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Artificial Intelligence Implementations Towards Shaping the Future of Digital World

THE OPPORTUNITY OF A BENCHMARKING TOOL FOR OBSTACLE AVOIDANCE IN AUTONOMOUS SHIPPING

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ABSTRACT

Due to the increasing interest in the Autonomous Driving research domain, we are following this approach to showcase the use of previous work when infused into the maritime industry. The opportunity of a modular and customizable solution to compare algorithms in Autonomous Shipping, in particular object avoidance, is analyzed based on scientometric data. We gradually narrow down the research domain of Autonomous Shipping to meet Artificial Intelligence based solutions and then to find research gaps when dealing with Object Avoidance and then we comparatively yield a conceptual map to show the need for a benchmark tool in this area. Some of the key criteria for the proposed benchmarking tool are safety, performance, efficiency, and scalability.

Keywords: Autonomous Shipping, Benchmarking, Scientometrics, Obstacle Avoidance

1. INTRODUCTION

In the research literature, we can find many references regarding vessel behavior that cover more years of studies. However, from the perspective of the new changes generated by the AI industry trends, the big AI players have generated a flow of new conceptual frames to foster generative production a step forward. On the verge of LLMs' (Large Language Models) development, the more and more complex algorithms tend to forget the nuances of meanings, driving us to a more robotic use of AI tools urged by development pressure. To overcome this, we aim to tune the architectural parts of the AI solution to meet the need for the challenges faced by vessel navigation and shipping based on the criteria of benchmarking. Nonetheless, we envisioned a tool that could lead to a shift in Autonomous Vessel/ Shipping since the Autonomous Driving domain is flooding some other transport engineering domains as well.
Thus, we asked the following question:
Q. "Is there an interest worldwide in Autonomous Shipping based on AI and, more precisely, in obstacle avoidance?"
The term Autonomous Shipping has a few similar terms, such as Maritime Autonomous Surface Ships (MASS), Autonomous cargo ships (ACS), and Unmanned Surface Vehicle (USV). We opted for the term "Autonomous Shipping" since it is simpler, even if it misses the idea of a surface vehicle, which is not essential in our approach. The field of Autonomous Shipping promises to revolutionize the shipping industry with enhanced efficiency, safety, and sustainability. At the heart of this transformation lies the development of robust and reliable autonomous navigation systems, particularly in the critical area of collision avoidance. This area has become a central focus of research, as evidenced by a recent surge in publications exploring diverse aspects of MASS navigation. These publications highlight the pressing need for a comprehensive benchmarking tool to systematically evaluate and compare the effectiveness of these emerging technologies.
A bibliometric analysis of the existing literature reveals several key themes shaping the development of autonomous ship collision avoidance systems. Researchers are actively investigating novel algorithms, such as the route-plan-guided artificial potential field method described in, seeking to improve the decision-making capabilities of these vessels in complex maritime environments.

Ensuring compliance with the International Regulations for Preventing Collisions at Sea (COLREGs) remains a top priority, with studies emphasizing the integration of these rules into path-planning and collision-avoidance strategies [1]. Furthermore, recognizing that real-world operations are rarely predictable, researchers are increasingly incorporating dynamic environmental conditions such as wind and waves into their simulations and algorithm designs [2]. The importance of human-AI interaction in both shore control centers and onboard systems is also gaining recognition, with studies examining how to optimize these interactions for safe and efficient operations [3]. Finally, research is expanding to address the complexities of formation control and multi-vessel coordination in constrained environments such as ports and waterways, highlighting the need for algorithms capable of navigating these challenging scenarios.

This diverse and rapidly expanding body of research underscores the critical need for a standardized benchmarking tool to evaluate the performance of different collision avoidance approaches. Such a tool should go beyond simply assessing the ability to avoid collisions; it must also consider adherence to COLREGs, efficiency in terms of fuel consumption and time to destination, computational performance, and human factor considerations in supervisory control situations [4]. Drawing on insights from these key publications, this article proposes a scientometric data-based framework for developing a benchmarking tool for autonomous ship collision avoidance. By analyzing research trends, identifying core evaluation criteria, and incorporating realistic environmental and operational parameters, this framework aims to provide a robust and standardized methodology for evaluating the safety and reliability of MASS navigation systems.

When faced with the challenges of the propagation medium, the water fluid mechanics look very different compared to the quasi-rigid experience of the tires running on the asphalt. However, when defined from the perspective of the routing algorithms, a simple solution arises to help us identify the optimal route. Changing to this simplified approach, we will be able to scaffold the research on routing algorithms based on a benchmarking solution that is at the same time modular enough to evolve and well-structured to rigorously compare complex solutions [4].

2. AI INFLUENCE ON THE MARITIME INDUSTRY

Branched into different environment parameters we are mainly interested in the overall ability of our solution to showcase different solutions in a brief manner and to be further extended into a more elaborate analysis of specific parameters by the specialists in the domain of vessel navigation.

The maritime industry is currently experiencing a surge in the development of intelligent systems driven by AI, with the potential to significantly transform various aspects of maritime logistics. AI's ability to process vast amounts of data, learn from experience, and make complex decisions is opening up new possibilities for optimizing operations, enhancing safety, and promoting sustainability across the entire maritime supply chain [5].

One prominent area of AI influence is autonomous ship navigation. As discussed previously, the development of MASS hinges on robust and reliable collision avoidance systems. AI algorithms, such as route-plan-guided artificial potential fields and deep reinforcement learning approaches like Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), are being investigated for their ability to enable safe and compliant autonomous navigation [6]. These algorithms hold the potential to not only prevent collisions but also optimize routes, reduce fuel consumption, and minimize human error, leading to more efficient and environmentally friendly shipping operations.

Beyond navigation, AI is also impacting other critical areas of maritime logistics. AI-powered systems are being used to optimize cargo stowage planning, predict vessel arrival times, and manage port operations. Machine learning algorithms can analyze historical data, real-time sensor inputs, and weather forecasts to enhance decision-making in areas such as berth allocation, container handling, and yard management. These applications of AI promise to improve the overall efficiency, predictability, and resilience of maritime logistics, leading to reduced costs, shorter lead times, and increased customer satisfaction [7].

Further research is crucial to address these challenges and unlock the full potential of AI in maritime logistics. Developing explainable AI systems, establishing robust safety protocols, and designing effective human-machine interfaces are key areas for future investigation. As the field continues to evolve, the collaboration between AI experts, maritime professionals, and regulatory bodies will be essential to ensure the responsible and beneficial integration of AI into the maritime industry.

2.1. Methodology

When confronted with a large quantity of scientific information, the Scientometric methods allow the determination of meaning and research gaps discovery in large and emerging scientific sources, to obtain a better overview of an existing or emerging research field [8].

Different perspectives may be obtained by filtering based on topics, keywords, and publication research forums. The dynamic of the analyzed researched area may be seen evolving in time and geographical regions, and between researchers and research groups, highlighted by citations [9].

We choose to take a gradual approach to answer Q1 and Q2, that is to first have a glance at the larger domain of Autonomous Shipping, based on keywords. Then, filter them based on the emerging AI research direction and, in parallel, on the challenging area of obstacle avoidance.

In this respect, three important and representative research sources were utilized to engage in a balanced study: Web of Science (WoS), Scopus, and IEEE Xplore digital library. For each research database, we searched for recent articles until present (January 2024), that have as keywords/topics in the following four stages:

A. "Autonomous shipping" (some equivalent terms were automatically generated in WoS)

B. 1."Autonomous Shipping" AND "Artificial Intelligence"

   2. "Autonomous Shipping" AND "Object Avoidance"

C. "Autonomous Shipping" AND "Artificial Intelligence" AND "Object Avoidance".

Specific format data files were downloaded as primary data from the Web of Science (plain text), Scopus (.csv), and IEEE Xplore DL (.ris) and uploaded into VOS Viewer software version 1.6.20 and analyzed [10]. The results are presented in the following sections.

2.2. Results

When performing stage A, the first result indicates that the three used sources (databases) differ in a large amount: the term "Autonomous Shipping" is present in 3446 articles in WoS, 926 in Scopus, and 2685 in IEEE Xplore.

When performing stage B1 by adding the term "Artificial Intelligence", the number of articles decreased to 156 (WoS), 93 (Scopus), and 300 (IEEE). This shows a potential research opportunity for using the emergent domain of AI in "Autonomous Shipping". This was complemented by the stage B2, where "Autonomous Shipping" AND "Object Avoidance" gave 250 (WoS), 6 (Scopus), and 49 (IEEE) articles. In stage C, by narrowing down to all three terms ("Autonomous Shipping", "Artificial Intelligence", and "Object Avoidance"), we found a number of 18 (WoS), 6 (Scopus), and 7 (IEEE) articles.

The authors further used VOS Viewer [10] to analyze the relevant identified articles in the 3 databases from a bibliometric point of view. Figures 1, 2, and 3 represent the co-occurrence maps of keywords in the researched domains. The keyword clusters are colored differently (red, green, blue, yellow) and are connected by lines (with full-color or degrade) indicating the link between the clusters:

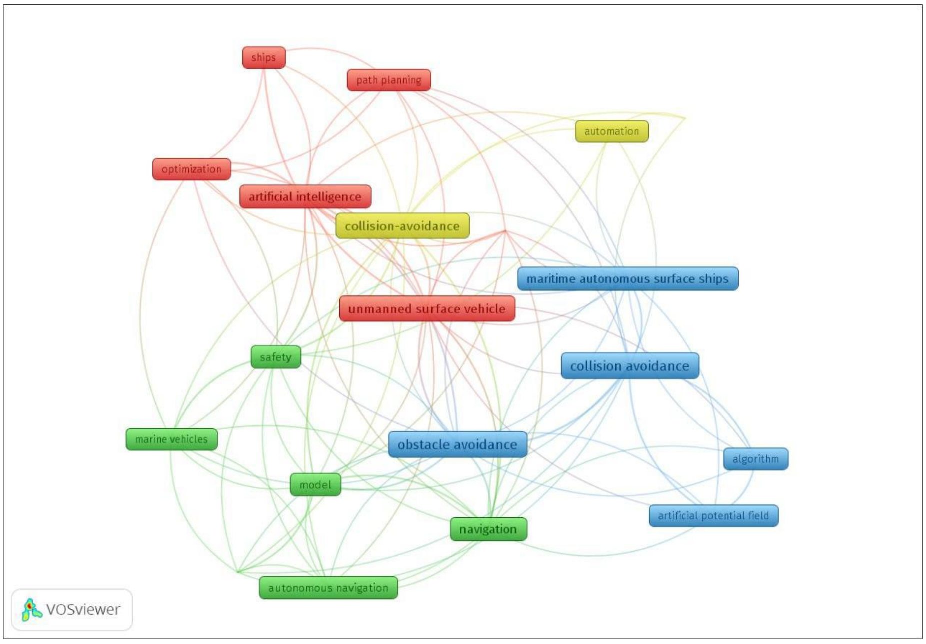

Figure 1. Keywords co-occurrence map in the field of Autonomous shipping and AI from the relevant selected 156 articles. Source: Web of Science (Clarivate Analytics) database content analyzed using VOSviewer [10]

Figure 1 showcases the keyword co-occurrence map based on publications indexed in the Web of Science database. The map visualizes the relationships between keywords used in research on autonomous shipping and AI. The proximity and thickness of links between keywords indicate the strength of their association.

This visualization reveals the major themes and trends in the research field. Analyzing the co-occurrence of keywords can help researchers identify the most frequently researched topics and emerging areas of interest. The keywords clusters such as "Collision Avoidance", "Path Planning", "Artificial Potential Field", and "COLREGs" suggest a strong focus on developing safe navigation algorithms for Autonomous Shipping. The prominence of terms like "Deep Learning", "Reinforcement Learning", and "Neural Networks" indicates that these are the most researched fields worldwide regarding the use of AI techniques in Autonomous Shipping.

Figure 2 also presents a keyword co-occurrence map, but it is based on the IEEE database:

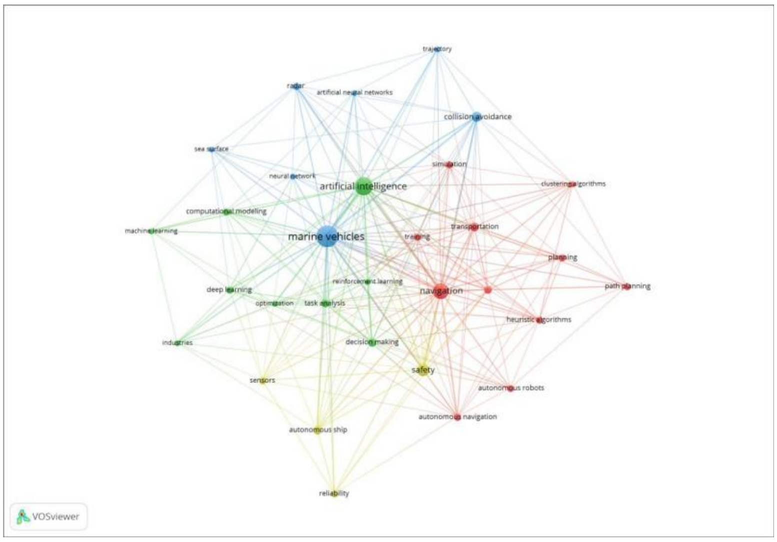

Figure 2. Keywords co-occurrence map in the field of Autonomous shipping and AI from the relevant selected 100 articles. Source: IEEE database content analyzed using VOSviewer [10]

In the co-occurrence map, the size of a keyword disc typically reflects its frequency of use. We may notice the dominance of three main clusters in the research field, the first is built-up around the keyword "marine vehicles" (in blue), connected with "collision avoidance" and "neural networks". The "artificial intelligence" center is connected to "computational modeling", "deep learning", "decision making", and "reinforcement learning". The red area is dominated by "navigation" connected to "path planning" and "autonomous navigation", to name a few. The least noticeable cluster is "safety", that is in relation to "autonomous ships" and "sensors".

Comparing Figures 1 and 2 allows for the identification of different focuses and trends between these two major research databases. For example, Figure 2 shows a larger cluster related to "control systems" or "sensor fusion", as compared to Figure 1, which suggests that the IEEE database has a greater emphasis on the engineering aspects of autonomous shipping. Conversely, a larger cluster around "machine learning" or "decision-making" in Figure 1 implies a stronger focus on AI algorithms in the Web of Science database.

These comparisons highlight the focus and strengths of each database. They also help researchers understand the research fields more comprehensively and select the most relevant databases for their specific research needs. By analyzing the differences in keyword co-occurrence across databases, there can be identified areas of convergence and divergence in research focus and potential gaps in knowledge between different research communities.

Figure 3 presents the keyword co-occurrence map using data from the SCOPUS database:

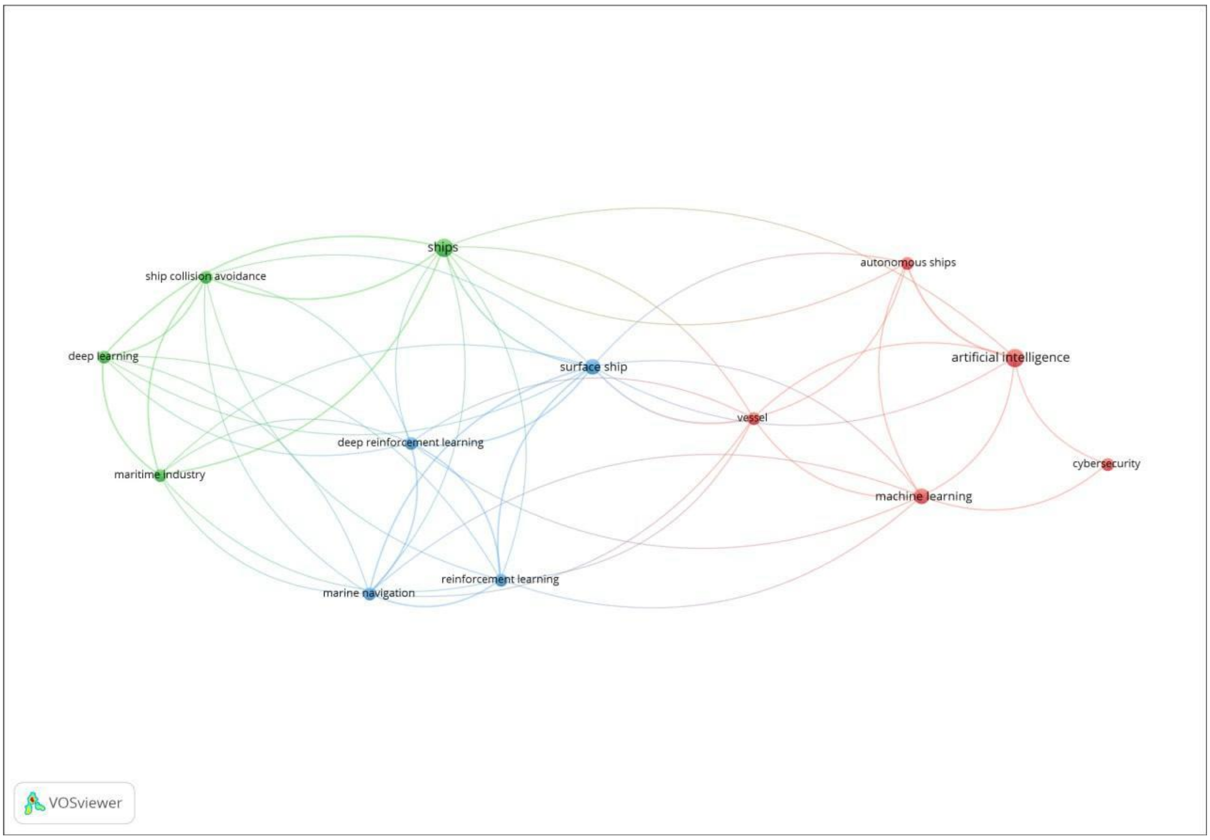

Figure 3. All keywords co-occurrence in the field of Autonomous shipping and AI. Data from SCOPUS database (93 relevant articles)

This is obviously more scattered due to a smaller amount of data. It can be observed the emergence of three main clusters in the research field, one dealing with autonomous ships, artificial intelligence, cyber security, and machine learning, the other one approaching concepts such as ship collision avoidance, and deep learning in the maritime industry, and another smaller one focusing on deep reinforcement learning and marine navigation.

Including a third major research database strengthens the analysis by providing a more comprehensive view of the research field. Researchers can identify consistent patterns and dominant themes across different research communities by comparing all three.

For example, all three figures consistently show large clusters related to "collision avoidance" and "Path Planning," confirming the central importance of these topics in Autonomous Shipping research. Conversely, variations in the prominence of other keywords, like "regulation," "human factors," or "cybersecurity," reveal differences in research priorities or emerging trends across different research communities. Analyzing these variations provides valuable insights into the diverse aspects of autonomous shipping research and highlights areas that may require further investigation.

3. A BENCHMARKING TOOL FOR AUTONOMOUS SHIPPING OBSTACLE AVOIDANCE

As the field of autonomous ship collision avoidance continues to evolve, the development of robust and standardized benchmarking tools is essential. These tools can play a crucial role in evaluating and comparing the performance of different algorithms and approaches, contributing to developing safer and more reliable MASS.

In a previous work [4], we proposed a modular and scalable driving benchmark solution that allows the fair comparison of different car paths and trajectory planning that run in a simulation environment with consideration for different driving parameters. The need for this Autonomous Driving benchmarking tool comes from theoretical and also practical experience in a moment when practical and quite mature solutions are already in nowadays car production and becoming a real-life experience.

From the Web of Science database, a number of 16 relevant scientific articles were filtered as being very relevant to the topic of this study. The articles that were analyzed explore the challenges and advancements in autonomous ship navigation and related technologies. They examine human-AI interaction in autonomous ship systems, focusing on safety, design, and regulatory hurdles. Several papers investigate the use of AI, particularly deep reinforcement learning, to improve collision avoidance, path planning, and cargo management in maritime operations. Specific algorithms and methodologies are presented and evaluated through simulations and, in some cases, real-world sea trials. A final paper explores using UAVs for shore-to-ship delivery, optimizing trajectories to account for wind gusts and safety regulations (Table 1):

Table 1. Relevant articles on autonomous shipping obstacle avoidance

Author(s), Year	Title	Description
Zhongxian *et al.*, 2023	A novel route-plan-guided artificial potential field method for ship collision avoidance: Modeling, integration and test	**Proposes an improved route-plan-guided Artificial Potential Field (APF) method for ship collision avoidance, demonstrating its effectiveness through simulation and real-ship testing, emphasizing the importance of a comprehensive approach that includes system modeling, integration, and testing [11].**
Lyridis *et al.*, 2021	An improved ant colony optimization algorithm for unmanned surface vehicle local path planning with multi-modality constraints	**Presents an enhanced Ant Colony Optimization algorithm for local path planning of unmanned surface vehicles, addressing multi-modality constraints like currents and obstacles to improve navigation safety and efficiency [12].**
Xiangyu *et al.*, 2022	Formation of MASS Collision Avoidance and Path following Based on Artificial Potential Field in Constrained Environment	**Focuses on formation control and collision avoidance for MASS in constrained environments using an improved Artificial Potential Field method, considering various**

		environmental factors and incorporating the Leader-Follower strategy for multi-ship navigation [1].
Wei *et al.* 2022	Intelligent Smart Marine Autonomous Surface Ship Decision System Based on Improved PPO Algorithm	Develops an intelligent decision-making system for smart marine autonomous surface ships based on an improved Proximal Policy Optimization (PPO) algorithm, highlighting the application of advanced reinforcement learning techniques in enhancing autonomous ship navigation [6].
Buddika *et al.*, 2022	Neuroevolutionary Autonomous Surface Vehicle Simulation in Restricted Waters	Demonstrates the use of neuroevolutionary methods for controlling an autonomous surface vehicle in restricted waters, showcasing the potential of evolutionary algorithms in training AI systems for safe and efficient navigation in complex environments [13].
Chengbo et al., 2019	Path Planning of Maritime Autonomous Surface Ships in Unknown Environment with Reinforcement Learning	Explores path planning for autonomous ships in unknown environments using reinforcement learning, emphasizing the ability of AI systems to adapt and learn in dynamic and unpredictable maritime settings [14].
Oucheikh et al., 2021	Rolling Cargo Management Using a Deep Reinforcement Learning Approach	Develops a deep reinforcement learning approach for managing rolling cargo on ships, highlighting the potential of AI in optimizing complex logistics operations and improving efficiency in the maritime industry [7].
Hinostroza and Lekkas, 2024	Temporal mission planning for autonomous ships: Design and integration with guidance, navigation and control	Presents a temporal mission planning system for autonomous ships, focusing on integrating the planning algorithm with the ship's guidance, navigation, and control system to ensure seamless execution of complex missions [15].
Higinio González et al., 2024	UAV Shore-to-Ship Parcel Delivery: Gust-Aware Trajectory Planning	Develops a gust-aware trajectory planning system for unmanned aerial vehicles (UAVs) performing shore-to-ship parcel deliveries, emphasizing risk mitigation by considering wind gusts and maintaining safety buffers around vessels using AIS data [16].
Xiaoyu et al. 2023	**Unmanned Vessel Collision Avoidance Algorithm by Dynamic Window Approach Based on COLREGs Considering the Effects of the Wind and Wave**	Proposes a collision avoidance algorithm for unmanned vessels based on the Dynamic Window Approach and COLREGs, considering environmental factors like wind and waves, demonstrating the integration of AI-based navigation systems with established maritime regulations and accounting for real-world conditions [2].

Based on these relevant sources, the following mind-map was created to highlight the clustering of the keywords, with an emphasis on the most frequent words – (Global/Local) Path Planning (a right-oriented arrow), COLREGs (a blue rectangle), and just one apparition of Collision/Obstacle Avoidance (light blue oval) (Figure 4):

It is important to notice that the concepts are diverse, even if "Path Planning" could be a central figure, "Collision/Obstacle Avoidance" is marginal. So, it shows a potential of a more in depth studies in that area of research in combination with AI algorithms (i.e. Reinforcement learning or Deep learning).

The cited articles from Table 1 offer several insights that are valuable in constructing a benchmarking tool for autonomous ship collision avoidance. The key criteria and parameters that we extracted from the relevant articles are as follows:

- COLREGs Compliance: The tool must assess an autonomous system's ability to adhere to the International Regulations for Preventing Collisions at Sea (COLREGs). This is crucial for legal acceptance, safety, and predictability in interactions with other vessels [18].
- Performance in diverse environments: The benchmarking framework should test algorithms across a range of realistic scenarios [19] that include:
    - Static obstacles: islands, coastlines, navigational markers, etc.
    - Dynamic obstacles: Other vessels (with realistic behaviors), wildlife, debris, etc.
    - Environmental conditions: wind, waves, currents, visibility.
- Effective path planning [20, 21]: The tool should evaluate both:
    - Global path planning: Ability to find an efficient route from origin to destination using prior knowledge.
    - Local path planning: Ability to react and adapt to unforeseen circumstances in real time.

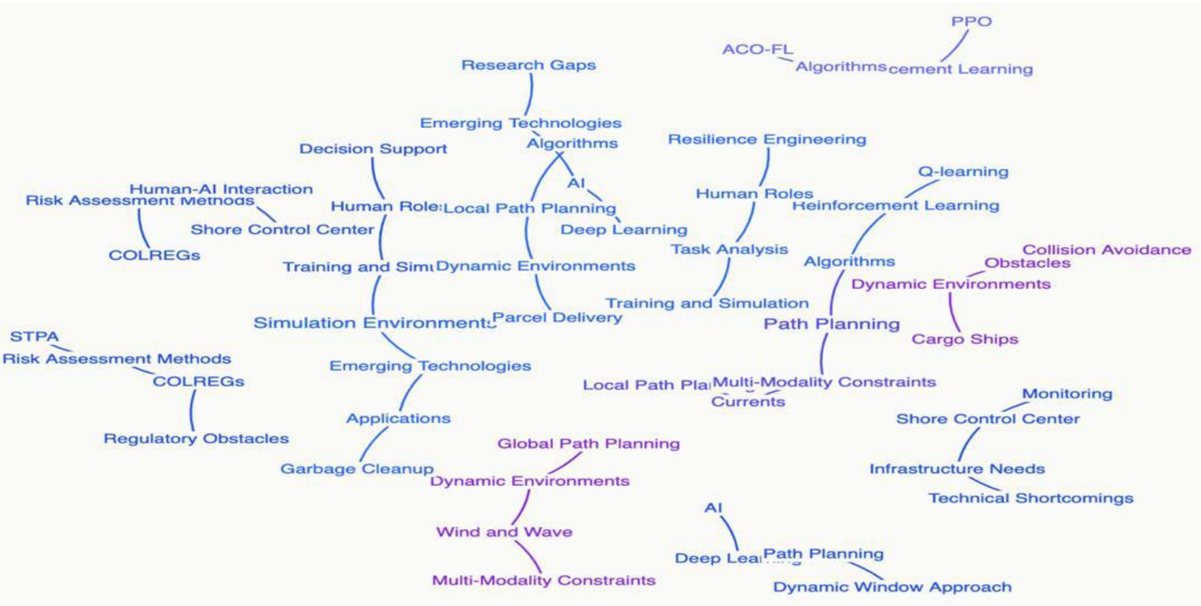

Figure 4. Mind map of topics regarding autonomous ship collision avoidance. Source: authors' research, built using https://app.thinkmachine.com/ [17]

As resulted from this analysis, some of the important parameters to be taken into consideration for such a tool should be [22]:

- • Safety: This is the overarching objective. Key metrics might include:
    - Number of collisions or near misses.
    - Minimum distance to obstacles/vessels.
    - Time spent in high-risk situations.
- Efficiency:
    - Time to reach destination.
    - Fuel consumption or energy efficiency.
    - Length of path taken.
- Computational Performance:
    - Algorithm runtime/latency (how quickly decisions are made).
    - Resource usage (memory, processing power).
- Human-AI Interaction (if applicable):
    - Clarity and usefulness of information presented to operators.
    - Ease of use and control for human supervisors.
    - Resilience to human error or unexpected situations.
- Scalability:

- Ability to handle increasing numbers of vessels or environmental complexity.
- Applicability across different ship types and sizes.

The development and deployment of autonomous ships rely heavily on the effectiveness of their collision avoidance systems. As these systems become more complex and sophisticated, the need for a standardized benchmarking tool to evaluate and compare their performance becomes increasingly crucial. The sources highlight several compelling reasons why such a tool is necessary.

Firstly, a benchmarking tool would provide a common framework for assessing the diverse range of collision avoidance algorithms currently being developed. As the previous discussion and the sources suggest, these algorithms employ a variety of approaches, including classical methods like DWA and APF, AI-based techniques such as Fuzzy Logic and Neural Networks, and hybrid systems that combine both. A standardized benchmarking tool would allow researchers to compare the strengths and weaknesses of different approaches in a consistent and objective manner, facilitating the identification of the most promising avenues for future research and development.

Secondly, a benchmarking tool would help to ensure that autonomous ship collision avoidance systems are robust and reliable in a variety of real-world scenarios. The analyzed articles emphasize the importance of considering dynamic environmental factors like wind and waves, as well as the complexity of multi-ship encounters and compliance with COLREGs. A comprehensive benchmarking tool should incorporate these factors into its evaluation criteria, providing a realistic assessment of a system's performance under challenging conditions. For instance, explores the integration of real-world data, like Electronic Navigational Charts (ENC) and Automatic Identification System (AIS) data, to create complex simulations for testing MASS collision avoidance in constrained environments.

Thirdly, a benchmarking tool could accelerate the development and adoption of autonomous ship technology. By providing a clear and objective measure of system performance, a benchmarking tool would build confidence among regulators, and industry stakeholders, paving the way for wider acceptance and deployment of autonomous ships. A robust benchmarking process would also aid in identifying and addressing potential safety concerns early in the development cycle, ultimately contributing to the realization of safer and more efficient maritime operations.

4. LIMITATIONS AND FUTURE WORK

We presented our work as an advance in the AI-based routing algorithms that allow us to rigorously compare the existing solutions, but this has some evident limitations in terms of vessel dynamic modeling and specific navigation medium characteristics.

Our proposal will be a framework for the researchers to come and fill these intended uncovered areas. Because we just illustrated a set of criteria for a benchmark (similar to [4]), we expect to develop further and propose a simulation environment where the existing routing parameters of the algorithms to cover navigation medium and vessel characteristics variability while keeping the benchmark simple and operable.

5. CONCLUSIONS

This article summarizes the most recent research on autonomous ship collision avoidance, particularly focusing on AI-based routing algorithms. The research identifies key trends in this field by analyzing relevant publications from prominent scientific databases such as Web of Science, Scopus, and IEEE Xplore. A significant focus is on the intersection of "Autonomous Shipping," "Artificial Intelligence," and "Obstacle Avoidance." The analysis reveals a substantial opportunity to leverage AI to enhance the safety and reliability of autonomous shipping, specifically in the area of collision avoidance.

One of the key contributions of the article is the proposal for a new Benchmarking Tool for Autonomous Ship Collision Avoidance. This tool is proposed to address a critical need for standardized and comprehensive methods to evaluate the effectiveness of different collision avoidance systems being developed. A standardized tool will help researchers, developers, and regulatory bodies assess and compare the diverse range of collision avoidance solutions currently under development, using a consistent set of criteria. It will enable the evaluation of how well these systems perform in realistic maritime environments, taking into consideration factors like obstacles, weather conditions, and the behavior of other vessels.

The Benchmarking Tool is essential because it will facilitate the fair and objective comparison of different algorithms, ensure that testing is conducted under realistic conditions that reflect the complexities of the maritime environment, and place a strong emphasis on compliance with the International Regulations for Preventing Collisions at Sea (COLREGs).

A well-designed Benchmarking Tool that incorporates these criteria will be invaluable for the development and advancement of autonomous shipping. It will provide a common framework for assessing, validating, and comparing various collision avoidance systems, ultimately leading to safer, more efficient, and more reliable maritime operations. Future research should focus on refining this tool, including incorporating aspects such as vessel dynamics modeling and detailed considerations of the navigation medium characteristics, to ensure accurate and robust evaluations of autonomous ship collision avoidance solutions.

6. ACKNOWLEDGMENTS

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