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A Bibliometric Review and Future Trends

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Review

Machine Learning in Maritime Safety for Autonomous Shipping: A Bibliometric Review and Future Trends

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Abstract: Autonomous vessels are becoming paramount to ocean transportation, while they also face complex risks in dynamic marine environments. Machine learning plays a crucial role in enhancing maritime safety by leveraging its data analysis and predictive capabilities. However, there has been no review grounded in bibliometric analysis in this field. To explore the research evolution and knowledge frontier in the field of maritime safety for autonomous shipping, a bibliometric analysis was conducted using 719 publications from the Web of Science database, covering the period from 2000 up to May 2024. This study utilized VOSviewer, alongside traditional literature analysis methods, to construct a knowledge network map and perform cluster analysis, thereby identifying research hotspots, evolution trends, and emerging knowledge frontiers. The findings reveal a robust cooperative network among journals, researchers, research institutions, and countries or regions, underscoring the interdisciplinary nature of this research domain. Through the review, we found that maritime safety machine learning methods are evolving toward a systematic and comprehensive direction, and the integration with AI and human interaction may be the next bellwether. Future research will concentrate on three main areas: evolving safety objectives towards proactive management and autonomous coordination, developing advanced safety technologies, such as bio-inspired sensors, quantum machine learning, and self-healing systems, and enhancing decision-making with machine learning algorithms such as generative adversarial networks (GANs), hierarchical reinforcement learning (HRL), and federated learning. By visualizing collaborative networks, analyzing evolutionary trends, and identifying research hotspots, this study lays a groundwork for pioneering advancements and sets a visionary angle for the future of safety in autonomous shipping. Moreover, it also facilitates partnerships between industry and academia, making for concerted efforts in the domain of USVs.

Keywords: maritime safety; machine learning; autonomous shipping; bibliometrics; evolutionary trends

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1. Introduction

In recent years, the concept of autonomous shipping has gained momentum on a global scale [1,2]. Leading nations such as Norway, China, and the US, alongside some companies such as Kongsberg Maritime, have been investing in R&D for autonomous vessels. Marked by the deployment of unmanned vessels capable of independent navigation and decision-making, it represents a significant advancement in the maritime industry. This transformative technology is poised to revolutionize various aspects of maritime operations, promising increased efficiency, reduced operational costs, and potentially safer voyages [3]. At the heart of this technological evolution lies the integration of machine learning (ML), a branch of artificial intelligence (AI) that equips autonomous systems with the ability to learn from data and improve their performance over time [4].

The importance of autonomous shipping extends beyond operational efficiency to encompass broader economic, environmental, and safety considerations. Economically, autonomous ships promise to lower operational costs associated with crew salaries, accommodation, and insurance premiums [5]. By combining the ship cost model and carbon pricing, it is proven that the significant economic benefit of autonomous ships was outdoing conventional ones [6]. Environmentally, they have the potential to optimize routes, reduce fuel consumption, and mitigate the ecological impact of maritime transport [7]. From a safety perspective, the concept of autonomous shipping has evolved from traditional piloted vessels to autonomous or unmanned ships equipped with advanced sensors, communication systems, and decision-making algorithms [8]. The primary drivers behind the development of autonomous shipping include the pursuit of operational efficiencies, reduction of human error, and compliance with increasingly stringent environmental regulations. Moreover, these technologies offer the possibility of enhanced situational awareness [9], collision avoidance, and rapid response capabilities in emergency situations, thereby bolstering overall maritime safety.

To achieve all-sided effects, machine learning has played a pivotal role in enabling the autonomy of maritime vessels and promoting maritime safety. In the domain of maritime transport, machine learning interprets real-time information about vessel position, environmental conditions, nearby obstacles, and other critical parameters. This capability enables autonomous ships to make informed decisions autonomously, such as route planning, speed adjustment, and collision avoidance, based on predictive analytics and probabilistic modeling. Currently, numerous meticulous studies have been conducted in the past years, covering various perspectives of maritime safety. The application of ML in the safety of autonomous shipping encompasses various domains, including but not limited to:

(1) Collision Avoidance: Besides some machine learning algorithms such as deep reinforcement learning (DRL) [10,11] or deep neural networks (DNN), several integrated methods were also used, such as an improved reinforcement learning with the knowledge transfer (KT) method [12], rule-guided vision supervised learning (RGVSL) [13], the multi-agent deep reinforcement learning (MADRL) [14], a distributed multi-USV navigation method based on deep reinforcement learning (DRL) [15], and novel Artificial Potential Fields (APFs) to perform obstacle and collision avoidance in marine environments [16]. These algorithms utilize supervised learning techniques to classify and predict collision risks based on real-time vessel dynamics and environmental conditions.

(2) Path planning: Machine learning models employ techniques such as deep reinforcement learning (DRL) [17,18], Deep Q-learning network [19], and Dynamic path guidance method [20,21] to optimize vessel routes. These models integrate data on weather forecasts, sea conditions, and historical voyage patterns to dynamically adjust routes and maximize efficiency while ensuring safety.

(3) Emergency Response: For emergency response, risk assessment and management come forth. Collision risk metric [22], deep learning multi-model integration method [23], and Bayesian belief network [24] were mainly used to analyze historical incident data, environmental factors, and human factors to assess risk levels and inform proactive risk

management strategies in autonomous shipping operations. After assessment, machine learning-driven emergency response systems utilize deep convolutional neural network (CNN) [25], deep learning [26], Bayesian networks [27], OCSVM [28] or ensemble learning (EL) [29] to prioritize emergency actions. These models integrate real-time data on vessel status, weather forecasts, and emergency protocols to simulate emergency scenarios and recommend optimal response strategies for crew safety and environmental protection.

(4) Environmental Adaptation: Machine learning algorithms such as lightweight volumetric convolutional neural network (VCNN) [30], deep learning recognition method [31], Learning-Without-Forgetting (LWF) approach [32], and ensemble learning methods [33] optimize vessel operations for environmental sustainability, a more accurate estimate of the environment [34,35], and overall safety. These models analyze data on emissions, fuel consumption, and regulatory requirements to dynamically adjust operational parameters and minimize the ecological footprint of maritime activities.

The aforementioned studies illustrate the diverse applications of machine learning (ML) in enhancing maritime safety, particularly in the context of autonomous shipping. With the increasing complexity of operational scenarios in unmanned surface vessels (USVs), ML technologies have been widely adopted to address critical challenges, including collision avoidance, route optimization, real-time risk assessment, and environmental adaptation. Specific techniques such as deep reinforcement learning (DRL), convolutional neural networks (CNNs), Bayesian networks, and generative adversarial networks (GANs) have demonstrated significant potential in enabling autonomous decision-making, predictive analytics, and adaptive control systems for maritime operations.

Despite these advancements, the field still faces several pressing questions that warrant further investigation: (1) What are the key research hotspots regarding ML applications in maritime safety for autonomous shipping? (2) Which institutions and collaboration networks have driven progress in ML-based maritime safety research, and how do they interact? (3) How have machine learning methods evolved to address the unique demands of maritime safety in recent years? (4) What emerging trends and technologies are shaping the future of ML in this domain?

Furthermore, while the interest in integrating ML into autonomous shipping continues to grow, according to the search results of WoS, there is a notable absence of a systematic literature review and featured bibliometric analysis regarding the maritime safety of autonomous shipping in the context of machine learning (ML). This gap highlights the need for a systematic examination of current research to identify trends, evaluate progress, and guide future innovations in this critical field. Hence, a bibliometric analysis is necessary to track the field's development and trends in the past years.

This paper aims to offer a comprehensive overview of the literature concerning the application of machine learning in ensuring the maritime safety of autonomous shipping. Emphasizing technological advancements and current research status, the study intends to meticulously analyze existing scholarly works to (1) map influential journals, authors, and keywords and their collaboration networks; (2) discuss prominent trends, challenges, and future prospects in this field; and (3) enhance understanding of the evolving field of machine learning and offer enlightening references to researchers in this field.

The remainder of the present paper is organized as follows. Firstly, Section 2 presents the data extraction and exclusion criteria and bibliometric analysis method and tool. Secondly, the results for the temporal and spatial distribution of publications, influential journals, author cooperation networks, citation and co-citation networks, and research subject categories, hotspots, and trends are demonstrated in Section 3. Thirdly, Section 4 details the discussions both for the bibliometric results and selected literature. Finally, the concluding remarks are addressed in Section 5.

2. Materials and Methods

2.1. Data Sources

The scientific publications analyzed in this study were retrieved on 31 May 2024 from Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI), Conference Proceedings Citation Index-Science (CPCI-S), and Conference Proceedings Citation Index-Social Science and Humanities (CPCI-SSH) citation index databases in the Web of Science (WoS) Core Collection, which are the most commonly used, authoritative, and the highest data quality databases for bibliometric analysis research domain [36–39].

The analysis for the topic "machine learning for maritime safety of autonomous shipping" mainly contains two parts: "machine learning" and "maritime safety of autonomous shipping". Moreover, the process of data analysis is the basis for conducting machine learning, and the safety of the autonomous shipping research areas also relates to various safety-related domains; thus, the search topic includes some strings/keywords, which can be seen in Table A1 in Appendix A.

Moreover, Boolean operators are often used in advanced search functions of database information. This paper uses Boolean operators "AND" and "OR" to combine the logical relationships between different field tags and different query sets (keywords) to create our query when searching in WoS. The iteration of the search on the website is shown in Figure 1.

Additionally, to provide the accurate retrieval, we also utilize double quotation marks for phrase retrieval, i.e., the exact phrase in double quotation marks would be searched as a whole when it is retrieved. For instance, when searching for papers related to autonomous ships. If you directly use the "autonomous ship" as the search term to retrieve the related publications, the obtained publications contain the autonomous ship research but also contain some research not related to autonomous ships, such as the research on autonomous cars or ordinary ships. When searching with "autonomous ship", the two words "autonomous" and "ship" in the search results need to appear in groups, which meets our search aims and ensures the search accuracy.

Furthermore, this paper uses wildcard characters which represent unknown characters in the literature search. Familiar wildcard characters include the asterisk (*), question mark (?), and dollar sign ($). The asterisk (*) represents any character group, including null characters, e.g., "safe*" can be used to search for "safety" or "safely", etc.; Similarly, "ship*" for "ships" or "shipping", etc.; "mari*" for "marine" or "maritime", etc. The question mark (?) represents any character, which is very useful for searching when the last character is uncertain, e.g., "los?" can be used to search for "lose", "loss" or "lost". The dollar sign ($) means zero or one character. It is usually used to find the English and American spellings of the same word, e.g., "man$euver" can be used to find "maneuver" or "manoeuver". The use of the above wildcard character symbols greatly avoids the related search missing and improves the search efficiency. The explanation of the related substitute words is shown at the bottom of Table A1 in Appendix A and the schematic drawing of the search is shown in Figure 1.

Although the Web of Science database covers publications from 1900 through 2024, very few relevant studies on unmanned vessels existed prior to 2000 due to the nascent state of computing power and machine-learning methods required for autonomous navigation. Therefore, this study only collected the publications after 2000. The language of publications was limited to English, the currently most widely utilized academic language. Moreover, as document types, the types of articles, review articles, and proceedings papers were included in our database.

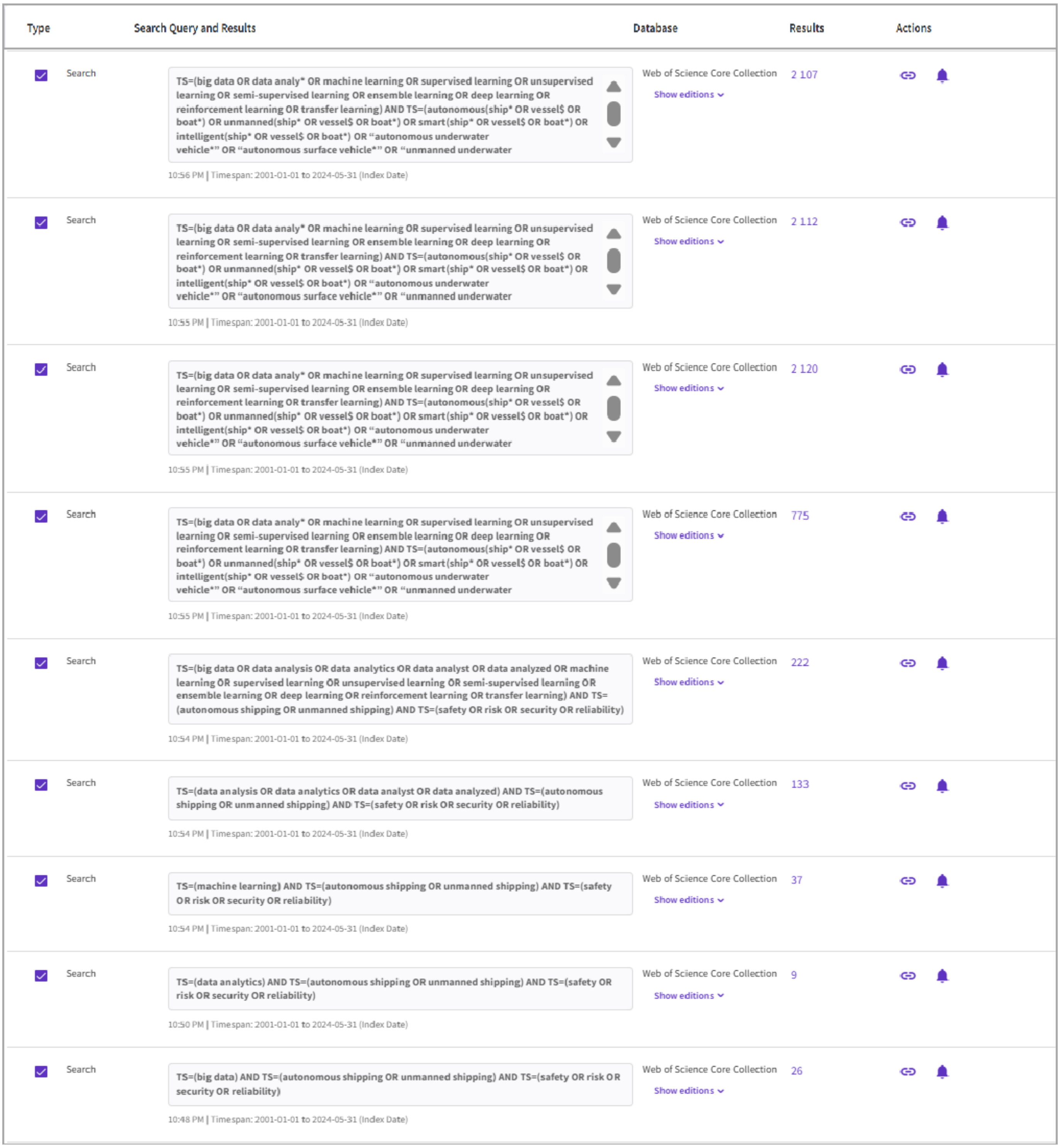


Figure 1. Data retrieval strategies in Web of Science. Note: TS = Topic; DT = Document Types; SCI-EXPANDED = Science Citation Index Expanded; SSCI = Social Sciences Citation Index; CPCI-S = Conference Proceedings Citation Index-Science; CPCI-SSH = Conference Proceedings Citation Index-Social Science and Humanities; The detailed description for each retrieval step and the presentation of the Boolean operators, double quotation marks, and wildcard characters are shown in Table A1 and the following corresponding context.

Moreover, due to the limitations of the search of WoS, it is necessary to further manually exclude documents in this dataset that do not address the explored topic, such as autonomous cars, autonomous drones, etc. The manual filtering was mainly conducted based on the titles and abstracts of the papers; for the specific paper, the paper's full text is also carefully overviewed. Note that the publications that only utilized the autonomous unmanned vessel as a tool to conduct research and do not promote the development of AUV technologies (i.e., the technology of target recognition, obstacle avoidance, navigation, and communication, etc.) are manually excluded.

Finally, 719 publications on machine learning for maritime safety of autonomous shipping are obtained for further bibliometric analysis. These documents included 2404 authors affiliated with 824 institutions in 66 countries, which obtained 11,124 citations in total (an average of 15.47 citations per document) and were published in 399 source journals and proceedings, citing 8218 references (Table 1). Additionally, there are three types of documents, including article = 453 (63.00%); proceedings paper = 251 (34.91%); review = 15 (2.09%), respectively. The full search records and cited references are saved as plain text. The framework of the search process and the steps to obtain the final analyzed dataset are shown in Figure 2.

Table 1. Data extraction and exclusion criteria.

Criteria	TS	TND	AU	SJP	SC	NI	TC	CR
Quantity	31 May 2001–31 May 2024	719	2404	399	66	824	11,124	8218

Note: TS = time span; TND = total number of documents; AU = authors; SJP = source journals and proceedings; SC = source countries; NI = number of institutions/organizations; TC = total number of citations; CR = cited references.

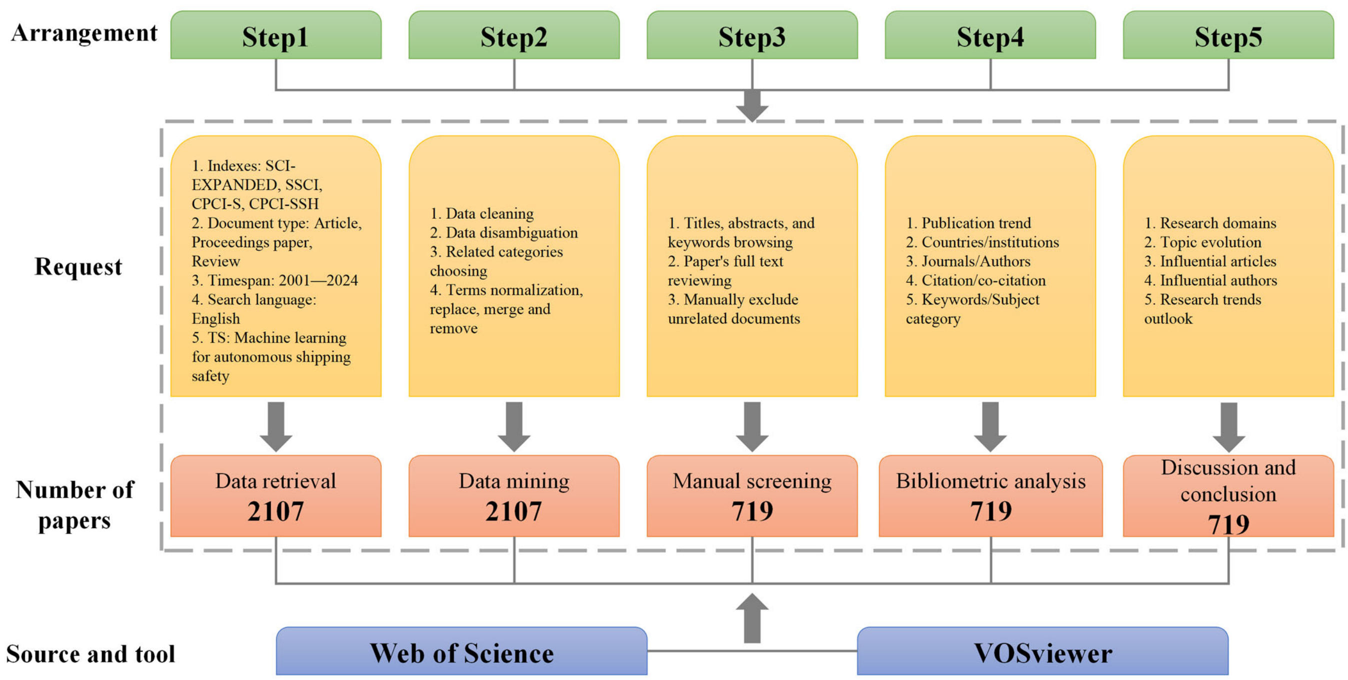


Figure 2. Methodological flowchart of the process of document analysis.

2.2. Bibliometric Analysis Method and Tool

Bibliometric analysis delivers a structural overview of a specific research domain by publications, authors, countries, institutions, journals, and keywords in terms of descriptive statistics, network analysis, and frequency analysis, etc. [40–42]. Additionally, bibliometric research is used to assimilate various viewpoints found in the research and provides a static, transparent, and systematic research perspective [40]. It enables the literature review and analysis to be more simple, objective, understandable, reproducible, and visual user-friendly [41,43].

Nowadays, bibliometric analysis has become popular, and more than 30 free-used tools have already been developed for bibliometric mapping, and visualization of similarity viewer (VOSviewer) software is one of the most internationally renowned analysis tools [44,45]. VOSviewer was developed by Dutch scholars van Eck and Waltman from the Advanced Bibliometric Methods group of the Centre for Science and Technology Studies of Leiden University [46]. It has become an effective auxiliary analysis tool for scientometric mapping research. Using advanced bibliometric methods and visualization, VOSviewer facilitates citation, collaboration, and keyword co-occurrence analyses for comprehensive mapping of a research field [47]. Moreover, several papers have already applied VOSviewer to do bibliometric mapping analysis in safety-related topics, e.g., output distributions and topic maps of safety-related journals [48], safety journal identification [49], safety culture [50], construction safety [51,52], process safety [53], domino effect [54], laboratory safety in universities [55], and road safety research [56], etc.

Therefore, in the present research, a bibliometric analysis method is employed, and the bibliometric mapping tool VOSviewer program is performed to graphically map the material and visually represent the bibliometric analysis and statistics results so as to facilitate the corresponding visual interpretations. Moreover, along with VOSviewer, the data analysis function of WoS was also utilized in this study. The analysis results mainly focus on the following aspects, i.e., temporal and spatial distribution of publications, influential journals, author collaboration networks, citation and co-citation networks, research subject categories and topics, etc.

3. Results

3.1. Temporal Distribution of Publications

A statistical analysis of the annual trends of publications in a particular field can be used to explore and understand the research domain's development from the temporal distribution [57]. The preliminary search in Section 2.1, as the comparable result of the eighth and ninth steps in Table A1 of Appendix A, shows that the productions in the WoS's core collection database had only records after the 2000s.

To more comprehensively analyze and understand the development process of machine learning technology utilized in the autonomous shipping safety research area, Figure 3 is shown to manifest the trend and variation of publication. The entire period's development process is divided into three stages: the initial germination stage (annual increased number of publications is not more than five), the initial growth stage (annual increased number of publications is more than five and not more than 25), and the rapid development stage (annual increased number of publications is more than 25), respectively, as can be seen from Figure 3 and Table 2.

Initial germination stage (2001–2010): In WoS core collection databases, the explored studies' documentation began until 2001. As shown in Table 2, prior to 2010, there were few documents on the relevant studies; the number of publications only accounts for 4.44% of the number of documents. In addition, the primary type of documents is the proceeding paper, accounting for 84.38% of the number of documents published in the initial germination stage. Moreover, the annual increased number of publications is not more than five, shown as the gray curve in Figure 3.

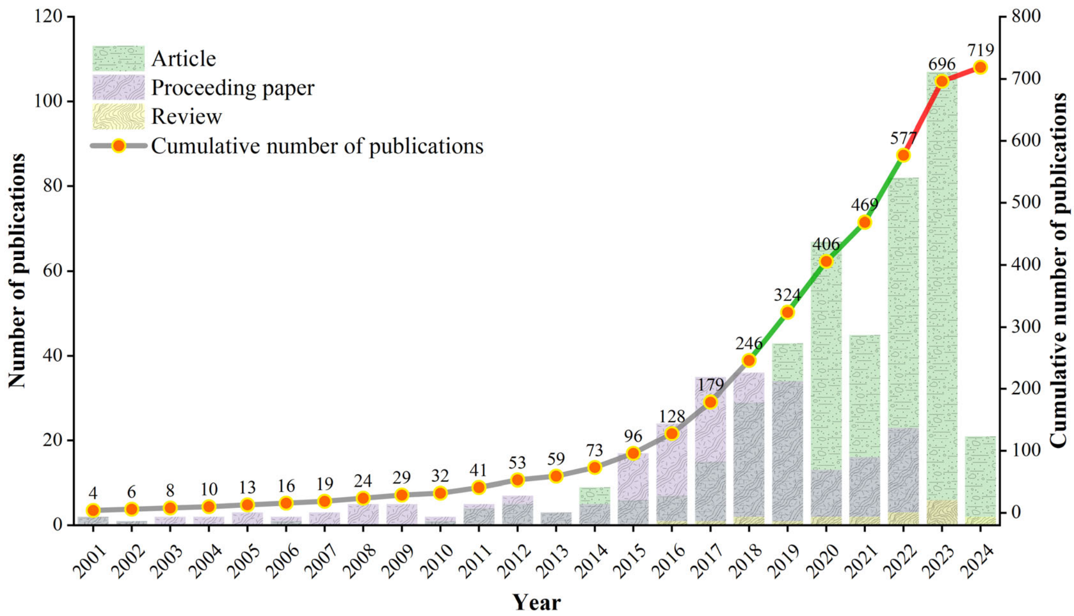


Figure 3. Annual trends of publications in maritime safety of autonomous shipping.

Initial growth stage (2011–2015): The initial growth period for the explored research area spans from 2011 to 2015, and the number of publications accounts for 8.90% of the total documents' number (Table 2). Shown as the green curve in Figure 3, although there were still a few publications on the relevant study in the period, the cumulative number of publications continues to increase with a low growth rate, and the annual increased number of publications is more than five and not more than 25. Additionally, the variation tendency of the publications' number indicates that the research in the area of machine learning for maritime safety of autonomous shipping has attracted the attention of scholars year by year.

Rapid development stage (2016 and beyond): After 2016, with the rapid development of computer technology and big data technology, machine learning methods have been widely used in autonomous shipping safety. Shown as the red curve in Figure 3, the number of publications exceeded 100 for the first time in 2016, and the annual increased number of publications is more than 25. In addition, the volume of publications on the explored studies had shown a rapid growth tendency (the number of publications in 2024 has not been fully counted yet due to there still being several months left in this year when the statistics were conducted); thus, this stage is named the rapid development stage. At this stage, in terms of the document's type, the number of journal articles (416) exceeds the number of proceeding papers (187) for the first time, and the number of publications accounts for 83.86% of the total documents' number (Table 2).

Table 2. The distributions of document types in various stages.

Stage	Time Span	Classification Criteria	Number of Articles	Proportion (%)	Number of Proceeding Paper	Proportion (%)	Number of Reviews	Proportion (%)	Total Number	Proportion (%)
Initial germination stage	2001–2010	$0 < AINP \leq 5$	5	0.69%	27	3.76%	0	0	32	4.44%
Initial growth stage	2011–2015	$5 < AINP \leq 25$	27	3.76%	37	5.15%	0	0	64	8.90%
Rapid development stage	2016 and beyond	$AINP > 25$	416	57.86%	187	26.01%	20	2.78%	603	83.86%
Total	-	-	448	62.31%	251	34.91%	20	2.78%	719	100.00%

Note: AINP = Annual increased number of publications.

3.2. Spatial Distribution of Publications

3.2.1. Publications Distribution in Pattern of Countries/Regions

Through the statistics for the authors' affiliations, the spatial distribution of various countries/regions and organizations for the explored publications was investigated. Due to the cooperative publication, one document might be conducted by more than one country and thus might belong to two or more countries, hence finally with a total of 937 records in this part. As shown in Figure 4, the academic publications' geographic distribution covers 64 countries/regions. Among them, 30 are from Europe, 19 from Asia, 3 from Africa (South Africa, Morocco, and Egypt), 3 from North America (USA, Canada, and Mexico), 3 from South America (Brazil, Argentina, and Colombia), 3 from Oceania (Australia, New Zealand, and New Caledonia), and 4 countries from Europe and Asia (Russia, Turkey, Azerbaijan, and United Arab Emirates). Note that the documents from England (60), Scotland (13), and Northern Ireland (2) merged to belong to the United Kingdom (UK, 75 documents) in Figure 4. There are 19 countries/regions (29.69%) publishing ten or more documents, and 32 countries/regions have produced less than three publications in the explored research domain. It is noteworthy that there are 303 documents from European countries, accounting for 32.34% of the total number of publications. Moreover, Figure 4 illustrates that among the top ten productive countries/regions of the explored domain during 2001–2024, China (341, 36.39%) is the most productive country, followed by the USA (101, 10.78%), the UK (75, 8.00%), South Korea (48, 5.12%), Germany (24, 2.56%), Spain (24, 2.56%), Italy (22, 2.35%), Australia (19, 2.03%), and Portugal (16, 1.71%), respectively.

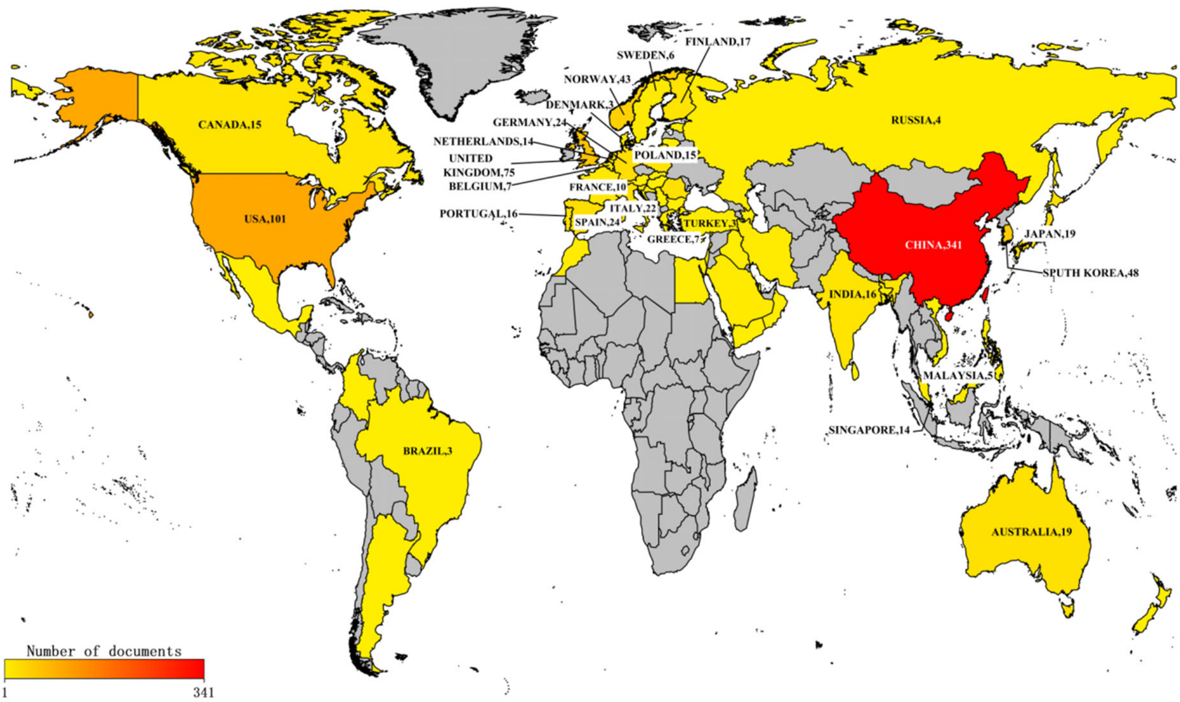
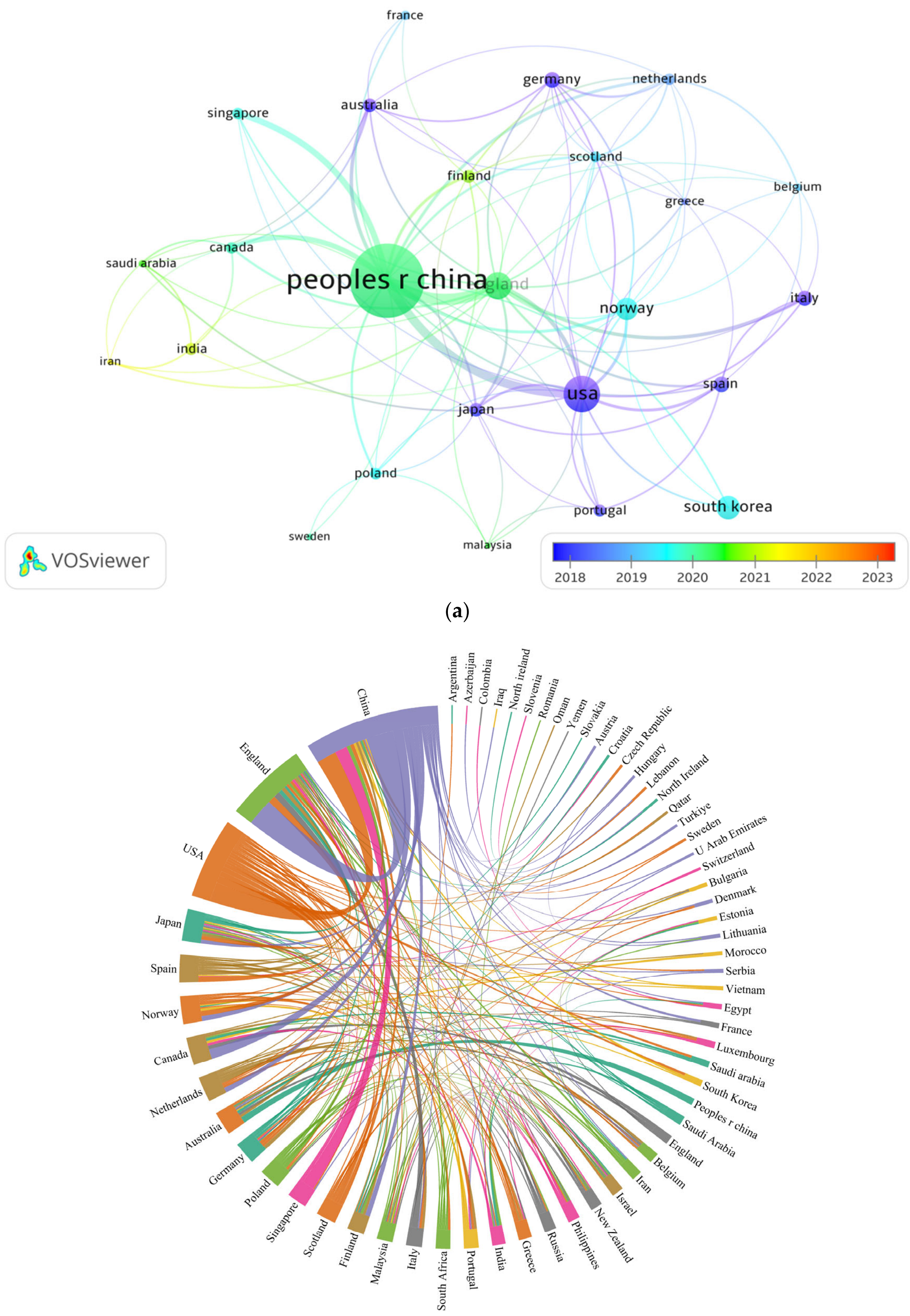


Figure 4. The number of publications distributed by countries/regions.

3.2.2. International Cooperation and Influential Research Institutions

The cooperation relation of countries/regions in the explored field was also visualized and analyzed by utilizing cooperation networks analysis to investigate affiliated countries and institutes through the VOSviewer software, shown in Figure 5a. It should be noted that a node is apportioned to each co-author of a publication in the networks. The nodes' color presents the average time for the publications of each country [57]. The nodes' size denotes the related publications' number, and the thickness of the links indicates the international collaborations' degree [54,58], i.e., the larger the node is, the more critical the country/region is, and the thicker the line is, the closer the cooperation relationship between countries/regions.



(**a**)

(**b**)

Figure 5. (**a**) Cooperation network and the timespan of the publications of various countries/regions; (**b**) Cooperation network among countries/regions.

Figure 5a indicates that China (21 links) and the USA (17 links) have been at the forefront and play the predominant roles in the explored machine learning for maritime safety of autonomous shipping studies. Meanwhile, Figure 5a,b show that China collaborates with the USA, Singapore, Norway, the Netherlands, Canada, Australia, Spain, and England, etc. Similarly, the close collaboration countries/regions with the USA are China, England, Spain, Italy, South Africa, Saudi Arabia, and Norway, etc. In addition, among the close collaboration countries/regions, China and the USA have the closest cooperation and research relationship in the explored research domain (with the link strength of 16). Moreover, as shown in Figure 5a, in terms of the publication time for the studies, Iran, India, and Finland are relatively active research countries recently and have the latest output in the explored field. Furthermore, the USA is among the first countries to carry out the related research and published the first journal paper in 2001 [59] according to the investigated results from the core database of the WoS. Generally, more international collaboration needs to be promoted and enhanced to share knowledge globally in the future.

According to the bibliometric analysis for authors' affiliation, 793 institutions were recognized. The top 10 affiliated research institutions that contribute to the publications on the explored domain are presented in Table 3. It can be seen that the institutions are mainly from China, for instance, Dalian Maritime University, Wuhan University of Technology, Ocean University of China, Harbin Engineering University, Chinese Academy of Sciences, Shanghai Jiaotong University, and Shanghai Maritime University. Among them, Dalian Maritime University (58, 8.07%) is the most productive and active institution related to the explored domain in China as well as globally, followed by Wuhan University of Technology (44, 6.12%) and Norwegian University of Science and Technology (26, 3.62%). Furthermore, Wuhan University of Technology has the highest total link strength (81), and Wuhan University of Technology also has the most links (55) with other institutions.

Table 3. The top ten research institutions in the explored research domain.

Rank	Institution	Country/Region	Links	TLS	NP	P (%)	TC	APY	AC
1	Dalian Maritime Univ.	China	53	68	58	8.07%	1161	2020.21	20.02
2	Wuhan Univ. Technol.	China	55	81	44	6.12%	1013	2020.30	23.02
3	Harbin Engn Univ.	China	17	21	30	4.17%	449	2019.10	14.97
4	Norwegian Univ Sci and Technol.	Norway	29	36	26	3.62%	407	2019.75	15.65
5	Ocean Univ China.	China	20	27	23	3.20%	266	2018.52	11.57
6	Chinese Acad. Sci.	China	25	34	18	2.50%	211	2020.61	11.72
7	Shanghai Jiaotong Univ.	China	14	26	18	2.50%	488	2021.06	27.11
8	Shanghai Maritime Univ.	China	19	20	13	1.81%	317	2020.00	24.38
9	Liverpool John Moores Univ.	UK	13	19	12	1.67%	169	2023.17	14.08
10	Univ Southampton.	UK	14	16	10	1.39%	276	2018.60	27.60

Note: TLS = total link strength; NP = number of publications; P (%) = the proportion of NP/TND; TND = total number of documents; TC = total number of citations; APY = average publications year; AC= average citations = TC/NP.

Moreover, the Norwegian University of Science and Technology (Norway), Liverpool John Moores University (UK), and University of Southampton (UK) also ranked in the top ten for the number of publications. It should be noted that the highest number of cited documents in the explored field is from Dalian Maritime University, with 1161 citations and an average of 20.02 citations. Additionally, except for the institutions that only published 1 document, the University of Southampton has the latest average publication year of 2023.17.

The VOSviewer software is utilized to establish a cooperative network map for the primary research institutions in the explored domain. Figure 6 demonstrates the interactions through joint publications among 98 institutions (with more than 3 publications, finally including 74 associated institutions) with 314 links (with the full counting method). It can be found that Dalian Maritime University is located in the middle of the cooperation network with the most prominent node, indicating that it has the greatest number of publications and broad cooperation with other institutions. Moreover, Wuhan University of Technology (55 links in total) has the most frequent cooperation with other institutions.

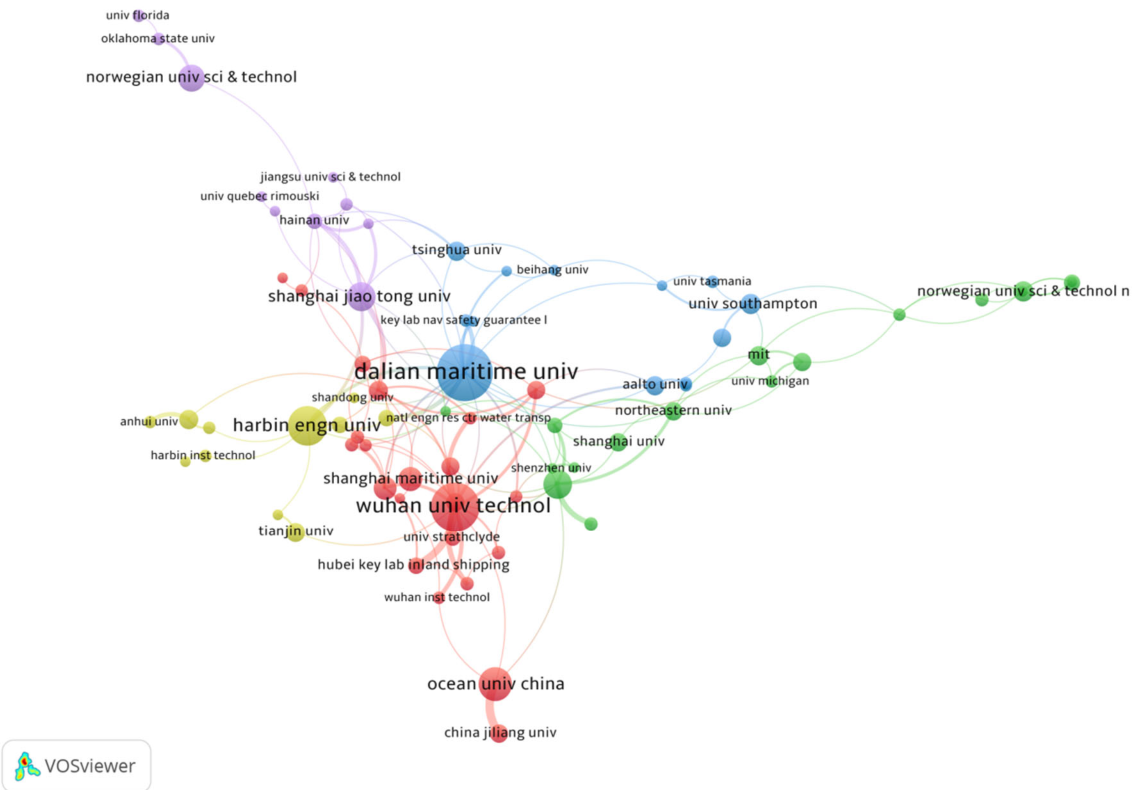


Figure 6. Cooperation network of institutions for the explored research domain.

According to the results of various classifications with different colors, the global cooperation network among different research institutions for machine learning in maritime safety of autonomous shipping studies has been initially formed. However, institutions primarily collaborate at the national level, with limited cross-continental partnerships. Scholars only carried out a certain degree of cooperation at a relatively low level, basically cooperation within each similar institution or an individual country. However, institutions need to be encouraged to cooperate in exchanging knowledge among scholars to obtain and promote the output for the highest research quality [60].

It should be noted that when utilizing the VOSViewer, the node's size presents the number of publications, the node's color reflects the cluster to which the node belongs, and the links between nodes denote cooperation between countries, respectively. In addition, the larger the node's size is, the greater the number of publications is, and the thicker the line is, the closer the cooperation relationship between institutions. Moreover, to clearly illustrate the cooperative relationship between the prominent institutions, 24 unassociated institutions were excluded when drawing Figure 6 in the software.

3.3. Influential Journal Analysis

Between 2001 and 2024, 399 publication sources contributed to the field. Table 4 summarizes the ten most prolific journals (≥3 publications), led by Ocean Engineering (68 papers, 9.45% of the total; 1396 citations; average 20.53 citations; total link strength = 220; Q1 in Engineering), followed by the Journal of Marine Science and Engineering (36 papers; highest mean publication year = 2022.44; impact factor = 2.7; 5-year IF = 2.8) and IEEE Access (29 papers). Other top outlets include Sensors (24), Applied Sciences-Basel (14), IEEE Journal of Oceanic Engineering (14), IEEE Transactions on Intelligent Transportation Systems (14), IEEE Transactions on Neural Networks and Learning Systems (8), Reliability Engineering and System Safety (8), and Applied Ocean Research (7)—all ranking Q1 in their primary research categories. Engineering, oceanography, and Computer Science emerge most frequently as subject areas among these journals. It should be noted that the specific research area category and the corresponding quartile are given if the classification is different in the subdivision area according to the journal citation reports from WoS; then the detailed information is separately marked.

In addition, as shown in Table 4, though the top 10 most prolific journals are analyzed; however, there is a significant difference in the number of citations of the specific journal. To further investigate the most influential journal related to the research domain of machine learning in autonomous shipping safety, mapping the sources with regard to the co-citations is depicted in Figure 7.

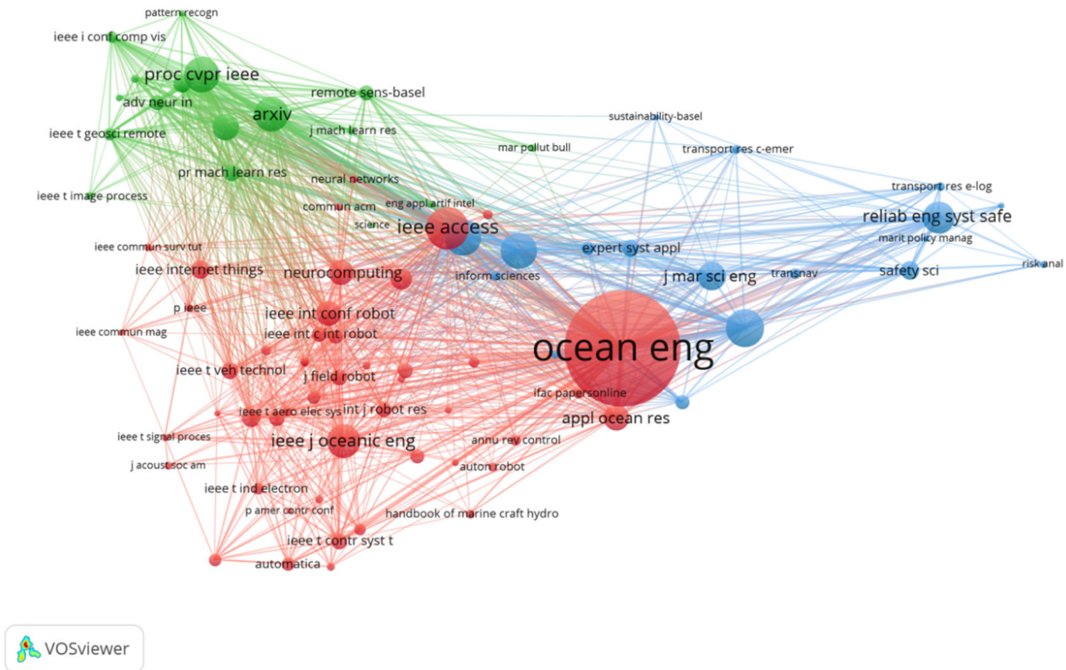


Figure 7. The mapping of the sources with regards to the co-citations.

The mutual relations between the journal sources are usually visualized by utilizing this type of bibliometric network analysis [36]. In addition, the minimum value of citations of a source is settled as 20. Herein, 67 of the 4774 sources meet the threshold. The weights are settled by the citations' number. Thus, four clusters are recognized using the full counting method for sources and the association strength method for data normalization in VOSviewer software.

The top five co-cited journals in this domain are Ocean Engineering (1563 citations), IEEE Access (438), the Journal of Navigation (387), Sensors (367), and IEEE Transactions on Intelligent Transportation Systems (358).

Table 4. The top 10 most prolific journals published on maritime safety of autonomous shipping research from 1981 to 2020.

Rank	Journal Title	Links	TLS	NP	P (%)	TC	APY	AC	IF	5 Year IF	Journal Category	Corresponding Quartile Rank
1	Ocean Engineering	58	220	68	9.45%	1396	2021.76	20.53	4.6	4.8	Engineering Civil; Engineering Marine; Engineering Ocean; Oceanography	Q1; Q1; Q1; Q1
2	Journal of Marine Science and Engineering	29	114	36	5.00%	271	2022.44	7.53	2.7	2.8	Engineering Marine; Engineering Ocean; Oceanography	Q1; Q2; Q2
3	IEEE Access	28	65	29	4.03%	635	2019.72	21.90	3.4	3.7	Computer Science; Electrical and Electronic; Telecommunication	Q2; Q2; Q2
4	Sensors	28	69	24	3.34%	507	2020.83	21.13	3.4	3.7	Chemistry; Electrical and Electronic; Instruments and Instrumentation	Q2; Q2; Q2
5	Applied Sciences	8	8	14	1.95%	143	2020.93	10.21	2.5	2.7	Chemistry; Engineering; Materials Science; Physics	Q2; Q1; Q3; Q2
6	IEEE Journal of Oceanic Engineering	8	8	14	1.95%	412	2015.64	29.43	3.8	4.2	Engineering Civil; Electrical and Electronic; Engineering Ocean; Oceanography	Q1; Q2; Q2; Q1
7	IEEE Transactions on Intelligent Transportation Systems	22	40	14	1.95%	327	2022.21	23.36	7.9	8.3	Engineering Civil; Electrical and Electronic; Transportation Science and Technology	Q1; Q1; Q1
8	IEEE Transactions on Neural Networks and Learning Systems	16	20	8	1.11%	243	2022.13	30.38	10.2	10.4	Artificial Intelligence; Hardware and Architecture; Theory and Methods; Electrical and Electronic	Q1; Q1; Q1; Q1
9	Reliability Engineering and System Safety	10	21	8	1.11%	217	2021.63	27.13	9.4	8.1	Engineering Industrial; Operations Research and Management Science	Q1; Q1
10	Applied Ocean Research	22	58	7	0.97%	250	2021.86	35.71	4.3	4.1	Engineering Ocean; Oceanography	Q1; Q1

Note: JT = journal title; TLS = total link strength; NP = number of publications; P (%) = the proportion of NP/TND; TND = total number of documents; TC = total number of citations; APY = average publications year; AC = average citations = TC/NP; IF = impact factor in 2019; JC = journal category; QR = corresponding quartile rank.

Figure 7 identifies five thematic co-citation clusters. The largest (red) cluster centers on ocean and marine engineering, robotics, and machine learning—anchored by Ocean Engineering and including Applied Ocean Research, IEEE ICRA, and Neural Networks. A green cluster focuses on computer vision and pattern recognition, led by CVPR proceedings and linked to IEEE TPAMI, Remote Sensing, and IJCV. The blue cluster emphasizes safety and system reliability, featuring the Journal of Navigation, Reliability Engineering and System Safety, and Accident Analysis and Prevention. The fourth cluster covers information technology and automation (e.g., IEEE Access, Automatica), while the fifth cluster concentrates on signal processing and control theory in maritime contexts, represented by the IEEE Journal of Oceanic Engineering and IEEE Transactions on Signal Processing.

3.4. Cooperation Network Analysis for the Authors

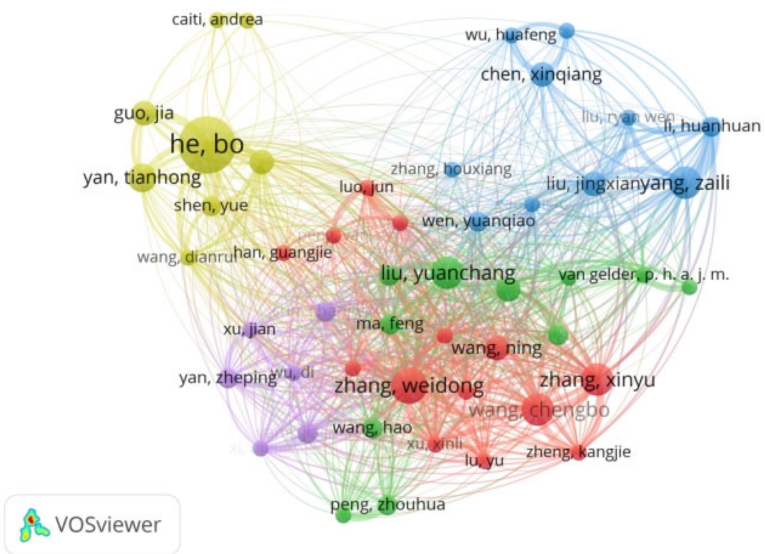
A total of 2597 authors have contributed to research on machine learning applications for maritime safety in autonomous shipping. Table A2 (Appendix A) identifies the top 20 authors by publication output and citation impact.

Bo He of Ocean University of China is the most prolific author, with 14 publications (1.95% of the corpus), while Zhouhua Peng of Dalian Maritime University attains the highest average citation rate (58 citations per paper). Furthermore, the most average number of citations (AC) is 58 (from Zhouhua Peng, Dalian Maritime University, China), and the average number of citations varies from 2.29 to 58 in this table.

In citation impact analysis, Weidong Zhang (Shanghai Jiaotong University) emerges as the most cited author (373 total citations; average 41.44 citations per paper). Furthermore, the average number of citations ranges from 6.25 to 48 in the table.

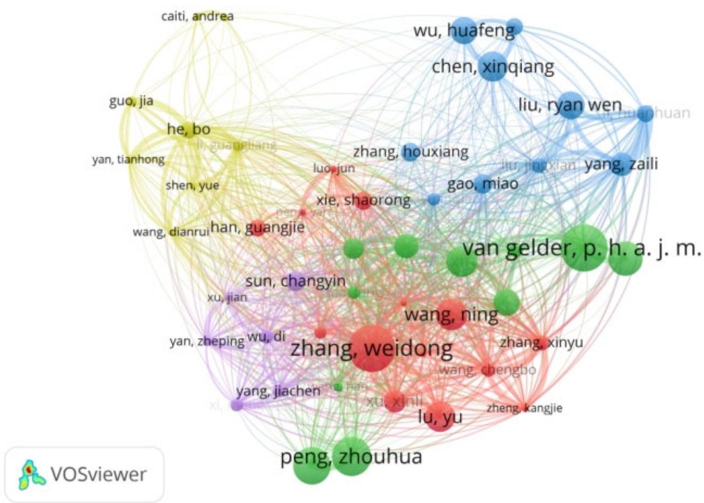
Across both productivity and citation metrics, Yuanchang Liu demonstrates the greatest collaborative influence, exhibiting the highest co-authorship network centrality (96 links; total link strength = 1803).

Figure 8a,b depict author co-authorship and co-citation networks, respectively, with node size proportional to publication or citation volume, link thickness denoting collaboration strength, and color clusters indicating distinct collaborative communities. Only authors with a minimum of four publications (49 out of 2597) meet the threshold for inclusion in these network visualizations.



(**a**)

Figure 8. *Cont.*



(**b**)

Figure 8. (**a**) Bibliographic coupling network of the authors for the investigated topic based on the weights of the number of documents; (**b**) Bibliographic coupling network of the authors for the investigated topic based on the weights of the number of citations.

3.5. Citation and Co-Citation Network Analysis for the Publications

3.5.1. Publications Citation Analysis

The publication citation analysis demonstrates the process of analyzing the number of citations that the documents of the explored domain have been cited by other publications through the database of WoS [58], and it is a method to measure the specific publication's quality and influence [61]. The most cited publication is authored by Peng et al. [62] in IEEE Transactions on Industrial Electronics (257 citations). Additionally, two publications authored by Huang et al. [63] and Cheng and Zhang [64], which are published in Safety Science (239 citations) and Neurocomputing (160 citations), rank as the second and third most frequently cited publications, respectively.

Among the three publications with the highest citation, Peng et al. proposed a neurodynamic-based output feedback scheme for distributed containment maneuvering of marine vessels guided by multiple parameterized paths without using velocity measurements [62]. This innovative approach, which operates without using velocity measurements, exemplifies the advanced control systems essential for the autonomous navigation and coordination of maritime vehicles guided by multiple parameterized paths, thereby enhancing their operational efficacy and reliability. Huang et al. offered a comprehensive overview of collision prevention techniques based on the three fundamental processes of determining evasive solutions: motion prediction, conflict detection, and conflict resolution [63]. Its thorough analysis and innovative approach have made it a cornerstone in the field of autonomous maritime navigation, significantly influencing subsequent research and providing a foundational framework for developing advanced collision avoidance systems. Cheng and Zhang introduced a novel Concise Deep Reinforcement Learning Obstacle Avoidance (CDRLOA) algorithm [64]. This method utilized the robust deep Q-networks architecture to smoothly address the usability challenges posed by the complex control laws inherent in traditional analytical approaches.

Note that since most of the influential works' research topics are cross fused with the research hotspots in Section 3.6, the related literature productions are not discussed and analyzed in detail in this section.

3.5.2. Publications Co-Citation Analysis

Publication co-citation analysis identifies pairs of documents that are frequently cited together, thereby quantifying their thematic similarity and revealing underlying narrative structures within a research domain. VOSviewer enables reference-level co-citation mapping, where nodes represent cited documents and node size reflects citation frequency. In this study, 59 of the 20,280 references, each cited at least 15 times across 719 retrieved publications, constitute the co-citation network (Figure 9).

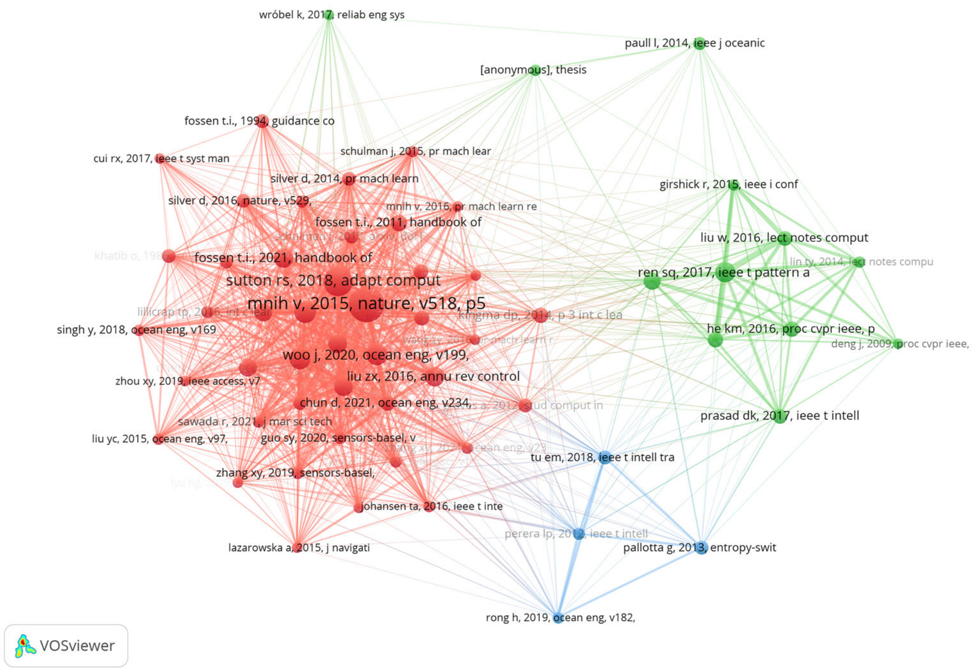


Figure 9. Map of co-cited reference network in explored research domain.

Figure 9 shows the references co-citation map for the documents cited more than 15 times by the explored publications. Herein, 59 of the 20,280 references cited by 719 retrieved documents on the explored domain meet the threshold. It can be seen that four clusters are recognized from 59 references in the map of the co-cited reference network, which demonstrates various research themes in the explored research domain. The blue cluster mainly focuses on trajectory prediction and AIS data application [65–68]. The document authored by Pallotta et al. [68] is the core and representative publication with the most citations (21), and Tu et al. [65] has the most links (33). Moreover, the red cluster mainly emphasizes machine learning methods, especially deep reinforcement learning [64,69–71]. The document authored by Mnih et al. [71] is the most influential publication, with the most citations (74) and links (52). In addition, the green cluster mainly concentrates on object detection and image processing [72–76]. Among them, the document authored by Ren et al. [72] has the most number of citations (35), and the document authored by Krizhevsky et al. [75] has the most number of links (28).

3.6. Research Subject Categories, Hot Topics, and Trends

3.6.1. Subject Categories Analysis

A total of 719 publications indexed in the Web of Science belong to 71 distinct subject categories, reflecting the inherently multidisciplinary character of machine learning research for maritime safety in autonomous shipping. As shown in Figure 10, the predominant categories are Engineering, Electrical and Electronic (222 publications; 30.88%), Oceanography (190; 26.43%), Marine Engineering (180; 25.04%), Ocean Engineering (175;

24.34%), and Civil Engineering (115; 16.00%), with substantial representation also observed in Automation and Control Systems, Computer Science (artificial intelligence), Computer Science (Information Systems), Telecommunications, and Robotics, each comprising between 8.8% and 12.9% of the rest. In general, the explored research is apparently multidisciplinary; moreover, the researchers range from scientists and engineers to marine ecologists. Note that one publication may belong to different categories.

Figure 10. The distribution of the explored documents into categories as various research areas.

3.6.2. Influential Authors' Research Interests and Domains

To figure out the main research topics relevant to the explored domain, the bibliographic coupling analysis is carried out for the 719 publications. Figure 11 demonstrates the 56 publications with at least 50 citations. Each node represents the specific publication, and the size of the node indicates the number of publication citations. Bibliographic coupling happens when two publications cite the same third publication and is denoted by the link curve between specific publications. As shown in Figure 11, there are five colors in the network, which indicate five clusters, and each cluster's topic can be recognized and summarized by the title and abstract of the documents. The red cluster contains most publications (14) and mainly concentrates on obstacle detection, object detection, and trajectory prediction. Moreover, the theme of the green cluster (10) focuses on path planning and optimization under deep reinforcement learning, and the blue cluster (9) presents control methods for collision avoidance and navigation. In addition, the yellow cluster (7) is related to the research topic of the intelligent decision-making method and system, while that in the purple cluster (7) represents the amelioration and enhancement of sensors, ship localization, and ship surveillance. The results indicate that the aforementioned topics attract the most attention in the explored research domain.

Generally, scholars with a considerable amount of highly cited publications dominate the research field's development direction and methodological trends and significantly influence the domain. Additionally, high-yield authors also usually have a relatively deep understanding of the research frontiers in the specific field and often have new outputs. Therefore, identifying and analyzing influential scholars from the highly cited and high-yielding levels allows obtaining insights and bringing inspiration into understanding the development of hotspots and trends in the explored research domain.

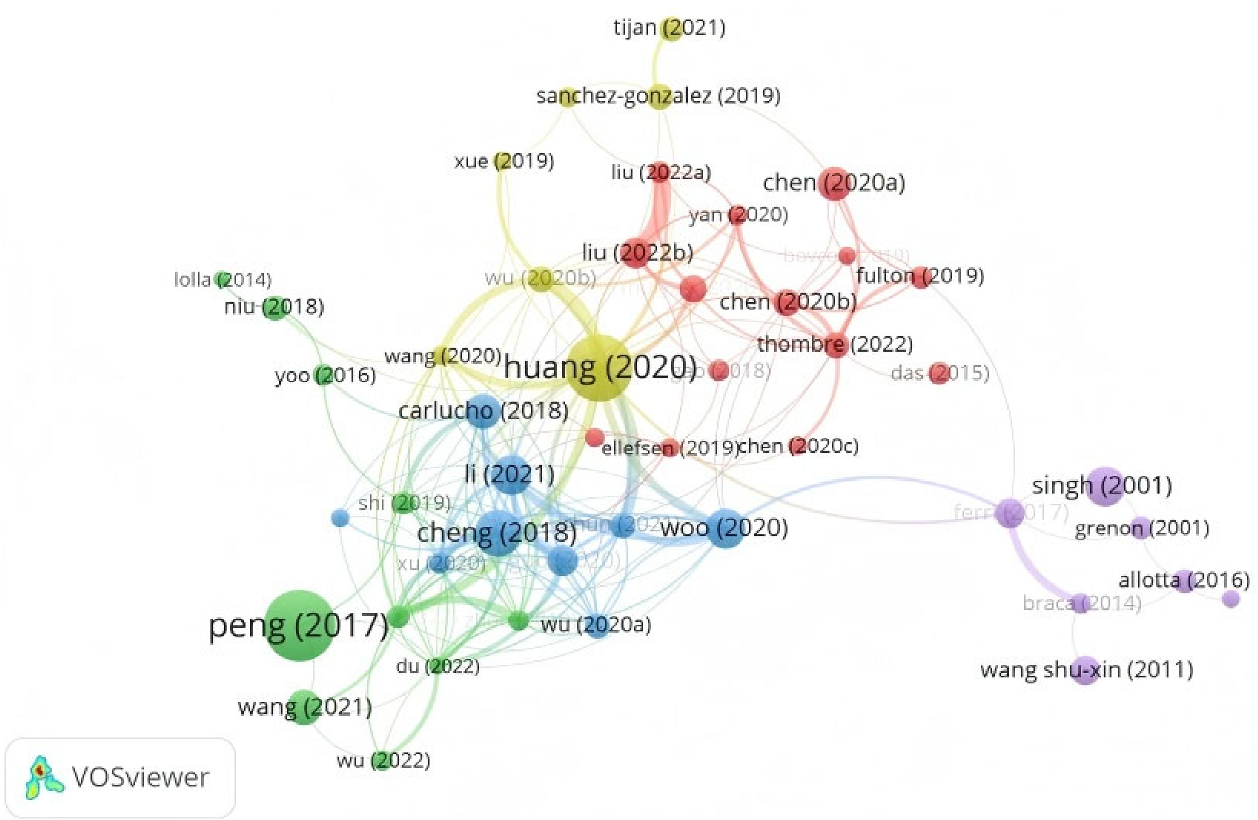


Figure 11. Bibliographic coupling network between publications on the explored domain.

Hence, in this paper, to further analyze the main research hot topics and trends, the top three authors in the top 20 most productive authors and the top 20 most cited authors are selected, respectively. Moreover, considering the average citations (AC) comprehensively and objectively reflect the number of publications and the influence of the author in a specific research field [77], the top three authors are also identified based on AC from the top 20 most productive and most cited authors, as presented in Table A2. Recognizing that citation counts alone may favor researchers with longer academic careers, the average publication year (APY) is also incorporated as an additional metric to account for the emerging influence of younger researchers. Specifically, APY, or average publication year, is a metric used to reflect the temporal distribution of an author's publications. It is calculated as the weighted average of the publication years of all works by an author, considering the publication count as the weighting factor.

By integrating these criteria, a total of 10 influential authors with 76 publications, accounting for 10.57% of the 719 publications, are identified. The selected authors' main research interests are then summarized based on information obtained from Google Scholar, ResearchGate, and affiliated universities or institutions, as shown in Table 5.

Table 5. Top 10 most influential authors in the explored domain and their research interests.

No.	Author	Country	Institution	NP	P (%)	TC	APY	AC	Main Research Interests
1	Zhang, Weidong	China	Shanghai Jiao Tong University	9	1.25%	**373**	2021.56	41.44	Image restoration; intelligent agriculture; deep learning; image processing and computer vision; control theory and pattern recognition theory and their applications in USV/UAV/AUV
2	Van Gelder, P. H. A. J. M.	Netherlands	Delft University of Technology	4	0.56%	370	2019.25	**92.50**	Risk analysis and optimization of systems; processes and structures; infrastructure safety; statistical modelling of high impact low probability (HILP)
3	Peng, Zhouhua	China	Dalian Maritime University	5	0.70%	290	2019.60	58.00	Guidance, control, and coordination of unmanned surface vehicles; multi-vehicle systems; unmanned surface vehicles; formation control; neural networks
4	He, Bo	China	Ocean University of China	**14**	**1.95%**	98	2018.14	7.00	Mobile robots; unmanned vehicles; precise navigation, and control and communication; AUV design and applications; AUV SLAM (simultaneous localization and mapping); AUV control; machine learning
5	Liu, Yuanchang	England	University College London	8	1.11%	155	2020.63	19.38	Autonomous system; artificial intelligence; marine robotics; statistical machine learning; automation and autonomy; guidance and control of intelligent and autonomous vehicles
6	Wang, Chengbo	China	Dalian Maritime University	8	1.11%	69	2022.25	8.63	Maritime autonomous surface ships; collision avoidance; decision-making; deep reinforcement learning
7	Yang, Zaili	England	Liverpool John Moores University	8	1.11%	149	**2023.25**	18.63	Maritime transport; risk analysis; analysis and modelling of safety; resilience and sustainability of transport networks; maritime and logistics systems
8	Zhang, Xinyu	China	Dalian Maritime University	8	1.11%	77	2021.88	9.63	Traffic organization optimization; intelligent navigation of USV; analysis and integration of maritime big data; three-dimensional maritime supervision methods; port traffic capability simulation

Table 5. *Cont.*

No.	Author	Country	Institution	NP	P (%)	TC	APY	AC	Main Research Interests
9	Yan, Xinping	China	Wuhan University of Technology	6	0.83%	216	2017.50	36.00	Intelligent transport system key technologies; energy efficiency management of vessel; marine system design and control; vessel condition monitoring and fault diagnosis; maritime safety; tribology and safety
10	Wang, Dan	China	Dalian Maritime University	4	0.56%	274	2018.75	68.50	Marine vehicle control; unmanned surface vehicles; multi-agent system control; tracking control; linear multiagent systems

Note: NP = number of publications; P (%) = the proportion of NP/TND; TND = total number of documents; TC = total number of citations; APY = average publications year; AC = average citations = TC/NP.

Note that the authors Yuanchang Liu, Chengbo Wang, Zaili Yang, and Xinyu Zhang all have 8 publications when choosing the top 3 authors among the top 20 most productive authors, so they are all listed in Table 5. Moreover, as shown in Table A2, the author Xinping Yan belongs to the top 3 authors based on average citations in the top 20 most productive authors. In addition, the fourth author, Dan Wang, belongs to the top 3 authors based on average citations in the top 20 most cited authors and is selected into the table list.

As shown in Table 5, the most cited author is Weidong Zhang from Shanghai Jiaotong University with 373 citations, followed by Van Gelder, P. H. A. J. M. (370) from Delft University of Technology, respectively. In addition, Bo He from the Ocean University of China is the most productive author with 14 publications, followed by Weidong Zhang (9) from Shanghai Jiao Tong University, Yuanchang Liu (8) from University College of London, Chengbo Wang (8) from Dalian Maritime University, Zaili Yang (8) from Liverpool John Moores University, and Xinyu Zhang (8) from Dalian Maritime University, respectively. Moreover, Zaili Yang is also the author with the largest average publications year (2023.25), which indicates the publications relatively have new updates. Additionally, Van Gelder, P. H. A. J. M. is also the author with the highest average citations of 92.50 per paper, followed by Dan Wang (68.50) from Dalian Maritime University and Zhijun Chen (62.33) from Wuhan University of Technology. Thus, the results reveal that their research has received extensive attention from other scholars.

From the primary research interest shown in Table 5, we could conclude that the influential authors mainly focus on AUV/USV reliability and safety-related topics in maritime industries, as well as advancements in intelligent systems for maritime applications. Key areas of focus include image processing, computer vision, control theory, and their applications in USV, UAV, and AUV; risk analysis and optimization of systems, processes, and infrastructures; guidance, control, and coordination of unmanned surface vehicles and multi-vehicle systems; and formation control using neural networks.

Additionally, these authors are keen on exploring autonomous systems design, precise navigation, communication, AUV control and design, and simultaneous localization and mapping (SLAM). By analyzing their interested fields, it can be inferred that machine learning, deep learning, artificial intelligence, and deep reinforcement learning are critical for enhancing decision-making and collision avoidance in marine robotics and autonomous vehicles. Energy efficiency management, vessel condition monitoring, fault diagnosis, tribology, and multi-agent system control also contribute to the safety of robust and efficient unmanned and intelligent systems in complex maritime environments.

3.6.3. Research Fields Identification and Analysis

Bibliometric analysis through keywords in a specific period has been used and developed for several years, and it has proved to be a very helpful and efficient way of discovering and revealing scientific research trends and hotspots [78–80]. Therefore, the core content and research topics of the papers can be summarized and represented by keywords. In addition, we can use the text mining technology through VOSviewer to infer the topics and trends in a specific research field from the text strings in keywords, titles, and abstracts of the documents in the database [77]. Thereby, in this paper, to investigate and explore the research fields and trends, the keywords of documents are visualized by utilizing the co-occurrence analysis module in VOSviewer software. The "All keywords" function, containing "Author keywords" and "Keywords plus", is employed. Figure 12 demonstrates the keywords co-occurrence map where the minimum number of occurrences of a keyword is 10 among the 719 retrieved publications. Herein there are 50 of the 2624 keywords, i.e., nodes, that meet the threshold (for example, among the 2624 keywords, 2080 keywords appeared only once while 152 keywords appeared more than 5 times). Note that a node presents the term gotten from the publications related to the explored research domain. Moreover, the node's size denotes the co-occurrence frequencies for the analyzed keywords [54].

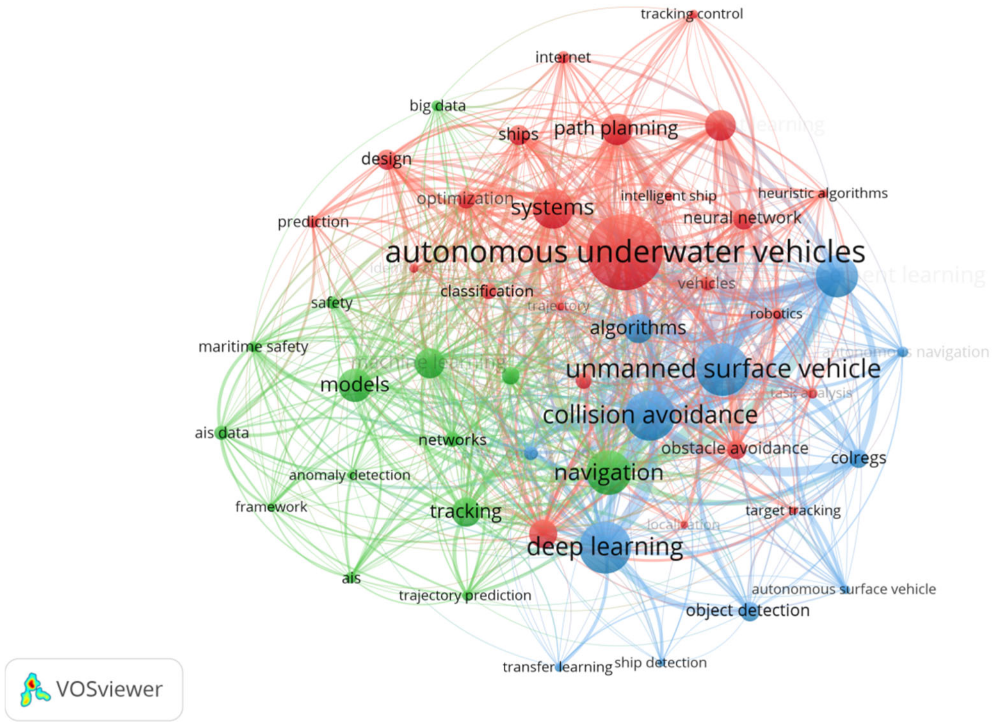


Figure 12. Keywords co-occurrence analysis for the explored research domain.

As shown in Figure 12, there are three clusters. The blue cluster concentrates mainly on new technologies and methods, including machine learning, deep learning, autonomous navigation systems, intelligent collision avoidance, and object detection, etc. In addition, the red cluster is associated with the applications of AUV and other types of marine robotics, covering prediction, localization, optimization, target tracking, etc. Furthermore, the green cluster mainly focuses on the foundation of AUV, including models, AIS data, networks, big data, artificial intelligence, etc.

3.6.4. Research Frontier and Evolutionary Process

Table A3 in the Appendix A summarizes the top 30 keywords in the explored research domain, which appeared most frequently in each period. Apparently, the most co-occurring keyword during all the investigated period is "autonomous underwater vehicle (AUV)", with 131 times, followed by "collision avoidance (83)", "deep learning (79)", "unmanned surface vessel (77)", "navigation (68)", "system (62)", "deep reinforcement learning (57)". Furthermore, "reinforcement learning (45)", "machine learning (43)", "model (43)", "tracking (41)", "path planning (39)", "algorithm (33)", etc., which are also the main keywords and research hotspots of the explored domain. These keywords are also highlighted in the density map, as shown in Figure 13a. Note that, for the data processing of this part, the keywords with the same meaning are summarized and replaced by the keyword that appears most frequently; e.g., the keyword "unmanned surface vehicle" is used to represent maritime autonomous surface ship (MASS), unmanned surface vessel, and autonomous surface vehicle (ASV). Similarly, the autonomous underwater vehicle represents the unmanned underwater vehicle/unmanned undersea vehicle (UUV), and the autonomous ship represents the keywords, such as autonomous vessel, smart ship, intelligent ship, unmanned ship, and autonomous sailboat, etc.

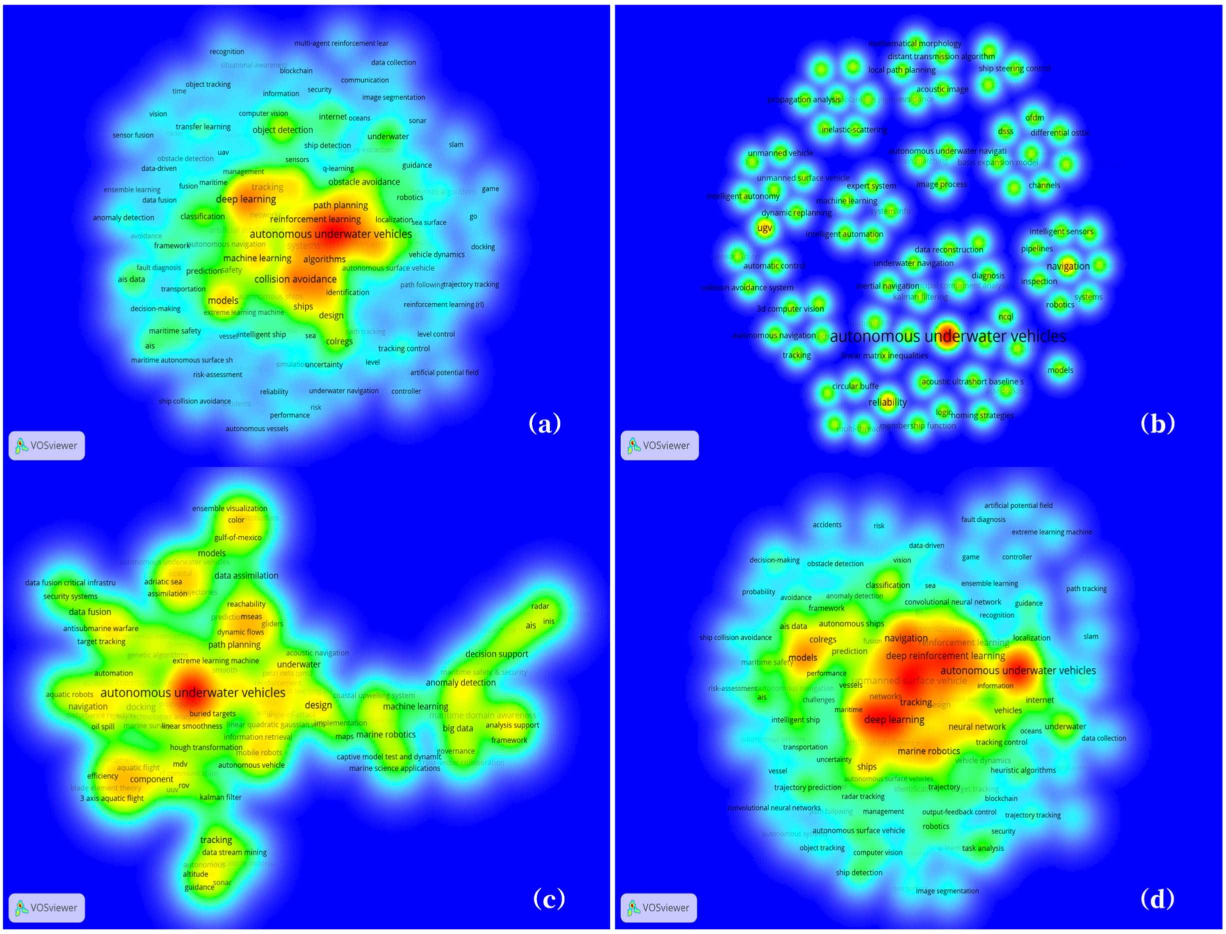


Figure 13. Heat maps of keywords in the explored domain during various time periods. (**a**) All time; (**b**) 2000–2010; (**c**) 2011–2015; (**d**) 2016–2024.

To further understand and analyze the research theme and development context and trend on the explored research domain in specific various periods. In this paper, the explored documents are separated into three parts based on the publication time: (i) 2001–2010, (ii) 2011–2015, and (iii) 2016–May 2024. Moreover, the research topics and main machine learning research methods during various periods are recognized and analyzed from keywords and presented and visualized through the density map function of VOSviewer (Figures 13 and 14). Note that the colors from green to red in the heat maps represent the occurrence frequency for various keywords, and the distance between two keywords demonstrates the association strength in the publications.

Period of 2001–2010: Figure 13b and Table A3 in the Appendix A present the hot keywords from 2001 to 2010. Obviously, the most occurring keyword in this period is "autonomous underwater vehicle", with 6 times, followed by "reliability (2)" and "navigation (2)", etc.

Period of 2011–2015: The keywords for the explored research domain from 2011 to 2015 are illustrated in Figure 13c. As shown in Table A3 in Appendix A, the top 5 frequent keywords are "autonomous underwater vehicle (20)", "design (5)", "system (4)", and "tracking (3)", etc.

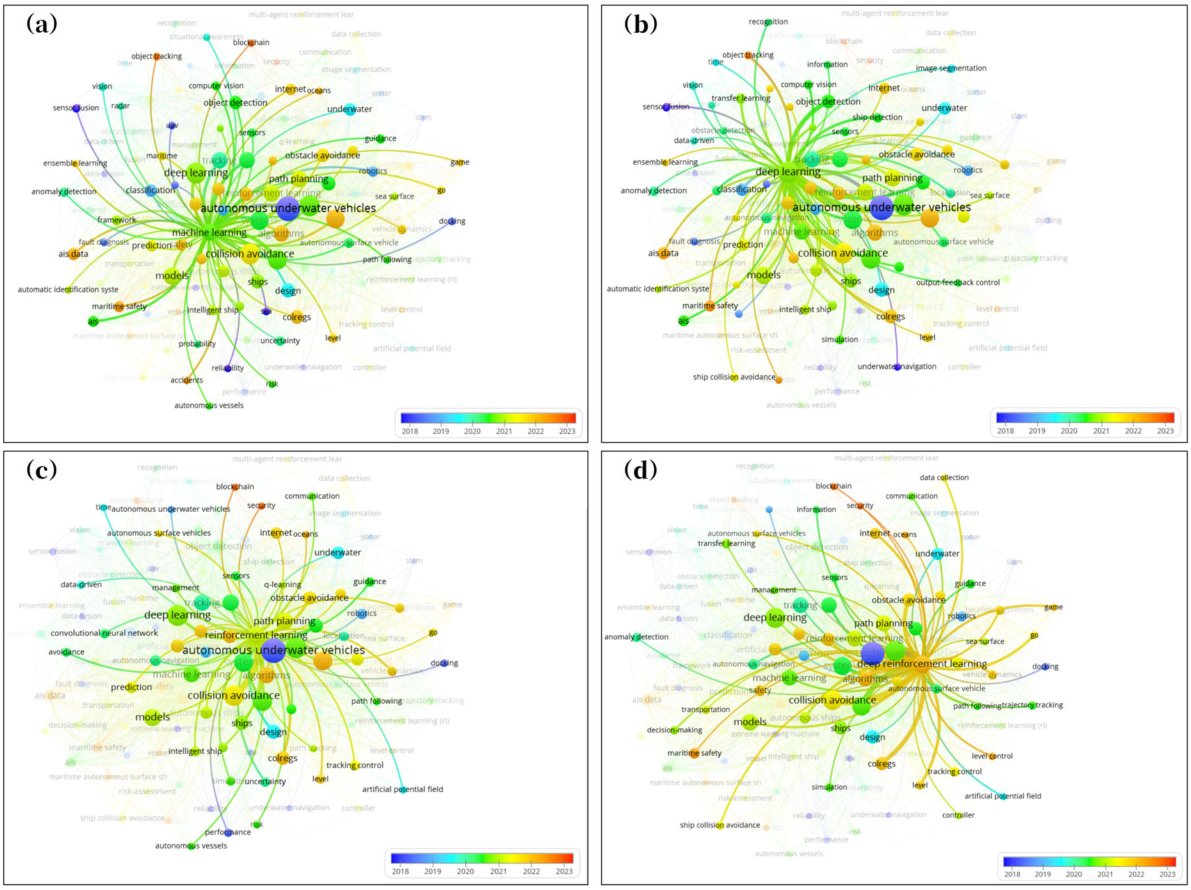


Figure 14. Co-occurrence analysis networks for the main machine learning methods used in the safety and security of maritime shipping. (**a**) Machine learning; (**b**) deep learning; (**c**) reinforcement learning; (**d**) deep reinforcement learning.

Period of 2016–2024: From 2016 to 2024, a total of 623 publications offered 2343 keywords, 248 of which appeared more than 3 times. The explored research boomed in this period. The hot keywords are "autonomous underwater vehicle (99)", "unmanned surface vehicle (80)", "deep learning (79)", "collision avoidance (76)", "navigation (64)", "deep reinforcement learning (63)", "system (55)", "models (46)", "path planning (44)", and "reinforcement learning (44)", etc., as shown in Figure 13d and Table A3 in the Appendix A.

By comparison among the three periods, the research in machine learning for the safety of autonomous shipping has progressed significantly over the past two decades. Between 2001 and 2010, the foundational work focused on autonomous underwater vehicles, emphasizing keywords such as reliability, navigation, and unmanned ground vehicles. This period laid the groundwork for understanding the basic capabilities required for autonomous navigation and system reliability. From 2011 to 2015, the research emphasis expanded to include design, system integration, and tracking technologies, highlighting the increasing complexity of autonomous systems. During this time, machine learning techniques were employed to enhance system robustness and decision-making processes.

From 2016 onwards, there was a notable shift towards incorporating advanced machine learning methodologies to improve safety and operational efficiency. Between 2016 and 2024, the field witnessed a significant boom in publications, with hot keywords such as deep learning, collision avoidance, and deep reinforcement learning emerging as focal points. This era marked the integration of sophisticated AI algorithms to address challenges in navigation, path planning, and real-time decision-making. Furthermore, the incorporation of technologies such as unmanned surface vehicles and sensor fusion indicated a trend towards multifunctionality and the amalgamation of diverse data sources. By utilizing satellite data, computer vision, and deep neural networks, researchers have enhanced the communication and intelligent decision-making capabilities of autonomous ships, ensuring safer maritime operations. These developments reflect a broader trend towards leveraging machine learning to achieve more reliable and autonomous maritime systems, setting new standards for safety in the industry.

To facilitate exploring and understanding the main machine learning methods used in the safety and security of maritime shipping, the co-occurrence analysis networks for the corresponding keywords are demonstrated in Figure 14. Additionally, four terms, i.e., "machine learning", "deep learning", "reinforcement learning", and "deep reinforcement learning", are selected so that the strongest related items are highlighted, and then the according words that show their respective application are conducted in Table A4 in the Appendix A.

According to Table A4 in the Appendix A, machine learning (ML), deep learning (DL), reinforcement learning (RL), and deep reinforcement learning (DRL) each have unique applications in autonomous shipping, dictated by their capabilities and the nature of the tasks they handle. Overall, these methods all aim to improve maritime safety by predicting potential hazards, optimizing routes, and enabling autonomous navigation, ultimately reducing the risk of accidents.

Machine learning is widely employed in structured data tasks such as fault diagnosis, classification, and anomaly detection, where its reliance on manual feature engineering and simpler models proves effective. It is also instrumental in applications such as path planning, navigation, and optimization, which benefit from its capacity to model deterministic tasks and optimize outcomes in well-structured environments. In contrast, deep learning excels at processing unstructured data, such as ship detection, image segmentation, and sensor fusion, where the automatic extraction of features from high-dimensional datasets is critical. Its versatility extends to more advanced domains, including autonomous ships, marine robotics, and AUV operations, where deep learning's ability to process sensory inputs and adapt to dynamic environments makes it indispensable. Reinforcement learning, with its focus on decision-making and adaptive learning through interaction with the environment, is well-suited for applications involving path following, obstacle avoidance, and tasks that require continuous adjustments to changing conditions. Deep reinforcement learning combines the strengths of DL and RL and is particularly effective in scenarios that require both perception and action, such as collision avoidance and multi-agent coordination. These applications are especially critical in complex maritime environments, where the integration of real-time data and strategic decision-making is essential for safe and efficient operations.

Given the unique capabilities and applications of each method, deep reinforcement learning (DRL) emerges as the most suitable approach for autonomous shipping. Its ability to integrate perception and decision-making, adapt to dynamic environments, and handle complex, multi-agent interactions make it the optimal choice for achieving safe, efficient, and intelligent ship operations in the future.

4. Discussion

4.1. Bibliometric Analysis Findings

4.1.1. Past and Current Trends

As is depicted in Figure 3, the evolution of research in maritime safety and autonomous shipping can be divided into 3 stages. Before 2010, the focus was primarily on foundational technologies for autonomous underwater vehicles (AUVs), emphasizing reliability and navigation. This period featured limited publications, mainly conference papers, indicating a nascent interest in exploring the fundamental capabilities of autonomous systems.

However, after the period, research expanded to include design, system integration, and tracking technologies. There was a moderate increase in publications, reflecting growing scholarly attention and a shift towards improving decision-making processes within autonomous systems. After 2016, there has been a significant rise in the use of advanced machine learning techniques, such as deep learning and reinforcement learning, to address challenges in navigation and collision avoidance. The number of publications has increased dramatically.

The publication trend in maritime safety and autonomous shipping is expected to continue increasing and reach a new breakthrough due to several factors: advancements in AI, a sustainability focus, industry-academia collaboration, and regulatory developments.

4.1.2. The Features of Social Structure

Regarding the geographic distribution of research on machine learning applications in maritime safety and autonomous shipping, the field is notably led by contributions from China, the USA, and European countries. Among these, China has emerged as the most prolific contributor, with its dominance reflecting strong governmental support, substantial investment in maritime technology, and a well-established academic infrastructure that promotes innovation. The USA and European countries also play significant roles, driven by their advanced technological capabilities and emphasis on addressing global maritime challenges. This distribution underscores a globally collaborative effort to advance the integration of machine learning in autonomous maritime technologies, as evidenced by the analysis of publication outputs and international cooperation networks in this study.

With regard to notable international collaborations, the cooperation, particularly between China and the USA, as well as with countries such as the UK, Norway, and Australia, underscores the importance of cooperative efforts in addressing global maritime challenges. These collaborations facilitate the exchange of knowledge and expertise, driving the development of more comprehensive and effective solutions. Furthermore, international cooperation is significantly reflected in institutional networks. Dalian Maritime University, Wuhan University of Technology, and Shanghai Jiaotong University serve as pivotal hubs in fostering collaboration between regional and international institutions within their respective clusters. This highlights their robust capacity to engage in international cooperation and resource integration. According to the VOSviewer analysis, Dalian Maritime University occupies a central position in the cooperation network, as evidenced by its prominent node, which reflects its substantial publication output and extensive collaboration with other institutions. Moreover, Wuhan University of Technology exhibits the highest number of cooperative links, emphasizing its active engagement with diverse institutions. These findings provide compelling evidence of the strong mutual cooperation links among Chinese institutions, underscoring their domestic strength and potential for further expanding international collaboration.

Regarding key institutions, Dalian Maritime University, Wuhan University of Technology, and Shanghai Jiaotong University play pivotal roles in advancing research, showcasing China's strong academic presence in this field. The concentration of research in these institutions suggests a well-established academic network that supports maritime safety and autonomous shipping. The presence of leading universities and research centers indicates a commitment to fostering innovation and advancing the capabilities of autonomous maritime systems.

When it comes to the influential authors, Weidong Zhang from Shanghai Jiao Tong University, Bo He from Ocean University of China, Zaili Yang from Liverpool John Moores

University, and Xinping Yan from Wuhan University of Technology have emerged as the leading figures. It is intriguing to note that these authors are affiliated with institutions renowned for their strong engineering programs, providing them with cutting-edge resources and collaborative environments that have fueled their research endeavors. Moreover, these authors have not only exhibited remarkable productivity (Bo he with the highest individual publication) and extensive influence (Van Gelder, P. H. A. J. M. with the highest average citation) but have also demonstrated significant activity (Zaili Yang with the latest publication year), particularly in the last three years.

4.1.3. Citation and Co-Citation Network Summary

In citation analysis, key works by Peng et al. [62], Huang et al. [63], and Cheng et al. [64] are highly cited, reflecting their foundational contributions to advanced control systems, collision avoidance, and reinforcement learning applications. The high citation count of these publications highlights their pivotal role in shaping current research directions and methodologies, serving as essential references for subsequent studies. The co-citation network reveals four main clusters focusing on trajectory prediction, machine learning methods, object detection, and system reliability. The clustering of co-cited documents highlights the interconnected nature of research topics, emphasizing the multidisciplinary approach necessary for advancements in maritime safety. The strong co-citation ties between foundational works illustrate the integrated research efforts driving innovation.

4.2. Comparison Analysis of Research Methods

Figure 15 presents an overview of the principal machine learning techniques and models employed in maritime safety for autonomous shipping from 2000 to 2024. This figure is based on data extracted from abstracts and keywords of 719 articles, compiled through a meticulous manual review and de-duplication process. The statistical analysis of methods used over different time periods reveals that although there is some significant variation between past and present methodologies, many traditional machine learning methods still hold their unshakable position. The development of technology has enriched their application scenarios and improved their accuracy.

(1) 2000–2005: Foundational Techniques

Between 2000 and 2005, the focus was on establishing foundational techniques that could support the nascent field of autonomous shipping. Reinforcement learning and artificial neural networks were among the early methods explored, emphasizing control systems and basic decision-making processes. While these methods provided a solid basis for understanding risks, they were often constrained by limited data availability and challenges in incorporating human factors and expressing uncertainty.

(2) 2006–2010: Enhanced Methods for Improved Precision

From 2006 to 2010, the focus shifted towards more sophisticated machine learning methods that could enhance precision and address complex maritime scenarios. Techniques such as deep learning (DL) and sensor fusion were introduced to improve data processing capabilities and accuracy. The period also saw the integration of Fuzzy Fault Trees and Neural Network-based Case-based Q Learning (NCQL), which provided more robust frameworks for dealing with uncertain data and decision-making processes. Principal Component Analysis (PCA) and ARTMAP models were employed for dimensionality reduction and adaptive pattern recognition. Furthermore, unsupervised machine learning methods such as clustering, Modular Network Self-Organizing Maps (MNSOM), and Radial Basis Function (RBF) neural networks were used to detect patterns and anomalies in data. Innovative approaches such as Distant Transmission (DT) algorithms, Self-learning

Behavior Agents, and Fuzzy Logic Representation were also explored to enhance system autonomy and adaptability in maritime environments.

Figure 15. Major methods and models used in maritime safety for autonomous shipping.

(3) 2011–2015: Emphasis on Data-Driven Approaches

The period from 2011 to 2015 marked a significant shift towards data-driven approaches in maritime safety, leveraging more advanced machine learning techniques to gain deeper insights into complex maritime systems. Extreme Learning Machines (ELM) and Support Vector Machines (SVM) became popular for their ability to efficiently handle large datasets and improve classification accuracy. Hidden Markov Models were utilized to model temporal dependencies and sequential data, providing a robust framework for predictive analysis. The integration of OpenGL and VC++ facilitated the visualization of complex data structures and simulations. Techniques such as K-Nearest Neighbors (KNN) and ID3 contributed to enhanced pattern recognition and decision tree analyses, while Lasso Model Predictive Control (MPC) was used for optimization in predictive modeling. Risk evaluation models and Gaussian Mixture Models (GMM) were developed to improve probabilistic assessments of maritime safety. Furthermore, situation analysis approaches and data mining techniques were employed to extract actionable insights from vast amounts of data. Controlled Lagrangian Particle Tracking (CLPT) and model-free reinforcement learning algorithms such as SARSA (lambda) were also explored to enhance real-time decision-making and adaptive learning capabilities in autonomous maritime systems.

(4) 2016–2024: Integration of Advanced Machine Learning and Multidisciplinary Methods

From 2016 to 2024, advancements in maritime safety for autonomous shipping were driven by key machine learning techniques such as deep reinforcement learning (DRL) and Long Short-Term Memory (LSTM) networks, which enhanced decision-making and predictive capabilities. Explainable AI (XAI) methods, including SHAP, improved transparency and trust in autonomous systems. Ensemble methods such as Random Forests (RF) and Genetic Algorithms (GA) increased model accuracy and resilience. Additionally, Transformers and Spatio-Temporal Graph Convolutional Networks (STGCNs) offered advanced modeling of spatial and temporal dependencies, while transfer learning and multi-agent deep reinforcement learning (MADRL) facilitated adaptive and collaborative decision-making. Overall, this period marked a shift towards more sophisticated and integrated approaches, reflecting the convergence of machine learning advancements with maritime safety needs. These methodologies have substantially enhanced the capability to ensure safe and efficient autonomous shipping, aligning with the industry's goal of reducing human intervention while maintaining high safety standards.

All in all, the evolution of methods in autonomous shipping safety from 2000 to 2024 highlights a continuous advancement toward more sophisticated, data-driven, and multidisciplinary approaches. While foundational methods remain relevant, the integration of cutting-edge technologies and methodologies has significantly enhanced the accuracy and applicability of risk assessments in maritime transport.

4.3. Future Research Trends

The advancement of machine learning for enhancing maritime safety in autonomous shipping has undergone substantial evolution. This bibliometric analysis delves into pertinent literature from the last 24 years to offer a thorough understanding of machine learning's role in this field. Over the years, research in maritime safety utilizing machine learning has progressed through three distinct phases. Initially, the focus shifted from conventional maritime practices to autonomous ships, with maritime autonomous surface ships (MASS) acting as an essential intermediary step. Following this, the research emphasis broadened to include three pivotal areas: risk assessment, modeling of ship behavior, and sophisticated decision-making techniques. Additionally, machine learning methodologies have advanced through three stages: the mathematical model stage, the rule-based algorithm stage, and the intelligent algorithm stage.

This evolution underscores the critical integration of traditional maritime research with modern machine learning techniques. By leveraging decades of accumulated knowledge and insights, substantial progress has been made toward achieving safe, efficient, and intelligent autonomous ship operations. These advancements promise to transform maritime safety, setting new standards for the future of autonomous shipping.

In the future, for the safety of intelligent ships under machine learning, further exploration can be carried out from the following 3 aspects.

4.3.1. Trends in Safety Objectives

The traditional objectives of maritime safety have predominantly focused on reactive measures, such as compliance with regulations and responding to incidents. However, with advancements in machine learning and AI, the safety objectives are shifting in new directions. To seek this change, the findings presented in this section are derived from the selected literature included in this study. Specifically, the inspiration for identifying the evolving safety objectives in the maritime domain stems from the co-occurrence analysis of keywords and the citation network mapping. By examining recurring terms in the keyword co-occurrence network in the exact literature, we traced how the research focus has shifted over time as follows.

(1) Proactive safety management: As MASS evolves to the unmanned ship stage, the factors affecting marine accidents need to focus on four factors: ship factors, environmental factors, management factors, and technical factors [81]. The new objective is to predict and prevent incidents before they occur. Machine learning models analyze historical and real-time data to identify patterns that indicate potential safety hazards, allowing for preemptive actions. For instance, by continuously monitoring weather conditions, traffic density, and mechanical health, these systems can dynamically update risk profiles and adjust operations accordingly to mitigate risks. A case in point can be illustrated in MLDet [82], a deep learning method that aims to clear and recycle obstacle wastes in the way. In the future, a systematic multi-scale collision risk estimation approach should be developed and upgraded to capture traffic conflict patterns under different spatial scales [83].

(2) Human-machine synergy: Human factors are always the key element of unsafe behaviors [84], and some research has provided insight into human interactions in remote ship operations and consequently facilitates performance improvement actions [85]. For example, it was found that seafarers tend to experience more anxiety when dealing with emergency situations, while marine pilots experience more anxiety during multi-ship encounter periods [86]. However, as artificial intelligence develops in a fast manner, emotional AI is a groundbreaking trend that focuses on the well-being of human crew members still present on autonomous ships. By monitoring physiological data, voice tones, and facial expressions, emotional AI can assess stress and fatigue levels, providing timely interventions to prevent human errors. This ensures that the remaining human operators are always in optimal condition to manage any critical situations.

(3) Autonomous collaboration: Swarm intelligence is a novel objective where multiple autonomous ships operate as a cohesive unit, sharing data and insights in real-time. Currently, swarm intelligence has been used in multi-ship path planning [87] and collision avoidance decision-making systems [88,89]. This collective intelligence enhances situational awareness and decision-making, reducing the likelihood of accidents and improving overall safety. For this reason, swarm intelligence is able to significantly enhance the capabilities of unmanned ships in several innovative ways in the future. These include coordinated search and rescue operations and disaster response, where vessels autonomously distribute search patterns and respond rapidly to emergencies, improving efficiency and reducing response times. Moreover, swarm-based ships can perform fleet defense and security patrols, maintaining maritime safety with dynamic patrols and coordinated responses. These vessels can also support collaborative scientific research missions, enabling comprehensive data collection and exploration, since automatic ship alarm systems, coastal radars, and coastal cameras are not alone sufficient equipment to build maritime awareness [90]. Finally, swarm intelligence can act as "police" to assist in maritime traffic management, improving safety, reducing congestion, and optimizing operations in busy waterways.

4.3.2. Trends in Safety Technology Based on Machine Learning

Machine learning technologies are evolving to meet the sophisticated needs of autonomous maritime operations, introducing new safety mechanisms:

(1) Natural Language Processing (NLP) for Multilingual Operations: NLP enhances communication between ship systems and human operators, especially during emergencies. AI-powered systems can interpret voice commands, generate detailed incident reports, and translate complex maritime regulations into actionable instructions, facilitating more effective management of incidents.

(2) Bio-Inspired Sensors: Autonomous ships are expected to extensively rely on perception sensors for situation awareness and safety during challenging operations, such as reactive collision avoidance [91]. Up to now, some new sensors have been devised in combination with machine learning [92,93]. As we look to the future, the evolution of these technologies suggests the potential for even more sophisticated solutions, such as bio-inspired sensors. By mimicking the sensory capabilities of animals such as bats and dolphins, these sensors can offer enhanced detection and navigation capabilities. Machine learning will play a critical role in this advancement, enabling these bio-inspired sensors to adapt to complex maritime environments and challenges. Thus, as sensor technology continues to advance, the combination of machine learning and bio-inspired designs may set new standards for autonomy and precision in marine navigation.

(3) Quantum Machine Learning: Quantum computing has been proven to excel in factorization issues and unordered search problems due to its capability of quantum parallelism [94]. So far, quantum technology has been used in malware detection on IoT-enabled maritime transportation systems [95], co-communication protocols of underwater sensor networks [96], etc. By leveraging quantum computing, machine learning algorithms can process and analyze vast amounts of data at unprecedented speeds. This capability is crucial for real-time safety applications, such as predicting sudden environmental changes or mechanical failures.

(4) Self-Healing Systems: Based on proactive safety management, future autonomous ships could leverage machine learning to significantly enhance their safety capabilities by incorporating self-healing materials and systems. Machine learning algorithms can continuously monitor the ship's structural integrity and detect anomalies or potential damage in real time. For example, if a hull breach is detected, the ship's machine learning system can analyze the severity and location of the damage, predict potential risks, and automatically activate repair mechanisms. These advanced materials can seal the breach autonomously while the ship navigates safely to a port for more extensive repairs. Additionally, machine learning can optimize the repair process by learning from past incidents, improving the system's efficiency and effectiveness over time. This approach not only minimizes human intervention but also ensures a higher level of safety and reliability in maritime operations.

4.3.3. Trends in Machine Learning Algorithms

Machine learning algorithms are continuously advancing, providing new possibilities for maritime safety:

In terms of maritime safety management, machine learning algorithms, such as LSTM, RNN, NLP, RL, UL, DRL, STMGCN, SVM, ANN, and so on, have been widely used for vessel trajectory prediction [97,98], ship behavior [99,100], fault diagnosis of marine diesel engines [101], collision avoidance [102,103], visual recognition [104,105], and environmental perception [106,107]. For instance, Jiang et al. proposed a diagnostic network combining a wide convolutional neural network (WDCNN) and an extreme learning machine (ELM) to precisely conduct AUV actuator fault diagnosis [108]. A double-gated recurrent unit neural network (GRU-RNN) [103] was constructed to learn unmanned surface vehicle (USV) collision avoidance decisions from the extracted data of successful encounters of ships. This GRU-RNN model contributes significantly to the increased efficiency and safety of sea operations. These above technologies can facilitate the deep application of maritime data and improve the accuracy of risk assessment models, which may still be one of the directions for future research in the field of maritime safety.

Additionally, some newly burgeoning machine learning methods in other fields are proposed and suggested for future development.

(1) Generative Adversarial Networks (GANs) for Simulation: GANs are emerging unsupervised deep learning models known for their ability to generate realistic samples that are used to amplify a number of failures within training datasets [109]. This method has been used in machinery monitoring [109] and multi-ship trajectory prediction [87,110]. GANs are expected to create realistic simulations of maritime environments and potential hazards, which are used to train machine learning models under a wide range of scenarios. This ensures that autonomous ships are prepared for even the most unexpected events.

(2) Hierarchical Reinforcement Learning (HRL): HRL has been designed to improve training speed and resolve planning conflicts within the formation [111]. It also shows excellence in high learning speed and performance [112]. This approach is believed to become particularly suited for managing the complex tasks faced by autonomous vessels. By breaking down operations into smaller, manageable sub-tasks, hierarchical reinforcement learning allows for more precise and effective decision-making processes.

(3). Explainable AI (XAI): As AI systems become more integral to safety-critical operations, there is a growing demand for transparency. To remedy this problem, a number of explainable AI methods have been presented, such as SHAP and LIME [113], and they have been widely used in the field of wireless communications [114] and autonomous driving systems [115–117]. Moreover, intelligent software [118] can also serve as an important way in the development of XAI, with the goal of greatly improving the service efficiency and the shipping security of maritime transport industries. Despite the fact that research about explainable AI in autonomous shipping is limited in number, explainable AI provides insights into how decisions are made by machine learning models, enhancing trust and facilitating regulatory approval.

(4). Federated Learning: In the latest research, federated learning is testified to be a novel machine learning method that can guarantee collaborative learning among all ships while preserving ships' privacy [119]. It is promising that this decentralized approach enables the training of models across multiple ships without sharing raw data. Federated learning enhances the ability of machine learning systems to generalize across diverse maritime conditions while maintaining data privacy and security.

4.3.4. Summary for Future Prospect

The future of machine learning in maritime safety is boundless. With continuous advancements in AI, autonomous vessels will become increasingly capable of operating safely and efficiently with minimal human oversight. The future of maritime safety in autonomous shipping is being reshaped by advanced machine learning technologies. This evolution involves a shift from reactive to proactive safety management, where AI predicts and prevents incidents, enhancing human-machine synergy and enabling swarm intelligence among ships. Key advancements in technology include NLP for multilingual operations, bio-inspired sensors for enhanced navigation, and quantum machine learning for rapid data processing. Explainable AI and federated learning further enhance transparency and collaboration while ensuring data privacy. The mentioned future trend evolution is depicted in Figure 16.

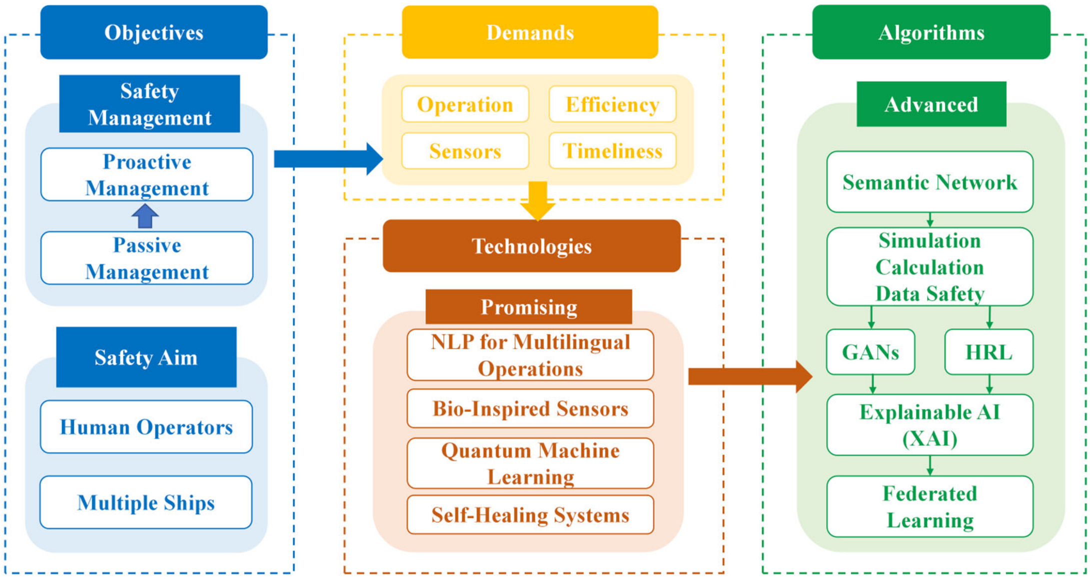


Figure 16. The trend analysis of machine learning for maritime safety.

Overall, extant literature has primarily concentrated on technological innovation and data analytics, yet the transformative impact of these advancements is contingent upon their systemic adoption within the maritime industry. Such adoption necessitates comprehensive institutional changes encompassing regulatory frameworks, organizational culture, commercial structures, and stakeholder trust—beyond mere technical feasibility. Critically, cybersecurity constitutes the foremost challenge to autonomous shipping, vulnerabilities in digital networks, data integrity, and control systems present significant threats to vessel safety, cargo security, and industry credibility. A recent comprehensive review of maritime cybersecurity research highlights not only a rapid escalation in both publicly reported and likely underreported cyber incidents, including ransomware, denial-of-service attacks, and sophisticated supply-chain compromises, but also a fragmented research landscape that lacks holistic, empirically validated frameworks for risk assessment and resilience [120]. Accordingly, future research should prioritize rigorous examination of cybersecurity within autonomous maritime contexts, including threat modeling, risk assessment methodologies, and the development of legal and regulatory mechanisms addressing data ownership, breach liability, and incident response. Realizing the full potential of autonomous shipping will require the establishment of robust international standards, interdisciplinary collaboration, and continual innovation in cyber-resilience to safeguard operational integrity and foster trust across the maritime ecosystem.

4.3.5. Bias and Limitations

Despite the valuable insights provided by this study, it is crucial to acknowledge several limitations inherent in the methodology and data sources utilized. Firstly, the exclusive reliance on the Web of Science (WoS) database for bibliometric analysis, while justified by its comprehensive coverage and high data quality, may have inadvertently excluded relevant publications from other databases such as Scopus or Google Scholar. This limitation could introduce a selection bias, potentially omitting significant contributions to the field of maritime safety and autonomous shipping, particularly from emerging or niche journals not indexed in WoS. Future research should consider integrating multiple databases to provide a more holistic view of the field.

Secondly, this study focused exclusively on English-language publications, as English remains the dominant medium of academic discourse. The exclusion of these works may limit the comprehensiveness of the analysis and overlook region-specific advancements or perspectives in maritime safety and machine learning.

Thirdly, the chosen time frame for the analysis, covering publications from 2000 to 2024, could influence the identified trends and patterns. While this period captures the rise of machine learning applications in autonomous shipping, earlier foundational research or very recent publications may not have been adequately represented.

Lastly, the design of the search query, including the selection of keywords and Boolean operators, may have unintentionally excluded relevant studies or broadened the scope to include less relevant papers. This methodological limitation highlights the need for more precise query designs and iterative refinements in future bibliometric studies.

5. Conclusions

In this paper, to provide a detailed overview of the key contributions in this research domain, a comprehensive bibliometric analysis of machine learning for maritime safety of autonomous shipping was conducted by utilizing 719 publications sourced from the WoS database. The analysis entailed the exploration of publication trends and the identification of influential authors, institutions, countries, notable articles, journals, disciplines, references, and keywords. Additionally, deeper insights were demonstrated of the international cooperation in ML research, explaining it from the perspectives of countries, institutions, and authors. Furthermore, we used a dual-function word analysis to identify prevalent keywords and the variation of them, thereby uncovering emerging research topics and trends. Finally, three future directions for the advancement of machine learning in maritime safety were brought forth, which provide ideas for the development of marine research.

The implications of these findings are significant for various stakeholders. For academic researchers, the results offer valuable insights into the current landscape of research in autonomous shipping and maritime safety, elucidating both the strengths and areas needing further exploration. This information can aid scholars in identifying potential collaborators for educational and research projects in the field of autonomous maritime systems. Such partnerships have the potential to advance not only sustainable marine technology development but also enhance related industrial sectors on a global scale.

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Appendix A

Table A1. The keywords and strings search in WoS.

Step	Keywords/Strings/Topics	Number of Papers
1	TS = (big data) AND TS = (autonomous shipping OR unmanned shipping) AND TS = (safety OR risk OR security OR reliability) Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024	26
2	TS = (data analytics) AND TS = (autonomous shipping OR unmanned shipping) AND TS = (safety OR risk OR security OR reliability) Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024	9
3	TS = (machine learning) AND TS = (autonomous shipping OR unmanned shipping) AND TS = (safety OR risk OR security OR reliability) Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024	37
4	TS = (data analysis OR data analytics OR data analyst OR data analyzed) AND TS = (autonomous shipping OR unmanned shipping) AND TS = (safety OR risk OR security OR reliability) Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024	133
5	TS = (big data OR data analysis OR data analytics OR data analyst OR data analyzed OR machine learning OR supervised learning OR unsupervised learning OR semi-supervised learning OR ensemble learning OR deep learning OR reinforcement learning OR transfer learning) AND TS = (autonomous shipping OR unmanned shipping) AND TS = (safety OR risk OR security OR reliability) Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024	222
6	TS = (big data OR data analy* OR machine learning OR supervised learning OR unsupervised learning OR semi-supervised learning OR ensemble learning OR deep learning OR reinforcement learning OR transfer learning) AND TS = (autonomous(ship* OR vessel$ OR boat*) OR unmanned(ship* OR vessel$ OR boat*) OR smart(ship* OR vessel$ OR boat*) OR intelligent(ship* OR vessel$ OR boat*) OR "autonomous underwater vehicle*" OR "autonomous surface vehicle*" OR "unmanned underwater vehicle*" OR "unmanned surface vehicle*" OR "autonomous marine robotic vehicle*" OR "unmanned marine robotic vehicle*" OR "underwater robotic vehicle*" OR "surface robotic vehicle*" OR "robotic underwater vehicle*" OR "robotic surface vehicle*" OR "untethered underwater vehicle" OR "untethered surface vehicle") AND TS = (safety OR risk OR security OR reliability) Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024	775
7	TS = (big data OR data analy* OR machine learning OR supervised learning OR unsupervised learning OR semi-supervised learning OR ensemble learning OR deep learning OR reinforcement learning OR transfer learning) AND TS = (autonomous(ship* OR vessel$ OR boat*) OR unmanned(ship* OR vessel$ OR boat*) OR smart(ship* OR vessel$ OR boat*) OR intelligent(ship* OR vessel$ OR boat*) OR "autonomous underwater vehicle*" OR "autonomous surface vehicle*" OR "unmanned underwater vehicle*" OR "unmanned surface vehicle*" OR "autonomous marine robotic vehicle*" OR "unmanned marine robotic vehicle*" OR "underwater robotic vehicle*" OR "surface robotic vehicle*" OR "robotic underwater vehicle*" OR "robotic surface vehicle*" OR "untethered underwater vehicle" OR "untethered surface vehicle") AND TS = (safe* OR risk* OR secur* OR reliab* OR resilience* OR emergen* OR danger* OR hazard* OR maintainab* OR los$ OR accident* OR incident* OR colli* OR encounter* OR ground* OR sink* OR list* OR capsiz* OR dragg* OR contact* OR damag* OR COLREG* OR fire* OR explosion* OR wind* OR "human factor*" OR marine* OR maritime* OR "maritime tra*" OR "maritime transportation system*") Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024	2120

Table A1. *Cont.*

Step	Keywords/Strings/Topics	Number of Papers
8	TS = (big data OR data analy* OR machine learning OR supervised learning OR unsupervised learning OR semi-supervised learning OR ensemble learning OR deep learning OR reinforcement learning OR transfer learning) AND TS = (autonomous(ship* OR vessel$ OR boat*) OR unmanned(ship* OR vessel$ OR boat*) OR smart(ship* OR vessel$ OR boat*) OR intelligent(ship* OR vessel$ OR boat*) OR "autonomous underwater vehicle*" OR "autonomous surface vehicle*" OR "unmanned underwater vehicle*" OR "unmanned surface vehicle*" OR "autonomous marine robotic vehicle*" OR "unmanned marine robotic vehicle*" OR "underwater robotic vehicle*" OR "surface robotic vehicle*" OR "robotic underwater vehicle*" OR "robotic surface vehicle*" OR "untethered underwater vehicle" OR "untethered surface vehicle") AND TS = (safe* OR risk* OR secur* OR reliab* OR resilience* OR emergen* OR danger* OR hazard* OR maintainab* OR los$ OR accident* OR incident* OR colli* OR encounter* OR ground* OR sink* OR list* OR capsiz* OR dragg* OR contact* OR damag* OR COLREG* OR fire* OR explosion* OR wind* OR "human factor*" OR marine* OR maritime* OR "maritime tra*" OR "maritime transportation system*") AND DT = (Article OR Proceedings Paper OR Review) Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024; Search language = English	2107
9	TS = (big data OR data analy* OR machine learning OR supervised learning OR unsupervised learning OR semi-supervised learning OR ensemble learning OR deep learning OR reinforcement learning OR transfer learning) AND TS = (autonomous(ship* OR vessel$ OR boat*) OR unmanned(ship* OR vessel$ OR boat*) OR smart(ship* OR vessel$ OR boat*) OR intelligent(ship* OR vessel$ OR boat*) OR "autonomous underwater vehicle*" OR "autonomous surface vehicle*" OR "unmanned underwater vehicle*" OR "unmanned surface vehicle*" OR "autonomous marine robotic vehicle*" OR "unmanned marine robotic vehicle*" OR "underwater robotic vehicle*" OR "surface robotic vehicle*" OR "robotic underwater vehicle*" OR "robotic surface vehicle*" OR "untethered underwater vehicle" OR "untethered surface vehicle") AND TS = (safe* OR risk* OR secur* OR reliab* OR resilience* OR emergen* OR danger* OR hazard* OR maintainab* OR los$ OR accident* OR incident* OR colli* OR encounter* OR ground* OR sink* OR list* OR capsiz* OR dragg* OR contact* OR damag* OR COLREG* OR fire* OR explosion* OR wind* OR "human factor*" OR marine* OR maritime* OR "maritime tra*" OR "maritime transportation system*") AND DT = (Article OR Proceedings Paper OR Review) Manually screened by relevance Indexes = SCI-EXPANDED, SSCI, CPCI-S, CPCI-SSH; Timespan = 1 January 2001–31 May 2024; Search language = English	719

Note: TS = Topic; DT = Document Types; SCI-EXPANDED = Science Citation Index Expanded; SSCI = Social Sciences Citation Index; CPCI-S = Conference Proceedings Citation Index- Science; CPCI-SSH = Conference Proceedings Citation Index- Social Science and Humanities; the following words which combined with wildcard (* and $) contain but not only the following words: analy* = analysis/analyze/analytics/analyst/analytical; ship* = ship/ships/shipping; vessel$ = vessel/vessels; boat* = boat/boats/boating; vehicle* = vehicle/vehicles/vehicules/vehicular; safe* = safe/safety/safely; risk* = risk/risks/risky; secur* = secure/security; reliab* = reliability/reliable/reliably; resilience* = resilience/resiliences; emergen* = emergency/emergence/emergencies/emergent; danger* = danger/dangers/dangerous/dangerously; hazard* = hazard/hazards/hazardous; maintainab* = maintainability/maintainable; los$ = loss/lose/lost; accident* = accident/accidents/accidentally/accidental; incident* = incident/incidents/incidental/incidentally; colli* = collision//collide/collided/colliding/collisions; encounter* = encounter/encounters/encountered; ground* = ground/grounds/grounded/grounding/groundings; sink* = sink/sinks/sinking; list* = list/lists/listing; capsiz* = capsize/capsized/capsizes/capsizing; dragg* = dragged/dragging/draggable; contact* = contact/contacts; damag* = damage/damaged/damages/damaging; colreg* = colreg/colregs; fire* = fire/fires; explosion* = explosion/explosion; wind* = wind/winds/windy; marine* = mine/mines; maritime* = maritime/maritimes; "maritime tra*" = "maritime traffic"/"maritime transport"/"maritime transportation"/"maritime trade".

Table A2. Top 20 authors with most publications and citations on machine learning for maritime safety of autonomous shipping research.

Rank	Top 20 Most Productive Authors									Top 20 Most Citation Authors								
	Author	Country	Links	TLS	NP	P (%)	TC	APY	AC	Author	Country	Links	TLS	NP	P (%)	TC	APY	AC
1	He, Bo	China	93	1542	14	1.95%	98	2018.14	7.00	Zhang, Weidong	China	84	2918	9	1.25%	373	2021.56	41.44
2	Zhang, Weidong	China	84	2918	9	1.25%	373	2021.56	41.44	Van Gelder, P. H. A. J. M.	Netherlands	78	1066	4	0.56%	370	2019.25	92.50
3	Liu, Yuanchang	England	96	1803	8	1.11%	155	2020.63	19.38	Peng, Zhouhua	China	61	865	5	0.70%	290	2019.60	58.00
4	Wang, Chengbo	China	76	1715	8	1.11%	69	2022.25	8.63	Wang, Dan	China	60	719	4	0.56%	274	2018.75	68.50
5	Yang, Zaili	England	64	3673	8	1.11%	149	2023.25	18.63	Wu, Chaozhong	China	46	628	4	0.56%	246	2019.25	61.50
6	Zhang, Xinyu	China	90	1670	8	1.11%	77	2021.88	9.63	Yan, Xinping	China	79	1232	6	0.83%	216	2017.50	36.00
7	Yan, Tianhong	China	56	598	7	0.97%	16	2017.43	2.29	Wang, Ning	China	86	981	6	0.83%	215	2021.83	35.83
8	Chen, Xinqiang	China	49	803	6	0.83%	205	2021.33	34.17	Chen, Xinqiang	China	49	803	6	0.83%	205	2021.33	34.17
9	Guo, Jia	China	32	576	6	0.83%	51	2018.50	8.50	Lu, Yu	China	73	792	4	0.56%	203	2019.00	50.75
10	Li, Guangliang	China	80	997	6	0.83%	52	2019.17	8.67	Chen, Zhijun	China	41	418	3	0.42%	187	2019.33	62.33
11	Liu, Jingxian	China	84	1326	6	0.83%	83	2021.00	13.83	Liu, Ryan Wen	China	58	912	4	0.56%	185	2020.50	46.25
12	Wang, Ning	China	86	981	6	0.83%	215	2021.83	35.83	Wu, Huafeng	China	45	548	4	0.56%	181	2021.00	45.25
13	Yan, Xinping	China	79	1232	6	0.83%	216	2017.50	36.00	Li, Zhixiong	China	80	491	5	0.70%	175	2016.60	35.00
14	Li, Huanhuan	China	62	2974	5	0.70%	98	2023.20	19.60	Liang, Maohan	China	45	530	3	0.42%	169	2019.67	56.33
15	Li, Zhixiong	China	80	491	5	0.70%	175	2016.60	35.00	Yang, Yongsheng	China	42	434	3	0.42%	168	2020.00	56.00
16	Ma, Feng	China	76	1278	5	0.70%	66	2019.80	13.20	Liu, Yuanchang	England	96	1803	8	1.11%	155	2020.63	19.38

Table A2. *Cont.*

Rank	Top 20 Most Productive Authors									Top 20 Most Citation Authors								
	Author	**Country**	**Links**	**TLS**	**NP**	**P (%)**	**TC**	**APY**	**AC**	**Author**	**Country**	**Links**	**TLS**	**NP**	**P (%)**	**TC**	**APY**	**AC**
17	Peng, Zhouhua	China	61	865	5	0.70%	290	2019.60	58.00	Wang, Yang	China	73	622	3	0.42%	150	2020.67	50.00
18	Shen, Yue	China	74	692	5	0.70%	20	2019.40	4.00	Yang, Zaili	England	64	3673	8	1.11%	149	2023.25	18.63
19	Sun, Changyin	China	85	1182	5	0.70%	113	2022.80	22.60	Xu, Xinli	China	79	1540	4	0.56%	138	2021.75	34.50
20	Wang, Hao	China	62	353	5	0.70%	42	2021.00	8.40	Zhang, Mingyang	China	71	617	3	0.42%	135	2021.67	45.00

Note: TLS = total link strength; NP = number of publications; P (%) = the proportion of NP/TND; TND = total number of documents; TC = total number of citations; APY = average publications year; AC = average citations = TC/NP.

Table A3. Top 30 keywords for the explored research domain in terms of various periods.

Rank	All Time		2000–2010	
	Keyword	**Frequency**	**Keyword**	**Frequency**
1	AUV	131	AUV	6
2	Collision avoidance	83	Navigation	2
3	Deep learning	79	Reliability	2
4	USV	77	UGV	2
5	Navigation	68	3D computer vision	1
6	System	62	Acoustic image	1
7	Deep reinforcement learning	57	Acoustic ultrashort baseline system	1
8	Reinforcement learning	45	Automatic control	1
9	Machine learning	43	Autonomous navigation	1
10	Model	43	Autonomous underwater navigation	1
11	Tracking	41	AUV docking	1
12	Path planning	39	Avoidance	1
13	Algorithm	33	Basis expansion model	1
14	Ship	29	Channels	1
15	Design	28	Circular buffe	1
16	Object detection	26	Collision avoidance system	1
17	Obstacle avoidance	26	Data logging	1
18	COLREGS	25	Data reconstruction	1
19	Optimization	25	Detection	1
20	Artificial Intelligence	24	Diagnosis	1
21	Classification	21	Differential detection	1
22	Marine vehicles	21	Differential OSTBC	1
23	Marine robotics	19	Distant transmission algorithm	1
24	AIS data	18	DSSS	1
25	Internet	16	Dynamic replanning	1
26	Prediction	16	Expert system	1
27	Safety	16	Fault detection	1
28	AIS	15	Fuzzy fault tree	1
29	Autonomous navigation	14	Homing strategies	1
30	Big data	14	Image process	1

2011–2015		2016–2024	
Keyword	Frequency	Keyword	Frequency
AUV	20	AUV	99
Design	5	USV	80
Systems	4	Deep learning	79
Tracking	3	Collision avoidance	76
Acoustic communication	3	Navigation	64
AIS	2	Deep reinforcement learning	63
Anomaly detection	2	System	55
Big data	2	Models	46
Component	2	Path planning	44

Table A3. *Cont.*

Rank	All Time		2000–2010	
	Keyword	Frequency	Keyword	Frequency
	Data assimilation	2	Reinforcement learning	44
	Data fusion	2	Algorithms	42
	Decision support	2	Machine learning	40
	Docking	2	Marine robotics	38
	Instantaneous angular speed	2	Tracking	37
	Intelligent systems	2	Neural network	29
	Machine learning	2	Ship	28
	Marine robotics	2	Object detection	26
	Maritime domain awareness	2	COLREGS	25
	Models	2	Obstacle avoidance	25
	Navigation	2	Optimization	25
	Path planning	2	Artificial Intelligence	24
	Underwater	2	Design	23
	Underwater communication	2	Classification	20
	UUV	2	Networks	20
	3 axis aquatic flight	1	Autonomous ships	19
	Accumulation	1	Underwater	19
	Acoustic navigation	1	Vehicles	18
	Adriatic sea	1	AIS data	17
	Air launch	1	Safety	16
	AIS data	1	Internet	15

Note: AUV = autonomous underwater vehicle; USV = unmanned surface vehicle; AIS = automatic identification system; UGV = unmanned ground vehicle; UUV = unmanned underwater vehicle.

Table A4. Summary of application field about four intelligent methods.

Number	Machine Learning	Deep Learning	Reinforcement Learning	Deep Reinforcement Learning
1	Sensor fusion	Sensor fusion	-	-
2	-	Ship detection	-	-
3	-	Image segmentation	-	-
4	Reinforcement learning	Reinforcement learning	-	Reinforcement learning
5	Optimization	Optimization	-	Optimization
6	Object detection	Object detection	-	-
7	-	Machine learning	-	Machine learning
8	-	Transfer learning	-	Transfer learning
9	-	-	COLREGs	COLREGs
10	-	-	Autonomous navigation	Autonomous navigation
11	-	Simulation	Simulation	Simulation
12	-	-	-	decision-making
13	Path planning	Path planning	Path planning	Path planning
14	-	-	Underwater vehicle	-
15	Fault diagnosis	Fault diagnosis	-	-
16	-	-	-	Data collection
17	Classification	Classification	-	-
18	Prediction	Prediction	Prediction	-
19	-	Marine robotics	-	Marine robotics
20	AUV	AUV	AUV	AUV
21	AIS data	AIS data	-	-
22	Anomaly detection	Anomaly detection	-	Anomaly detection

Table A4. *Cont.*

Number	Machine Learning	Deep Learning	Reinforcement Learning	Deep Reinforcement Learning
23	Computer vision	Computer vision	-	-
24	Navigation	Navigation	Navigation	Navigation
25	Robotics	Robotics	Robotics	Robotics
26	Tracking	Tracking	Tracking	Tracking
27	Models	Models	Models	Models
28	AIS	AIS	-	-
29	System	System	System	System
30	Uncertainty	-	Uncertainty	-
31	Design	Design	Design	Design
32	Neural network	Neural network	Neural network	Neural network
33	Algorithm	Algorithm	Algorithm	Algorithm
34	Marine vehicles	Marine vehicles	Marine vehicles	-
35	Deep learning	-	Deep learning	Deep learning
36	Autonomous ship	Autonomous ship	Autonomous ship	Autonomous ship
37	USV	USV	USV	USV
38	-	Convolutional neural Network	Convolutional neural Network	-
39	Collision avoidance	Collision avoidance	Collision avoidance	Collision avoidance
40	Sensors	Sensors	Sensors	Sensors
41	Obstacle avoidance	Obstacle avoidance	Obstacle avoidance	Obstacle avoidance
42	Path following	-	Path following	Path following
43	Ensemble learning	Ensemble learning	-	-
44	Maritime safety	Maritime safety	-	Maritime safety
45	-	Vision	-	-
46	Blockchain	-	Blockchain	Blockchain
47	-	-	Management	Management

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