. The transformation catalyzed by AI, from traditional practices to digitally oriented approaches, injects a fresh impetus towards the sustainability of coastal fisheries.

Our findings resonate with prior studies, illustrating AI's positive influence on fisheries' economic efficiency by optimizing resource allocation and facilitating technological advancements. AI's impact permeates the entire fishery production process, enhancing resource utilization efficiency, preventing overfishing, and reducing ecological harm. Additionally, in processing and distribution, AI optimizes supply chains, decreases energy consumption, and minimizes waste, enhancing both product quality and market competitiveness while bolstering green economic efficiency.

Addressing potential endogeneity concerns, our instrumental variable approach reaffirms AI's significant positive impact on green economic efficiency. Robustness tests and model adjustments further solidify this relationship, ensuring the reliability and consistency of our results.

Moreover, the synergistic effect between AI and green finance, trade openness, and R&D investment emerges is identified as a significant catalyst for fisheries sustainability. This collaborative support facilitates more effective investment in cutting-edge AI technologies, in turn boosting production efficiency and mitigating adverse impacts on fisheries. As a result, a comprehensive enhancement of financial and technological resources bolsters the green economic efficiency of marine fisheries.

The discussion on threshold effects underscores the pivotal role of green finance, trade openness, and R&D investment in determining the impact of AI on green economic efficiency. Under lower levels of green finance, trade openness, and R&D investment, due to financial and technological limitations, the influence of AI on green economic efficiency remains limited.

However, as green finance, trade openness, and R&D investment improve, the role of AI becomes increasingly significant, leading to broader and more advanced applications, thereby driving sustainable development in the fisheries sector.

Policy implications. Based on the above research conclusions; to enhance the green economic efficiency of the marine fishery sector in China's coastal regions and promote high-quality development in these areas, we propose the following recommendations:

(1) Given AI's significant role in enhancing the green economic efficiency of marine fisheries, policymakers in China and other emerging economies should establish special funds to support related projects, such as intelligent monitoring systems and precision fishing technologies. The government should encourage private and corporate investment through matching funds, low-interest loans, or risk guarantees. Additionally, strict intellectual property laws should be enacted, with increased penalties for infringements and a rapid response mechanism for handling intellectual property disputes.

(2) To effectively integrate AI in fisheries and enhance green initiatives, policymakers should refine the financial regulatory framework to address the unique requirements of AI technologies in this sector. This involves amending existing regulations to include provisions specifically addressing AI applications, while also formulating dedicated financial policies that provide clear guidelines and incentives for investments in green fishing projects. Additionally, collaboration with specialized assessment agencies is essential to develop tailored risk assessment protocols and introduce credit rating systems specifically designed for AI-driven fishing projects.

(3) Given that trade openness significantly enhances AI's role in improving the green economic efficiency of marine fisheries, policymakers should actively negotiate with multilateral trade organizations to secure favorable terms in fisheries product trade negotiations, such as tariff reductions and simplified import-export procedures. Furthermore, they should establish bilateral or multilateral fisheries cooperation agreements with major trade partners, including technological cooperation and resource sharing. Setting up an international AI technology exchange center would facilitate regular international seminars and technology exhibitions.

(4) To further strengthen AI's positive impact, policymakers should increase fiscal support and incentives for AI technology R&D. Additionally, creating joint research centers and laboratories involving universities, research institutions, and enterprises will promote both technological innovation and its commercialization. Talent development should also be a priority, with programs like scholarships and dedicated research funds designed to attract top domestic and international talent to marine fisheries AI technology R&D.

This study unveils the intricate interplay between AI, green finance, trade openness, R&D investment, and the sustainability of marine fisheries. In the face of changing environmental challenges, embracing advanced AI and complementing it with sound green finance and R&D investments and a liberal open environment, is a promising pathway to steer coastal fisheries towards sustainability, ensuring resource preservation and economic efficiency.

Data availability

The datasets publicly available should be through https://doi.org/10.7910/DVN/TLNTIC

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Appendix A. Super epsilon-based measure (EBM) of MFGEE

Consider a scenario with k DMUs, where each DMU_n utilizes m inputs to produce j desired outputs and p undesired outputs. $x_n = (x_{1n}, \ldots, x_{mn})^{\mathrm{T}}$, $y_n = (y_{1n}, \ldots, y_{jn})^{\mathrm{T}}$, and $u_n = (u_{1n}, \ldots, u_{pn})^{\mathrm{T}}$ represent the column vectors of inputs, desirable outputs, and undesirable outputs, respectively. The formula for the Super-EBM model is as follows:

$$\rho^* = \min \frac{\theta - \varepsilon^- \sum_{m=1}^{M} \frac{w_m^- s_m^-}{x_{k,m}}}{\varphi + \varepsilon^+ \left(\sum_{j=1}^{J} \frac{w_j^+ s_j^+}{y_{k,j}} + \sum_{p=1}^{P} \frac{w_p^{u-} s_p^{u-}}{u_{k,p}} \right)}$$

$$s.t. \begin{cases} \sum_{n=1, n\neq k}^{N} x_{n,m}^t \lambda_n^t + s_m^- \leq \theta x_{k,m} \\ \sum_{n=1, n\neq k}^{N} y_{n,j}^t \lambda_n^t - s_j^+ \geq \varphi y_{k,j} \\ \sum_{n=1, n\neq k}^{N} u_{n,p}^t \lambda_n^t + s_p^{u-} \leq \varphi u_{k,p} \\ \lambda \geq 0, s_m^- \geq 0, s_j^+ \geq 0, s_p^+ \geq 0 \end{cases}$$

In the model, ρ^* represents the marine fisheries green economic efficiency (MFGEE) of each coastal province. k denotes the number of DMUs, t represents the year. $x_{k,m}$, $y_{k,j}$ and $u_{k,p}$ signify the mth input, jth desired output, and pth undesired output for the kth DMU. The weights for inputs, desired outputs, and undesired outputs are denoted by w_m^-, w_j^+ and w_p^{u-}, respectively. The slack variables for inputs, desired outputs, and undesired outputs are represented as s_m^-, s_j^+ and s_p^{u-} respectively. The term λ represents the relative weights of influencing factors, while θ and φ denote the radial components. A critical parameter in the model is ε, which represents the combination degree of radial and non-radial slack, constrained within the range of 0 to 1.

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QW: Conceptualization, methodology, software, data curation, writing—original draft preparation, supervision, writing—reviewing and editing. TS: Methodology, software, data curation, investigation writing—original draft, writing—reviewing and editing. RL: Conceptualization, methodology, data curation, investigation writing—original draft, writing—reviewing.

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