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Autonomous Shipping: Applying AI to Unmanned Ships Using Gray Relationship Analysis

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Abstract

Autonomous shipping has both the potential and the obstacles to impact the evolution of maritime logistics. While AI-powered navigation, environmental perception technologies, and fleet optimization solutions have provided significant advances, significant challenges remain. Concerns related to safety, risk assessment, and regulatory compliance must be addressed to facilitate a smooth transition toward autonomous maritime operations.

Research Significance: Maritime logistics is a key component of global trade, accounting for more than 80% of goods transported worldwide. However, the industry continues to face challenges such as human error, high operational costs, and environmental impact. The adoption of autonomous shipping, powered by artificial intelligence, offers a revolutionary solution to these issues. By using AI-powered navigation, fleet management, and enhanced safety systems, autonomous ships can improve efficiency, reduce costs, and promote sustainability in maritime operations.

Methodology: AI-Driven Navigation, Autonomous Cargo Handling, Smart Collision Avoidance Systems, AI-Enhanced Communication Systems, Unmanned Vessels with Remote Monitoring,Fully Autonomous Shipping Fleets. Evaluation Parameters: Safety, Efficiency, Cybersecurity Risks, Public Perception.

Result: These findings reveal that unmanned ships with remote monitoring received the highest ranking, and fully autonomous ship fleets received the lowest ranking.

Conclusion: The value of the dataset for Autonomous Shipping: Leveraging AI in Unmanned Vessels, according to the Grey Relation Analysis method, Unmanned Vessels with Remote Monitoring achieves the highest ranking.

Introduction

Maritime logistics is essential to global trade, helping to transport more than 80% of international goods by sea. However, the industry faces many challenges, such as human error, high operational costs, and environmental issues. AI-powered Thanet aims to reduce reliance on human crews, improve safety and optimize shipping routesAutonomous navigation systems: Research has led to the development of AI-based systems designed for collision avoidance and efficient route optimization.

Environmental Awareness: Machine learning models such as convolutional neural networks (CNNs) are used for obstacle recognition and maritime scene interpretation. Ship optimization: AI-powered solutions improve fleet management by improving deployment strategies and fuel efficiency. Automation in maritime operations can be categorized into four main options: Traditional ships with automated decision support systems such as collision avoidance technology. Semi-autonomous ships that operate independently in specific situations such as nighttime, open waters, or favorable weather. Fully autonomous ships that can navigate within ports and at sea. Fully autonomous, unmanned ships designed without onboard facilities for personnel. For the second and third options, an unmanned shore control center (SCC) on land would be necessary to oversee operations.[1]As with conventional shipbuilding, the design and development of autonomous ships is overseen and controlled by humans. As a result, the quality of a ship is determined by the decisions, knowledge, and oversight made at every stage of the project, from initial planning and design to construction and completion. Later in the ship's life cycle, any "mistakes" or concessions made in the design of automated systems can lead to uncertainty and safety issues.

Due to the complexity of autonomous ships and their internal systems, non-navigational accidents (such as internal fires and system failures) are likely to increase, while navigational incidents (such as collisions and groundings) are predicted to decrease in unmanned ships.[2]In other words, gaining technological superiority over the sophisticated military capabilities of strategic competitors (mostly traditional militaries) can help reduce the risks posed by the use of unsafe, unverified, and unreliable autonomous weapons systems (AWS). As a result, the primary risk to sustainability and scalability today lies in the technical limitations of current AI machine learning software, including issues such as fragility, lack of interpretability, unpredictability, vulnerability to data manipulation or "data poisoning," and the tendency for AI systems to acquire biases. [3] The current approach to assessing risk in the maritime sector has

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several notable weaknesses. While this is a common decision-making difficulty, autonomous shipping makes it even more important. A notable feature of autonomous shipping is that it uses new technology that has been recently developed and tested in a limited number of trials, which makes its application unique. Another important factor is the heavy reliance on software to control ships. This has several implications for risk analysis: There are no established databases for autonomous ships.The available data for significant accident types, such as collisions and groundings, are not highly relevant, and it may be questionable whether existing models are sufficient.

The addition of software introduces more complexity to systems, making them more difficult to analyze. There is a higher likelihood of not fully understanding how the system operates, which could lead to errors in designing the software and hardware. [4]Some of the key features of the project include the ability to use an autonomous navigation system to operate the vessel (under the supervision and control of land-based operators), reducing the risk of collision and adhering to the International Regulations for the Prevention of Collisions at Sea (COLREG), and safely and effectively locating objects. [5] This highlights the urgent need for relevant research. However, research in the areas of internal control systems and information technology is a major hurdle in the form of autonomous ships. Autonomous ships will be able to travel much further and operate over wider areas than autonomous automobiles. Based on their level of autonomy, research has classified ships into three categories: ordinary ships, where the crew makes all the decisions and performs all the functions; smart ships, where the crew makes the decisions but the functions are automated; and autonomous ships, where the crew makes all the decisions and performs all the functions. [6]There is significant disagreement among academics about the feasibility and benefits of widespread deployment of autonomous ships.

These technologies, according to their proponents, offer significant cost savings and increased efficiency, thus paving the way for the future of maritime operations. However, critics raise ethical and technical issues regarding the use of AI in place of human judgment. They draw attention to the socio-economic and ethical issues that need to be addressed in addition to the technical questions, as they are essential for understanding the bigger picture of autonomous shipping.[7] In the past, the laws governing navigation and how they are implemented have shown the ability to adapt and react to advances in technology. The maritime sector is governed by national, regional and international frameworks that continuously encourage the development of new technologies and the improvement of existing ones. The construction of nuclear power plants and the widespread implementation of containerization under the Safety of Life at Sea (SOLAS) laws are two prominent examples of this, as they have led to the development of new legal frameworks and the strengthening of port state control (PSC). [8]Autonomous underwater vehicles (AUVs) are generally considered unmanned objects, and therefore require new legal and regulatory frameworks. However, compared to the development of autonomous ships at sea, this presents a significantly different challenge. Due to the positioning techniques used in these missions, AUVs are often deployed in close proximity to the mother ship. However, systems that use both surface and underwater vehicles without a human presence are emerging as advanced tools for exploring the marine environment; however, they have the difficulties associated with both types of vehicles.

[9]Exploring the key concerns surrounding autonomous shipping and their effects on industry, technology, and law in their larger context is crucial to the successful introduction and integration of Maritime Autonomous Surface Ships (MASS) and associated infrastructure into the maritime sector.[10] For example, “hardware” failures caused by human errors, maintenance issues, or failure to follow instructions can increase the likelihood of a drone accident. At the same time, “planned improper operation” is less likely to affect drone safety because multiple entities, including the ship’s control system and shore-based operators, can implement and verify path planning at different levels. [11]A theoretical perspective on the commercial viability of unmanned ships is provided by these critical issues, based on a review of the literature on autonomous commercial vessels. This article casts doubt on the prospect of fully autonomous ships sailing the seas in the future, arguing that the assumption of total reliability and dependability of automation on ships is unrealistic. Given the cost of the equipment and the impact of weather, it is still unclear whether the machines can actually match the skills of experienced sailors.[12]Drones and autonomous cars have become popular and are now used in various military, maritime exploration and coastal surveillance missions. Unmanned commercial vessels are not yet sufficiently developed, however, they are widely deployed and used. The possibilities of autonomous unmanned vessels and their human-centric automatic management from shore-based facilities during long-distance deep-sea voyages are being explored by the EU project MUNIN (Maritime Unmanned Navigation via Intelligence in Networks). By using slow steam techniques, the unmanned vessel model seeks to improve working conditions on shore, increase sailor safety and reduce its impact on the environment.[13] Especially in a hybrid situation, the collision avoidance strategy of unmanned vessels should not revolve around contact with the target vessel. Assessing the potential influence of unmanned vessels in ship collision accidents is very important, as the hybrid situation will persist until all manned vessels are removed. [14] In addition, this discovery will initiate a paradigm shift in the transportation industry by opening the door to autonomous domestic cargo ships. According to the authors, an experimental test bed that is useful to the industry will provide important insights into the potential of unmanned domestic cargo ships. As a result, they raised the following question: How can a test bed be developed to assess the reliability and current or potential obstacles of unmanned domestic cargo ships? Needless to say, not every research problem can be predicted in advance, and not every possible answer can be fully tested on a research ship.[15]

Materials and Method

Gray relational analysis (GRA) is an essential method for examining gray data in uncertain systems. This study highlights that, due to variations in the shape and threshold of different sequences, A particular model that is sensitive to data normalization is the absolute GRA (AGRA) model. Hence, normalization should be conducted as an initial step before performing gray correlation analysis.

Finding the optimal solution from a limited number of potential options that are evaluated based on various quantitative and qualitative criteria is the goal of multi-attribute decision making (MADM) challenges. In recent years, researchers from various fields have paid much attention to MADM.

Gray system theory is a technique for analyzing uncertainty, which is very helpful in the mathematical study of systems with uncertain information. According to gray system theory, a system is called a white system if all its information is known, and a black system if all its information is unknown.

A gray system is one in which only partially known information is available. Gray prediction, gray relational analysis (GRA), gray decision, gray programming, and gray control are the five primary areas of gray system theory. The GRA component of gray system theory is very helpful in solving problems with large numbers of variables and complex relationships between components.

The GRA approach is often used to solve problems of uncertainty when there is no unique data and insufficient information. Furthermore, GRA is a widely used method for decision making in multi-attribute situations and for exploring the relationships between multiple unique data sets. The primary advantages of the GRA method are its reliance on original data, its ease of use and calculation, and its effectiveness as a tool for business decision making.

Since its introduction by Deng in 1982, gray system theory has been widely used in many different domains (Lin, Chang, & Chen, 2006). It has proven effective in dealing with imprecise, ambiguous, and partial information. One component of gray system theory, gray relational analysis (GRA), is very helpful in solving problems involving complex relationships between multiple components.

Many MADM problems have been successfully solved with GRA, such as hiring decisions (Olson & Wu, 2006), power distribution system planning reconfiguration (Chen, 2005), integrated-circuit coding process analysis (Jiang, Daci, & Wang, 2002), quality function hierarchy modeling (Wu, 2002), silicon wafer slicing defect detection (Lin et al., 2006), and many others.

Finally, the gray correlation quality between each comparison sequence and the reference sequence is calculated using the gray correlation coefficients. The optimal option will be the one that provides the maximum gray correlation quality between the reference sequence and its comparison sequence.

Gray correlation generation is the first step in the GRA process, which involves converting the performance of each option into a comparison order. Based on these orders, a reference order - the best target order - is generated. The Gray correlation coefficient between the reference order and all comparison orders is then determined.By combining all the performance attribute values for each alternative into a single value, GRA solves MADM problems. As a result, the initial problem is reduced to a choice problem with a single attribute. As a result, following the GRA procedure, it is easy to compare options with different features.

Strong protein-protein interactions with GRA6, mostly mediated by hydrophobic interactions, enable GRA4 to associate with network barriers. GRA6 that has undergone phosphorylation exhibits a higher affinity for network membranes inside the vacuole. Furthermore, a multimeric complex that is consistently related to an intravacuolar network—possibly implicated in the transport process—is formed when cross-linked GRA4 and GRA6 bind particularly to GRA2. of proteins or nutrients into the vacuole.

A process derived from early GRA (Grey Relational Analysis) models fundamentally depends on the correlation coefficients of specific points for general models. GRA models assess integrated or overall perspectives and similarities based on how closely related or similar the models are to each other, considering their proximity in the evaluation

Alternative

AI-powered navigation is the use of artificial intelligence in navigation systems to improve their capabilities and performance. In the context of autonomous shipping, it is the use of AI to analyze real-time data from sensors, cameras, and GPS to assess a ship's surroundings, determine the best routes, and make immediate navigation decisions. The goal is to improve safety, efficiency, and flexibility in maritime operations.

Autonomous cargo handling involves the use of AI and robotic systems to automate the loading, unloading, and management of cargo on ships, eliminating the need for human operators. This includes technologies such as automated cranes, robots, and conveyors that improve efficiency, reduce labor costs, improve safety, and increase operational efficiency in maritime logistics.

Smart collision avoidance systems rely on advanced sensors, AI, and real-time data analysis to detect potential obstacles or collisions in a ship's path. By assessing variables such as weather, nearby ships, and hazards, these systems help autonomous ships make necessary adjustments, avoiding accidents and ensuring safe navigation.

AI-enhanced communication systems use artificial intelligence to improve communication between ships, ports and operators. By processing data in real time, these systems improve decision-making, improve operations and increase safety. They facilitate smooth information sharing, reduce human error, improve situational awareness and promote better coordination of maritime operations.

Remotely monitored unmanned vessels are autonomous vessels that operate without a crew and are controlled and monitored remotely from land. These vessels use sensors, AI and communication technologies to help operators monitor navigation, performance and safety in real time, ensuring safe and efficient operations from afar.

Fully autonomous shipping fleets are unmanned vessels that operate autonomously without human intervention, using advanced AI, sensors, and automation technologies. These vessels can navigate independently, manage cargo, and communicate, reducing ship capacity, safety, and labor costs, while being remotely monitored for efficiency and safety.

Evaluation Parameters:

Safety: Higher values represent better safety.

Efficiency: Higher values indicate more efficient systems.

Cybersecurity Risks: Higher values indicate greater vulnerability to cyber threats or risks.

Public Perception: Higher values indicate a more favorable public perception.

Analysis and Dissection

Table 1. Autonomous Shipping: Leveraging AI in Unmanned Vessels

	DATA SET			
	Safety	Efficiency	Cybersecurity Risks	Public Perception
AI-Driven Navigation	9	8	8	6
Autonomous Cargo Handling	7	9	8	4
Smart Collision Avoidance Systems	9	7	6	8
AI-Enhanced Communication Systems	7	6	4	6
Unmanned Vessels with Remote Monitoring	9	8	7	4
Fully Autonomous Shipping Fleets	7	5	9	7

The dataset in Table 1 presents key evaluation criteria for various autonomous ship technologies, with a particular focus on AI applications in unmanned ships. It rates six alternatives based on four key parameters: safety, efficiency, cybersecurity risks, and public perception, with scores ranging from 1 to 10, where 10 is the most favorable.Safety: The highest safety ratings, 9, are assigned to unmanned ships with AI-driven navigation, smart collision avoidance systems, and remote monitoring, indicating that these technologies are particularly effective in preventing accidents and ensuring ship safety. In contrast, autonomous cargo handling and fully autonomous ship fleets receive lower safety scores (7), indicating concerns about aspects such as cargo operations and fleet management.Efficiency: Autonomous cargo handling is ranked as the most efficient with a score of 9, followed by unmanned ships with AI-driven navigation and remote monitoring, both of which receive a score of 8. These technologies improve operational efficiency by reducing delays and increasing productivity. On the other hand, fully autonomous fleets receive a low score of 5, indicating the challenges of managing complex, large-scale autonomous fleets.Cybersecurity risks: Fully autonomous fleets receive a high score of 9 for cybersecurity risks, highlighting potential security vulnerabilities due to the integration of multiple autonomous ships. Both AI-driven navigation and autonomous cargo handling receive scores of 8, indicating that while they offer benefits, they still face cybersecurity concerns.Public perception: Public acceptance of autonomous shipping technologies varies. Smart collision avoidance systems are viewed most favorably with scores of 8, likely due to their focus on safety and navigation. In contrast, unmanned ships with autonomous cargo handling and remote monitoring receive low scores (4), indicating public concerns or skepticism about automation in cargo handling and remote shipping operations.

Table 2: Presents normalized data that evaluates various autonomous ship technologies

	Normalized Data			
	Scalability	Recognition	Complexity	Adoption Difficulty
AI-Driven Navigation	1.0000	0.6667	0.0000	0.5000
Autonomous Cargo Handling	0.0000	1.0000	0.0000	1.0000
Smart Collision Avoidance Systems	1.0000	0.3333	0.5000	0.0000
AI-Enhanced Communication Systems	0.0000	0.0000	1.0000	0.5000
Unmanned Vessels with Remote Monitoring	1.0000	0.6667	0.2500	1.0000
Fully Autonomous Shipping Fleets	0.0000	-0.3333	-0.2500	0.2500

Table 2 presents normalized data that evaluates various autonomous ship technologies based on four key factors: scalability, acceptance, complexity, and difficulty of adoption. These factors are measured on a scale from -1 to 1, with higher values indicating more favorable outcomes. The table assesses the performance of six different technologies on these dimensions.Scalability: Technologies such as AI-driven navigation, smart collision avoidance systems, and unmanned ships with remote monitoring each receive a score of 1.0000, indicating that they are highly scalable and can be efficiently expanded to larger fleets or more complex operations. In contrast, autonomous cargo handling and fully autonomous ship fleets receive 0.0000 or negative values, indicating potential difficulties in effectively scaling these technologies.Acceptance: Autonomous cargo handling achieves the highest acceptance score of 1.0000, reflecting its widespread industry acceptance. On the other hand, fully autonomous ship fleets receive a negative score of -0.3333, indicating potential resistance or low acceptance in the market. Unmanned ships with AI-driven navigation and remote monitoring both receive scores of 0.6667, indicating moderate industry acceptance.Complexity: AI-driven communication systems receive the highest scores in terms of complexity with a score of 1.0000, indicating that they are very complex to implement. Smart collision avoidance systems receive a score of 0.5000, indicating a moderate level of complexity, while unmanned ships with AI-driven navigation and remote monitoring have low complexity scores, indicating that they are relatively easy to use.Difficulty of adoption: Autonomous cargo handling and unmanned ships with remote monitoring both receive a score of 1.0000, indicating that they are very challenging technologies to adopt due to implementation and integration difficulties. Smart collision avoidance systems score 0.0000, indicating moderate adoption difficulty, while AI-powered navigation and fully autonomous ship fleets score lower, indicating easier adoption processes.

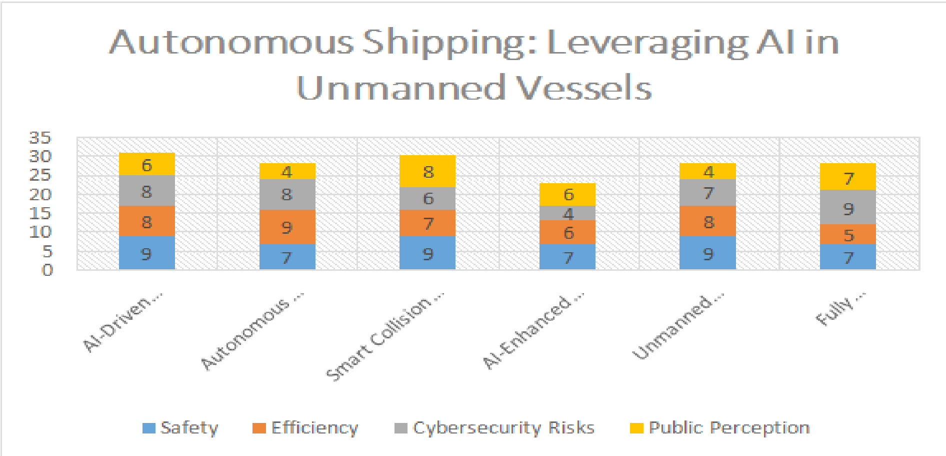

Figure 1 : Autonomous Shipping: Leveraging AI in Unmanned Vessels

The bar chart, titled "Autonomous Shipping: Leveraging AI in Unmanned Ships," provides a comparative assessment of the key factors shaping AI-powered maritime autonomy. It examines different autonomous ship models based on four essential parameters: safety, efficiency, cybersecurity risks, and public perception. These features are visually differentiated using different colors, with numerical values assigned to each category.Each bar represents a specific level or autonomous ship type, including AI-driven, autonomous, smart collision, AI-enhanced, unmanned, and fully autonomous models. The figures within the bars illustrate how each model performs with respect to the given factors.Safety (blue) is consistently rated highly across all models, with scores ranging from 7 to 9, indicating a strong emphasis on safety regardless of the level of automation. Performance (orange) varies more significantly, with values ranging from 5 to 9, indicating that some models are more optimized for performance.Cybersecurity risks (gray) emerge as a significant concern, with ratings ranging from 6 to 9. While some models appear to be managing cybersecurity threats effectively, others remain vulnerable due to increased automation. Meanwhile, public opinion (yellow) fluctuates from 4 to 8, reflecting varying levels of confidence, concerns about security, and broader ethical considerations of autonomous shipping.

Table 3: Shows the deviation order for various autonomous ship technologies

	Deviation sequence			
	Scalability	Recognition	Complexity	Adoption Difficulty
AI-Driven Navigation	0.0000	0.3333	1.0000	0.5000
Autonomous Cargo Handling	1.0000	0.0000	1.0000	0.0000
Smart Collision Avoidance Systems	0.0000	0.6667	0.5000	1.0000
AI-Enhanced Communication Systems	1.0000	1.0000	0.0000	0.5000
Unmanned Vessels with Remote Monitoring	0.0000	0.3333	0.7500	0.0000
Fully Autonomous Shipping Fleets	1.0000	1.3333	1.2500	0.7500

Table 3 shows the deviation order for various autonomous ship technologies based on four essential factors: scalability, acceptance, complexity, and difficulty of adoption. The values in this table indicate how much each technology deviates from a baseline, with higher values indicating a greater deviation from the standard in each category.Scalability: Autonomous cargo handling has the highest deviation in scalability with a score of 1.0000, indicating that scaling this technology poses significant challenges. In contrast, AI-driven navigation, smart collision avoidance systems, unmanned ships with remote monitoring, and fully autonomous ship fleets all have deviation values close to zero, meaning that these technologies are generally scalable with minimal challenges. AI-enhanced communication systems also score 1.0000, indicating potential scalability issues.Recognition: Fully autonomous ship fleets show the highest deviation in recognition with a score of 1.3333, indicating that they may face significant barriers to gaining industry acceptance. Similarly, AI-enhanced communication systems have a high deviation of 1.0000, indicating challenges in gaining recognition in the industry. Smart collision avoidance systems have a moderate deviation of 0.6667, while unmanned ships with AI-driven navigation and remote monitoring show a small deviation (0.3333), indicating the best recognition in the market. Autonomous cargo handling has a deviation of 0.0000, meaning it faces the least difficulty in gaining recognition.Complexity: Fully autonomous ship fleets have a high deviation in complexity with a score of 1.2500, indicating that it is a very complex technology to implement. Both AI-driven navigation and autonomous cargo handling show high deviations of 1.0000, indicating that they are very complex to use. Smart collision avoidance systems show a moderate deviation of 0.5000, and unmanned ships with remote monitoring show a deviation of 0.7500, indicating a significant but not overwhelming level of complexity. Difficulty of adoption: Smart collision avoidance systems have the highest deviation in difficulty of adoption with a score of 1.0000, indicating that their adoption is expected to be very challenging. Unmanned ships with autonomous cargo handling and remote monitoring have the lowest deviation (0.0000), indicating that adoption of these technologies is relatively easy. AI-driven navigation and fully autonomous ship fleets show moderate deviations in difficulty of adoption (0.5000 and 0.7500), reflecting some challenges, but not to the same extent as others.

Table 4: Presents the Gray relationship coefficients for several autonomous ship technologies

	Grey relation coefficient			
	Scalability	Recognition	Complexity	Adoption Difficulty
AI-Driven Navigation	1.0000	0.6000	0.3333	0.5000
Autonomous Cargo Handling	0.3333	1.0000	0.3333	1.0000
Smart Collision Avoidance Systems	1.0000	0.4286	0.5000	0.3333
AI-Enhanced Communication Systems	0.3333	0.3333	1.0000	0.5000
Unmanned Vessels with Remote Monitoring	1.0000	0.6000	0.4000	1.0000
Fully Autonomous Shipping Fleets	0.3333	0.2727	0.2857	0.4000

Table 4 presents the Gray relationship coefficients for several autonomous ship technologies across four key factors: scalability, acceptance, complexity, and difficulty of adoption. The Gray relationship coefficient measures how closely the alternatives are related, with values ranging from 0 to 1, where higher values indicate stronger relationships or more favorable outcomes.Scalability: AI-powered navigation, smart collision avoidance systems, and unmanned ships with remote monitoring all achieve the highest scalability score of 1.0000, indicating that these technologies are highly scalable and can be easily adapted to larger operations. In contrast, autonomous cargo handling and fully autonomous ship fleets score the lowest (0.3333), indicating that these technologies face greater challenges when it comes to scalability.Recognition: Autonomous cargo handling ranks highest in recognition with a coefficient of 1.0000, reflecting its strong acceptance and recognition within the industry. AI-powered navigation and unmanned ships, with a remote monitoring score of 0.6000, indicate a moderate level of industry acceptance. Smart collision avoidance systems have a score of 0.4286, while fully autonomous ship fleets have a very low acceptance score of 0.2727, indicating that this technology is struggling to gain industry acceptance. Complexity: AI-enhanced communication systems have a very high complexity score of 1.0000, indicating that they are very complex to implement. Smart collision avoidance systems have a moderate complexity score of 0.5000, indicating that they are moderately complex to use. In comparison, AI-powered navigation, unmanned ship fleets with remote monitoring, and fully autonomous ship fleets have low scores, indicating that they are less complex to implement.Difficulty of adoption: Unmanned shipping fleets with autonomous cargo handling and remote monitoring score highest on difficulty of adoption with coefficients of 1.0000, indicating that these technologies are very difficult to adopt. AI-driven navigation, AI-enhanced communication systems, and smart collision avoidance systems show moderate difficulty of adoption with scores between 0.3333 and 0.5000, while fully autonomous shipping fleets have a low score of 0.4000, indicating that they are easier to adopt than the others.

Table 5: Shows the Gray Relative Grade (GRG) for various autonomous shipping technologies

	GRG
AI-Driven Navigation	0.6083
Autonomous Cargo Handling	0.6667
Smart Collision Avoidance Systems	0.5655
AI-Enhanced Communication Systems	0.5417
Unmanned Vessels with Remote Monitoring	0.7500
Fully Autonomous Shipping Fleets	0.3229

Table 5 shows the Gray Relative Grade (GRG) for various autonomous shipping technologies, which provides an overall measure of their performance across four factors: scalability, authentication, complexity, and difficulty of adoption. The GRG is calculated by combining the Gray Relationship Coefficients from all factors, with higher values indicating better overall performance.AI-driven navigation scores a GRG of 0.6083, which represents a solid performance relative to other technologies. It performs well on scalability, complexity, and difficulty of adoption, making it a strong contender in autonomous shipping. Its GRG positions it as a competitive option when evaluating all key factors.Autonomous cargo handling stands out with the highest GRG of 0.6667, showing strong performance across factors, particularly authentication. This technology is widely adopted in the industry, balancing scalability and ease of adoption, although it faces some challenges in complexity and scalability. Smart collision avoidance systems achieve a GRG of 0.5655, indicating moderate performance across all factors. While it excels in recognition and complexity, it faces difficulties in scalability and adoption, leading to a very moderate GRG. However, it remains an important technology for ensuring the safety of autonomous ships.AI-enhanced communication systems have the lowest GRG of 0.5417, making them the least favorable technology among those evaluated. It performs well in terms of complexity, but struggles with scalability and recognition, affecting its overall performance.Unmanned ships with remote monitoring achieve the second highest GRG of 0.7500, indicating that it performs well in terms of scalability, recognition, and ease of adoption. This technology appears to be a very viable solution for large-scale deployment in autonomous shipping.Fully autonomous ship fleets, with a very low GRG of 0.3229, show weak performance despite its strong scalability. It faces significant barriers in recognition, complexity, and difficulty of adoption, reducing its competitiveness compared to other alternatives.

Table 6: Grey Relational Grade (GRG)

	Rank
AI-Driven Navigation	3
Autonomous Cargo Handling	2
Smart Collision Avoidance Systems	4
AI-Enhanced Communication Systems	5
Unmanned Vessels with Remote Monitoring	1
Fully Autonomous Shipping Fleets	6

Table 6 shows the ranking of different autonomous shipping technologies based on their overall performance, determined by the Grey Relational Grade (GRG) values. These rankings reflect the effectiveness of each technology in terms of Scalability, Recognition, Complexity, and Adoption Difficulty.Unmanned Vessels with Remote Monitoring ranks first, with the highest GRG score. This technology excels in scalability, recognition, and ease of adoption, making it the most promising option for large-scale autonomous shipping. Its top ranking indicates that unmanned vessels are well-suited for widespread implementation and industry acceptance. Autonomous Cargo Handling ranks second, demonstrating strong overall performance, particularly in recognition. It is well-accepted within the industry and offers a good balance between scalability and adoption. While its performance in scalability and complexity is slightly lower, it remains a viable choice, securing its place in the second position despite challenges in certain areas.AI-Driven Navigation is ranked third, showing solid performance across the evaluated factors. While its overall ranking is lower than Autonomous Cargo Handling and Unmanned Vessels with Remote Monitoring, its strong scalability and moderate adoption difficulty make it a competitive technology for autonomous shipping. The third-place ranking signifies its effectiveness as an alternative option.Smart Collision Avoidance Systems takes the fourth spot, with a balanced performance across all factors. While it excels in recognition and complexity, challenges in scalability and adoption ease prevent it from ranking higher. Despite this, its critical role in safety gives it an important place in the development of autonomous shipping technologies.AI-Enhanced Communication Systems ranks fifth, with its struggles in scalability and recognition affecting its overall performance. Despite performing well in complexity, these challenges place it lower in the rankings

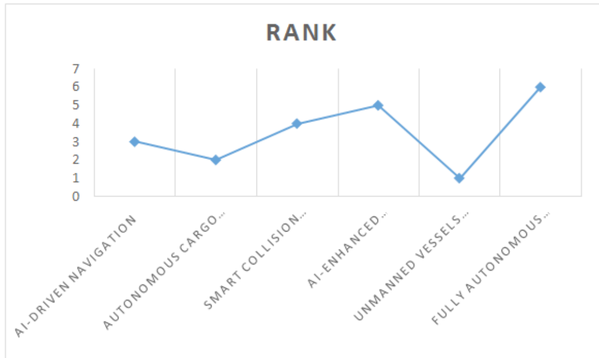

Figure 2: Provides a ranking of various autonomous shipping technologies based on factors such as scalability, authentication, complexity, and ease of adoption

Figure 2 provides a ranking of various autonomous shipping technologies based on factors such as scalability, authentication, complexity, and ease of adoption. The chart provides a clear view of which technologies are performing well and which areas may need further development. A lower ranking indicates more favorable performance, with the technology in the top spot showing the greatest promise for implementation.Unmanned ships with remote monitoring take the top spot, reflecting its superior performance across most of the evaluation criteria, including scalability, authentication, and ease of adoption. Its high ranking indicates that it is well-positioned for large-scale deployment and enjoys significant industry support, indicating that it is a leader in autonomous shipping. Autonomous cargo handling is in second place. While it faces challenges related to scalability and complexity, its strong industry recognition enhances its position. Its ability to balance operational efficiency with industry acceptance makes it a promising candidate for automating shipping logistics.AI-driven navigation is in third place, showing strong overall performance. It stands out for its scalability and relatively low adoption barriers, although it does not excel in every area. This mid-ranking position indicates room for improvement, particularly in improving industry recognition.Smart collision avoidance systems are ranked fourth, showing moderate performance. While they play a key role in operational safety with effective collision detection, their scalability and adoption issues limit their potential for higher rankings.AI-enhanced communication systems and fully autonomous ship fleets are ranked fifth and last, respectively, indicating that these technologies face significant challenges. AI-enhanced communication systems struggle with scalability and recognition, while fully autonomous ship fleets, despite strong scalability, face significant barriers to recognition, complexity, and adoption. This ranking highlights the need for further development before these technologies become leading solutions in autonomous shipping.

Conclusion

The future of autonomous shipping is shaped by ongoing technological advancements, evolving regulations, and operational challenges. While maritime autonomous surface ships (MASS) have the potential to transform the maritime industry, significant uncertainties and limitations must be addressed before widespread adoption is possible. From conventional ships with automated support systems to fully autonomous ships without onboard crew facilities – the four primary automation options each offer different levels of autonomy, with unique implications for safety, operational efficiency, and risk management.One of the biggest challenges in autonomous shipping is ensuring the quality and reliability of AI-powered decision-making systems. The performance of autonomous ships depends on their ability to navigate complex maritime environments, adapt to unexpected conditions, and mitigate cybersecurity risks. While advances in AI-powered navigation, smart collision avoidance, and remote monitoring have been significant, issues such as machine learning constraints, vulnerabilities to data manipulation, and system unpredictability remain pressing concerns. Furthermore, the lack of comprehensive databases for autonomous ships complicates risk assessment, as existing accident models are primarily designed for traditional, manned ships.From a regulatory perspective, existing maritime laws and legal frameworks need to evolve to allow autonomous shipping. Historically, the maritime industry has adapted to major technological changes, such as the introduction of containerization under SOLAS regulations. However, autonomous ships present unique legal and operational challenges, including liability in the event of accidents, compliance with international maritime regulations, and the integration of unmanned ships into existing port infrastructure. Addressing these issues is critical to ensuring a smooth transition to autonomous shipping.Beyond the technical and regulatory challenges, the socio-economic impact of replacing human-operated ships with autonomous systems must also be considered. While proponents argue that automation can improve efficiency, reduce costs, and enhance safety, critics highlight concerns about the loss of human expertise and the ethical implications of fully autonomous maritime operations. In addition, the high costs of implementing and maintaining autonomous technologies, along with their sensitivity to environmental conditions, raise questions about their long-term practicality and economic viability. Despite these obstacles, research efforts such as the MUNIN project and the development of experimental testbeds continue to evaluate the feasibility of unmanned domestic cargo vessels. Analytical methods such as gray relational analysis (GRA) and multi-attribute decision making (MADM) provide valuable tools for evaluating various automated strategies. These models help assess critical factors—including safety, performance, cybersecurity risks, and public perception—to identify the most viable approaches to integrating MASS into the maritime sector.

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