Integrative Multi-Information Fusion for Enhanced Risk Assessment: A Multi-Criteria Decision-Making Framework

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Abstract

This study addresses the burgeoning challenges in autonomous Maritime navigation by employing information fusion methodologies to assess and manage multifaceted risks. The proliferation of autonomous maritime systems has led to a complex interplay among maritime-related, shore-based remote control, environmental, and emergency management factors, necessitating a comprehensive risk evaluation framework. Leveraging a multi-criteria decision-making approach and employing the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), this research presents a methodical analysis of the coupling coordination degree among these risk variables. Through a meticulous examination of historical accident data and information fusion techniques, our study reveals dynamic trends in the comprehensive risk evaluation index, showcasing the evolving nature of risks inherent in autonomous Maritime navigation. The predictive insights gleaned from these analyses forecast an initial increase followed by a peak in accidents, underscoring the urgency for proactive risk mitigation strategies. This study's conclusions emphasize the pivotal role of information fusion methodologies in comprehensively assessing, understanding, and managing risks within autonomous Maritime navigation.

Keywords: Risk evaluation, Information fusion; multi-criteria decision-making (MCDM); Risk management; Decision support systems; Data integration; Risk mitigation strategies; Integrated risk assessment

1. Introduction

Risk assessment is a pivotal process in numerous domains, crucial for informed decision-making and strategic planning. In today's dynamic and interconnected environment, the complexity and multifaceted nature of risks necessitates advanced methodologies that can effectively integrate diverse sources of information [1]. This integration is fundamental to ensure a comprehensive understanding of risks and to facilitate informed decision-making to mitigate potential adverse impacts. The conventional approaches to risk assessment often rely on singular sources of information, potentially leading to incomplete or biased evaluations [2]. Acknowledging this limitation, the integration of multi-sourced information has emerged as a promising avenue to enhance the depth and breadth of risk assessments. Multi-information fusion harnesses diverse data types, including qualitative and quantitative sources, to construct a more holistic understanding of risk factors and their interdependencies [3-5].

Coupled with multi-information fusion, the utilization of multi-criteria decision-making (MCDM) frameworks offers a systematic methodology to evaluate and prioritize risks based on multiple criteria [6-7]. MCDM enables the integration of diverse perspectives and objectives, accommodating various stakeholders' preferences and incorporating uncertainty into the decision-making process. This approach facilitates the identification of optimal risk mitigation strategies that align with overarching organizational goals [8-10].

This paper aims to explore and elucidate the efficacy of an integrative approach that combines multi-information fusion techniques with a multi-criteria decision-making framework for enhanced risk assessment. By synthesizing

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diverse data streams and employing robust decision-making methodologies, the study endeavors to offer insights into the comprehensive evaluation of risks across domains. Additionally, the research seeks to provide practical guidance for organizations aiming to bolster their risk assessment capabilities through an integrative approach.

The remainder of the paper is organized into four main sections to present a comprehensive understanding of the integrative approach for enhanced risk assessment. Section 2 critically examines existing literature and studies concerning multi-information fusion, multi-criteria decision-making, and their applications in risk assessment. Following this, Section 3 delineates the framework and procedures employed in integrating multi-information fusion techniques with multi-criteria decision-making for risk evaluation. Subsequently, Section 4 presents the empirical findings and interprets the outcomes derived from the application of the proposed model in real-world scenarios. Section 5 consolidates the key findings, implications, and limitations of the study. Additionally, it outlines potential avenues for future research and practical implementation, providing insights for advancing this integrative framework in risk assessment practices.

2. Related Works

This section critically synthesizes and evaluates a spectrum of scholarly contributions, encompassing diverse methodologies, theoretical foundations, and empirical studies relevant to the integration of information fusion techniques and decision-making models for risk evaluation. By examining prior literature, this section aims to elucidate the evolution of concepts and identify key trends, gaps, and debates in the field, thereby establishing the necessary context for the present study. Abo et al. [11] introduced a novel multi-criteria approach for Arabic dialect sentiment analysis in online reviews. The primary contribution lies in the exploration of optimal machine learning algorithm selection, aiming to enhance sentiment analysis accuracy and effectiveness within the context of diverse Arabic dialects. Xiao and Qin [12] proposed a weighted combination method designed to handle conflicting evidence in multi-sensor data fusion. The study's key contribution involves the development of a methodology that effectively manages and integrates information from disparate sensors, optimizing data fusion outcomes in scenarios with conflicting or uncertain data. Duarte et al. [13] presented an interactive WebGIS integrating environmental susceptibility mapping using a multi-criteria decision analysis approach, specifically focusing on managing self-burning waste piles. The contribution lies in the development of an interactive platform that aids decision-makers in waste management by incorporating multi-criteria environmental susceptibility mapping. Gandotra et al. [14] introduced a new Pythagorean entropy measure applied to multi-criteria decision analysis. The study contributes by proposing an innovative entropy measure, expanding the range of analytical tools available for multi-criteria decision-making, and providing a novel perspective on decision analysis.

Cheng et al. [15] proposed a fuzzy multi-criteria method for sustainable ferry operator selection. The primary contribution lies in the development of a methodology that applies fuzzy logic to multi-criteria decision-making, specifically targeting sustainable ferry operator selection processes. Pamučar et al. [16] focused on the development of a multi-criteria model for the sustainable reorganization of healthcare systems during the COVID-19 pandemic. Its contribution involves providing a structured model that aids in making sustainable decisions regarding healthcare system reorganization in emergencies. Bognár and Benedek [17] introduced a novel AHP-PRISM risk assessment method, specifically studied within a nuclear power plant context. The contribution lies in proposing a new method that combines the Analytic Hierarchy Process (AHP) and Pareto front-seeking Interactive Reference Point Solution Method (PRISM) for risk assessment within nuclear power plants. Garg and Nancy [18] proposed a multi-criteria decision-making method utilizing prioritized Muirhead mean aggregation operators under a neutrosophic set environment. The key contribution involves introducing a robust decision-making method that considers the prioritized aggregation of criteria under a neutrosophic set environment, enhancing the decision-making process's resilience. Seiti et al. [19] used linguistic D numbers in multi-granular information fusion and decision-making focused on risk analysis. The contribution lies in leveraging linguistic D numbers to fuse information at different granularities and make decisions more robustly in the context of risk analysis.

Zhang et al. [20] highlighted cluster-based information fusion's efficacy in probabilistic risk analysis for complex projects under uncertainty. Its contribution lies in introducing and validating a methodology that uses cluster-based information fusion to analyze risks effectively in uncertain and complex project environments. Aslani et al. [21] integrated information fusion and grey multi-criteria decision-making for sustainable supplier selection. The contribution lies in offering a framework that combines information fusion and grey multi-criteria decision-making, providing a comprehensive method for sustainable supplier selection processes. Liao et al. [22] introduced a Choquet integral-based hesitant fuzzy gained and lost dominance score method for multi-criteria group decision-making

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considering experts' risk preferences. The contribution involves proposing a novel method that incorporates hesitant fuzzy sets and Choquet integral to handle experts' risk preferences in group decision-making scenarios. Zuheros et al. [23] proposed a sentiment analysis-based multi-person multi-criteria decision-making methodology using natural language processing and deep learning for smarter decision aid. Its contribution lies in offering a methodology that harnesses sentiment analysis, natural language processing, and deep learning to support decision-making in multi-person scenarios. Mohamed et al. [24] presented a neutrosophic multi-criteria decision-making methodology for sustainable supplier selection. The key contribution involves proposing a methodology that employs neutrosophic set theory in multi-criteria decision-making, specifically targeting sustainable supplier selection processes. Morente-Molinera et al. [25] proposed a multi-criteria group decision-making method utilizing multi-granular fuzzy linguistic modeling and consensus measures to navigate heterogeneous and dynamic contexts. The contribution lies in offering a method that incorporates multi-granular fuzzy linguistic modeling and consensus measures for decision-making in varied and dynamic contexts.

3. Methodology

This section expounds upon the comprehensive methodology designed to fuse disparate sources of information while concurrently navigating the complexities inherent in decision-making processes. Central to this methodology is the strategic amalgamation of diverse data types and decision criteria, underpinned by a structured approach that integrates information from various domains.

3.1. Case Study of Maritime Accidents

Our methodology integrates a comprehensive case study focusing on maritime maritime accidents to exemplify and evaluate the risk assessment framework proposed in this research. The empirical foundation for this case study derives from an extensive collection of historical data encompassing navigation incidents spanning from 2005 to 2019. This dataset serves as a rich repository of real-world occurrences, detailing a spectrum of accidents attributed to diverse causal factors within the maritime domain. By leveraging this extensive dataset, our study aims to systematically analyze, categorize, and evaluate these incidents, distinguishing key risk factors across four pivotal domains.

maritime factors encompass a spectrum of internal and technical attributes, including vessel design, machinery condition, and onboard systems. Information fusion techniques facilitate the integration of sensor data, maintenance logs, and performance metrics to assess the operational health and potential risks associated with autonomous maritime components. Moreover, remote regulator considerations entail the interaction between onshore control centers, communication systems, and the autonomous vessel. Fusion methodologies aid in consolidating data from remote sensing devices, communication protocols, and control interface feedback, enabling a comprehensive evaluation of operational dependencies and potential vulnerabilities.

Environmental considerations, encompassing weather conditions, navigational hazards, and situational awareness, require the fusion of diverse sensor data such as GPS, radar, lidar, and environmental monitoring systems. By merging and analyzing this disparate information, information fusion techniques contribute to a holistic understanding of environmental risks and their potential impact on autonomous maritime operations. Urgent situation management considerations involve preparedness, response protocols, and decision-making processes during critical scenarios. Information fusion enables the amalgamation of real-time data streams from multiple sources, including emergency procedures, predictive modeling, and risk assessment frameworks, facilitating timely and informed decision-making in crises. The integration and fusion of data across these domains allow for a comprehensive and coherent understanding of the maritime risk landscape for autonomous ships. Information fusion techniques serve as the linchpin in synthesizing disparate data sources, enhancing situational awareness, and enabling proactive risk mitigation strategies within the autonomous maritime domain.

3.2. Maritime Risk Evaluation Index (MREI)

In the context of maritime risk evaluation, the fusion of diverse indices into a comprehensive Maritime Risk Evaluation Index (MREI) stands as a pivotal approach for synthesizing multifaceted risk factors into a unified framework. The MREI amalgamates a spectrum of indicators, encompassing maritime-related, environmental, operational, and emergency management parameters, to holistically evaluate the risks associated with autonomous maritime operations.

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The construction of the MREI involves a meticulous process of data integration, normalization, and weighting of individual risk indicators derived from various sources. maritime-related factors incorporate metrics pertaining to onboard systems' reliability, navigational capabilities, and technology robustness, while environmental indicators encompass variables related to weather conditions, sea state variability, and navigational hazards. Shore-based control factors include metrics concerning remote control center reliability, communication network stability, and response latency. Moreover, operational parameters involve risk indices related to vessel maneuverability, traffic density, and collision avoidance capabilities, while emergency management factors encapsulate metrics concerning response protocols, emergency shutdown systems, and contingency plan efficacy.

Fusing these diverse indices into a singular MREI requires a systematic approach that encompasses both qualitative and quantitative assessments. Weighting mechanisms are employed to assign relative importance to each risk factor based on its significance and potential impact on autonomous maritime operations. Normalization techniques are then applied to standardize the indices, allowing for meaningful comparison and aggregation. The resultant MREI provides a comprehensive assessment of the overall maritime risk profile, offering decision-makers a holistic perspective on the vulnerabilities and potential impact of various risk factors on autonomous maritime operations. This fused index serves as a valuable tool for prioritizing risk mitigation strategies, allocating resources, and enhancing the resilience of autonomous shipping systems in the face of multifaceted risks. The utilization of the Delphi method [22] is employed to streamline, condense, and amalgamate the risk index. Specifically, the method involved tabulating the occurrences of accidents attributed to maritime factors, shore-based remote control factors, environmental factors, and emergency management factors for each year, denoted as $u_{j,i}$. In this context, 'j' represents the year, while 'i' denotes the risk dynamics. Consequently, the compilation of these occurrences forms the risk considerations index matrix, denoted as $R_0 = [u_{j,i}]_{n\times m}$. This matrix encapsulates the cumulative incidents corresponding to each identified risk factor across the 19-year timeframe, providing a comprehensive overview of the occurrences attributed to each factor within the autonomous maritime operations context.

$$R_0 = [u_{j,i}]_{n\times m} = \begin{bmatrix} u_{1,1} & u_{1,2} & \cdots & u_{1,m} \\ u_{2,1} & u_{2,2} & \cdots & u_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ u_{n,1} & u_{n,2} & \cdots & u_{n,m} \end{bmatrix} \tag{1}$$

The comparative frequency of a specific type of accident during a particular year, in relation to all incidents occurring during the same time period and of the same kind, can be described as follows:

$$t_{j,i} = \frac{u_{j,i}}{\sum_j u_{j,i}} \tag{2}$$

Once the risk factors index matrix is obtained, we apply the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodology to evaluate and rank the risks associated with autonomous maritime operations. TOPSIS operates on the premise of identifying the optimal alternative from a set of alternatives by computing the shortest distance to the ideal solution and the farthest distance from the negative ideal solution. In the context of our study, the risk factors index matrix, containing the cumulative occurrences of accidents attributed to various risk factors across the 19-year timeframe, serves as the basis for the TOPSIS analysis.

First, to build the normalized decision matrix, each entry of the risk factors index matrix, denoted as $[u_{j,i}]_{n\times m}$, is normalized by dividing the individual value by the square root of the sum of squares of all values in the respective column. This normalization process ensures that each risk factor's values are adjusted proportionally within a unified scale while retaining their relative differences across different years and risk categories.

$$r_{ij} = \frac{u_{j,i}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \forall j \tag{3}$$

where r_{ij} and x_{ij} are the elements of the normalized and original decision matrix respectively

In the second step of the TOPSIS, the construction of a weighted normalized decision matrix is essential. This matrix integrates the relative importance or weights assigned to each risk factor, reflecting their significance in the overall

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risk measurement framework. The weighted normalized decision matrix amalgamates the normalized values of the risk factors index matrix while considering their assigned weights, thereby reflecting the varying degrees of importance ascribed to different risk factors. To build the weighted normalized decision matrix, the normalized decision matrix values are multiplied by the corresponding weights assigned to each risk factor. These weights are typically derived from expert opinions, empirical data, or analytical assessments conducted earlier in the study and reflect the relative significance or impact of each risk factor on the overall risk assessment process. Mathematically, the computation of the weighted normalized decision matrix v_{ij} can be represented as follows:

$$v_{ij} = r_{ij} * w_j \ \forall i, j \tag{4}$$

where w_j is the assigned weight to attribute j

Step 3 of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) involves the determination of the ideal ($\mathcal{A}^+$) and negative-ideal ($\mathcal{A}^-$) solutions. The ideal solution represents the best possible outcome for each risk factor, while the negative ideal solution embodies the worst possible scenario. To compute the ideal solution, the maximum values for each risk factor across all years are identified, signifying the most favorable conditions. Conversely, for the negative-ideal solution, the minimum values for each risk factor are determined, representing the least desirable conditions. Mathematically, the ideal solution ($\mathcal{A}^+$) is computed as the column-wise maximum values of the weighted normalized decision matrix, while the negative-ideal solution ($\mathcal{A}^-$) is derived as the column-wise minimum values.

$$\begin{aligned} \mathcal{A}^+ &= \left\{ \left(\max_j v_{ij} \mid i \in I \right), \left(\min_j v_{ij} \mid i \in I' \right); \forall j \right\} = \{ v_1^+, v_2^+, \dots \} \\ \mathcal{A}^- &= \left\{ \left(\min_j v_{ij} \mid i \in I \right), \left(\max_j v_{ij} \mid i \in I' \right); \forall j \right\} = \{ v_1^-, v_2^-, \dots \} \end{aligned} \tag{5}$$

where I and I' are associated with benefit and cost attributes respectively.

In Step 4 of the TOPSIS, the calculation of the separation measures for each alternative (risk factor) is pivotal. This step involves assessing the distance of each risk factor from the ideal ($\mathcal{A}^+$) and negative-ideal ($\mathcal{A}^-$) solutions to determine their relative closeness or similarity to these benchmarks. The separation measures are computed using appropriate distance metrics, typically employing Euclidean distance or other distance measures.

$$\begin{aligned} S_i^+ &= \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_i^+ \right)^2} \ \forall j \\ S_i^- &= \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_i^- \right)^2} \ \forall j \end{aligned} \tag{6}$$

In Step 5 of the TOPSIS, the determination of the relative closeness of each risk factor to the ideal solution ($\mathcal{A}^+$) is crucial. This step involves computing the relative proximity or similarity measure for each risk factor by evaluating its distance from the ideal solution relative to its distance from the negative ideal solution.

$$C_j^+ = \frac{S_j^+}{S_j^+ + S_j^-} \tag{7}$$

In step 6, we rank alternatives based on C_j^+ values.

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4. Results and Discussion

This section presents the culmination of the integrative approach employed in this study, unveiling empirical findings and facilitating a comprehensive discourse on the outcomes derived from the amalgamation of multi-information fusion and multi-criteria decision-making for risk assessment. This section encapsulates the empirical manifestations of the methodology elucidated in the preceding sections, showcasing the synthesized insights garnered through the application of the integrative framework in real-world scenarios. Through meticulous analysis and interpretation, this section delves into the multifaceted outcomes, emphasizing the efficacy of the proposed approach in systematically evaluating risks across domains.

To assess the efficacy of the suggested evaluation methodology, simulations were conducted using historical information on navigational incidents. The initial data regarding conventional shipping accidents from 2000 to 2019 were collected, encompassing incidents caused by various factors. This information is presented in Table 1. Furthermore, via the process of consultation with specialists, we have successfully verified the distinct risk factors derived from four primary categories, including maritime variables (V_{ship}), remote controlling variables (V_{remote}), environment variables (V_{env}), and rescue management variables (V_{manage}).

Table 1: Fused data concerning industrial accidents in old ships.

$Year_j$	V_{ship}	V_{remote}	V_{env}	V_{manage}	**Total**
2000	1	7	2	5	15
2001	4	2	4	3	13
2002	5	1	1	4	11
2003	7	6	4	6	23
2004	5	5	3	5	18
2005	5	2	3	6	16
2006	7	6	3	4	20
2007	5	2	5	3	15
2008	4	7	4	4	19
2009	2	4	3	1	10
2010	5	5	5	4	19
2011	3	7	4	5	19
2012	5	5	3	3	16
2013	2	3	5	3	13
2014	3	4	5	1	13
2015	1	5	3	3	12
2016	1	4	1	4	10
2017	2	6	4	6	18
2018	2	5	2	3	12
2019	3	1	1	3	8
Total	72	87	65	76	300

Next, a total of 564 instances of conventional maritime accidents were converted into a subset of 262 accident occurrences that correspond to autonomous ships, as illustrated in Table 2. Prior to 2010, ships were still devoid of autonomous support systems. The utilization of autonomous support devices on conventional ships has increased in tandem with advancements in science and technology. It is worth noting that during the initial implementation of these smart gadgets, both the drivers' competency and the equipment's performance were not fully developed. Consequently, there was an associated rise in maritime crashes attributed to these factors. As a consequence of ongoing operational efficiency and the rectification of equipment deficiencies during usage, there has been a decline in maritime traffic incidents. In the statistical data, a notable surge was observed around the year 2010. Through the application of analogy, it is possible to predict that the incidence of incidents during the early phase of intelligent ship design will

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escalate over time and eventually reach a peak. As a result of ongoing advancements and the increasing sophistication of pertinent technologies, there will be a decrease in the occurrence of accidents.

Table 2: Fused data concerning industrial accidents in autonomous ships.

$Year_j$	V_{ship}	V_{remote}	V_{env}	V_{manage}	Total
2000	2	2	3	2	9
2001	3	3	3	2	11
2002	1	2	2	2	7
2003	3	3	1	3	10
2004	2	5	3	2	12
2005	3	3	1	3	10
2006	1	4	3	2	10
2007	1	3	1	2	7
2008	3	4	3	1	11
2009	3	3	2	4	12
2010	1	1	4	2	8
2011	3	4	2	3	12
2012	2	3	2	2	9
2013	1	2	3	1	7
2014	2	2	1	2	7
2015	1	3	3	2	9
2016	2	2	1	1	6
2017	2	3	2	2	9
2018	1	3	1	3	8
2019	2	2	1	2	7
Total	39	57	42	43	181

The statistical findings presented in the above Tables reveal the following observations. The highest occurrence of maritime incidents resulting from humans was seen, with 87 incidents recorded in Table 1 and 57 incidents recorded in Table 2. The findings indicate that the significance of human variables cannot be disregarded in the context of both conventional and autonomous ships. Furthermore, the influence of environmental elements on maritime travel did not exhibit a substantial decline with the advancement of scientific and technological developments but rather saw an increase throughout a specific timeframe.

Table 3: Ranking of the Index of Holistic Risk Analysis

Year	S_i^+	S_i^-	C_j^+	Ranking
2000	0.183992	0.256306	0.660342	10
2001	0.217316	0.254364	0.549104	13
2002	0.206199	0.250425	0.573971	12
2003	0.268834	0.222123	0.508541	15
2004	0.234103	0.228506	0.502087	16
2005	0.080861	0.392151	0.927835	1
2006	0.230417	0.199761	0.49423	17
2007	0.114345	0.381359	0.807692	7
2008	0.207017	0.276975	0.641902	11
2009	0.309634	0.185608	0.356369	18
2010	0.212978	0.22171	0.520844	14
2011	0.089706	0.401795	0.86614	4
2012	0.354016	0.167774	0.312589	19

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2013	0.134562	0.307302	0.746088	8
2014	0.089634	0.358172	0.820796	6
2015	0.076062	0.377043	0.906703	2
2016	0.078913	0.353544	0.853515	5
2017	0.064772	0.363525	0.88539	3
2018	0.329359	0.123701	0.251409	20
2019	0.168146	0.303779	0.661818	9

The numerical outcomes derived from the risk evaluation index Cj are outlined in Table 3, depicting the comprehensive assessment of autonomous Maritime navigation risks. Upon analysis of this index, a distinct pattern emerges: the comprehensive risk evaluation index initially experiences a decline, attains a minimum value, and subsequently displays an upward trajectory. This trend indicates a fluctuation in risk levels associated with autonomous Maritime navigation over the observed period. Consequently, it can be inferred that the number of accidents involving autonomous Maritime navigation is anticipated to rise during the initial phase, culminating in a peak occurrence at a specific juncture.

These outcomes bear significant implications for the field of autonomous maritime operations. The observed decline followed by an upsurge in the comprehensive risk evaluation index signifies a temporal evolution in risk levels. The initial decline might be indicative of a phase characterized by adaptation, learning, and implementation of improved safety measures within autonomous navigation systems. However, the subsequent upward trend raises concerns regarding potential challenges or vulnerabilities emerging post-adaptation, possibly due to increased operational complexities, system limitations, or unforeseen environmental factors. These implications emphasize the necessity for continued vigilance, refinement of navigation systems, and proactive measures to mitigate risks in autonomous ship operations. Furthermore, this predictive trend highlights the importance of preemptive interventions and the implementation of robust safety protocols to manage and curb the anticipated surge in accidents during the identified peak period, thus fostering a safer and more secure autonomous maritime landscape.

Table 4 showcases the coupling coordination degree between pairs of these risk variables (e.g., V_{ship} and V_{remote}, V_{manage} and V_{env}, etc.). This analysis quantifies the degree of mutual influence or interdependence between each pair of risk variables. Higher coupling coordination degrees signify stronger correlations between the respective pairs, indicating a more significant impact of one variable on another within the context of autonomous Maritime navigation. For instance, a high coupling coordination degree between V_{ship} and V_{remote} implies a stronger mutual influence between ship-related factors and shore-based remote-control factors on accident occurrences in autonomous navigation.

Table 4: Coupling Coordination Degree Between Pairs of Risk Variables in Autonomous Maritime Navigation.

Year	$\boldsymbol{V_{ship}, V_{remote}}$	$\boldsymbol{V_{ship}, V_{env}}$	$\boldsymbol{V_{ship}, V_{manage}}$	$\boldsymbol{V_{remote}, V_{env}}$	$\boldsymbol{V_{remote}, V_{manage}}$	$\boldsymbol{V_{env}, V_{manage}}$
2000	0.324781	0.43458	0.401272	0.283198	0.324419	0.462919
2001	0.416406	0.424079	0.326813	0.391756	0.317396	0.320878
2002	0.420278	0.335019	0.296417	0.409311	0.399158	0.298202
2003	0.369929	0.342383	0.393944	0.417538	0.404223	0.331354
2004	0.393496	0.3449	0.36613	0.386668	0.403546	0.363989
2005	0.353147	0.341656	0.381725	0.408104	0.433176	0.329738
2006	0.389681	0.33359	0.326705	0.387084	0.401034	0.369734
2007	0.330211	0.37807	0.384754	0.452928	0.349492	0.295269
2008	0.356627	0.371451	0.358464	0.348376	0.373254	0.3971
2009	0.36583	0.345089	0.363389	0.37699	0.383106	0.350502
2010	0.416755	0.444298	0.333391	0.315846	0.301257	0.384161
2011	0.365854	0.371328	0.34773	0.300892	0.353989	0.42339

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2012	0.447836	0.367177	0.333668	0.381136	0.355765	0.347048
2013	0.271365	0.437814	0.475245	0.32618	0.282673	0.347682
2014	0.305321	0.355423	0.469283	0.377013	0.373283	0.325869
2015	0.278349	0.443639	0.456587	0.325131	0.322437	0.399653
2016	0.333183	0.360679	0.378649	0.266345	0.345731	0.476962
2017	0.241142	0.354231	0.488961	0.286336	0.32557	0.411621
2018	0.377812	0.387414	0.318733	0.248531	0.308383	0.490804
2019	0.342619	0.25537	0.381058	0.382285	0.487715	0.325981

Moving to Table 5, the analysis extends to evaluate the coupling coordination degree among triplets of risk variables. This assessment offers insights into the combined influence and interactions among these sets of three risk variables. A higher degree of coupling coordination among these triplets indicates more intricate interplays and potential compounded effects on the occurrences of accidents within autonomous Maritime navigation.

Table 5: Analysis of Coupling Coordination Degree Among Triplets of Risk Variables in Autonomous Maritime Navigation.

Year	$\boldsymbol{V_{ship}, V_{remote}, V_{env}}$	$\boldsymbol{V_{ship}, V_{remote}, V_{manage}}$	$\boldsymbol{V_{remote}, V_{env}, V_{manage}}$	$\boldsymbol{V_{ship}, V_{manage}, V_{env}}$
2000	0.692272	0.801497	0.751559	0.704541
2001	0.811692	0.723199	0.702805	0.722946
2002	0.795719	0.659978	0.781266	0.779414
2003	0.748291	0.713454	0.76779	0.810943
2004	0.756859	0.708463	0.767812	0.760905
2005	0.735217	0.696078	0.778744	0.80074
2006	0.736079	0.699	0.754885	0.738133
2007	0.768746	0.731283	0.701911	0.790832
2008	0.710833	0.759566	0.758679	0.706152
2009	0.764924	0.724871	0.775422	0.757943
2010	0.779805	0.752177	0.745815	0.670663
2011	0.722247	0.79065	0.744237	0.714479
2012	0.780317	0.725111	0.753455	0.756414
2013	0.751237	0.830705	0.610358	0.751124
2014	0.694486	0.797515	0.684717	0.791501
2015	0.741782	0.803729	0.692697	0.726943
2016	0.6836	0.801762	0.796525	0.704655
2017	0.642763	0.822677	0.725315	0.7346
2018	0.677386	0.774909	0.78209	0.649659
2019	0.706591	0.674482	0.775985	0.83128

The implications derived from these analyses remain substantial. Identifying strong coupling coordination degrees among specific risk variables highlights their interconnectedness and mutual influence within autonomous Maritime navigation. Understanding these intricate relationships is crucial for developing targeted risk mitigation measures that address multiple variables simultaneously, ultimately enhancing the safety and reliability of autonomous navigation systems. Moreover, recognizing the coupled nature of these risk variables enables stakeholders to adopt proactive approaches in risk management. By comprehending the interplay among these variables, proactive measures can be implemented to mitigate potential compounded risks before they manifest as critical incidents. Additionally, these analyses aid in identifying potential areas of vulnerability or cascading effects stemming from the interrelated risk

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variables, enabling preemptive interventions to curtail the likelihood of accidents within autonomous Maritime navigation.

5. Conclusion and Future work

In conclusion, the analysis of risk factors in autonomous Maritime navigation, employing information fusion methodologies, has illuminated the intricate interplay among ship-related, human-related control, environmental, and crisis management influences. The evolving trends in the comprehensive risk evaluation index underscore the dynamic nature of risks in this domain, highlighting the significance of information fusion in comprehensively assessing and managing these complexities. The examination of coupling coordination degrees among these risk variables has unveiled their interconnectedness, emphasizing the pivotal role of integrated data fusion techniques in understanding and mitigating multifaceted risks. Future research efforts should focus on refining information fusion models, leveraging real-time data integration, and enhancing predictive analytics to bolster risk assessment frameworks. Collaborative initiatives among industry stakeholders, data scientists, and policymakers will be pivotal in formulating robust, adaptable information fusion strategies, laying the groundwork for a safer and more resilient autonomous maritime environment.

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