Journal of
Marine Science and Engineering

MDPI

Review

The Application of Artificial Intelligence Technology in Shipping: A Bibliometric Review

Guangnian Xiao [1], Daoqi Yang [1], Lang Xu [2], Jinpei Li [3] and Ziran Jiang [4,*]

[1] School of Economics and Management, Shanghai Maritime University, Shanghai 201306, China; gnxiao@shmtu.edu.cn (G.X.); 202230710114@stu.shmtu.edu.cn (D.Y.)
[2] College of Transport and Communications, Shanghai Maritime University, Shanghai 201306, China; xulang@shmtu.edu.cn
[3] School of Economics and Management, Beijing University of Chemical Technology, Beijing 100029, China; jinpeili@mail.buct.edu.cn
[4] School of Geography and Environmental Sciences, Zhejiang Normal University, Jinhua 321004, China
* Correspondence: jzr729@zjnu.cn

Abstract: Artificial intelligence (AI) technologies are increasingly being applied to the shipping industry to advance its development. In this study, 476 articles published in the Science Citation Index Expanded (SCI-EXPANDED) and the Social Sciences Citation Index (SSCI) of the Web of Science Core Collection from 2001 to 2022 were collected, and bibliometric methods were applied to conduct a systematic literature of the field of AI technology applications in the shipping industry. The review commences with an annual publication trend analysis, which shows that research in the field has been growing rapidly in recent years. This is followed by a statistical analysis of journals and a collaborative network analysis to identify the most productive journals, countries, institutions, and authors. The keyword "co-occurrence analysis" is then utilized to identify major research clusters, as well as hot research directions in the field, providing directions for future research in the field. Finally, based on the results of the keyword co-occurrence analysis and the content analysis of the papers published in recent years, the research gaps in AIS data applications, ship trajectory, and anomaly detection, as well as the possible future research directions, are discussed. The findings indicate that AIS data in the future research direction are mainly reflected in the analysis of ship behavior and AIS data repair. Ship trajectory in the future research direction is mainly reflected in the deep learning-based method research and the discussion of ship trajectory classification. Anomaly detection in the future research direction is mainly reflected in the application of deep learning technology in ship anomaly detection and improving the efficiency of ship anomaly detection. These insights offer guidance for researchers' future investigations in this area. In addition, we discuss the implications of research in the field of shipping AI from both theoretical and practical perspectives. Overall, this review can help researchers understand the status and development trend of the application field of AI technology in shipping, correctly grasp the research direction and methodology, and promote the further development of the field.

Keywords: artificial intelligence; shipping; machine learning; deep learning; bibliometric analysis

check for updates

Citation: Xiao, G.; Yang, D.; Xu, L.; Li, J.; Jiang, Z. The Application of Artificial Intelligence Technology in Shipping: A Bibliometric Review. *J. Mar. Sci. Eng.* **2024**, *12*, 624. https://doi.org/10.3390/jmse12040624

Received: 26 February 2024
Revised: 1 April 2024
Accepted: 3 April 2024
Published: 7 April 2024

1. Introduction

With the rapid advancement of modern technology and data information technology, artificial intelligence (AI) has begun to be widely used in many fields, including medicine, finance and trade, law, heavy industry, and many other industries [1]. At present, researchers around the world are seeking breakthroughs in AI technology in the industry, constantly exploring new research directions to improve the level of intelligence in the industry [2].

The academic concept of AI first appeared in 1956, when people were exploring how to make machines use language to solve problems that only humans can solve, and subsequently, after a long period of continuous evolution and development, the meaning of AI has been further enriched and expanded [3]. At present, the international unified definition of AI mainly refers to the use of machines to achieve the goal of simulation of human thinking and consciousness through the algorithm of training data, so that the computer can imitate human thought and consciousness [4]. As an emerging discipline of multidisciplinary cross-fertilization, AI has received extensive attention from researchers due to its superior feature-learning capability [5]. In the past few decades, researchers have developed machine learning, deep learning, and other AI techniques, which have been widely used in many fields [6].

In the last decade, research on the integration of AI technologies with shipping has been growing rapidly, covering a wide range of disciplines [7,8]. Shipping is one of the oldest and most traditional industries, and shipping occupies an important position in international trade due to its outstanding advantages, such as large capacity, minimal energy consumption, and low costs [9,10]. With the accelerating process of world economic integration, the shipping industry is also developing rapidly and playing an increasingly important role in the international economic arena [11,12]. In this context, research on the combination of AI technology and shipping is continuing to grow rapidly [13,14]. Since entering the 21st century, neural networks and genetic algorithms have been first applied in shipping. For example, regarding the ship's domain, which is the domain around a ship that the ship maintains around it and does not want other ships or objects to enter, a wide variety of ships' domain models have been derived by studying different waters and different states of rendezvous. Zhu et al. [15] raised a neural network-based approach for constructing a ship domain model that incorporates the influences of visibility and maneuverability, and which can respond quickly to a wide range of ships within a certain range. Zubaydi et al. [16] presented a neural network approach for identifying structural damage on ships that combines stochastic reduction techniques with neural network algorithms for recognizing the scope and whereabouts of damage in the model. Zeng [17] proposed a control system based on the genetic algorithm, in which the genetic algorithm introduces a new way of genetic coding, and individual genes are constructed by using the ship's position; speed; and factors such as tides, winds, waves, etc., and is verified with the automatic collision avoidance simulation system developed in VC++ language and the actual ship, and the results of the study show that this method is a more effective way to search for the optimal safe path.

As machine learning and deep learning methods continue to mature, they are increasingly being utilized in the shipping industry. Pagoropoulos et al. [18] constructed a model based on multi-class support vector machines to achieve energy efficiency improvement through a performance evaluation of tanker operations. The results showed that machine learning algorithms play an important role in improving the energy efficiency of ships. Chen et al. [19] suggested a ship sports categorization algorithm utilizing convolutional neural network, which learns labeled AIS data by training the neural network to effectively classify unlabeled AIS data, thus realizing the classification of ship sports. The experimental results also showed that the ship sports categorization algorithm utilizing convolutional neural network proposed in this paper has better performance in classifying AIS data compared with several classical classification algorithms, such as K-nearest neighbor and decision tree. Capobianco et al. [20] presented a deep learning method utilizing recurrent neural networks to leverage historical ship trajectory data for future ship trajectory prediction. The article also emphasized that the deep learning method utilizing recurrent neural networks outperforms baseline methods based on linear regression or multilayer perceptron architecture for ship trajectory prediction. Yang et al. [21] presented a vessel trajectory prediction approach using AIS data and Bi-LSTM, showing superior results compared to other models, like Support Vector Regression, recurrent neural networks, and LSTM models.

Due to the speedy advancement of AI technique, its application in shipping has become particularly important, but there are few review studies of the implementation of AI technique in shipping, thus creating a gap in the academic literature [22]. To our knowledge, there are currently two review studies on AI in shipping. Imran et al. [23] did not use a systematic literature selection method, and their literature search process was somewhat abstract, which may lead to non-repeatability. Also, since this review only examined artificial neural networks and collision-avoidance algorithm AI techniques, this may also make it a somewhat partial study. Munim et al. [24] used a relatively systematic literature search process, but the choice of search terms was not comprehensive enough, only considering "artificial intelligence" and "machine learning", but not considering some specific algorithms in machine learning and deep learning to be included in the search terms, which may have led to the research of the article being a bit one-sided. A systematic approach to literature selection requires that the sources, screening criteria, and procedures for searching the literature be clearly defined to ensure the objectivity and reproducibility of the research results; comprehensive search criteria can cover all aspects of the literature resources to avoid omitting key information, thus ensuring the inclusiveness and accuracy of the research. Based on this, the current research is more extensive than prior studies. This study first introduces the reader to the data collection and research methodology; analyzes annual publication trends and journal statistics; conducts a collaborative network analysis, examining collaboration between countries, institutions, and authors; and, finally, explores keywords' co-occurrences.

The rest of this study is organized as follows. Section 2 outlines the data collection and the methodology of the study. Section 3 presents the bibliometric analysis and the study's findings. Section 4 introduces the gap in research hot area and future research directions. Section 5 recommends the practical and theoretical implications. Finally, Section 6 offers the conclusions.

2. Date and Methodology

2.1. Data Collection

2.1.1. The Source of Data Collection

Web of Science (WoS) is an information service platform developed by Clarivate Analytics, covering the world's most important and influential research results, and has become an internationally recognized major search tool for scientific statistics and assessment [25]. The data sources for our review are the Science Citation Index Expanded (SCI-EXPANDED) and Social Sciences Citation Index (SSCI) from the core collection of WoS.

2.1.2. Information Retrieval

This paper focuses on the application of AI technologies in shipping, so it was necessary to limit the query subject to "shipping" and "artificial intelligence". For the subject search term "artificial intelligence", we believe that it may not cover all the key technologies. Based on the research findings of Ahmed et al. [26], we chose some keywords (such as machine learning, deep learning, genetic algorithm, neural network, support vector machine, convolutional neural network, long- and short-term memory, etc.) which are strongly associated with AI as supplementary subject retrieval words to increase the comprehensiveness of the retrieved data. The following keywords were searched in the topic to increase the rate of the literature search:

TS = ("shipping" OR "maritime") AND ("Artificial Intelligen*" OR "AI" OR "big data" OR "data mining" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network*" OR "genetic algorithm*" OR "support vector machine*" OR "SVM" OR "convolutional neural network*" OR "CNN" OR "artificial neural network*" OR "ANN" OR "recurrent neural network*" OR "RNN" OR "long short term memory" OR "LSTM").

We set the type of literature to "journal article" and "review article", the language to "English", and the year of publication to "2001–2022". The reasons for this choice are that journal articles are peer-reviewed and of high academic standards and quality, and the review article helps to understand the status and development trends of research in the field. English is the main language of international academic communication, which can enhance the quality and credibility of the literature, thus promoting global exchange and cooperation in research. On the one hand, the year "2001–2022" helps to focus on the recent research results, provide the latest information and insights, and ensure the timeliness and scientific validity of the literature review; on the other hand, due to the lag in the publication of journals, some journals may not have published the articles of 2023 yet, and so the articles of 2023 were not included in the search criteria [27]. Research areas are limited to Engineering, Computer Science, Oceanography, Transportation, and Telecommunications. In the experiment, it was found that this search result included some articles on non-shipping-related AI technology applications. Then, we carried out further screening by first excluding articles related to engineering machinery, human engineering, and engineering manufacturing in the Web of Science Categories; excluded articles on the topics of image segmentation, speech recognition, drones, and magnetorheology in the Citation Topics Micro; and, finally, screened to obtain 476 documents. Among them, 460 were journal articles and 16 were review articles. The final retrieval criteria are shown in Table 1.

Table 1. Search criteria.

Project	Content
Database	SCI-EXPANDED and SSCI
Time range	2001–2022
Document type	journal article OR review article
Language	English
Search formula	TS = (("shipping" OR "maritime") AND ("Artificial Intelligen*" OR "AI" OR "big data" OR "data mining" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network*" OR "genetic algorithm*" OR "support vector machine*" OR "SVM" OR "convolutional neural network*" OR "CNN" OR "artificial neural network*" OR "ANN" OR "recurrent neural network*" OR "RNN" OR "long short term memory" OR "LSTM"))

2.2. Research Methodology

2.2.1. Bibliometric Methods

The bibliometric approach, first proposed by Pritchard (1969), is a method of literature review that uses statistics to provide a comprehensive quantitative analysis of articles of published research in a specific field [28]. This analytics allows for data mapping of the current state, topicalities, and leading edges of the research field, visualizing large data sets, which can help researchers to understand the structural and dynamic characteristics of the field [29]. The advantage of bibliometrics over other literature review methods is that it produces more objective and reliable results that provide researchers with complete information about developments in a field [30]. Shipping, as a type of transportation system, began later and developed more slowly compared to aviation, rail, and road transportation systems, so the research on the application of AI technology in shipping also started later. The relatively short development time of AI in the shipping industry has led to a more concentrated focus on research hotspots and timelines. Utilizing bibliometrics can provide a more thorough analysis of the current research status and future development trends in this field. Initially, researchers used bibliometrics to analyze published studies based on counts of articles, authors, and subject terms. With the continuous development of bibliometric methods and literature visualization and analysis software, we can map and visualize research areas and topics through techniques such as document co-citation analysis, collaborative network analysis, or keyword co-occurrence analysis [31].

2.2.2. Analytical Measures

The h-index is a mixed index of quantification, a novel approach to assessing academic accomplishments, initially introduced by American researcher J. E. Hirsch in 2005; it aims to quantify the research results of scientific researchers. Hirsch pointed out that if a scientist publishes N_p papers with h papers cited at least h, and none of the other (N_P-h) papers is cited more than h, then the scientist's h-index is h [32]. With h denoting "high citations", a higher h-index for an author signifies that this/her paper has a greater impact. However, the h-index used to measure academic achievement also has certain limitations. For example, in terms of the influence of the time factor, young researchers may not be able to achieve a high h-index due to a shorter research time, which may lead to an unfair assessment of their academic achievements; in terms of the variability of disciplinary fields, there may be differences in citation behaviors between different disciplinary fields, which may affect the accuracy of the h-index; and in terms of the citation counts, there may exist inaccurate citation counts, especially in interdisciplinary or cross-linguistic research, which may result in the h-index not accurately reflecting the true academic impact of scholars. The h-index was utilized in this study to quantify the combined impact of a country or journal's scholarship applied to AI and shipping.

3. Results and Analysis

3.1. Annual Publication Trends

This article reviews the study of the application of AI technology in the shipping industry published during the period of 2001–2022, and the analysis of the quantity of publications over the years provides an understanding of the changes in the research hotspots in this field and the future development trend [33,34]. Figure 1 contains the statistics of the quantity of publications on the study on the application of AI technology in the shipping industry in the past ten years. At the early stage of the 21st century, due to the slow evolution of AI technology, the study on AI technology in the shipping industry was lower, so we chose the quantity of articles issued in this field in the last ten years for analysis. As can be seen from the Figure 1, from 2013 to 2017, the study of the application of AI technology in the shipping industry was in the stage of steady development. Although the quantity of publications in this field was low each year, the quantity of publications each year was steadily increasing compared to the previous year. During the period from 2018 to 2022, the study of the application of AI technology in the shipping industry is in a phase of rapid growth. The number of articles published per year has continued to increase compared to the previous period. In particular, the number of publications in the last three years accounts for more than 70% of the number of articles selected for this review. This indicates that more and more academics have started to focus on the study of the application of AI technology in the shipping industry in recent years.

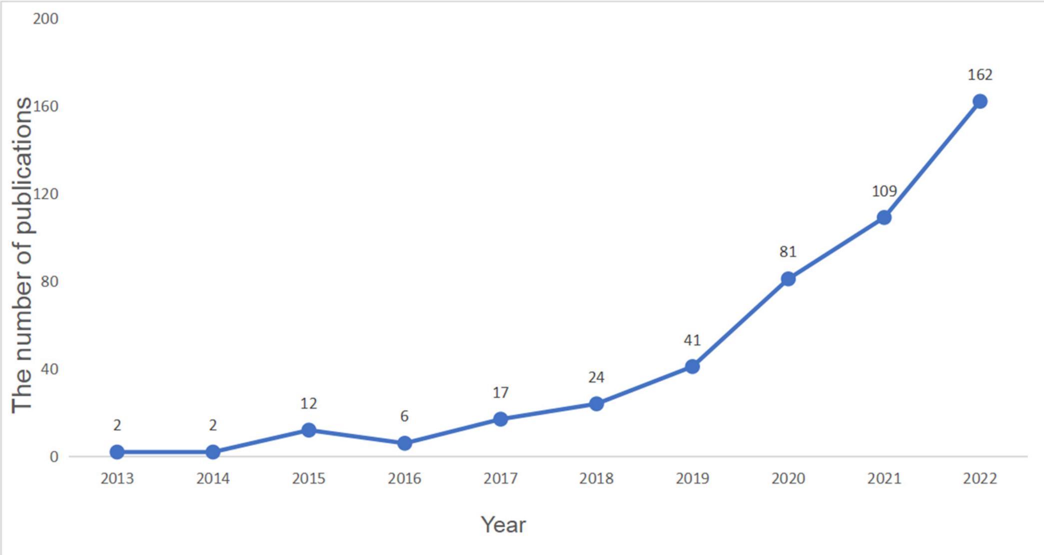

Figure 1. Annual number of publications from 2013 to 2022.

3.2. Statistics Analysis of Source Journals

The 476 articles selected for this review were printed in 107 journals. Table 2 lists the first ten highly productive journals, which published more than 60% of the number of articles selected for this review. Among them, *Ocean Engineering* is the highest-producing journal, with 86 articles published. It is closely followed by the *Journal of Marine Science and Engineering* (65 papers) and *IEEE Access* (49 papers). These three journals published about 42% of the number of articles selected for this review, which may indicate that they are the most impactful publications in the domain of AI technology applications in the shipping industry, giving researchers an important reference for their studies in this field. *Ocean Engineering* is also the most influential journal in terms of citation rate, with an h-index of 24. However, the higher number of articles published by a journal does not necessarily mean that it has a superior h-index. For example, the quantity of articles published by the *Journal of Maritime Science and Engineering* and *Maritime Policy Management* are 65 and 21, respectively, and there is a big difference in the number of papers published by these two journals in the domain of AI technology application in shipping industry, but their h-indexes are 13, which may indicate that *Maritime Policy Management* has a higher citation rate in the domain of AI application in the shipping industry.

Table 2. Most productive journals.

Journal Name	Publications	Percentage (%)	H-Index
Ocean Engineering	86	18.07	24
Journal of Marine Science and Engineering	65	13.65	13
IEEE Access	49	10.29	12
IEEE Transactions on Intelligent Transportation Systems	31	6.51	13
Maritime Policy Management	21	4.41	13
Journal of Navigation	13	2.73	10
Maritime Economics Logistics	11	2.31	7
Journal of Advanced Transportation	10	2.10	4
Applied Ocean Research	8	1.68	6
Polish Maritime Research	7	1.47	3

3.3. Cooperation Network Analysis

3.3.1. Authors Cooperation Analysis

Analyzing the author information of a paper can help researchers understand the top scholars in the field of AI technology applications in the shipping industry [35]. Table 3 lists the most impactful authors in the domain of AI technology applications in the shipping industry. The top ten authors have published more than 6 papers, among which Ryan Wen Liu has published the greatest number of articles, i.e., 16. In terms of citation rate, Ryan Wen Liu has an h-index of 11, which is also the highest among the top ten authors. The top authors' research in the field of AI technology applications for the shipping industry concentrates on ship trajectory, ship collision, and ship behavior recognition. For ship trajectory analysis, the primary techniques employed by researchers include CNN, LSTM, and others. In the realm of ship collision research, authors predominantly utilize methods like support vector machine, RNN, LSTM, and others. When it comes to ship behavior recognition, scholars primarily rely on techniques such as CNN, Bi-LSTM, and others. Liu et al. [36] developed an augmented convolutional neural network to improve ship detection under different weather conditions, proposing a flexible data augmentation strategy by expanding the size and diversity of the original data set to train a learning-based ship detection method. This strategy can make our CNN-based detection results more reliable under severe weather conditions. Liu et al. [37] established a fuzzy quaternion ship domain model of the home ship and the target ship, which is solved by support vector machine classification and geometric methods. Based on the law of conservation of momentum, the consequences of ship collision are calculated considering the mass ratio of the two ships, ship type, collision speed, etc., and a ship collision risk assessment model is proposed. Yuan et al. [38] proposed a multi-source data-processing method and a real-time fuel consumption calculation method, considering the effects of navigational state and environmental factors such as water depth, water speed, wind speed, etc., as well as a customized LSTM neural network, and established a real-time fuel consumption prediction model. The experimental results show that the established model has a better performance than some regression models and traditional RNN models.

Table 3. Most productive authors.

Author	Publications	Percentage (%)	H-Index
Ryan Wen Liu	16	3.36	11
Guoyou Shi	9	1.89	7
Jingxian Liu	8	1.68	7
Yuanchang Liu	7	1.47	5
Lokukaluge Prasad Perera	7	1.47	6
Xinqiang Chen	6	1.26	4
Lazakis Iraklis	6	1.26	5
Yan Li	6	1.26	6
Zhao Liu	6	1.26	4
Jian Wang	6	1.26	4

In order to analyze the collaboration between authors in the domain of AI technology applications in shipping industry, we used the VOSviewer software (version 1.6.19 of VOSviewer) to construct a collaborative network of authors [39]. Figure 2 shows a cooperative network between authors with a minimum of 3 documents, containing 25 items, 51 links, and 7 clusters. The specific steps of the algorithm are shown in Table 4. Each item corresponds to an author, with the size indicating the number of papers that he or she has published. The links between items represent the collaboration between authors, with the thickness indicating the intensity of their collaboration (i.e., the number of papers they have worked on together). The color of the items indicates the result of clustering, and according to the color division, items of the same color (i.e., authors) belong to the same research team. As shown in Figure 2, due to scholarly collaboration among authors, several research teams have been established around AI technology application within the shipping industry. Among them, the research team of Ryan Wen Liu, Jingxian Liu, and Huanhuan Li; the research team of Guoyou Shi, Liangbin Zhao, and Jiao Liu; and the research team of Xinqiang Chen, Qinyou Hu, and Tianrui Zhou have published several papers in the domain of AI technology applications in the shipping industry, making great commitments to the advancement of this area. In addition, the distribution of clusters in Figure 2 shows that there are fewer cluster-to-cluster connections, and most of them are intra-cluster connections. The reason may be that the research in the domain of AI technology application in the shipping industry is still in the development stage, and at this stage, it is limited to the closer cooperation within the research team, and the cooperation between the team and the team needs to be further explored, so the cooperation between the research teams is less [40].

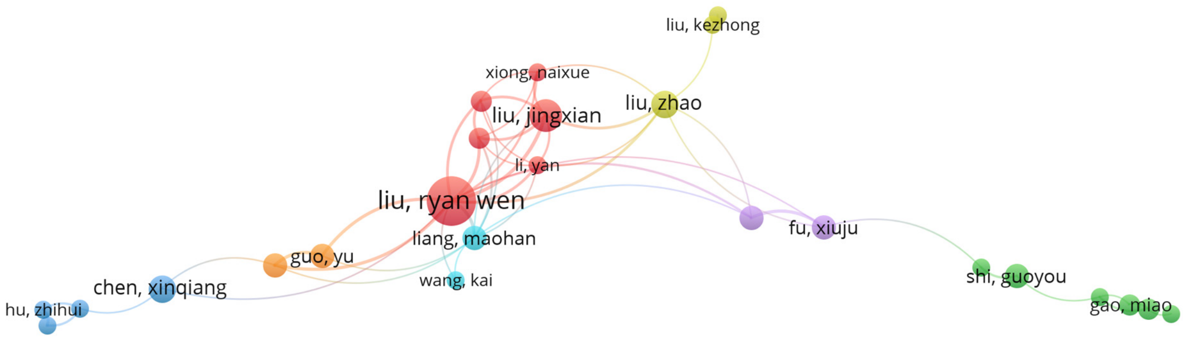

Figure 2. Cooperation network of authors.

Table 4. Search steps used for the cooperation network of authors.

No.	Search Query
#1	Choose type of data set to create a map based on bibliographic data.
#2	Choose data source set to read data from bibliographic database files.
#3	Select files set to Web of Science.
#4	Type of analysis set to co-authorship; unit of analysis set to authors.
#5	Minimum number of documents of an author set to 3; minimum number of citations of an author set to 0.
#6	Select the largest set of connected items instead of all items.

3.3.2. Institutions Cooperation Analysis

The 476 articles selected for this review were published by a total of 591 institutions. Table 5 lists the most active institutions in the applied study of AI technologies in the shipping industry. The first ten institutions contribute to nearly 50% of all institutional publications, seven of which are from China, while the other three are from the UK (University of Strathclyde), Singapore (Nanyang Technological University), and Turkey (Istanbul Technical University). Among them, the Wuhan University of Technology ranked first in terms of publications and citations, with 54 publications, accounting for more than 10% of the total, and with an h-index of 19. This indicates that the Wuhan University of Technology has made a great contribution to the development of AI technology applications in the shipping industry.

Table 5. Most productive institutions.

Institution	Publications	Percentage (%)	H-Index
Wuhan University of Technology	54	11.35	19
Dalian Maritime University	47	9.87	16
Shanghai Maritime University	33	6.93	13
National Engineering Research Center for Water Transport Safety	23	4.83	10
University of Strathclyde	16	3.36	9
Nanyang Technological University	12	2.52	9
Chinese Academy of Sciences	11	2.31	6
Harbin Engineering University	10	2.10	6
Istanbul Technical University	10	2.10	6
Shanghai Jiao Tong University	9	1.89	6

To analyze the collaborative relationships between institutions in the domain of AI technology applications in the shipping industry, we used the VOSviewer software to construct a collaborative network of institutions. Figure 3 shows a cooperation network between institutions, with the minimum number of documents set to five, containing 23 items, 50 links, and a total link strength of 93. The specific steps of the algorithm are shown in Table 6. In Figure 3, each item represents an institution, with the size indicating the number of papers published. The links between the items show the collaborative relationship between institutions, and the thickness of the chain indicates the intensity of collaboration between institutions (i.e., the number of collaborated papers). The item size shows that the Wuhan University of Technology is the institution that publishes the most papers. Among them, there are nine institutions that have cooperation with the Wuhan University of Technology, and the total cooperation intensity is 38. This indicates that the Wuhan University of Technology plays a bridging role in the cooperation network. From the link strength, the cooperation between the Wuhan University of Technology and the National Engineering Research Center for Water Transport Safety (WTS Center) is the closest, with a cooperation strength of 12. This may be due to the dependency and geographical location between the two institutions.

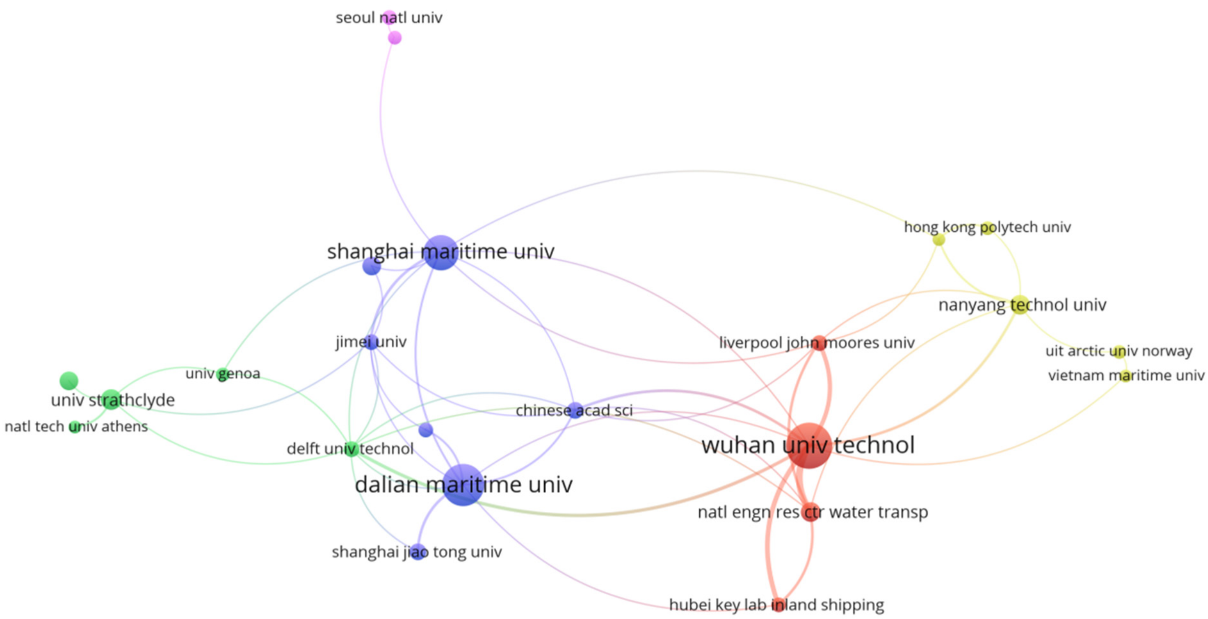

Figure 3. Cooperation network of institutions.

Table 6. Search steps used for the cooperation network of institutions.

No.	Search Query
#1	Choose type of data set to create a map based on bibliographic data.
#2	Choose data source set to read data from bibliographic database files.
#3	Select files set to Web of Science.
#4	Type of analysis set to co-authorship; unit of analysis set to organizations.
#5	Minimum number of documents of an organization set to 5; minimum number of citations of an organization set to 0.
#6	Select the largest set of connected items instead of all items.

Zhang et al. [41] exemplified, in many ways, the benefits of collaboration between the WTS Center and Wuhan University of Technology in the field of AI technology applications in the shipping industry. The authors, from different colleges of various institutions, shared their expertise and accelerated knowledge dissemination through collaborative research. Additionally, these institutions exchange and complement resources, enhancing research efficiency and quality. The WTS Center, a national research platform, excels in data collection, while the Wuhan University of Technology, a strong shipping university, specializes in shipping industry research. The collaboration between the two organizations leverages their strengths to advance AI in shipping. Their location in Wuhan, China, is also conducive for the local government to introduce relevant policies to facilitate more cooperation between the two organizations. Given the emerging nature of AI in shipping, collaborative research is crucial for driving innovation in AI applications within the industry. It can also be seen in Figure 3 that the cooperation between institutions is not close, especially the institutions at the edge of the cooperation network, as they do not constitute a research community among multiple institutions. This may be because the application of AI technologies in the shipping industry involves complex algorithms and data processing that require specialized knowledge and skills. In addition, the shipping industry also involves complex technologies and specialized knowledge, which may lead to compromised cooperation between institutions. As an emerging field of development, the field of AI in shipping also has high industry barriers, and the capital and resources invested by various institutions are very different, thus making it difficult to carry out in-depth cooperation. To advance the utilization of AI technology applications in the shipping industry, there should be more cooperation among institutions to share their knowledge and research experience in this field, which is very important to promote the research in this field [42]. Through the cases of successful inter-institutional cooperation, some insights can be provided for the innovation in the application field of AI technology in the shipping industry: firstly, institutions can work together to set clear goals and visions for cooperation and establish a mutually trusting and beneficial partnership to work together on the development of innovation in this field; secondly, the sharing of resources and technical exchanges between institutions can improve the efficiency of research and accelerate the output of innovative results; and, thirdly, institutions can cross the boundaries of disciplinary fields and explore new research directions, combining the expertise in the field of shipping and AI technology to realize cross-innovation.

3.3.3. Country Cooperation Analysis

Analyzing the country information of the papers can help researchers to understand the research contribution of each country in the domain of AI technology applications in shipping, as well as the communication and cooperation between countries. From 2001 to 2022, 55 countries have contributed to researching AI technology applications in shipping by publishing papers in the SCI and SSCI databases. Table 7 reveals the first ten countries in the number of papers published. The country that has published the highest number of papers in the domain of AI technology applications in shipping industry is China, with a total of 239 papers. It is followed by the United States (37 papers), South Korea (36 papers), and the United Kingdom (33 papers). In addition, China has published more than 50%

of all the papers in the domain of AI technology application in shipping—far more than other countries—demonstrating that China has provided a crucial impetus to the growth of this domain. In regard to the citation rate, China is also the most influential country, with an h-index of 33. In general, the number of publications is positively correlated with the h-index. However, there are countries that have a high h-index with a low number of publications, thus suggesting that their papers are widely recognized [43]. For example, the USA and England have published 37 and 33 papers, respectively, but their h-index is 13 and 14, respectively.

Table 7. Most productive countries.

Country	Publications	Percentage (%)	H-Index
China	239	50.21	33
USA	37	7.77	13
South Korea	36	7.56	14
England	33	6.93	14
Norway	26	5.46	13
Singapore	23	4.83	12
Turkey	20	4.20	9
Scotland	17	3.57	9
Italy	16	3.36	8
Australia	15	3.15	7

To analyze the cooperation between countries, we utilized VOSviewer software to establish a collaboration network among countries. Figure 4 shows the cooperation network between countries for a country with the minimum number of papers set to 5, containing 26 items, 76 links, and a total cooperation intensity of 172. The specific steps of the algorithm are shown in Table 8. In Figure 4, each item represents a country, with its size indicating the number of published papers by that country. The links connecting the items indicate the collaborative relationship between countries, and the thickness of the chain indicates the intensity of collaboration between countries (i.e., the number of papers collaborated). The item size shows that China is the country that publishes the most papers. Among them, 22 countries have collaborated with China, and the total collaboration intensity is 95, followed by the United States (10 collaborating countries, 33 total collaboration intensity), and South Korea (5 collaborating countries, 11 total collaboration intensity). The coarseness of the chain shows that collaboration between China and the UK is the closest, with an intensity of cooperation of 17. This is followed by cooperation between China and the US (with an intensity of cooperation of 15), and cooperation between China and Singapore (with an intensity of cooperation of 10). However, we can also see from Figure 4 that some countries have a small number of publications and a small intensity of cooperation with other countries (e.g., Greece, India, Croatia, etc.), and there are even many countries that do not appear in this cooperation network. On the one hand, this may be because developing intercountry cooperation in the field of shipping AI may involve the sharing of intellectual property rights and the distribution of benefits, which may affect the development of cooperation if consensus cannot be reached. On the other hand, different countries may have different understandings of and requirements for the standards and norms of AI technology, which may become an obstacle to national cooperative research. If there are large differences in technical standards and norms between countries, it may lead to incompatibility and increase the difficulty of national cooperative research. Therefore, international academic cooperation in the domain of AI technology applications in shipping requires further enhancing for future research. First, technical standards and data formats can be jointly developed between countries to reduce barriers to technology integration and data sharing and to promote the smooth progress of cooperative research. Second, government departments can organize regular policy dialogues and cooperation meetings to promote policy research and application of AI technology in the shipping industry.

Finally, an international cooperation platform should be established to promote academic exchanges and cooperation between different countries and provide a mechanism for information sharing and resource integration.

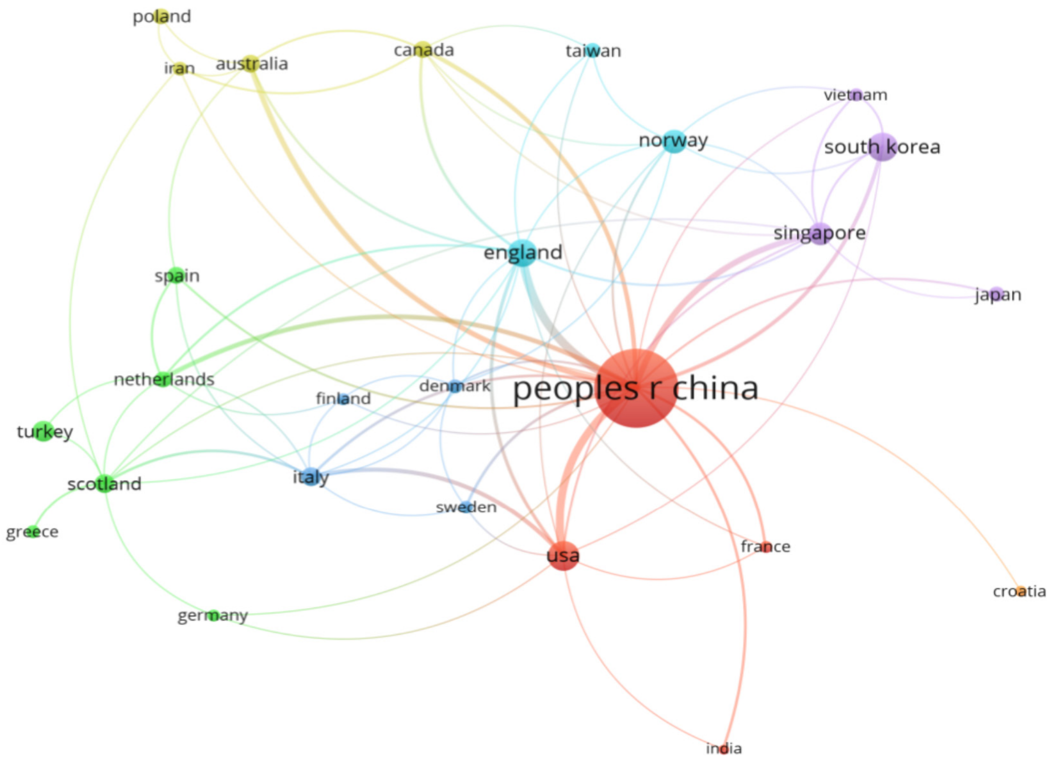

Figure 4. Cooperation network of countries.

Table 8. Search steps used for the cooperation network of countries.

No.	Search Query
#1	Choose type of data set to create a map based on bibliographic data.
#2	Choose data source set to read data from bibliographic database files.
#3	Select files set to Web of Science.
#4	Type of analysis set to co-authorship; unit of analysis set to countries.
#5	Minimum number of documents of a country set to 5; minimum number of citations of a country set to 0.
#6	Select all items.

3.4. Keyword Co-Occurrence Analysis

Keywords serve as a concise summary of a paper's core content, and a bibliometric analysis using keywords can identify the main research clusters within the realm of AI technology applications in the shipping industry [44]. We used VOSviewer software to construct an author keyword co-occurrence network, depicted in Figure 5. In this network, each item represents a keyword, with its size indicating the frequency of occurrence. Keyword co-occurrence means that two keywords appear at the same time, where the distance between two items (i.e., keywords) indicates the intensity of the relationship, with a smaller distance indicating a stronger association. The color of the items indicates the result of clustering, items of the same color indicate that they are in the same cluster, and items of different colors indicate that they are in different clusters. Connections in the network indicate co-occurrence relationships among keywords, with the thickness of the connections indicating the strength of these relationships.

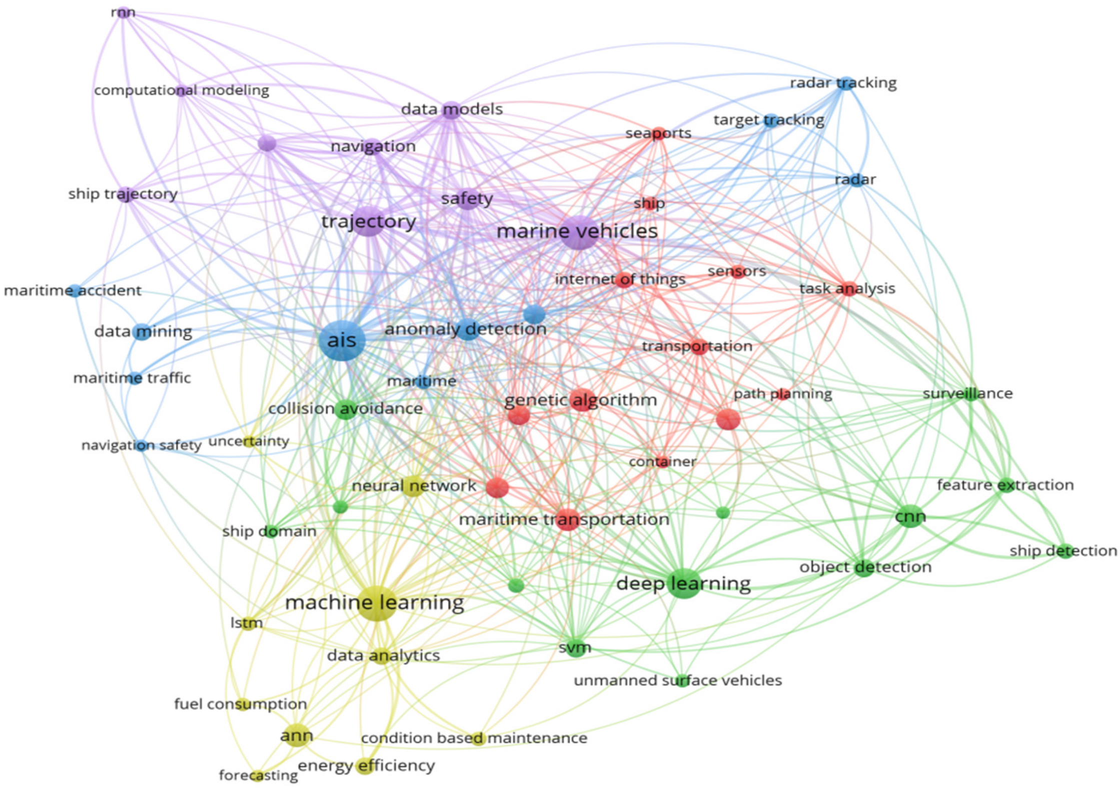

Figure 5. Keyword co-occurrence network.

Figure 5 shows the keyword co-occurrence network, with a minimum occurrence threshold set to 6 and the unit of analysis as the author keywords, using the VOSviewer thesaurus file function to merge similar terms (e.g., combining "artificial neural network" and "artificial neural networks" as "ANN", "Automatic Identification System (AIS)" and "Automatic Identification Systems" as "AIS", etc.). The resulting network graph contains 56 items, 5 clusters, 463 links, and a total link intensity of 961. Table 9 lists the top ten high-frequency keywords. Among them, "AIS" is the most frequent keyword, with 68 occurrences. The main keywords co-occurring with AIS are machine learning, trajectory, deep learning, and marine vehicles. AIS, as an aid to navigation, was originally expanded to avert ship collisions and has been utilized in the shipping industry for more than twenty years [45].

Table 9. High-frequency keywords.

Keyword	Occurrences	Links	Average Year Published
AIS	68	42	2020.59
Machine learning	51	34	2020.94
Marine vehicles	48	42	2021.19
Trajectory	39	34	2020.97
Deep learning	38	31	2021.24
CNN	23	20	2021.52
Genetic algorithm	23	12	2019.43
ANN	22	10	2019.32
Safety	21	31	2021.48
Anomaly detection	20	32	2020.40

For the last few years, the topics covering AIS have become increasingly diverse, as AIS data have become widely used [46]. Xiao et al. [47] used the 2021 U.S. AIS data as the basis for calculating pollutant emissions from ships in 30 ports to analyze the factors affecting pollutant emissions from ships. Chen et al. [48] proposed an AIS-based ship security system that improves the network security and data integrity of AIS by establishing a trust verification mechanism, distributed denial-of-service attack prevention, and geofencing mechanism, while utilizing AI and 5G networks to achieve ship intelligence and security. Li et al. [49] developed a model based on AIS data to assess the navigational risk in different sea areas by extracting and analyzing relevant data from AIS information. In addition, there are 51 keywords co-occurring with machine learning and 38 keywords co-occurring with deep learning. Among them, the keywords co-occurring with "machine learning" are mainly "energy efficiency", "ship collision avoidance", "data analysis", and "optimization"; and the keywords co-occurring with "deep learning" are mainly "target detection", "ship trajectory", "unmanned surface vehicles", and "reinforcement learning". As can be seen from Table 9, the "average publication year" of the first ten high-frequency keywords extends from 2019 to 2022, indicating that these high-frequency keywords have been the focus of research in the domain of AI technology applications in the shipping industry in recent years.

In this co-occurrence network, the yellow cluster studies the application of machine learning algorithms to shipping. The green cluster studies the application of deep learning algorithms to shipping. These two clusters are also the current research hotspots for the application of AI technology in the shipping industry, which also provides directions for future research in this field. Table 10 presents various AI approaches from these two clusters and briefly outlines their specific applications in the paper. It also showcases the practical implementations of these approaches in the shipping industry, paving the path for innovation in the field of shipping AI [50,51].

Table 10. AI technology relevant to shipping.

AI Technology	Method Description	Applications in Shipping	Ref.
Machine learning	A model based on ship hydrodynamics is proposed to estimate ship fuel consumption and emissions by using AIS, ship information database, and marine data and introducing machine learning techniques.	For predicting ship fuel consumption.	[52]
Machine learning	Ship fuel consumption data were trained using Back Propagation Neural Network and Gaussian Process Regression in machine learning, and the trained models were used to predict ship fuel consumption.	For ship fuel consumption optimization and greenhouse gas reduction.	[53]
Machine learning	A data-driven machine learning approach is proposed to predict ship speed through regression algorithms, which include linear regression, Gaussian process regression, and support vector machines.	For predicting ship speed and optimizing ship performance.	[54]
Deep learning	Ship detection using a deep learning-based detection model, followed by ship localization and tracking using a deep learning model that determines the ship's heading in the image to achieve ship awareness.	For ships to sense their surroundings and prevent accidents at sea.	[55]
Deep learning	A deep learning-based passive human tracking system is proposed to eliminate the effects of noise, interference, and movement in ships to solve the problem of accuracy degradation of wireless localization and tracking systems in mobile ship environments.	For location detection of staff on cruise ships and evacuation in emergency situations.	[56]
Deep learning	A lightweight deep learning method, consisting of forward and backward gated recurrent unit networks, is proposed to improve ship trajectory curve fitting performance by bi-directional scaling of training trajectory data.	For analyzing maritime trade trends, maritime weather forecasting, etc.	[57]
Deep learning	An evidence-based regression model based on recurrent neural networks is proposed, which predicts ship trajectories at future time steps and then uses AIS data to detect anomalous maritime trajectories.	For detecting marine traffic anomalies.	[58]

4. Gap in Research Hot Area and Future Research Directions

Despite the rapid development in the field of AI technology applications for the shipping industry in recent years, there are still some challenges that need to be addressed. In this part, based on the results of keyword co-occurrence analysis and the content analysis of published papers in recent years, the gaps in the current research hot areas, as well as the possible future research directions, are discussed. The results of the study can provide a reference for researchers' future exploration in this field.

4.1. AIS Data Applications

AIS is an automatic tracking system installed on ships that plays an important role in the safe navigation of ships. AIS data are the status information of the ship during navigation collected by various types of sensors and sent by AIS equipment. In recent years, as AIS data have received widespread attention, and the application fields of AIS data have become more and more extensive. At present, the research on the application of AIS data mainly focuses on ship collision risk, ship trajectory prediction, and ship collision avoidance systems. Liu et al. [59] proposed a modeling, visualization and prediction framework for ship collision risk analysis and used AIS data from Chengshantou waters to verify the reliability and robustness of the framework. The results of this study can help ship pilots to judge ship collision risks in advance and take relevant measures in time to avoid potential ship collision risks. Chen et al. [60] introduced a deep learning-based framework to accurately predict ship trajectories, supported by AIS data, which predicted the trajectory changes in single and multiple ships, and this study can help maritime regulators make reasonable traffic control and management decisions. Zhu et al. [61] proposed a scenario-based test validation method for ship collision avoidance systems, which solves the potential flaws in previous ship collision avoidance algorithms by mining historical AIS data and randomly producing virtual test scenarios to quickly create appropriate test scenarios. However, there are data-quality and -acquisition problems with AIS data, and such problems may lead to the application of AIS data in some shipping fields being hindered. For example, maritime environmental monitoring is limited by the fact that ships are equipped with AIS equipment and the vagaries of the maritime environment, which may lead to incomplete data, as well as delays in data acquisition and transmission due to environmental factors, which can affect the accuracy and reliability of maritime environmental monitoring, thus limiting the depth and breadth of related research. In addition, as the quality of AIS data improves, the applications of AIS data are becoming more diverse, meaning that researchers are faced with tougher challenges.

Future research: Despite the growing maturity of research on AIS data, future research on AIS data should consider applications in other directions, such as analyzing ship behavior from AIS data. Ma et al. [62] proposed a method to identify and analyze the waiting behavior of ships outside the port based on AIS data, and it is of great significance to enhance port-traffic management and optimize ship sailing plans. In addition, due to the problems of AIS equipment, the collection of AIS data will inevitably contain missing and abnormal problems. Zhang et al. [63] proposed an AIS data repair method that can effectively deal with long-distance data loss and large-volume data, indeed, by using temporal convolutional networks and bidirectional long- and short-term memory to repair AIS data, thus providing a reference for future researchers to collect AIS data.

4.2. Ship Trajectory

Research on ship trajectories mainly includes trajectory prediction, trajectory clustering, and trajectory tracking. In the research on trajectory prediction, deep learning-based methods are more widely used. Zhang et al. [64] reviewed the existing methods for ship trajectory prediction in maritime transportation, including simulation methods, statistical methods, hybrid methods, machine learning methods, and the current state-of-the-art deep learning methods, and summarized the current challenges in the field, which is of great significance to ensure the safety and efficiency of maritime transportation. Li et al. [65]

proposed a data-mapping and density-based clustering method for ship trajectories, aiming to improve the accuracy and computational efficiency of clustering, and realized the clustering and identification of ship trajectories, which are of great significance for trajectory visualization and safe path planning. With the development of intelligent ships, the research about ship trajectory tracking has also become an important task in the intelligent navigation of ships. Ahmed et al. [66] proposed a spatiotemporal trajectory correlation algorithm for the trajectory tracking of ships at sea, solving the problems of missing ship identifiers and time intervals. Moreover, when constructing a ship trajectory model based on deep learning, researchers need to spend a lot of time selecting an appropriate model and adjusting the parameters of the model. Therefore, choosing an optimal model for ship trajectory-related research may be a tricky problem based on the current small amount of research on ship trajectory. Meanwhile, in the research on ship trajectory prediction, factors such as currents, winds, tides, and changes in the maritime environment are rarely considered in the current research in this field, considering the rapidly changing conditions at sea. With the continuous expansion of maritime traffic, the research about ship trajectory has increasingly become one of the important topics in the shipping industry.

Future research: In the context of the rapid development of the shipping industry, the research on ship trajectory prediction is still necessary and urgent to ensure the safety of ship trajectories and reduce the occurrence of maritime accidents. In future research, the traditional machine learning-based method for ship trajectory prediction will be subject to more and more restrictions, and the deep learning-based ship trajectory prediction method should receive more and more attention from researchers [67]. In addition, future research on ship trajectories can also try to classify ship trajectories in order to further determine the behavior behind the trajectories and provide assistance to the work of maritime regulatory authorities [68].

4.3. Anomaly Detection

As the acquisition of AIS data and application research continue to deepen, maritime anomaly detection has also received more and more attention from researchers and has gradually become a hot research direction in the field of shipping. Maria et al. [69] discussed the importance of maritime anomaly detection in ensuring the safety of ship traffic and maritime security and provided a comprehensive summary of maritime anomaly detection from four categories: data, methods, systems, and user aspects. Possible research directions and challenges of maritime anomaly detection were outlined. Wei et al. [70] designed a maritime anomaly detection algorithm based on the support vector machine, considering the spatiotemporal and motion characteristics of the trajectory, and the experimental results show that the algorithm can effectively perform maritime anomaly detection. In addition, due to the special characteristics of the maritime environment, real-time anomaly detection becomes very important in the research in this field, but there are few research studies addressing real-time anomaly detection, mainly since the transmission speed and variability of the data affect the effectiveness of the anomaly detection methods, thus leading to the real-time anomaly detection becoming difficult to deal with.

Future research: With the development of the world economy, the impact of maritime transportation on global trade is becoming more and more important. The detection of the abnormal behavior of ships is an important aspect to improve the safety of maritime traffic. In future research, multi-source data such as images and videos will become an important factor to improve the accuracy of anomaly detection, and deep learning technology also shows good application prospects in ship anomaly detection [71]. In addition, the efficiency of ship anomaly detection can also be improved through the detection of ship speed anomalies, another issue of great significance to maritime navigation safety [72].

Overall, interdisciplinary collaboration in applied research on the shipping industry and AI technologies can help to develop a more comprehensive and in-depth research perspective, while facilitating exchanges between different disciplines. Promoting the application of AI technology in the shipping industry can rapidly realize the digital transformation of the shipping industry and promote the change and progress of the industry. In addition, it is important to encourage collaboration between AI researchers, maritime experts, and environmental scientists. Firstly, regular interdisciplinary workshops are organized to invite AI researchers, maritime experts, and environmental scientists to share the latest research results in their respective fields, through which the exchange of interdisciplinary cooperation can be promoted. Secondly, establishing a data-sharing platform so that experts in different fields can share resources can help accelerate research progress. Finally, government departments can formulate policies and standards to support interdisciplinary cooperation and, at the same time, establish relevant incentive mechanisms to motivate experts in different fields to achieve results and breakthroughs in interdisciplinary cooperation.

5. Practical and Theoretical Implications

By examining the bibliometric analysis in the AI field of shipping, we can see that the utilization of AI technology in shipping introduces new research avenues in AIS data applications, ship trajectory, and anomaly detection. Additionally, it enhances the decision-making and operations of shipping companies and maritime administrations in the industry. Firstly, the theoretical study of AI technology in AIS data applications not only advances the development of data processing and analysis methods in the shipping industry but also enhances the theory of informatization management in shipping. Exploring the application of AIS data can offer theoretical support for informatization construction and intelligent development in the shipping sector. In practical terms, AIS data enable shipping enterprises to access crucial functions like real-time ship positioning and route planning, and they enhance ship transportation efficiency, thereby aiding companies in better ship management and boosting economic benefits. Secondly, the theoretical research on AI technology in ship trajectory focuses on trajectory prediction, trajectory clustering, and trajectory tracking. Trajectory prediction aids in collision avoidance, trajectory clustering helps in identifying various ship behaviors, and trajectory tracking enables real-time monitoring and warning capabilities. In practice, trajectory prediction enhances navigation safety, reduces accident risks, and serves as a vital reference for optimizing ship routes. Trajectory clustering assists shipping enterprises in understanding ship behaviors better and optimizing ship scheduling. Trajectory tracking helps in promptly identifying any abnormal ship situations to safeguard the ship and crew's safety. Lastly, the theoretical study of anomaly detection can offer more scientific guidance for safety management and risk control in the shipping industry. In practical applications, anomaly detection plays a crucial role in enhancing the level of maritime safety management.

Research in the field of AI in shipping not only enhances understanding of the shipping industry in theory but also enhances efficiency and safety for shipping companies and maritime administrations in practical applications. By consistently advancing the use and study of AI technology in shipping, the industry will embrace a more intelligent and sustainable future.

6. Conclusions

This study reviews the literature related to the application area of AI technologies in the shipping industry. A bibliometric approach was used to collect 476 articles published from 2001 to 2022 based on the SCI-EXPANDED and SSCI databases. This study shows that the literature in the field of AI technology applications in the shipping industry has become more and more extensive over the last decade, and the number of articles published in this field has been growing rapidly, especially from 2018 onward. The study also shows that the *Ocean Engineering* journal, the *Journal of Marine Science and Engineering*, and the *IEEE Access* journal have published significantly more papers in this field than the other journals, indicating that they are the most influential publications in this field, giving researchers a certain reference for their research in this field.

According to the country analysis, China is one of the most important contributors to the literature in the field of AI technology applications in the shipping industry, with the highest number of publications (239), followed by the United States, South Korea, and the United Kingdom. Also, China has the highest h-index. The analysis of the national cooperation network constructed by VOSviewer software shows that China is in the leading position in terms of the number of published papers, cooperation between countries, and the closeness of the cooperation relationship, indicating that China has made a very important contribution to research in the field of the application of AI technology in the shipping industry, and that the results of the academic research in this field are of some significance. This may be because China is a world leader in the application of AI technology, and the Chinese government has been committed to promoting the development of AI technology, laying the foundation for China to play a leading role in the application of AI technology in the shipping industry. However, international academic cooperation in this field is somewhat weak and needs to be further strengthened in future research. Shipping is a global industry that requires countries to work together to address challenges. Different countries have their own advantages and expertise in the field of AI, and strengthening international cooperation can realize knowledge complementarity and promote the comprehensive development of AI research in shipping. Strengthening international cooperation can also promote knowledge exchange, resource sharing, and technological innovation, providing a broader platform and opportunities for the application and development of AI technology in the shipping industry. According to the institutional analysis, the Wuhan University of Technology, Dalian Maritime University, and Shanghai Maritime University have published many papers in the field of AI technology application in the shipping industry that have made great contributions to the development of this field. However, it is found from the institutional cooperation network diagram that the cooperation between institutions is not close. To promote the development of the field, the institutions should strengthen their cooperation and share their knowledge and research experience. Through the cooperation, the organization can form a stronger joint force, expand its market influence in the field of AI technology application in shipping industry, and contribute to the promotion and application of the research results. Meanwhile, it is found from the authors' cooperation network that although some authors have published more papers, the academic cooperation in this field is still limited to the intra-research team, and the team-to-team cooperation is still less. In future research, cooperation between teams needs to be strengthened, which can broaden research horizons, introduce diversified thinking and methods, avoid limitations due to a single point of view, and improve the authority of research results.

The keyword "co-occurrence analysis" shows the main research clusters in the field of AI technology applications in the shipping industry. The fact that "AIS" is the most frequent keyword indicates that it is a research hotspot in the field. The study also shows that the clusters where machine learning and deep learning are located are current research hotspots in the field. Currently, machine learning and deep learning are often combined with ship energy efficiency, ship collision avoidance, ship trajectory, AIS data, etc., thus laying a solid foundation for the development of the application area of AI technology in the shipping industry. Then, based on the results of the keyword co-occurrence analysis and the content analysis of the published papers in recent years, the research gaps in the application of AIS data applications, ship trajectory, and anomaly detection, as well as the possible future research directions, are discussed to provide a reference for the researchers' future explorations in this field. Finally, the implications of research in the field of shipping AI are discussed in terms of both theory and practice. From the perspective of the shipping industry, ship information provided by AIS data can better provide decision support for ship management and operation. Ship trajectory research based on AI technology can provide intelligent path planning for ships to improve navigation efficiency and safety. It can also provide a basis for ship behavior analysis and prediction by identifying different patterns of ship trajectories, such as berthing and sailing. Maritime anomaly detection based on AI technology can improve the level of maritime safety detection, reduce the possibility of accidents, and provide a continuous step forward to push the shipping industry toward intelligent development.

The findings of this paper can help scholars understand the development trend of the application area of AI technology in the shipping industry, better understand the status of the field, and explore potential research opportunities. At the same time, this study has some limitations that deserve further exploration. Moreover, our study is based only on SCI-EXPANDED and SSCI in the WoS database, which may affect the coverage of publications in the research area. Additionally, the keywords of the literature search may not reflect the full picture of the research area, and with the continuous development of AI technology, future studies may include more keywords.

Author Contributions: Conceptualization, G.X. and D.Y.; methodology, G.X., D.Y., L.X., J.L. and Z.J.; writing—original draft preparation, G.X. and D.Y.; writing—review and editing, G.X., L.X., J.L. and Z.J.; funding acquisition, G.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number 52002243; Beijing Natural Science Foundation, grant number 9244032; and The Youth Foundation of Humanities and Social Science Research of the Ministry of Education (2022YJCZH070).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Readers can access our data by sending an email to the corresponding author, Ziran Jiang.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Li, X.; Jiang, H. Artificial intelligence technology and engineering applications. *Appl. Comput. Electromagn. Soc. J.* **2017**, *32*, 381–388.
2. Zhang, C.; Lu, Y. Study on artificial intelligence: The state of the art and future prospects. *J. Ind. Inf. Integr.* **2021**, *23*, 100224. [CrossRef]
3. McCarthy, J.; Minsky, M.L.; Rochester, N.; Shannon, C.E. A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, august 31, 1955. *AI Mag.* **2006**, *27*, 12.
4. Ding, W.; Abdel-Basset, M.; Hawash, H.; Ali, A.M. Explainability of artificial intelligence methods, applications and challenges: A comprehensive survey. *Inf. Sci.* **2022**, *615*, 238–292. [CrossRef]
5. Barredo Arrieta, A.; Diaz-Rodriguez, N.; Del Ser, J.; Bennetot, A.; Tabik, S.; Barbado, A.; Garcia, S.; Gil-Lopez, S.; Molina, D.; Benjamins, R.; et al. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Inf. Fusion* **2020**, *58*, 82–115. [CrossRef]
6. Górriz, J.M.; Ramírez, J.; Ortíz, A.; Martínez-Murcia, F.J.; Segovia, F.; Suckling, J.; Leming, M.; Zhang, Y.-D.; Álvarez-Sánchez, J.R.; Bologna, G.; et al. Artificial intelligence within the interplay between natural and artificial computation: Advances in data science, trends and applications. *Neurocomputing* **2020**, *410*, 237–270. [CrossRef]
7. Sanchez-Gonzalez, P.-L.; Diaz-Gutierrez, D.; Leo, T.J.; Nunez-Rivas, L.R. Toward digitalization of maritime transport? *Sensors* **2019**, *19*, 926. [CrossRef]
8. Li, J.; Ren, J.; Ma, X.; Xiao, G. Environmental efficiency of ports under the dual carbon goals: Taking China's Bohai-rim ports as an example. *Front. Mar. Sci.* **2023**, *10*, 1129659. [CrossRef]
9. Yang, Z.; Xiu, Q.; Chen, D. Historical changes in the port and shipping industry in Hong Kong and the underlying policies. *Transp. Policy* **2019**, *82*, 138–147. [CrossRef]
10. Xu, L.; Zou, Z.; Liu, L.; Xiao, G. Influence of emission-control areas on the eco-shipbuilding industry: A perspective of the synthetic control method. *J. Mar. Sci. Eng.* **2024**, *12*, 149. [CrossRef]
11. Tong, H. The future development and restructuring of the international shipping industry: Conference report. *Mar. Policy* **2022**, *137*, 104956. [CrossRef]
12. Xiao, G.; Cui, W. Evolutionary game between government and shipping enterprises based on shipping cycle and carbon quota. *Front. Mar. Sci.* **2023**, *10*, 1132174. [CrossRef]
13. Jian, L.; Guo, J.; Ma, H. Research on the impact of digital innovation driving the high-quality development of the shipping industry. *Sustainability* **2022**, *14*, 4648. [CrossRef]
14. Xu, L.; Yang, Z.; Chen, J.; Zou, Z.; Wang, Y. Spatial-temporal evolution characteristics and spillover effects of carbon emissions from shipping trade in EU coastal countries. *Ocean Coast. Manag.* **2024**, *250*, 107029. [CrossRef]
15. Zhu, X.; Xu, H.; Lin, J. Domain and its model based on neural networks. *J. Navig.* **2001**, *54*, 97–103. [CrossRef]

16. Zubaydi, A.; Haddara, M.R.; Swamidas, A.S.J. Damage identification in a ship's structure using neural networks. *Ocean Eng.* **2002**, *29*, 1187–1200. [CrossRef]
17. Zeng, X. Evolution of the safe path for ship navigation. *Appl. Artif. Intell.* **2003**, *17*, 87–104. [CrossRef]
18. Pagoropoulos, A.; Møller, A.H.; McAloone, T.C. Applying Multi-Class Support Vector Machines for performance assessment of shipping operations: The case of tanker vessels. *Ocean Eng.* **2017**, *140*, 1–6. [CrossRef]
19. Chen, X.; Liu, Y.; Achuthan, K.; Zhang, X. A ship movement classification based on Automatic Identification System (AIS) data using Convolutional Neural Network. *Ocean Eng.* **2020**, *218*, 108182. [CrossRef]
20. Capobianco, S.; Millefiori, L.M.; Forti, N.; Braca, P.; Willett, P. Deep learning methods for vessel trajectory prediction based on recurrent neural networks. *IEEE Trans. Aerosp. Electron. Syst.* **2021**, *57*, 4329–4346. [CrossRef]
21. Yang, C.; Wu, C.; Shao, J.; Wang, Y.; Hsieh, C. AIS-based intelligent vessel trajectory prediction using Bi-LSTM. *IEEE Access* **2022**, *10*, 24302–24315. [CrossRef]
22. Yang, D.; Wu, L.; Wang, S.; Jia, H.; Li, K.X. How big data enriches maritime research—A critical review of Automatic Identification System (AIS) data applications. *Transp. Rev.* **2019**, *39*, 755–773. [CrossRef]
23. Imran, M.; Ayob, A.; Jamaludin, S. Applications of artificial intelligence in ship berthing: A review. *Indian J. Geo Mar. Sci.* **2021**, *50*, 855–863.
24. Munim, Z.H.; Dushenko, M.; Jimenez, V.J.; Shakil, M.H.; Lmset, M. Big data and artificial intelligence in the maritime industry: A bibliometric review and future research directions. *Marit. Policy Manag.* **2020**, *47*, 577–597. [CrossRef]
25. Zhu, J.; Liu, W. A tale of two databases: The use of Web of Science and Scopus in academic papers. *Scientometrics* **2020**, *123*, 321–335. [CrossRef]
26. Ahmed, S.; Alshater, M.M.; Ammari, A.E.; Hammami, H. Artificial intelligence and machine learning in finance: A bibliometric review. *Res. Int. Bus. Financ.* **2022**, *61*, 101646. [CrossRef]
27. Xiao, G.; Chen, L.; Chen, X.; Jiang, C.; Ni, A.; Zhang, C.; Fang, Z. A hybrid visualization model for knowledge mapping: Scientometrics, SAOM, and SAO. *IEEE Trans. Intell. Transp.Syst.* **2024**, 1–14. [CrossRef]
28. Mukherjee, D.; Lim, W.M.; Kumar, S.; Donthu, N. Guidelines for advancing theory and practice through bibliometric research. *J. Bus. Res.* **2022**, *148*, 101–115. [CrossRef]
29. Ellegaard, O.; Wallin, J.A. The bibliometric analysis of scholarly production: How great is the impact? *Scientometrics* **2015**, *105*, 1809–1831. [CrossRef] [PubMed]
30. Wallin, J.A. Bibliometric methods: Pitfalls and possibilities. *Basic Clin. Pharmacol. Toxicol.* **2005**, *97*, 261–275. [CrossRef] [PubMed]
31. Zupic, I.; Čater, T. Bibliometric methods in management and organization. *Organ. Res. Methods* **2015**, *18*, 429–472. [CrossRef]
32. Hirsch, J.E. An index to quantify an individual's scientific research output. *Proc. Natl. Acad. Sci. USA* **2005**, *102*, 16569–16572. [CrossRef]
33. Torku, A.; Chan, A.P.C.; Yung, E.H.K. Age-friendly cities and communities: A review and future directions. *Ageing Soc.* **2021**, *41*, 2242–2279. [CrossRef]
34. Adnan, A.R.; Widowati, R.; Nuryakin. Evolution and trends in indonesian green marketing research: A systematic review (2018–2023). *J. Green Econ. Low-Carbon Dev.* **2023**, *2*, 162–174. [CrossRef]
35. Xu, C.; Yu, D.; Yang, H.; Yu, S. 20 years of economic corridors development: A bibliometric analysis. *J. Appl. Econ.* **2021**, *24*, 173–192. [CrossRef]
36. Liu, R.W.; Yuan, W.; Chen, X.; Lu, Y. An enhanced CNN-enabled learning method for promoting ship detection in maritime surveillance system. *Ocean Eng.* **2021**, *235*, 109435. [CrossRef]
37. Liu, J.; Shi, G.; Zhu, K. A novel ship collision risk evaluation algorithm based on the maximum interval of two ship domains and the violation degree of two ship domains. *Ocean Eng.* **2022**, *255*, 111431. [CrossRef]
38. Yuan, Z.; Liu, J.; Zhang, Q.; Liu, Y.; Yuan, Y.; Li, Z. Prediction and optimisation of fuel consumption for inland ships considering real-time status and environmental factors. *Ocean Eng.* **2021**, *221*, 108530. [CrossRef]
39. Waltman, L.; Eck, N.J.; Noyons, E.C.M. A unified approach to mapping and clustering of bibliometric networks. *J. Informetr.* **2010**, *4*, 629–635. [CrossRef]
40. Chen, Y.; Wang, W.; Chen, X.M. Bibliometric methods in traffic flow prediction based on artificial intelligence. *Expert Syst. Appl.* **2023**, *228*, 120421. [CrossRef]
41. Zhang, Z.; Huang, L.; Peng, X.; Wen, Y.; Song, L. Loitering behavior detection and classification of vessel movements based on trajectory shape and convolutional neural networks. *Ocean Eng.* **2022**, *258*, 111852. [CrossRef]
42. Debrah, C.; Chan, A.P.; Darko, A. Artificial intelligence in green building. *Autom. Constr.* **2022**, *137*, 104192. [CrossRef]
43. Hou, Y.; Wang, Q. Big data and artificial intelligence application in energy field: A bibliometric analysis. *Environ. Sci. Pollut. Res.* **2023**, *30*, 13960–13973. [CrossRef]
44. Yu, D.; Xu, Z.; Fujita, H. Bibliometric analysis on the evolution of applied intelligence. *Appl. Intell.* **2019**, *49*, 449–462. [CrossRef]
45. Robards, M.; Silber, G.; Adams, J.; Arroyo, J.; Lorenzini, D.; Schwehr, K.; Amos, J. Conservation science and policy applications of the marine vessel Automatic Identification System (AIS)—A review. *Bull. Mar. Sci.* **2016**, *92*, 75–103. [CrossRef]
46. Du, L.; Goerlandt, F.; Kujala, P. Review and analysis of methods for assessing maritime waterway risk based on non-accident critical events detected from AIS data. *Reliab. Eng. Syst. Saf.* **2020**, *200*, 106933. [CrossRef]
47. Xiao, G.; Wang, T.; Luo, Y.; Yang, D. Analysis of port pollutant emission characteristics in United States based on multiscale geographically weighted regression. *Front. Mar. Sci.* **2023**, *10*, 1131948. [CrossRef]

48. Chen, M.; Wu, H. An automatic-identification-system-based vessel security system. *IEEE Trans. Ind. Inform.* **2022**, *19*, 870–879. [CrossRef]
49. Li, L.; Lu, W.; Niu, J.; Liu, J.; Liu, D. AIS data-based decision model for navigation risk in sea areas. *J. Navig.* **2018**, *71*, 664–678. [CrossRef]
50. Kaur, S.; Kumar, R.; Singh, K.; Huang, Y. Leveraging artificial intelligence for enhanced sustainable energy management. *J. Sustain. Energy* **2024**, *3*, 1–20. [CrossRef]
51. Kilibarda, M.; Andrejić, M.; Popović, V. Research in logistics service quality: A systematic literature review. *Transport* **2020**, *35*, 224–235.
52. Guo, B.; Liang, Q.; Tvete, H.A.; Brinks, H.; Vanem, E. Combined machine learning and physics-based models for estimating fuel consumption of cargo ships. *Ocean Eng.* **2022**, *255*, 111435. [CrossRef]
53. Hu, Z.; Jin, Y.; Hu, Q.; Sen, S.; Zhou, T.; Osman, M.T. Prediction of fuel consumption for enroute ship based on machine learning. *IEEE Access* **2019**, *7*, 119497–119505. [CrossRef]
54. Bassam, A.M.; Phillips, A.B.; Turnock, S.R.; Wilson, P.A. Ship speed prediction based on machine learning for efficient shipping operation. *Ocean Eng.* **2022**, *245*, 110449. [CrossRef]
55. Lee, W.; Roh, M.; Lee, H.; Ha, J.; Cho, Y.; Lee, S.; Son, N. Detection and tracking for the awareness of surroundings of a ship based on deep learning. *J. Comput. Des. Eng.* **2021**, *8*, 1407–1430. [CrossRef]
56. Liu, K.; Yang, W.; Chen, M.; Zheng, K.; Zeng, X.; Zhang, S.; Liu, C. Deep-Learning-based wireless human motion tracking for mobile ship environments. *IEEE Internet Things J.* **2022**, *9*, 24186–24198. [CrossRef]
57. Chen, J.; Chen, H.; Zhao, Y.; Li, X. FB-BiGRU: A Deep Learning model for AIS-based vessel trajectory curve fitting and analysis. *Ocean Eng.* **2022**, *266*, 112898. [CrossRef]
58. Singh, S.K.; Fowdur, J.S.; Gawlikowski, J.; Medina, D. Leveraging graph and deep learning uncertainties to detect anomalous maritime trajectories. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 23488–23502. [CrossRef]
59. Liu, R.W.; Huo, X.; Liang, M.; Wang, K. Ship collision risk analysis: Modeling, visualization and prediction. *Ocean Eng.* **2022**, *266*, 112895. [CrossRef]
60. Chen, X.; Wei, C.; Zhou, G.; Wu, H.; Wang, Z.; Biancardo, S.A. Automatic identification system (AIS) data supported ship trajectory prediction and analysis via a deep learning model. *J. Mar. Sci. Eng.* **2022**, *10*, 1314. [CrossRef]
61. Zhu, F.; Zhou, Z.; Lu, H. Randomly testing an autonomous collision avoidance system with real-world ship encounter scenario from AIS data. *J. Mar. Sci. Eng.* **2022**, *10*, 1588. [CrossRef]
62. Ma, J.; Zhou, Y.; Zhu, Z. Identification and analysis of ship waiting behavior outside the port based on AIS data. *Sci. Rep.* **2023**, *13*, 11267. [CrossRef] [PubMed]
63. Zhang, W.; Jiang, W.; Liu, Q.; Wang, W. AIS data repair model based on generative adversarial network. *Reliab. Eng. Syst. Saf.* **2023**, *240*, 109572. [CrossRef]
64. Zhang, X.; Fu, X.; Xiao, Z.; Xu, H.; Qin, Z. Vessel trajectory prediction in maritime transportation: Current approaches and beyond. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 19980–19998. [CrossRef]
65. Li, H.; Liu, J.; Wu, K.; Yang, Z.; Liu, R.W.; Xiong, N. Spatio-temporal vessel trajectory clustering based on data mapping and density. *IEEE Access* **2018**, *6*, 58939–58954. [CrossRef]
66. Ahmed, I.; Jun, M.; Ding, Y. A spatio-temporal track association algorithm based on marine vessel automatic identification system data. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 20783–20797. [CrossRef]
67. Li, H.; Jiao, H.; Yang, Z. Ship trajectory prediction based on machine learning and deep learning: A systematic review and methods analysis. *Eng. Appl. Artif. Intell.* **2023**, *126*, 107062. [CrossRef]
68. Luo, D.; Chen, P.; Yang, J.; Li, X.; Zhao, Y. A new classification method for ship trajectories based on AIS data. *J. Mar. Sci. Eng.* **2023**, *11*, 1646. [CrossRef]
69. Riveiro, M.; Pallotta, G.; Vespe, M. Maritime anomaly detection: A review. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2018**, *8*, e1266. [CrossRef]
70. Wei, Z.; Xie, X.; Zhang, X. Maritime anomaly detection based on a support vector machine. *Soft Comput.* **2022**, *26*, 11553–11566. [CrossRef]
71. Wang, Y.; Liu, J.; Liu, R.W.; Liu, Y.; Yuan, Z. Data-driven methods for detection of abnormal ship behavior: Progress and trends. *Ocean Eng.* **2023**, *271*, 113673. [CrossRef]
72. Zhang, L.; Zhu, Y.; Ren, J.; Lu, W.; Yao, Y. A method for detecting abnormal behavior of ships based on multi-dimensional density distance and an abnormal isolation mechanism. *Math. Biosci. Eng.* **2023**, *20*, 13921–13946. [CrossRef] [PubMed]