Human-MASS Interaction in Decision-Making for Safety and Efficiency in Mixed Waterborne Transport Systems

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Human-MASS Interaction in Decision-Making for Safety and Efficiency in Mixed Waterborne Transport Systems

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Delft University Technology

Human-MASS Interaction in Decision-Making for Safety and Efficiency in Mixed Waterborne Transport Systems

Proefschrift

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aan de Technische Universiteit Delft,

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voorzitter van het College voor Promoties,

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Dedicated to
my parents

Preface

Writing this thesis marks the end of a long and challenging journey, during which I experienced not only the ups and downs of academic research but also moments of personal growth. Looking back, this process has been far more than completing a research project. It has been a transformative experience that shaped how I think, work, and relate to others. I feel deeply grateful for the people who accompanied me along the way and made this journey meaningful.

First and foremost, I would like to express my sincere gratitude to my three supervisors: Prof. dr. ir. Pieter van Gelder, Prof.dr. Rudy R. Negenborn, and Dr. Eleonora Papadimitriou. I feel truly fortunate to have been guided by all of them, each of whom has shaped my PhD journey in their own way. I would especially like to thank Prof. dr. ir. Pieter van Gelder and Prof.dr. Rudy R. Negenborn, the key initiators of this project. It was through their joint efforts that the foundation of this research was established, and I am truly grateful for the opportunity they gave me to pursue my PhD studies and work here. To my first promoter, Prof. dr. ir. Pieter van Gelder, thank you for your warm and approachable supervision. Your patience, generosity, and friendly manner made it easy for me to share ideas and concerns throughout the process. Your broad perspective and steady encouragement helped me build confidence and move forward step by step. To my second promoter, Prof. dr. Rudy. R. Negenborn, I am especially grateful for being a steady and responsible guide throughout this journey. Your rigorous and responsible attitude toward research, along with your consistent involvement and attention to detail, ensured that the work progressed with clarity and focus. To my copromoter, Dr. Eleonora Papadimitriou, thank you for always being there during difficult moments. Your willingness to share your own experiences and challenges as a researcher made a big difference, especially when things felt overwhelming. Your understanding, encouragement, and readiness to help in every way possible meant a lot to me. Each of you played a unique and irreplaceable role in this journey. I am deeply thankful for your guidance, support, and trust.

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Lastly, I would like to express my heartfelt thanks to my family, especially my parents, for their unconditional support, understanding, and quiet strength throughout these years. Even though we were far apart, their encouragement was always with me, giving me the courage to keep going.

最后，我要衷心感谢我的家人，特别是我的父母，感谢他们这些年来无条件的支持、理解和默默的支持。尽管这个过程中我们相隔甚远，但他们的鼓励始终伴随着我，给了我继续前进的勇气。

This thesis may mark the end of one chapter, but it is also the beginning of another. As I step forward into the next stage of my academic life, I carry with me not only the knowledge gained but also the values and lessons learned from everyone who walked alongside me.

Rongxin Song,

Delft, May 2025

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Chapter 1. Introduction

Maritime Autonomous Surface Ships (MASS) are increasingly regarded as a promising solution to enhance navigational safety and efficiency in maritime transportation. However, their integration into Mixed Waterborne Transport Systems (MWTS), where autonomous and manned vessels coexist, introduces several challenges. These include ensuring effective collision avoidance without direct communication between vessels, accommodating the situational awareness of MASS in various maritime environments, human-mimic collision avoidance strategies in decision-making processes, and human trust in the decision-making of MASS to enhance coordination between human operators and autonomous systems. Addressing these challenges is essential to ensure seamless interaction while maintaining both the safety and efficiency of the navigation in an MWTS.

Motivated by the need to bridge these gaps, this research aims to develop a decision-making framework that integrates situational awareness, human-mimic navigation, and trust as key components. This chapter is organised as follows: Section 1.1 introduces the research context. Section 1.2 identifies the key challenges in mixed waterborne transport. Sections 1.3 and 1.4 formulate the research questions and describe the methodologies adopted to address them. Section 1.5 specifies the research scope of the thesis, while Section 1.6 highlights the contributions. Finally, Section 1.7 presents the outline of the structure of the thesis.

1.1 Transition to Mixed Waterborne Transport

Global shipping is the backbone of international trade, transporting 90% of goods trade by volume worldwide. This vital system ensures the seamless movement of essential resources, such as raw materials, energy, and food. Specifically, it becomes more important for the Dutch economy. 90% of imports and two-thirds of exports are via sea and inland shipping. These exports contribute more than 30% to the Dutch GDP. With a total added value of 56.5 billion euros and 590,000 employees, maritime is one of the largest pillars of the Dutch economy[1]. The critical role underscores the importance of shipping in maintaining the smooth functioning of either the international or domestic economy. Any disruption in shipping operations, including accidents, inefficiencies, and limitations of logistical capabilities, may lead to supply chain disruptions, severe threats to human lives, and significant economic losses.

Safety remains a fundamental concern in the maritime industry, as accidents result in consequences for human life and economic losses. As such, when we focus on the issues of accidents, ensuring the safety of maritime transport is essential. According to the report [2] issued by the European Maritime Safety Agency (EMSA) in 2022, navigation accidents, including collisions, groundings, and contacts, account for 28% of all marine casualties reported in the European Marine Casualty Information Platform (EMCIP) database. The analysis, based on 8,800 occurrences involving vessels flying EU Member State flags within Member States' territorial waters or linked to European interests spanning 2011 to 2021, highlights critical safety concerns, particularly in collision-related incidents. Collisions are among the most frequent types of accidents, with manoeuvring and turning operations (3,108 cases) and port areas (711 cases) identified as high-risk contexts. Importantly, human errors contribute to 83.5% of collision-related events, manifesting through delayed decision-making, missed observations, and inadequate planning during navigation phases. These results underscore the pressing need for effective collision avoidance to mitigate navigational risks and enhance maritime safety.

Efficiency, on the other hand, is equally critical in ensuring the sustainability of maritime operations. The optimisation of travel routes and fuel consumption not only reduces operational costs but also minimises environmental impact, aligning with global sustainability goals. Additionally, delays caused by port congestion or suboptimal routing can disrupt global supply chains, leading to economic losses across multiple industries. Achieving operational efficiency, therefore, involves both improving navigational efficiency and ensuring smooth interactions between vessels, particularly in high-risk areas such as ports.

In response to these challenges, Maritime Autonomous Surface Ships (MASS) have emerged as a promising solution, offering the potential to reduce human error, a main cause of maritime accidents[3], and optimise operational efficiency. Over the years, several MASS-related projects have been initiated globally. For example, MUNIN [175], AAWA [23], and NOVIMAR

[1] https://maritiemland.nl/en/maritime-master-plan/

[2] https://www.emsa.europa.eu/newsroom/latest-news/item/4830-safety-analysis-of-emcip-data-analysis-of-navigation-accidents.html

[3] https://www.emsa.europa.eu/safemed-iv-project/component-5-human-element-in-maritime-safety.html

[77]. These initiatives underscore the growing interest in commercial autonomous shipping and their potential towards addressing safety and efficiency concerns.

To ensure the integration of MASS into existing maritime frameworks, the International Maritime Organisation (IMO) categorizes MASS into four levels of autonomy, as shown in Table 1-1. This classification ranges from ships with basic automation to fully autonomous ships capable of making independent decisions. Besides, to meet specific needs, a more detailed Level of Autonomy for MASS [126] and a new classification for autonomous surface vessels [184] regarding the overall system and sub-systems were proposed. Importantly, the autonomy level of a MASS may vary across different operational phases [132]. For instance, an open sea transit may be fully automated, requiring minimal human intervention, while port approaches open require significant human oversight. These classifications underscore the challenges MASS face in practical applications, particularly in the interaction between vessels of varying autonomy levels and manned ships or operators.

Table 1-1 Classification of the autonomy degree of maritime autonomous surface ships by IMO

Degree in Maritime Autonomous Surface Ships		Description
1	Ship with automated processes and decision support	Seafarers are on board to operate and control shipboard systems and functions. Some operations may be automated.
2	Remotely controlled ship with seafarers on board	The ship is controlled and operated from another location, but seafarers are on board.
3	Remotely controlled ship without seafarers on board	The ship is controlled and operated from another location. There are no seafarers on board.
4	Fully autonomous ship	The ship's operating system is able to make decisions and determine actions by itself.

Given the background of the autonomy levels of MASS and application scenarios, mixed waterborne transport systems (MWTS) will become inevitable in the short future, where MASS and manned ships will co-exist. However, the integration of MASS into the MWTS will introduce new challenges regarding safety and efficiency in high-risk navigational contexts. Unlike fully autonomous systems capable of cooperative navigation and communication, MWTS may be limited in the exchange of timely and effective navigational intentions. Thus, MASS should be capable of not only avoiding collisions with surrounding manned vessels in various situations but also maintaining efficient interaction and operations in an MWTS.

1.2 Problem statement

Drawing on the challenges identified in the background, the thesis addresses three critical aspects of MASS operations: situational awareness, navigational preference-aware human-mimic collision avoidance, and human trust. By focusing on these dimensions, the research seeks to design a decision-making framework for MASS that ensures safe and efficient navigation for MASS in an MWTS.

First, **situational awareness** is crucial for the safe navigation of autonomous ships, involving the comprehensive capability construction of both human seafarers and autonomous systems to perceive, understand, and predict the maritime environment. Effective situational awareness requires not only sensors on board but also integrating domain knowledge and expertise of seafarers to build a reliable understanding of the navigational context. In this way, MASS can make timely decisions across various navigational scenarios. While prior studies have investigated framework design [68], requirements [225], sensor technologies [205], computation and evaluation [163] for enhancing situational awareness, most of the studies fail to fully address the unique challenges of integrating MASS into mixed-traffic environments, particularly the transparency of MASS decision-making to human operators and surrounding vessels. For example, how to generate explainable actions based on multi-source data towards an increased transparent decision-making process remains underexplored. Addressing this gap is essential for fostering human trust, improving situational understanding, and ensuring safer navigation within an MWTS.

Second, navigational preference-aware **human-mimic** collision avoidance is necessary to ensure that autonomous vessels can adapt to the behaviours of surrounding manned vessels for safe and efficient interaction. Various algorithms have been designed and developed to improve the safety and efficiency of autonomous ships. For example, Velocity Obstacle [91], reinforcement learning [223], and model predictive control [53] have greatly improved the evasive capabilities of autonomous vessels. However, most existing studies simulate surrounding vessels on fixed trajectories and focus on enhancing the evasive algorithms of MASS, limiting their adaptability in an MWTS. An evasive model involving the human navigational preferences of manned ships in collision avoidance is crucial to providing proactive and mutually understandable navigation strategies within the MWTS, avoiding potential conflicts while maintaining operational efficiency.

Finally, **human trust** in autonomous systems is critical during high-risk scenarios such as collision avoidance. A lack of trust may lead to unnecessary interventions by operators, undermining the reliability of MASS in such scenarios. Recent advances in trust theories in human-autonomy interaction have focused on three aspects, including framework [86], measurement [136], investigation methods [218], and computational models [232]. In the maritime domain, studies have begun to explore the impact of trust on the decision-making process of MASS operators in a remote monitoring centre [130][132]. However, understanding trust dynamics during decision-making processes in collision avoidance scenarios remains underexplored. It is the foundation of developing and maintaining trust, which is critical for reliable and transparent decision-making between operators and autonomous systems.

Overall, addressing situational awareness, human preferences, and human trust is essential for ensuring the safe and efficient navigation of MASS in an MWTS. By bridging the gaps in transparency, adaptability, and reliability, this research aims to develop a comprehensive decision-making framework that facilitates seamless interaction between autonomous and manned vessels.

1.3 Research questions

The main research question addressed in this thesis is:

How can a decision-making framework for collision avoidance, incorporating situational awareness, human preferences, and human trust, be developed to ensure safe and efficient interaction between autonomous and manned vessels in mixed waterborne transport systems?

To address the main research question, we will answer the following sub-questions:

(1) Questions on the state of the art:

(i) What is the state of the art on the safety and efficiency of human-MASS interaction?

(ii) What factors should be considered in the decision-making framework?

(2) Questions on the situational awareness modelling:

(iii) How can data from multiple sources be effectively integrated for situational awareness?

(iv) How can a local path planning algorithm tailored to 3 degrees of freedom vessels be developed, integrating the results of situational awareness?

(3) Questions on the human preferences for human-mimic collision avoidance:

(v) How can AIS data be utilised to extract the navigational preferences of conventional vessels for collision avoidance?

(vi) How can past vessels' trajectories be used to develop a real-time movement prediction model with improved accuracy and interpretability based on human navigational preferences?

(vii) How does the prediction result support the interactive collision avoidance of MASS in a mixed waterborne environment?

(4) Questions on human trust:

(viii) How can human trust in MASS in collision avoidance be measured, analysed, and modelled within controlled experimental settings?

1.4 Research approach

To address the research questions, this research adopts a systematic and integrated research approach. The proposed approach develops a decision-making framework by addressing gaps in situational awareness, human-mimic collision avoidance, and trust dynamics. The following paragraphs describe how each aspect of the framework is designed.

To achieve situational awareness, we leveraged ontology capabilities to organise multi-source information and developed the knowledge maps model for MASS. This model facilitates the perception and understanding of navigational contexts, providing real-time support for decision-making. To address collision avoidance, we designed a local path-planning algorithm, Dynamic Window Approach (DWA), tailored for 3-degrees-of-freedom (DOF) MASS. The rapid search capabilities enable efficient navigation in dynamic environments. Furthermore, a collision avoidance decision-making framework was proposed, integrating real-time results from knowledge maps, referred to as Knowledge Maps-based Dynamic Window Approach (KM-DWA), to ensure safe and informed decision-making.

For human-mimic navigation, we utilised AIS data to detect collision candidates and employed an LSTM-Autoencoder to classify and analyse navigational preferences. These preferences were incorporated into a proposed trajectory predictor, which leverages past trajectories of both the vessel and surrounding ships to predict future movements. This predictor simultaneously forecasts the trajectories of the MASS and nearby vessels, enabling collision avoidance strategies that align with human navigational preferences. The proposed decision-making framework combines these human-mimic trajectories to ensure safety with the KM-

DWA local path planner. This integration allows real-time obstacle detection; in high-risk scenarios, the system executes local collision avoidance manoeuvres before returning to the recommended human-mimic trajectories.

To explore trust dynamics, we conducted simulator-based experiments to investigate observer trust during collision avoidance scenarios. A linear mixed model was applied to identify the main and interaction factors influencing trust. Building on these insights, a Bayesian network-based trust model (TBN) was constructed to model trust dynamics across different stages of the collision avoidance process. This model identified critical factors affecting key trust, including proper avoidance timing and strategies for adherence to collision-avoidance regulations. These findings provide actionable insights for proactive collision avoidance strategies, enhancing trust between autonomous and human operators.

In summary, this research integrates situational awareness, human-mimic navigation, and trust into a comprehensive decision-making framework for collision avoidance in MWTS. By leveraging knowledge maps, the trajectory predictor, and the trust model, the proposed framework provides support for safe and efficient interaction between autonomous and manned vessels.

1.5 Research scope

The scope is defined by the following considerations:

(1) To ensure clarity, safety in this thesis refers to navigational safety, focusing on collision-free vessel operations. Efficiency denotes the optimal utilisation of navigational resources, i.e., minimising voyage time.
(2) This study focuses on Level 3 MASS, which are capable of autonomous navigation and collision avoidance. These vessels are supervised remotely, and shore-based operators are responsible for monitoring the system and taking control when necessary, especially in unexpected or high-risk situations.
(3) This thesis examines the interaction between autonomous vessels and human-operated vessels within mixed waterborne transport where direct exchange of navigational intentions is not feasible. The *interaction* studied in this thesis is defined as a proactive response by autonomous vessels to ensure safety and efficiency, relying on observable behaviours of nearby vessels to interpret and react to the surrounding navigational context.
(4) Fixed surrounding vessel behaviour**:** The thesis does not control surrounding vessels in real time but considers their interactions as part of the navigational context. Instead, the trajectories of surrounding vessels are predefined based on actual AIS data for navigation experiments or kept constant across scenarios in situation-aware decision-making experiments and simulator-based trust studies. In all experiments, the surrounding vessel's behaviour is unaffected by the changes in the autonomous vessel's actions. Real-time control is limited to the autonomous vessel itself.

1.6 Contributions

This thesis contributes to advancing the safe and efficient integration of MASS into the MWTS through an integrated decision-making framework, which is summarised as follows:

(1) **An integrated decision-making framework**: This research proposes an integrated decision-making framework for MASS in MWTS based on a systematic literature review, focusing on situational awareness, navigational preference-aware human-mimic collision avoidance, and human trust in the decision-making of MASS. **Impact**: This work lays the foundation for coordinated collision avoidance between autonomous and manned vessels to reach seamless interaction in MWTS restricted by the exchange of navigational intentions. (The systematic literature review and decision-making framework design are discussed in *Safety and Efficiency of Human-MASS Interactions: Towards an Integrated Framework* (published in *Journal of Marine Engineering and Technology* [191])).

(2) **Situational awareness through knowledge maps**: The thesis introduces a situational awareness model based on ontology-driven knowledge maps, enabling the integration of multi-source information for dynamic maritime environments. A DWA algorithm tailored for 3-DOF vessels further supports real-time collision avoidance. This work extends situational awareness by integrating navigational rules with reactive path planning, addressing transparency and decision-making challenges in autonomous navigation. **Impact**: The approach enhances MASS's adaptability and responsiveness to dynamic navigational scenarios, improving safety and efficiency outcomes. (Methodology and results are presented in *Integrating Situation-Aware Knowledge Maps and Dynamic Window Approach for Safe Path Planning by Maritime Autonomous Surface Ships* (published in *Ocean Engineering* [192])).

(3) **Navigation preference-aware human-mimic collision avoidance**: By analysing AIS data, the research develops a novel trajectory prediction model that incorporates human navigational preferences. The approach integrates past vessel trajectories into a multi-task learning seq2seq LSTM attention framework to enable preference-aware collision avoidance. **Impact**: The results contribute to proactive and interpretable collision avoidance strategies, fostering seamless, safer, and more efficient interactions in MWTS. (This contribution is elaborated in *Enhancing Collision Avoidance in Mixed Waterborne Transport: Human-Mimic Navigation and Decision-Making by Autonomous Vessels* (under review)).

(4) **Trust Dynamics in Human-MASS Interaction**: The thesis models trust dynamics between operators and MASS through a Trust Behaviour Network, informed by experimental findings on trust evolution during collision avoidance tasks. This work introduces both statistical and probabilistic approaches to understanding and modelling trust in collision avoidance scenarios, identifying key factors such as evasion timing and actions. **Impact**: The findings provide insights for designing MASS's decision-making systems that align with human operator's expectations. (The results are detailed in *Experimental Trust Dynamics Modelling in the Supervised Autonomous Ship Navigation in Collision Avoidance Scenarios* (under review))

1.7 Thesis outline

The outline of this thesis is shown in Figure 1-1. This thesis is structured into six chapters, each addressing key aspects of the research and contributing to the development of a comprehensive decision-making framework for collision avoidance in an MWTS. Each chapter corresponds to specific research questions (RQs) as outlined below:

Chapter 1. **Systematic Literature Review** (addresses **RQ1-i, ii**). This chapter conducts a systematic literature review to evaluate the current state of human-MASS interaction, with a focus on safety and efficiency. The analysis identifies research gaps, including situational awareness, human preferences, and human trust. Based on these findings, a comprehensive decision-making framework is then proposed, integrating these three critical factors to address these gaps.

Chapter 2. **Situational Awareness through Knowledge Maps** (addresses **RQ2-iii, iv**). This chapter introduces a situational awareness model based on ontology-driven knowledge maps, enabling the integration of multi-source information to support navigation decisions. An adaptive DWA local path-planning algorithm designed for 3-DOF vessels is developed to facilitate real-time collision avoidance in dynamic environments. The proposed decision-making framework incorporates DWA with knowledge maps-based situational awareness capabilities, ensuring transparent and safe collision avoidance.

Chapter 3. **Human-Mimic Navigation** (addresses **RQ3-v, vi, vii**). This chapter focuses on extracting navigational preferences and predicting trajectories for human-mimic navigation. Using AIS data, an LSTM-autoencoder combined with K-means clustering is employed to classify and analyse ship manoeuvring preferences during collision avoidance scenarios. Furthermore, a Multi-Task Learning Sequence-to-Sequence LSTM model with attention (MTL-Seq2Seq-LSTM-Att) is developed to predict the future trajectories of both the own ship and neighbouring vessels. By integrating preference-aware trajectory predictions into the decision-making framework, the study achieves safer, more efficient, and proactive interactions in MWTS.

Chapter 4. **Trust Dynamics in Collision Avoidance** (addresses **RQ4-viii**). This chapter investigates the dynamics of human trust in MASS during collision avoidance scenarios. Trust was measured through post-scenario evaluations using a quantitative survey and analysed with a linear mixed model to capture stage-specific trust variations. The findings reveal distinct trust evolution patterns across stages, highlighting critical factors such as decision-making strategies and timing. A Trust Behaviour Network was developed to model trust dynamics, emphasising the critical role of system competence. Diagnostic analysis further demonstrated the importance of proactive right-turn strategies with proper timings in enhancing trust. These insights provide actionable guidance for designing transparent and trustworthy MASS systems that align with observer expectations.

Chapter 5. **Conclusion and Future Work**. The final chapter summarises the research contributions, discusses the practical implications of the findings and outlines potential directions for future research.

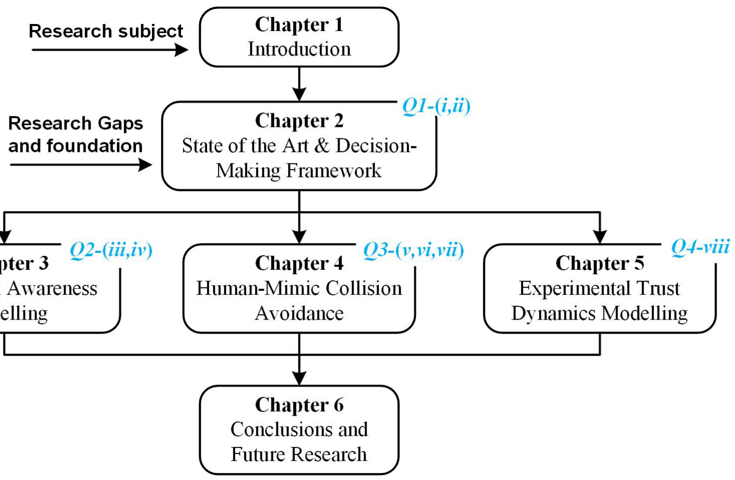

Figure 1-1 The outline of this thesis

Chapter 2. Literature Review & Decision-Making Framework

This chapter provides a comprehensive review of the existing research on the interaction between human operators and Maritime Autonomous Surface Ships (MASS), with particular emphasis on key factors influencing the safety and efficiency of MASS. By addressing research questions RQ1-i and RQ1-ii, the chapter examines the state of the art in human-MASS interaction and identifies the factors that should be considered in a decision-making framework. Building upon the insights and gaps identified in the literature, a decision-making framework is developed.[1] *The chapter is organised as follows: Section 2.1 outlines the methodology and approach used to conduct the review. Section 2.2 presents the results of the state-of-the-art research. Section 2.3 identifies the findings and gaps and proposes the decision-making framework. Finally, Section 2.4 summarises the conclusion.*

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[1] The contents of this chapter have been published in [191].

2.1 Introduction

The objective of this chapter is to review and discuss several key issues related to the safety and efficiency of MASS and the importance of carefully considering them during both the design and operation phases. For this purpose, the chapter starts by formulating four research questions, which are detailed in Table 2-1.

Table 2-1 Research questions related to human-MASS interaction

Questions	Section
What is the state of the art on the safety and efficiency of human-MASS interaction?	3.1
How can situational awareness be applied to MASS safe navigation, and how can it be measured?	3.2
How can MASS make decisions to avoid collision with manned ships or ships with different degrees of autonomy?	3.3
What factors could influence human trust in MASS, and how can trust be measured?	3.4

- **Review scoping**

The process of literature review, as depicted in Figure 2-1, was conducted systematically to ensure a comprehensive and focused analysis of relevant studies. Initially, a detailed search was carried out across two databases, including Scopus and Web of Science, using carefully selected keywords that align with the research themes, as detailed in Table 2-2. This search, conducted up to May 2024, yielded a total of 209 English records (85 from Web of Science and 124 from Scopus). The results of this screening process, including the number of papers related to each topic, are summarised in Table 2-3.

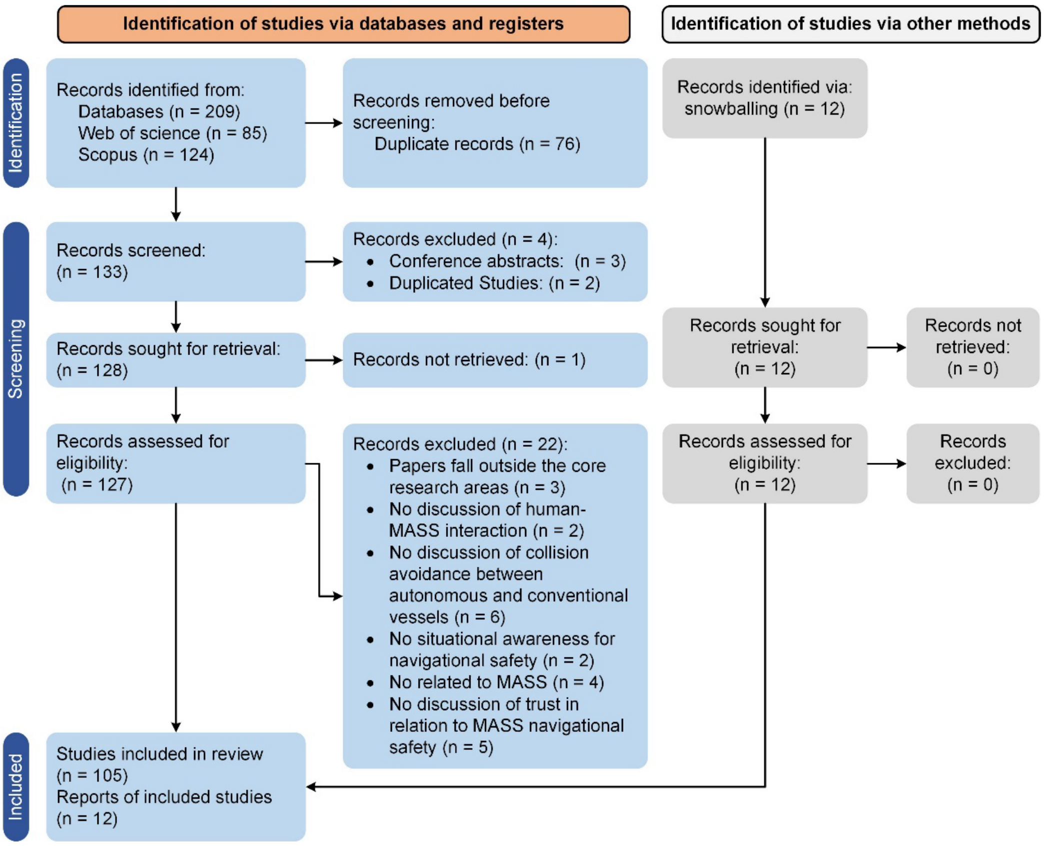

Figure 2-1 The flow diagram of the literature screening process

An eligibility assessment was then performed on the remaining records, which led to the exclusion of 22 studies due to reasons such as their falling outside the core research areas, not discussing relevant MASS safety mechanisms, or not addressing key aspects like trust or human-MASS interaction.

To ensure the breadth of the literature covered, a snowballing technique was employed, which identified 12 additional studies that were not captured during the initial database searches. Ultimately, this process resulted in the selection of 105 studies for detailed analysis. These included both empirical studies and 12 key reports, which were then examined to address the research questions.

- **Structure of review**

To provide a clear picture of the interplay between these topics and human-MASS interaction, we first present an in-depth overview of situational awareness, decision-making strategies, and human trust in MASS as they relate to safety and efficiency in an MWTS. Through this approach, we aim to uncover the connections among these themes and highlight their significance.

Additionally, we perform a detailed analysis of the relationships between the three sub-research topics and human-MASS interaction, specifically in the context of safety and efficiency. This analysis provides insights into the relationship between individual research themes in human-ship interaction and their correspondence to the broader themes of safety and efficiency.

The bibliometric approach is used here to investigate the relationships between key concepts in the literature on human interaction with MASS using the term co-occurrence analysis method. The visualisations presented in Figure 2-2 and Figure 2-3 demonstrate the connections between various research themes.

Figure 2-2 shows a network of colours where each colour stands for a different theme: green for safety, yellow for efficiency, purple for human-MASS interaction, red for situational awareness, teal for human trust, and brown for decision-making. The width of the lines connecting these themes indicates how often they are mentioned together in the literature; wider lines mean more frequent mentions.

Figure 2-3 zooms in on the interplay between safety and efficiency. The visual articulation, using the same colour coding, emphasises the substantial overlap between these directions. This intersection underscores a salient research trend: considerations of efficiency are rarely isolated from safety imperatives. The emergent pattern from this confluence indicates that safety considerations form the primary context within which efficiency is situated and discussed.

From these figures, we draw two main conclusions: firstly, safety is a major concern and is often discussed along with efficiency, reflecting a tendency to consider them jointly rather than separately. Secondly, there is a noticeable gap when it comes to human trust, especially in connection with safety and efficiency. This gap suggests that more research is needed to understand how trust in autonomous systems can affect the adoption and use of MASS.

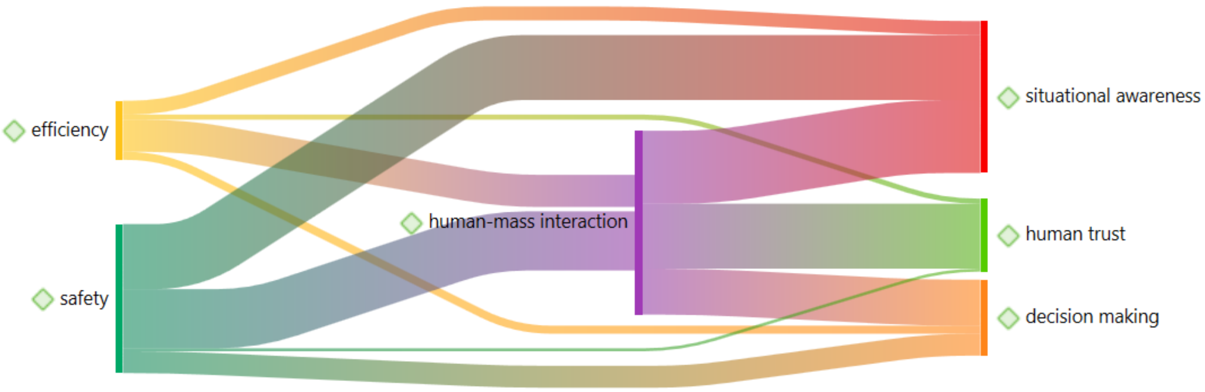

Figure 2-2 The visualisation of overall co-occurrence analysis of various research themes.

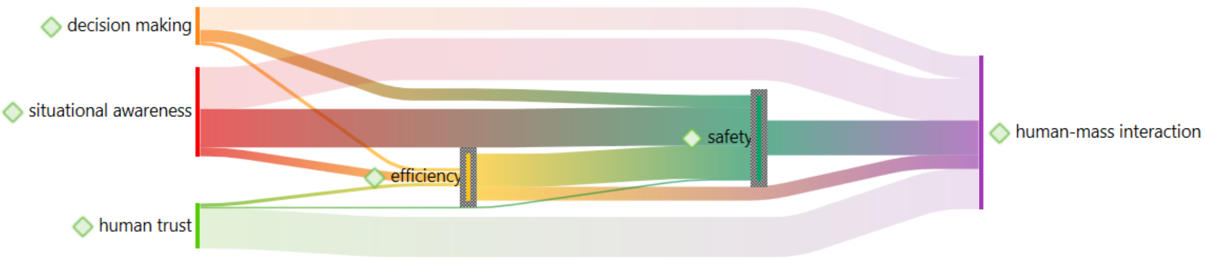

Figure 2-3 The visualisation of co-occurrence among three directions and human-MASS interaction considering safety and efficiency.

Table 2-2 Keywords corresponding to each research question

No.	Keywords	Scopus	Web of Science
1	TS = (“Human” AND (“autonomous ship*” OR “maritime autonomous surface ship*” OR “autonomous vessel*” OR “maritime autonomous surface vessel*”) AND (“interact*” OR “cooperat*”)” AND (“safety” OR “efficiency”))	46	29
2	TS = (“Situation* awareness” AND “human” AND (“autonomous ship*” OR “maritime autonomous surface ship*” OR “autonomous vessel*” OR “maritime autonomous surface vessel*”))	41	30
3	TS = ((“Autonomous ship*” OR “maritime autonomous surface ship*” OR “autonomous vessel*” OR “maritime autonomous surface vessel*”) AND (“manned ship*” OR “conventional ship*” OR “ manned vessel*” OR “conventional vessel*”) AND “collision avoidance”)	25	28
4	TS = (“Trust” AND (“autonomous ship*” OR “maritime autonomous surface ship*” OR “autonomous vessel*” OR “maritime autonomous surface vessel*”))	28	16

2.2 Review results

2.2.1 Human-MASS interaction for safety and efficiency

2.2.1.1 Human factors

The concept of human complementary in the maritime domain has gained much attention in recent years. It involves the collaboration between MASS and human operators to enhance safety, efficiency, and overall performance in water areas. The human factor is of paramount importance in the successful implementation of human-MASS interaction, particularly in ensuring safety. In this regard, extensive research has been conducted in this area to investigate the various facets of the human factor in the context of MASS operations.

Table 2-3 The overview of the relevance between literature and research questions

References	State of the art			$SA^{\dagger}$	$CA^{\dagger}$	$HT^{\dagger}$
	$HMI^{\dagger}$	Safety	Efficiency			
[247]			✓		✓	
[14]			✓	✓	✓	
[223][238]		✓			✓	
[216] [160]		✓		✓		
[193]		✓		✓	✓	
[205]		✓	✓	✓		✓
[229][24] [165]	✓					
[222]	✓					✓
[89]	✓				✓	
[202]	✓				✓	✓
[133]	✓			✓		
[131] [55]	✓			✓	✓	
[70]	✓			✓		✓
[135] [73]	✓			✓	✓	✓
[215]	✓		✓			✓
[42]	✓		✓		✓	
[174] [214] [209] [28] [208] [162] [3] [94] [203] [207] [13]	✓	✓				
[171] [4] [83] [2] [243] [242] [227] [82] [47] [11] [154]	✓	✓			✓	
[213] [60] [105] [118] [225] [39] [16] [254] [168] [188]	✓	✓		✓		
[163] [207] [237] [153] [172] [252]	✓	✓		✓	✓	
[134]	✓	✓		✓	✓	✓
[212] [211] [66] [99] [101]	✓	✓	✓			
[166] [117] [167] [137]	✓	✓	✓	✓		
[56]	✓	✓	✓	✓		✓
[140] [44] [230] [6]	✓	✓	✓	✓	✓	
[201] [100]	✓	✓	✓	✓	✓	✓

$SA^{\dagger}$ = situational awareness
$CA^{\dagger}$ = collision avoidance
$HT^{\dagger}$ = human trust

(1) Frameworks for Human Involvement in MASS

Several studies have explored the integration of humans as an essential part of MASS operations. A framework involving humans as one element of the system was proposed by [99] to improve team performance, suggesting human monitoring will be diminished to exploit the potential of fully autonomous MASS as trust develops. Furthermore, In the study referenced by [100], it is highlighted that human factors, including cultural and social aspects, may impact the effectiveness of remote ship operations and the interactions between operators in shore control centres. Specifically, these factors affecting operators responsible for MASS at Remote Control Centres (RCC) are identified and organised into thirteen distinct categories.

(2) Changes in Operator Cognition & Situational Awareness

Operator cognition and situational awareness have been studied extensively, particularly in challenging environments. The study [195] discussed the challenges of using the digital system on the vessel in the Arctic environment and highlighted the considerations that need to be taken into account when designing maritime navigation systems. Additionally, the unmanned ship was focused on investigating possible human benefits and challenges regarding ship safety [216]. In this study, situational awareness was discussed, indicating the importance of proactive communication between MASS and manned ships in an MWTS. Furthermore, Human takeover times during the operation of automated ships were analysed in [188]. The study revealed that takeover times are often longer than expected, requiring situation-specific management strategies to ensure safe and autonomous operations.

(3) Trust, Decision-Making, and Human-System Interaction

Trust between human operators and autonomous systems has been identified as a critical factor for successful collaboration. In the study [4], human elements were discussed in the MASS, which is remotely controlled. In this study, the author argued that it is critical to keep aware of the situation of human operators at RCC, which directly influences the safety and efficiency of the MASS. Moreover, it is stressed that the behaviour of MASS would influence the behaviour of the conventional ships in an MWTS. Human elements were analysed by [135] and [134] for future autonomy, where trust, situational awareness, and training were discussed based on interviews. In this study, the relationships among trust, situational awareness, and decision-making in the autonomous system were stressed. Moreover, the relationship between human trust in autonomy and professional commitment was investigated by [1]. The study finds that higher professional commitment correlates with lower trust in autonomy. This study highlights the importance of addressing human factors to foster trust in autonomous systems.

Additionally, challenges in designing the Shore Control Center (SCC) for MASS were addressed by [55], with a focus on human-machine interaction. The paper emphasised that optimising human-system interfaces is critical for operators to maintain situational awareness and make informed decisions in remote environments. Focusing on the mental health effects of humans involved in the MASS controlled remotely, the study conducted by [201] investigated in-depth human factors. It is found that the difference in situational awareness and trust discrepancy between human operators and the autonomous system could lead to high stress on humans and wrong decisions accordingly.

In order to identify potential risks in the scenario of collaborative human-MASS navigating, a method of scenario analysis was applied on a virtual remote manoeuvring platform for MASS [83]. With that method, human factors related to potential risks within human-MASS interaction can be found effectively by observing the reaction of participants. Accordingly, decision-making can be considered in the ship design phase in advance for remote-controlled MASS.

(4) Risk Assessment and Operator Error Analysis

Risk assessment and operator error analysis are critical for enhancing the safety and reliability of MASS. Numerous studies have explored the two aspects, aiming to develop models and methods that mitigate the risk of human error and improve system performance.

In terms of risk assessment, several studies have utilised advanced analytical methods to evaluate the risks associated with human factors in MASS operations. For instance, The study by [103] applied a Bayesian network method, identifying that human factors interactions and operator issues are the main factors leading to accidents. Similarly, By using Evidential Reasoning and a Rule-based Bayesian Network, risk levels of main hazards on MASS were assessed for MASS by [28]. It is stressed that the risk from the interactions for MASS within an MWTS and human failure on MASS should receive more attention. Additionally, the study by [203] evaluated the applicability of the existing 64 risk models for MASS, revealing that none of them are fully suitable for direct use. This study highlights the need for new models that incorporate multiple considerations like software performance, control algorithms, and human-machine interaction, as mentioned in the study, to ensure the safety of autonomous vessels.

When examining operator error analysis, several studies have focused on the vulnerabilities and potential failures in human interactions. For example, the study by [174] explored potential human failure events within RCC operations, revealing that human errors can occur due to system alert failures, remote operations, and ship takeover processes. Furthermore, to investigate potential human failures in MASS during collision avoidance scenarios, a task analysis methodology complemented by a cognitive model is employed to outline collision avoidance procedures facilitated by human operators [2]. This study illustrates how the integration of human interventions with autonomous system capabilities can navigate threats effectively, emphasising the critical role of human oversight in emergency situations. Moreover, the potential human failures were also discussed by [173] with a method of Fault Trees, where failure events that occurred in human-MASS interaction could be identified and predicted.

Additionally, the study by [118] utilised an approach of the Success Likelihood Index Method under interval type-2 fuzzy sets to identify the possible errors of human-MASS interaction with the human operator remotely and MASS. The results of the study provide insights into the human factors (i.e., Stress, task difficulty, level of preparation (preparation), experience level (experience), fatigue, event-related factors (event factors), etc.) that can contribute to operational errors in autonomous ships. Furthermore, techniques and challenges of human and organisational factors in the maritime domain were analysed by [229]. In this study, it is stressed that human factors that may influence ship safety would also widely exist in future transport. For example, the possible high stress of human operators could be caused by the remote supervision of multiple vessels at a time and the failure of the collaboration between conventional ships and MASS with different degrees of autonomy.

Similarly, the critical role of the human element in autonomous maritime navigation was explored in the study [210]. The work underscores the persistence of human errors not just operationally but also in the design and remote control of both unmanned and manned vessels, highlighting the potential for autonomous ships to alter seafarer behaviour on manned ships, posing additional risks. Furthermore, the research by [39] examined human errors in human-autonomy collaboration in autonomous ships, particularly in collision avoidance scenarios. Using the human reliability analysis method and virtual experiments, the study identifies key performance-shaping factors influencing human errors. It contributes to understanding human factors in MASS operations, which is crucial for improving safety and efficiency.

(5) Technologies for Improving Operator's Situational Awareness

Various technologies have been employed to enhance operator situational awareness. It is pointed out by [56] that the transparency of dynamic systems varies with the levels of situational awareness, arguing that human trust in an autonomous system should be calibrated to reach efficient cooperation. In addition, in the study by [215], an Immersive Virtual Reality method was used to evaluate the human experience on a MASS and a manned ship. In this study, the factors of trust, stress, and perceptual risk from human operators were measured under various scenarios regarding environmental settings by means of a post-hoc questionnaire for a comparison between the MASS and manned ships. Similarly, in the study by [208], Augmented reality and Virtual reality were explored as a means of training seafarers for the remote operation of autonomous ships. The study highlighted the importance of equipping operators with the necessary skills to manage complex systems remotely, suggesting that these training methods could improve safety and operational efficiency in the autonomous maritime environment.

Research on human factors has highlighted the essential role of human oversight in MASS operations. This encompasses the collaboration between MASS and human operators to bolster safety and performance. Studies emphasise that while automation is advancing, human situational awareness and the establishment of trust are critical for safety. The research spans various dimensions, including cultural and social aspects affecting remote operations and emphasises the need for effective communication strategies. A key point is the evaluation and calibration of human trust in autonomous systems, which aligns with the enhancement of situational awareness and underscores the importance of incorporating human factors in the design phase to mitigate potential errors and stress-induced decisions. These findings highlight the critical nature of human oversight and the interplay between human operators and MASS.

2.2.1.2 Available techniques supporting the autonomy of MASS

The development of autonomous systems for MASS relies on a range of techniques to ensure efficient decision-making and collision avoidance. The available techniques can be broadly classified into two categories: sensor integration and communication for situational awareness and collision avoidance algorithms. Each plays a crucial role in enhancing the situational awareness, operational safety, and autonomy of MASS.

(1) Sensor Integration and Communication for Situational Awareness

Advances in sensor technology form the backbone of MASS situational awareness, providing essential data for navigation and operational safety. The sensors that are available for situational awareness of MASS were reviewed by [205], where how to fuse sensor data using AI technologies was discussed. Additionally, rule-based approaches represent another important way to improve situational awareness and further collision avoidance [88] [246]. Furthermore, The study by [239] focused on a rule-based method to analyse maritime traffic, which can enhance situational awareness among traffic service operators. Another specific method to enhance situational awareness is the ship domain model, which helps define safe operational spaces for vessels. The study by [225] introduced a model where the declarative domain represents a theoretically safe area, while the effective domain reflects real-time human decisions based on situational factors.

Communication systems are vital to enhancing situational awareness, especially in an MWTS. For example, an efficient procedure of intent exchange between MASS and conventional ships in an MWTS was given by [153]. This paper argued that communication is necessary for situational awareness of ships for a clear and rule-compliant interaction when the collision risk is higher than the predetermined threshold that is set for triggering information exchange. Additionally, the study by [154] introduced a process map for collision avoidance based on information exchange between autonomous vessels and manned ships. The study found that autonomous ships can avoid collisions more safely by exchanging navigational intentions with other vessels rather than acting independently.

Moreover, e-Navigation is another critical technology for enhancing situational awareness. E-Navigation is the integration of navigation systems, information exchange, and communication technologies. The principles of e-Navigation include safety, efficiency, interoperability, and so on. In the study [167], e-Navigation is suggested as a way to solve the interaction between MASS and conventional ships in an MWTS. A novel concept of Moving Havens was introduced in that paper to enhance traffic safety. Besides, the study conducted by [6] suggested applying e-Navigation to improve the collaboration performance of ships, especially for collaborative collision avoidance. Based on the analysis of the benefits of e-Navigation for conventional ships and the feature of collision avoidance between MASS, an innovative strategy was proposed, that is, combining those two to improve traffic safety.

(2) Collision Avoidance Algorithms

Various computational models and algorithms have been developed to ensure that MASS can autonomously avoid collisions in real-time. One of the foundational approaches to collision avoidance in MASS relies on traditional rule-based systems, which are often grounded in established maritime regulations such as COLREGs. These algorithms typically focus on ensuring compliance with navigational rules by encoding expert knowledge into decision-making processes. For instance, the study by [243] proposed a ship decision-making model for collision avoidance by integrating expert experience and prior knowledge with a Bayesian Network, ensuring reliable navigation safety. Similarly, as noted by [217], the refinement of rule-based methods enables MASS to dynamically interpret traffic conditions, improving decision-making in real-time and supporting safer autonomous operations.

To further emulate human-like decision-making, the study by [14] employed a Fuzzy Logic approach to evaluate compliance with COLREGs. This method allows MASS to process navigational situations through a human lens, enabling more flexible interpretations of the rules and ensuring safer navigation in complex environments. These approaches, while effective in structured and rule-defined scenarios, often face challenges when dealing with highly dynamic or multi-vessel environments. Furthermore, to investigate how human navigators interpret the term “safe speed” in the COLREGs, a study was conducted by [47]. This study stresses that navigators assess speed based on situational control rather than fixed metrics. This dynamic interpretation presents a challenge for autonomous ships, which must be programmed to understand and apply human-like decision-making to comply with maritime regulations and operate safely alongside conventional vessels.

In contrast to rule-based methods, data-driven and adaptive learning approaches focus on the ability of MASS to learn from the environment and continuously adapt their decision-making processes. Machine learning, particularly deep reinforcement learning, plays a key role in these techniques. For example, the work by [247] introduced an Artificial Potential Fields (APF)-Deep Reinforcement Learning (DRL) method for collision avoidance. This approach combines APF with an ontology-based system for classifying encounter scenarios, allowing MASS to optimise decision-making while remaining compliant with COLREGs. Expanding on the APF methodology, the study conducted by [133] used a method of modified APF for MASS. It was demonstrated how the algorithms performed in the scenario of encountering a single surrounding vessel, as well as multiple surrounding vessels, considering a COLREGs-constrained strategy and a reactive avoidance strategy in case of a violation from the surrounding vessel. Similarly, a DRL model is applied to multi-ship collision avoidance [223]. The study divided encounter situations into four regions based on COLREGs, transforming navigational goals into corresponding rewards, such as collision avoidance and path following. This method allows MASS to navigate safely in environments with multiple vessels, further highlighting the capabilities of adaptive learning systems in complex and multi-agent scenarios.

Hybrid optimisation and predictive approaches combine the strengths of traditional rule-based methods with advanced computational techniques to enhance decision-making in uncertain environments. These approaches often involve optimisation algorithms and predictive models that allow MASS to handle dynamic obstacles and multiple surrounding vessels scenarios more effectively. For instance, a greedy interval-based motion planning model was proposed by [66] based on the Velocity Obstacle method. This method enables MASS to navigate efficiently while predicting the movements of surrounding vessels, making it an effective solution for avoiding both stationary and dynamic obstacles in maritime traffic systems.

In terms of risk-based decision-making, a risk-aware approach by incorporating a risk evaluation model was introduced into a DRL framework by [82]. This method enables MASS to balance between path-following and collision avoidance behaviours dynamically, adapting to the level of risk present in real-time maritime scenarios. The study showed great improvements in decision-making capabilities when navigating complex environments, particularly in high-risk situations. Additionally, to address the uncertainties present in mixed-obstacle environments, the study [252] introduced a decision-making model that combines a Partially Observable Markov Decision Process (POMDP) with Proximal Policy Optimization (PPO). This hybrid approach proved to be more effective than conventional algorithms in enhancing navigational safety, as it allows MASS to make more accurate decisions in uncertain and partially observable environments.

Another hybrid approach was developed by [230], who proposed a proactive decision-making model that integrates human risk preferences into the navigation process. In this model, human preferences for risk, such as aggressive, neutral, or cautious approaches, can override autonomous decisions. This allows MASS to make flexible and adaptive decisions based on the risk tolerance of the human operator, ensuring that navigation is both safe and efficient under varying conditions. Furthermore, in scenarios where MASS operates alongside manned vessels, human-machine interaction becomes a key area of focus. Human-machine integration approaches aim to combine human judgment and preferences with the autonomous capabilities of MASS. For example, A study utilising a maritime simulator to evaluate the available algorithms was carried out by [207], where the decisions made by human navigators and the autonomous navigator driven by algorithms were compared. The scenarios in this study considered the interaction between MASS and manned ships, providing a potential approach for future research and testing on the interaction in an MWTS with different competencies of human operators.

Additionally, the work by [47] explored the challenges of programming MASS to interpret and apply the concept of safe speed in the context of COLREGs. The study highlighted that human navigators assess speed based on situational control rather than fixed metrics, which presents a challenge for autonomous ships. MASS must be able to replicate this dynamic decision-making process to operate safely alongside conventional vessels. Moreover, a Double Deep Q Network (DDQN) that integrates human experience with COLREGs was developed by [238] for collision avoidance. This system allows MASS to learn from human navigational practices, enabling rule-compliant and efficient decision-making. The DDQN model helps improve safety by learning how human operators react in real-world environments and applying similar decision-making strategies autonomously. In order to improve the capability of collision avoidance of MASS, the study conducted by [93] provides adaptive collision avoidance systems (CAS) to enable the MASS to avoid collisions with manned ships in an MWTS. By focusing on the surrounding vessel's manoeuvring behaviours, particularly the manned ships, a simulator-based method was used to collect the navigational data that would be used to adjust the sensitivity of CAS collision avoidance.

Investigations into MASS autonomy have concentrated on the development of sensor integration, communication systems for situational awareness, and collision avoidance algorithms. These tools are crucial for maintaining situational awareness and executing collision avoidance strategies. The analysis indicates a focus on designing algorithms that not only comply with maritime regulations such as COLREGs but also incorporate human operation practice in decision-making processes. The emerging theme is a concerted effort toward systems that balance autonomy with human-like responsiveness, emphasising the need for seamless human-machine interaction.

2.2.1.3 System analysis and design for human-MASS interaction

This chapter reviews the frameworks and methodologies proposed in the literature aimed at developing systems for human-MASS interaction. The approaches discussed cover various requirements of the MASS system, as well as the implementation of system designs that ensure both operational safety and efficiency.

(1) Systems Analysis of MASS

Research on the systems analysis of MASS has focused on constructing frameworks for human-MASS interaction. Two kinds of design in human-robot interaction (HRI) serve as the basis for developing frameworks for human-MASS collaboration: Human Emulation and Human Complementary [61]. While human emulation focuses on mimicking human decision-making processes, human complementary approaches combine and utilise both human and computer abilities. MASS, regarded as a robot for executing different procedural tasks, is closer to the human complement [90]. There has also been some work with the human emulation approach, such as a human-like knowledge base for the autonomous ship on the basis of expert experience for autonomous ships [12] [108] [109]. It was concluded that both kinds of approaches are feasible for MASS.

Several studies have explored these frameworks in detail. For instance, the study [211] used field study observations, semi-structured interviews, and theoretical sampling to investigate a design of collaboration work in the control room by advocating for a collaborative approach that leverages the strengths of both human and AI components. This study suggests that training and certification programs are necessary to equip navigators with the skills required for human-AI collaboration. Similarly, the study by [13] developed a data-driven method to create realistic test scenarios for testing MASS. By using large-scale traffic data from AIS, digital maps, and vessel registries, the study constructs complex navigation scenarios that simulate real-world conditions such as collisions, grounding risks, and vessel-to-vessel interactions.

It is worth noting that transparency is an important factor that has been the focus of various studies on the framework of human-MASS interaction. A framework for human-automation interaction was presented in [169], focusing on automation transparency. The study proposed interface designs that allow operators to quickly regain situational awareness in emergencies, ensuring timely intervention and enhancing overall safety. Besides, Automation transparency was also examined by , where the authors proposed methods for MASS to communicate their state and intentions to nearby vessels and stakeholders. The research concluded that improving transparency is key to ensuring safe navigation and interaction between autonomous and manned vessels. The study proposed interface designs that allow operators to quickly regain situational awareness in emergencies, ensuring timely intervention and enhancing overall safety. Moreover, focusing on improving human supervision of autonomous collision avoidance systems by enhancing agent transparency, the study by [144] identified specific situational awareness requirements and cognitive activities needed to verify agent performance.

Furthermore, safety concerns are important in autonomous system designs. In the study [44], a sovereign-based control system design integrates human supervision, where decision-making starts with situational awareness and ends with actions executed by the human operator. Other studies, such as [105], explored safety challenges for MASS related to the interaction between MASS and conventional ships with varying degrees of autonomy. For example, Technical challenges (malfunction, communication interference, cyber threats, as noted by [127] [24], environmental challenges (adverse weather, limited visibility, dynamic navigational conditions), and human-related challenges (responsibility confusion, human competence, human error), can all pose safety risks for autonomous ships in mixed navigational environments. The safety of interactions between humans and systems was analysed by [38] for the MASS controlled or supervised by the operator at the shore control centre. The study proposed an approach that integrates the human cognitive model and system theoretic process analysis to identify safety risks.

With respect to the system analysis of ship collision avoidance, the study by [88] reviewed the methods of collision avoidance for ships, where the strategy discrepancy of collision avoidance was pointed out. It is suggested to enable the MASS to be user-friendly for human operators by exploring the functions in conventional vessels. In addition, a decision-making framework of collaborative collision avoidance for MASS and manned ships was proposed by [6]. The study takes advantage of the communication and cooperation between ships and the shore control centre to accurately predict and avoid collisions, utilising real-time data from various sources, including ship sensors and global navigation satellite systems, to provide a comprehensive view of the navigational environment. Furthermore, the paper by [104] provided a methodology for legally correcting collision avoidance actions according to COLREGs by utilising a decision-making tree and quantitative analysis methods for COLREGs. It offers a framework for legal compliance in collision avoidance between autonomous and manned ships. Besides, considering the issues of information acquisition and situational awareness that may arise in an MWTS, several potential proposals were discussed by [176] in relation to Vessel traffic management, Traffic separation schemes, etc.

In addition, several other approaches have also been employed for the autonomous system of MASS. In [165], a fuzzy logic approach was introduced to define levels of automation in MASS. The study aimed to address the imprecision in the current level of automation taxonomies and proposed a clearer framework to improve the interaction between human operators and autonomous systems. Furthermore, in the work by [171], the authors argued that the tasks of humans and the system are changeable, with the level of autonomy of the MASS being different. Using the human-system interaction in autonomy method, tasks involving monitoring ship status and surroundings and evaluating potential risks were examined for human-MASS collaboration in collision avoidance scenarios. Additionally, a System Theoretic Process Analysis was applied by [213] to determine the relationship between the hazards and the degree of autonomy of MASS. A key finding of this study is that situational awareness could fail due to the failure of the sensors, which supports that the design of humans in the loop and redundant sensors for situational awareness are necessary for MASS. Additionally, the resilience of MASS was discussed in [60], where human-MASS interaction was included. It is highlighted that the situational awareness of MASS contains several types: navigational awareness for safe navigation, operational awareness for information sharing, and distributed situational awareness for collaborative navigating on a remote-controlled ship. Moreover, a Bayesian belief network was applied in [202] to assess human-automation collaboration performance on unmanned underwater vehicles. In this study, the capability of situational awareness and the reliability of the autonomous system are suggested to support a smooth collaboration.

Additionally, a human-machine model was given by [59] to evaluate seafarer competencies in automated systems. It emphasises the importance of training and assessing human factors to ensure safety in maritime operations. Functional requirements for Onshore Operation Centres supporting autonomous ships were outlined in [3]. The study discussed the technological, navigational, and operational needs of Onshore Operation Centres, concluding that robust communication technologies and real-time monitoring are essential for supporting safe and efficient vessel operations.

Moreover, risk assessment frameworks were also proposed for MASS. In [162], a high-level risk analysis of autonomous vessels was conducted, combining simulation-based testing with safety assessments. The study demonstrated that systematic testing is vital to mitigate potential risks before full-scale deployment, ensuring the safety and reliability of ship automation systems. A framework for analysing risk coupling in different operational modes of MASS was proposed by [58], focusing on the interaction with the environment and internal and external systems related to MASS. The study identified that 15 common failure modes could be classified into the risk factors related to humans, organisations, ships, environments, and technology, with the example of grounding accidents.

(2) Implementation of System Design

Human-centred design methods prioritise human needs and capabilities in the design of MASS systems. For instance, the study conducted by [212] outlines a process that includes user analysis, requirements specification, system design, and evaluation, ensuring that the designs align with operator expectations and capabilities. Another innovative approach was the introduction of the “ship immune system” proposed by [214], which highlights adaptive risk management strategies that anticipate and mitigate potential risks in real time, supporting the safety of MASS operations. Additionally, integrating AI in marine navigation is key to improving human-MASS collaboration. The study conducted by [211] investigated the integration of AI in marine navigation, underscoring the discrepancy between designers' and navigators' perspectives on human-AI collaboration. It suggests designing AI systems that incorporate social cues that articulate human work and that visualise computational activities to better support human cooperation.

In the realm of collision avoidance, various systems have been developed by integrating human and machine intelligence. A collision avoidance system was designed by [88], where human operators playing various roles within different navigational scenarios were discussed in detail. This system supports the MASS in making correct and reliable decisions for cooperative MASS navigation. In [140], a decision-making system was also designed for safe and efficient navigation of MASS, consisting of five components: real-time data collection and processing, decision-making algorithms, human-in-the-loop decision-making, communication and information exchange, and human-AI collaboration.

Literature on system design and analysis points to the importance of integrating human insights and advanced technology to ensure safety and efficiency. It focuses on enhancing transparency and situational awareness within autonomous maritime systems through the development of collaborative frameworks that balance human and machine capabilities. These systems are crucial for enabling effective communication and decision-making between manned and autonomous vessels, emphasising the need for adaptive risk management strategies and human-centred designs to address the dynamic complexities of the MWTS.

2.2.1.4 Potential requirements for human-MASS interaction regarding regulations

The successful implementation of MASS within existing maritime operations hinges not only on technological advancements but also on regulatory and human competency adaptations.

(1) Regulatory Framework Development

In recent years, IMO has been exploring the amendment of IMO standards for MASS based on the current standards. That means MASS not only pursues high efficiency and lower risks of navigation but should also comply with existing regulations at least as successfully as the conventional ship. Therefore, safety and efficiency [205] are the primary goals for MASS.

Regarding compliance with regulatory standards, the study by [158] emphasises the regulatory requirements to ensure safe and secure MASS operations.

With respect to the amendment of COLREGs, the study by [166] emphasises the ambiguity in terminologies within COLREGs, which may lead to discrepancies in communication between MASS and traditional vessels. Possible solutions, namely increasing the transparency of actions, were discussed, as well as improving safety and efficiency.

(2) Human Competency and Skill Development

Incorporating MASS into maritime operations also requires a shift in the skills and competencies of human operators, particularly those working in Remote Control Centres. Several studies highlight the need for continuous development in human oversight skills as automation becomes more integral to maritime navigation.

The study [94] emphasised the importance of human factors in MASS operations, identifying key skill sets required for operators managing highly automated systems. The research concluded that the continuous development of human competencies is essential for the successful integration of autonomous technologies in maritime operations. With a systematic literature review, several findings came up in [209]. In particular, the human operator plays the role of more than a backup regarding MASS safety, and new competency requirements need to be improved for human operators at RCC to deal with emerging issues.

Furthermore, a study analysed and explored possible competency requirements for remote operators at RCC by [237]. By conducting an interview, potential threats were found, and thus, additional requirements were suggested to be satisfied by operators for safety-critical supervision of MASS. For example, the ability to recognise necessary information from a display of equipment and other items at RCC under restricted conditions and the ability to confirm the accuracy of the information obtained from restricted ship sense, radar display and other items.

The successful integration of MASS into maritime operations depends on a multi-faceted approach that encompasses regulatory framework development, human competency enhancement, and improving transparency in autonomous systems. Research shows that updating international regulations, such as COLREGs, is crucial to ensuring the safe operation of MASS. Equally important is the ongoing training and development of human operators, who play a central role in overseeing autonomous systems. In parallel, fostering transparency in MASS operations, particularly in high-risk scenarios like collision avoidance, is essential for preventing misunderstandings and ensuring cooperative interactions between autonomous and manned vessels.

Research in human-MASS interaction focuses on four domains: human factors, support for MASS autonomy through technological advancements, system analysis and design for human-MASS interaction, and potential regulatory requirements. These studies highlight the necessity of enhancing interactions between MASS and human operators from various perspectives. Collectively, these studies reveal a critical perspective: It is essential to ensure safe and efficient collaboration between humans and autonomous systems. A detailed analysis of the research is given in Section 2.5.1.

2.2.2 Focusing on situational awareness of MASS

Ensuring safety is a major concern in the maritime industry, particularly important across various operational states such as underway, anchoring, or mooring. The underway state, in particular, requires detailed attention due to its dynamic and complex navigational challenges.

Situational awareness is fundamental to maintaining safety under these conditions. The concept was proposed by [56] to describe what is happening, what it means, and what might happen next. This framework includes perception, comprehension, and projection as its core components.

In the maritime domain, research related to situational awareness has focused on four topics, as presented in Table 2-4: Architecture development of SA, Investigation of SA requirements for MASS, Enhancement of SA comprehension and projection capabilities, and Quantification of SA. Three types of methods have been employed to explore those topics, including literature reviews, algorithm-based approaches, and mathematical models.

Recent research has increasingly focused on the situational awareness challenges in human-MASS interactions, especially as human operators transition to supervisory roles over autonomous vessels. The study [158] investigated the challenges of the SA of MASS through a questionnaire that gauged seafarers' experiences across different human operational modes. Focusing on a similar problem, the research [144] explored potential solutions to enhance human operators' understanding of autonomous systems, advocating for greater transparency in autonomous behaviours to facilitate adaptation to supervisory roles.

The studies conducted by [130][132] highlighted the importance of SA of MASS by drawing parallels between challenges in MASS and uncrewed aerial vehicles, suggesting that lessons learned in aviation could inform maritime operations. A distributed situation awareness framework for a mixed waterborne transport system was proposed by [194], suggesting improvements through the integration of service information, which could lead to a more interconnected navigational environment. Additionally, a study examining the impact of immersion levels on SA and human trust was conducted by [70] using virtual reality, revealing how immersion of instruments influences human operators' perception and decision-making process.

Despite extensive research into SA for both conventional and autonomous maritime vessels, there is a gap in foundational studies that specifically address the SA principles necessary for MASS operation within an MWTS. These principles are essential for the development of decision-support systems that support the navigational needs of MASS, including (1) Perception of elements in the environment within a volume of time and space, (2) Comprehension of their meaning for supporting MASS' navigation, and (3) Projection of the situation for MASS in the context of MWTS. The need to develop comprehensive models that integrate all elements of situation awareness is critical for creating reliable and transparent systems that can support proper trust levels among human operators, MASS, and services. This issue, along with proposed solutions to bridge the gap, will be further discussed in Section 2.4.3.

2.2.3 Implications on decision-making for collision avoidance

Based on proper situational awareness, good decision-making can be obtained, as stated in [57]. Many studies have investigated the fully autonomous MASS decision-making [95] [20], for example, path planning [253] [248], ship control [80] [250], trajectory tracking [79] [249], and multi-vessels cooperation [30] [51] [50]. They promote the MASS to be more autonomous and further as a teammate of human operators in the human-MASS team to perform tasks independently or collaboratively.

In terms of collision avoidance decision-making for MASS within an MWTS, a summary of applications is given in Table 2-5. It can be found that most studies considered the COLREGs to force the MASS to avoid collision with manned ships. It is worth noting that the surrounding vessels set in their experiments are often regarded as vessels keeping course and speed the same without combining the human experience, such as preference, which is unrealistic in practice.

For this reason, some studies consider human operators' navigational data to improve the capability of collision avoidance of MASS. For example, the research conducted by [93] analysed and extracted seafarers' manoeuvres and tested the collision avoidance system of the unmanned vessel with the extraction results. The study of extracting navigational features of manned ships from AIS data was investigated by [119], the results of which were applied to train MASS through the reinforcement learning method. These studies have contributed to the enhancement of MASS's capability to avoid collisions in an MWTS.

In the field of human-robot interaction, many scholars tried to model human behaviour for robot inference and prediction [206] [69] [196], which can be referenced in the context of the navigation of MASS in an MWTS. For example, search and rescue [21] [226], human-multi-robots collaboration [178], and so on. Among them, the mainstream is the application of decision theory in economics on HRI [113]. Specifically, the focus is to obtain a suitable model to depict the human decision process, such as the noisily rational model [111] and the risk-aware model [98]. In terms of these models, there are several kinds of methods to solve, for example, inverse reinforcement learning [69] [157] and reinforcement learning [123] [180]. A summary of the results of human models for decision-making is given in Table 2-6.

In conclusion, in current research, there is a noteworthy gap in addressing the navigational preferences of manned vessels within complicated maritime environments. Most studies tend to model surrounding vessels as operating on simulated trajectories and improve the capability from the perspective of evasive algorithms, which ensure navigational safety between manned ships and MASS. While the MASS is equipped with robust collision avoidance capabilities, the real challenge lies in proactive engagement during the avoidance phase. Proactive collision avoidance is key to maritime safety, as passive avoidance strategies may lead to misunderstandings of navigational intent, potentially resulting in new collision conflicts. Therefore, it is essential to incorporate a model of human navigational preferences and decision-making processes. This would enable autonomous systems to predict and adapt to the manoeuvres of manned vessels more effectively, ensuring smoother and safer interactions.

2.2.4 Trust in human-MASS collaborative navigation

The introduction of MASS aims to augment maritime safety by minimising human error, a critical factor in maritime incidents. Nevertheless, this does not negate the essential role of human operators. Instead, it transforms it by positioning it as a critical overseer for autonomous operations. This model leverages human judgement alongside autonomous technology to strengthen safety protocols. Therefore, the efficacy of MASS hinges on human operators' trust in these systems' situational awareness and decision-making capabilities, ensuring they can intervene when unexpected challenges arise [2] [138].

Trust in HRI is a priority topic that is gaining increasing attention in human-robot collaboration. With properly aligned trust, humans as supervisors can decide in time on the actions to be taken based on the belief in the robot. Trust is defined in [107] as a multidimensional latent variable that mediates the relationship between events in the past and the former agent's subsequent choice of relying on the latter in an uncertain environment. Trust refers to the function of successful and proven operations that are assessed by human operators from the perspectives of social norms and technology acceptance in [134]. In that study, human trust is extracted through interviews about the potential impact of autonomous technologies, where 10 participants from both academia and industry were recruited to respond to questions related to their trust in autonomous ships.

Several studies indicated that the more human operators understand the robot's decision-making process, the more properly aligned trust they have in the robot [236]. Therefore, better performance for MWTS can be obtained if each vessel within the current WTS can interact with one another to share its intentions to avoid misunderstandings. Properly aligned human trust in the autonomous system's true capabilities is the foundation of high-performance human-system teaming. Both over-trust and under-trust are undesirable in HRI, which may lead to poor collaboration performance [107]. In an MWTS, likewise, there will also be the collaboration between humans and MASS, such as MASS auto-docking at a conventional berth, collision avoidance for the conventional ship and the MASS, and so on, where trust is a critical factor to be considered affecting the collaboration performance [209]. An overall summary of the research results of human trust in the autonomous system of MASS is given in Table 2-7.

For the sake of ship safety, humans can generally take over control of the MASS in emergency situations that the MASS cannot handle. Due to cognitive differences, humans may diverge when encountering certain new situations. In addition, seafarers on board the ship and managers at RCC have differences in the level of trust in sensors [219], which may lead to a discrepancy in situational awareness. In order to obtain good and seamless collaboration and to further reduce the human workload, it is desirable that the MASS take reasonable and human-satisfactory actions. That is, the autonomous system of MASS is supposed to be safe, reliable, and trustworthy [209].

Taking human trust into account, recent research has focused on the impact of human trust on the performance of the MASS system. As discussed in Section 3.2, the impact of human trust on the decision-making process of MASS and human operators is highlighted by [131], [132], [158], [70] and [1], which should be considered carefully in the design of MASS and seafarers training. The research by [25] investigated seafarers' trust in the autonomous system of unmanned vessels through interviews with 100 seafarers with varying navigational experiences. The results indicated that trust discrepancies existed among participants, with higher-ranking participants having similar perceptions of autonomy as those with less experience.

In conclusion, increasing attention is being given to the role of human trust in the context of human-MASS interaction, particularly regarding its integration into decision-making processes. However, this area of research has not yet been extensively developed and requires more focus. Effective integration of human trust is essential for ensuring safety and efficiency in the MWTS. Further research is necessary to understand and implement trust evaluation within MASS operations, promoting better collaboration between human operators and autonomous systems.

Table 2-4 Current research on situational awareness in the maritime domain

Ref	Architecture	Requirements	SA comprehension and projection	SA quantification	Literature review	Algorithm-based	Mathematical method
[56] [68] [140] [76] [19]	✓						
[202]	✓	✓					✓
[193]	✓	✓	✓				
[44] [143] [183]	✓		✓				
[216]	✓				✓		
[225] [17]		✓					✓
[205] [105] [213] [73] [170] [185] [201] [112] [75]		✓			✓		
[166] [60] [153] [167] [145] [194]		✓	✓				
[163]		✓	✓	✓			✓
[27] [132] [45] [173] [102]		✓					
[135] [134]		✓	✓	✓	✓		✓
[255] [70]				✓			✓
[160] [26] [150]			✓				
[91] [49] [197] [144] [190] [22] [182]			✓			✓	

Table 2-5 Review of approaches of collision avoidance in an MWTS

Ref.	Method	COLREGs-considered		Human element-considered		Objects Setting	
		Own ship	Surrounding vessel	Own ship	Surrounding vessel	Dynamic	Stationary
[223]	Reinforcement learning	✓	✓			✓	
[230]	Risk appetite-considered	✓	✓		✓	✓	
[90]	HMI-CAS	✓		✓	✓	✓	
[238]	Reinforcement learning	✓		✓		✓	
[66]	Velocity Obstacle algorithm					✓	
[133]	APF	✓			✓	✓	
[247]	APF-Deep Reinforcement Learning	✓				✓	✓
[93]	Velocity obstacle algorithm	✓			✓	✓	
[36]	Blockchain-based communication	✓	✓			✓	
[104]	Decision-making tree	✓			✓	✓	
[119]	Deep reinforcement learning	✓			✓	✓	✓
[114]	Firefly algorithm and ant colony optimisation	✓				✓	
[35]	Scan-searching method combined with APF	✓			✓	✓	
[159]	Model predictive control and radial basis function	✓			✓	✓	

Table 2-6 Brief review of popular human decision models in HRI

Ref.	Parameters	Method	Outputs	Setting	Type
[113]	Information amount of decisions, time, risks, and corresponding human actions	Cumulative Prospect Theory	The probability of behaviours anticipated	Human driver decision-making under uncertainty and risks	Risk-aware
[98]	Subjective feeling to consequences; human detection cost	Regret theory	Risk awareness degree	Robots ordering in human-multi-robots task allocation	Risk-aware
[21]	Command, geometrical data, robot status, etc.	Dynamic Bayesian Network	The probability of being involved in the task	Multi-Robot Interaction in Search and Rescue Missions	Noisy rational
[180]	Reward control and reward affect desired human actions	Reinforcement learning	Coordinated plans	Autonomous planning for autonomous vehicles coordinating with human-driven cars	Noisy rational
[40]	Human preference for trajectories	Reinforcement learning	The optimal strategy for action-taking	Human Preferences learning	Noisy rational
[69]	Driving behaviour features lane, Time-to-collision, Timeheadway, etc.	Inverse reinforcement learning	Reward cost function	Modelling driver behaviour	Noisy rational

2.3 Synthesis and identified gaps

In the context of waterborne transport, the safety of the ship is of utmost importance and must be prioritised over any other objective. However, to meet the expectations of various stakeholders such as ship companies, seafarers, and other service providers, it is also crucial to improve the efficiency of the system.

Table 2-7 Overview of human trust in the autonomous system of MASS

References	Methods	Parameters	Outputs	Setting
[215]	Immersive virtual reality & post-session Questionnaires	Beliefs and observations of the robot's surroundings, goals, actions, etc.	Trust values	Evaluating human experience on a MASS and a manned ship
[209]	Literature review		The importance of trust in the human-autonomy interaction system	Human-autonomy collaboration performance
[42]	Survey		The importance of trust in the human-autonomy interaction system	Interoperability of multiple Unmanned Marine Vehicles
[202]	Bayesian belief network	Object status, reward function	Human interference rate	Assessing human-autonomy collaboration performance
[135] [134]	Interview		Potential effects of trust	Exploring the potential effects of MASS
[201]	Survey		The impact of trust on human stress	Mental health effects on the MASS
[158]	Questionnaires		Training needs	Maritime operations, remote operations
[1]	Questionnaires	Professional commitment, age of officers	Trust values	The relationship between Professional commitment and Trust in autonomy
[132]	Literature review	Decision-making factors	Design recommendations for MASS	Remote Control Centre operations
[131]	Interview		Key topics related to human trust in the decision-making process	The decision-making operation of the MASS investigation
[25]	Interview		Trust levels	The investigation of trust in autonomy
[70]	Simulated RCC interfaces, Virtual Reality	Levels of Immersion in HMI	Trust in systems	The effect of immersion on the trust level of RCC operators
[10]	Interview		Passenger trust in ferries	Trust in the use of autonomous urban ferries

It is noteworthy that various research topics that were previously studied independently must be considered in a more holistic manner in the MWTS. These include the situational awareness required to support the safe navigation of MASS, navigational preference-aware collision avoidance of MASS and conventional ships, and the assessment of human trust in the autonomous systems of MASS. All of these topics are interrelated.

There are still several findings and gaps in the existing state of the art, as well as gaps of knowledge, as detailed below.

2.3.1 Findings

Research in human-MASS interaction is broadly categorised into four main domains: human factors, technologies that support MASS autonomy, system analysis and design, and potential regulatory requirements for interactions. Key findings from each of these areas are outlined below:

- **Human Factors:** Studies indicate that human factors such as situational awareness and trust are important in MASS operations. Human errors, such as misjudgments caused by human errors or decreased situational awareness, can lead to operational failures. The establishment of trust between human operators and autonomous systems is critical for safe and efficient interaction, especially in remote control scenarios.
- **Technological Advancements:** There have been great developments in sensor integration and collision avoidance algorithms, enhancing the autonomous capabilities of MASS, especially in terms of situational awareness. These advancements support the independent operation of MASS but still necessitate human oversight.
- **System Analysis and Design:** There is a focus on designing human-machine frameworks or systems that enhance operator interaction with MASS. Clear and transparent system designs and well-defined human roles are crucial for maintaining operator situational awareness, particularly in emergency situations. Additionally, hybrid systems that integrate human decision-making with autonomous capabilities offer more reliable solutions for managing the complexities of the operational environment for MASS.
- **Regulatory Considerations:** As the roles of human operators shift from direct control to supervision, monitoring, and emergency response, there is a pressing need to update training and certification to align with these new responsibilities. Regulations, including COLREGs, must evolve to address the legal and operational challenges posed by MASS, particularly in ensuring seamless collaboration between manned and autonomous vessels.

2.3.2 Gaps

Based on the review of current literature on human-MASS interaction within the contexts of safety, efficiency, and regulatory compliance, several gaps have been identified:

(1) **Situational Awareness Specific to MASS:** While situational awareness has been well-developed in maritime operations, specific applications to MASS require further development. Current models do not fully address the unique challenges of integrating MASS into mixed-traffic environments. There is a need for situational awareness models specifically tailored for MASS within an MWTS, which should incorporate the role of human operators during the human-MASS interaction process. This inclusion can enhance the reliability and clarity of MASS's decision-making processes. Furthermore, advanced situational awareness can also support human operators, assisting operators in managing complex situations. This serves as an intermediate step from manned operations to fully autonomous MASS, ensuring a smoother transition and improved safety.

(2) **Navigational Preference-aware Collision Avoidance in an MWTS:** There is a gap in research addressing the navigational preferences of manned vessels within complicated maritime traffic scenarios. Most existing studies simulate surrounding vessels on fixed trajectories and focus on enhancing the evasive algorithms of MASS. An evasive model involving the navigational preferences of manned ships in collision avoidance is crucial for ensuring navigational safety, which can provide proactive and mutually understandable navigation strategies within the MWTS.

(3) **Trust evaluation and modelling in Human-MASS Interaction:** Efficient collaboration between human operators and MASS relies on a proper level of trust. Current research does not sufficiently cover trust evaluation and modelling methodologies between human operators and MASS. Developing robust mechanisms for trust calibration is essential to ensure balanced human oversight and autonomous operation (neither under-trust nor over-trust), enhancing teamwork and safety in the MWTS.

2.3.3 Limitations

Despite the comprehensive literature review employed in this chapter, several limitations should be acknowledged, which may have impacted the findings and interpretations. Firstly, while a comprehensive keyword strategy was employed, there is always a possibility that the chosen keywords may have inadvertently excluded relevant studies due to variations in terminology. Secondly, subjectivity in the screening process, despite efforts to mitigate it through consensus and multiple reviewers, may have influenced study selection. Lastly, the eligibility criteria, such as restricting the review to English-language and peer-reviewed studies, may limit the generalisability of the findings. These limitations suggest that the results should be interpreted with caution, and future research should address these challenges.

2.4 Integrated decision-making framework

In this chapter, taking the research gaps discussed above, we propose an integrated framework for human-MASS interaction, ensuring the safety and efficiency of MASS navigation. Firstly, we propose a taxonomy of interactions between humans and MASS within an MWTS by means of 11 future scenarios shown in Figure 2-4. Furthermore, in order to gain insight into these interactions, the scenarios are classified into four categories based on the participation status of different stakeholders: MASS, manned ships, services, and RCC, divided into mandatory and optional participation, as presented in Table 2-8.

The term “services” in this context refers to various supportive entities that play crucial roles in maritime operations. These services include but are not limited to: Traffic Management Services, Pilotage Services, and Search and Rescue, see examples 1, 3, 5, 6, 8, 10, and 11 in Figure 2-4.

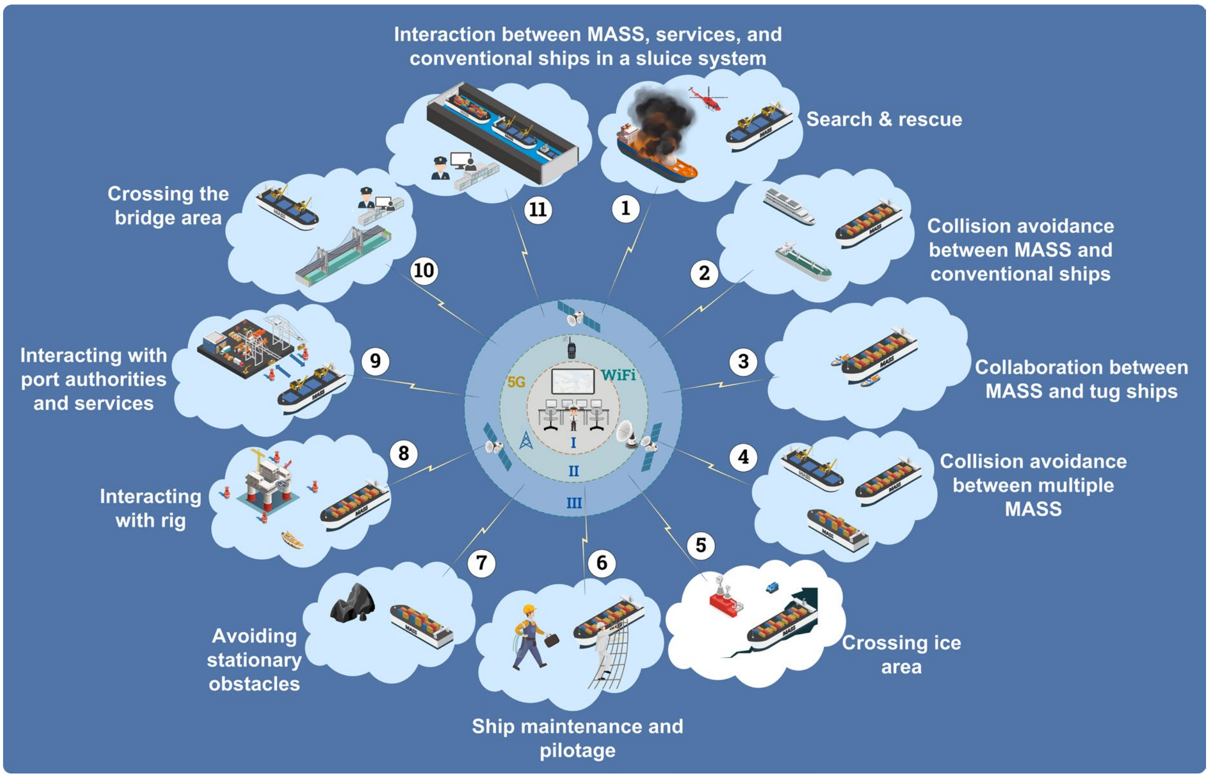

Figure 2-4 Taxonomy of scenarios of future interaction between humans and MASS.

2.4.1 Module Descriptions and Functions

A diagram depicting the integrated framework for human-MASS interaction illustrates the critical components and their interrelationships, as shown in Figure 2-5. The framework is built on three key modules: situational awareness, navigation preferences of manned ships (hereafter referred to as “navigation preferences”) and human trust. Each module is adapted to the type of interaction specified in Table 2-8, with different scenarios determining the level of involvement of MASS, manned vessels, services and RCC.

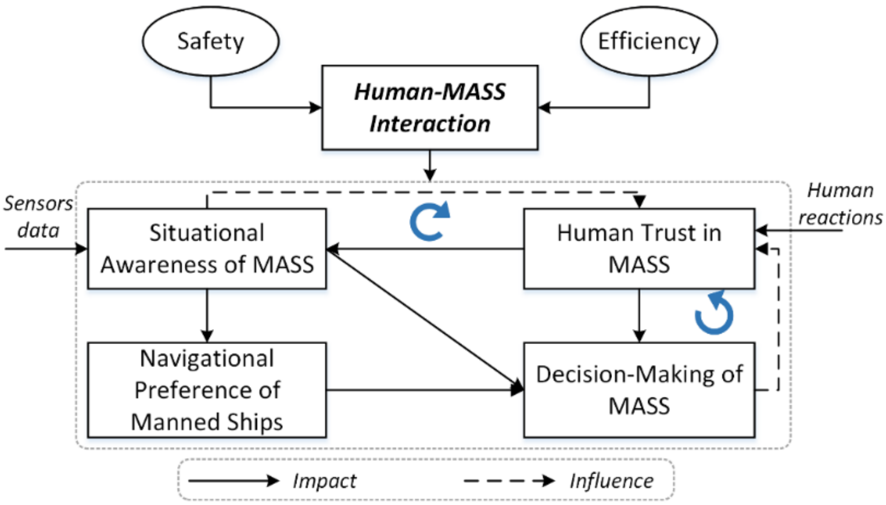

Figure 2-5 The diagram of human-MASS interaction for safe and efficient navigation.

Table 2-8 The classification of future human-MASS interaction

No.	Scenarios	MASS	Manned ships	Services	Remote control centre	Interaction types
1	The tasks of search and rescue	*	*	*	+	I
2	Collision avoidance between MASS and conventional ships	*	*	+	+	II
3	Collaboration between tug ships and MASS	*	*	+	+	II
4	Collision avoidance between multiple MASS	*	*	+	+	II
5	MASS crossing ice area	*	+	*	+	III
6	The task of maintenance for MASS by human operators	*	+	*	+	III
7	MASS avoiding stationary obstacles	*	+		+	IV
8	MASS interacting with rig	*	+	*	+	III
9	The interaction between MASS and port authorities and services	*	+	*	+	III
10	MASS being crossing bridge waterways	*	+	*	+	III
11	The collaboration between MASS, services, and conventional ships in a sluice system	*	*	*	+	I

Note: * indicates this attribute must be presented, whereas + means that this attribute is optional in this scenario.

In this thesis, it is crucial to distinguish between “impact”, a direct and immediate effect on decision-making processes and “influence”, which refers to more gradual and subtle effects on the system’s operations.

(1) **Situational Awareness Module**: This module captures real-time data from MASS sensors and external sources to create a comprehensive view of the surrounding navigational environment. The accuracy of situational awareness relies not only on the sophistication of the sensors for perception but also on its capability of comprehension and projection to the situation correctly. It considers factors including the status of the own ship, proximity to nearby obstacles, weather/sea conditions, regulatory requirements, etc.

(2) **Navigational Preferences Module**: This module integrates learned preferences and historical patterns of manned vessels to predict the behaviours and preferences of manned ships in the vicinity, facilitating friendly and proactive evasive decision-making of MASS in an MWTS.

(3) **Human Trust Module:** This module is an essential component in human-MASS interaction to evaluate and adjust human trust, which could be captured by analysing the reactions of human operators to a proper level based on the interaction types classified in Table 2-8. For each type of interaction, whether involving direct operational collaboration or more autonomous functions, the module is dynamically adjusted. This ensures that MASS operates in accordance with human expectations and safety requirements. The trust settings are related to the participation of various stakeholders in each scenario, influencing the decision-making process of the autonomous system of MASS.

2.4.2 Decision-Making Process

In the proposed framework (see Figure 2-5), sensor data are first processed by the situational awareness module to construct a semantic understanding of the navigational environment. This information, modulated by human trust—which affects the extent of operator oversight—feeds into the identification of potential conflicts and informs the extraction of navigational preferences from surrounding manned ships. These two inputs jointly support the decision-making module, which generates collision avoidance actions such as course or speed adjustments. The resulting navigational outputs not only guide vessel behaviour but are also observable to human operators, thereby influencing trust levels and completing a dynamic feedback loop within the system.

The decision-making process within this framework is structured into three stages:

(1) In the first stage, human trust and situational awareness are involved in the decision-making of MASS. Data from various sources are processed to create a comprehensive understanding of the environment, which is used to assess the situation, determine the level of risk in the next step, and generate recommended actions to deal with it.

The situational awareness module integrates the human trust evaluation module for safe and reliable situational assessment. Human trust may affect the results of the situational awareness module due to the cognitive discrepancy, which may be caused by the human operator's experience and the degree of environmental awareness. The operator with high trust would give more autonomy to the vessel to be aware of the situation and plan further. On the contrary, humans check situational awareness from an autonomous system frequently and correct the results with low trust.

Regarding the method for investigating the impact of human trust on situational awareness in MASS, a method based on the combination of self-reported questionnaires, behavioural observations, and direct inquiry could be used, aiming to capture a comprehensive understanding of the relationship between human trust and situational awareness. More specifically, this method includes:

1) Self-reported Questionnaires: Tailored to evaluate operators' trust towards the autonomous system's capabilities, these questionnaires should focus on eliciting responses that reflect trust levels in various operational scenarios.

2) Behavioural Observations: This involves monitoring operators' interactions with MASS systems under simulated conditions to identify behaviours that signify trust, such as the frequency of system overrides or reliance on autonomous decisions.

3) Direct Inquiry: This method allows participants, such as MASS operators or navigational personnel, to record their trust levels in real time based on their experiences or hypothetical scenarios involving autonomous systems.

(2) In the second stage, the navigational preference module participants when there is an obstacle in the vicinity, which may lead to potential collision conflict justified by the situational awareness module. The MASS makes decisions based on a comprehensive understanding of the situation, factoring in both situational awareness and the navigational preferences of nearby vessels. With the outcome of the situational awareness module as input, the module, along with the situational awareness module, provides evasive strategies to the decision-making module to make informed decisions in an MWTS.

(3) The final stage is to evaluate the performance of the MASS when considering the impact of human trust on its decision-making processes. In order to do that, the following steps

should be considered: (i) selection of performance metrics for safety & efficiency; (ii) designing scenarios with varying levels of risk and uncertainty and across various interaction types categorised in Table 2-8. (iii) data collection from ship sensors and cameras, human reactions, and environmental conditions; (iv) data analysis for comparing MASS performance under different levels of human trust; (v) evaluating MASS performance using the selected performance metrics.

2.5 Conclusions

This chapter conducted a systematic literature review of human-MASS interaction in the MWTS, focusing on safety and efficiency. The review addressed three critical aspects: situational awareness, collision avoidance, and human trust in the autonomous decision-making of MASS. The findings revealed that existing research is concentrated in four primary domains: human factors, technologies supporting MASS autonomy, system design for human-MASS interaction, and regulatory frameworks. These domains are interconnected and collectively shape the safety and efficiency of MWTS operations.

The review identified that several gaps existed that hindered the seamless integration of MASS into MWTS, as listed below:

(1) **Situational awareness**: Current models inadequately address the unique challenges of MASS in mixed-traffic environments, such as the need for transparency and adaptability in decision-making.
(2) **Collision avoidance**: Existing approaches often neglect the navigational preferences of manned vessels, limiting the interpretability and proactivity of collision avoidance strategies.
(3) **Human trust**: Limited exploration exists on trust evaluation and its incorporation into decision-making processes, particularly in high-risk scenarios such as collision avoidance.

To address these gaps, this chapter proposed an **integrated decision-making framework** for human-MASS interaction, prioritising safety and efficiency. This framework incorporates three modules: **situational awareness**, **navigational preferences**, and **human trust evaluation**, which are adaptable to various interaction types in MWTS. It offers a conceptual foundation for enabling MASS to interact seamlessly with human-operated vessels while ensuring regulatory compliance and operational transparency.

This chapter answered two sub-research questions: **RQ1-i:** *What is the state of the art in human-MASS interaction?* and **RQ1-ii:** *What factors should be considered in a decision-making framework?* By identifying the research gaps and proposing a decision-making framework, this chapter establishes a foundation for the thesis. This chapter provides the foundation for subsequent chapters, with Chapters 3–5 addressing the three identified gaps through focused research on situational awareness modelling, human-mimic navigation, and trust dynamics investigation and modelling.

Chapter 3. Situational Awareness Modelling for MASS

Building on the integrated decision-making framework proposed in Chapter 2, this chapter delves into the situational awareness module development for ensuring safe and efficient navigation of Maritime Autonomous Surface Ships (MASS). The framework outlined in Chapter 2 includes three modules: situational awareness, navigation preferences, and human trust. Among these, situational awareness serves as the foundation for understanding the navigational context, supporting real-time decisions in dynamic navigational environments. This chapter focuses on developing a situational awareness model for MASS. Through an ontology-driven knowledge map, this model enables the integration of diverse data sources, including sensor inputs and domain knowledge, to construct a comprehensive situational understanding. Additionally, to enable the practical application of this framework, the Dynamic Window Approach (DWA) is introduced as the path planner to show the process from situational understanding to the implementation of actionable navigation decisions. By addressing research questions RQ2-iii and RQ2-iv, this chapter establishes a situational awareness model and its integration into the decision-making framework.

The chapter is organised as follows: Section 3.1 introduces the research context. Section 3.2 presents recent work on situational awareness and decision-making in MASS. Section 3.3 details the methodology employed in developing the knowledge maps model and its integration with the adapted DWA. Section 3.4 validates the proposed model through implementation and comparison with the basic DWA algorithm. Section 3.5 concludes this chapter.[1]

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[1] The contents of this chapter have been published in [192] and [193].

3.1 Introduction

Navigating safely and efficiently in dynamic maritime environments presents considerable challenges for Maritime Autonomous Surface Ships (MASS). A foundational capability enabling this navigation is situational awareness (SA), which allows MASS to perceive, comprehend, and predict their navigational context. SA supports compliance with maritime regulations, such as the COLREGs, and facilitates timely collision avoidance. To enable the practical application of situational awareness, it is necessary to introduce a decision-making module to achieve navigational decisions based on real-time translation of contextual understanding. Through the integration of the two modules, MASS can dynamically respond to dynamic maritime scenarios while ensuring safety, efficiency, and regulatory compliance.

This chapter introduces the Dynamic Window Approach (DWA) as a path-planning mechanism designed to serve as the decision-making foundation for MASS. Originally developed for robotic navigation, DWA evaluates feasible trajectories by optimising safety, efficiency, and other goals. Its application in the maritime domain is supported by its adaptability to dynamic environments and compatibility with the unique motion characteristics of ships. By incorporating the outputs of situational awareness as constraints and objectives, DWA enables the transformation from contextual information to navigational actions.

To achieve this integration, this chapter addresses the following three objectives. First, an ontology-based knowledge maps (KM) model is developed to provide a semantic framework for representing, organising, and interpreting multi-source data, such as motion constraints, navigational tasks, and environmental conditions. Furthermore, navigational regulations, such as COLREGs, are embedded into the KM model to guide decision-making processes, enabling MASS to construct a comprehensive understanding of its navigational environment and regulation requirements. Second, the classic DWA algorithm is adapted to accommodate the three degrees of freedom (3-DOF) motion of MASS by replacing the velocity-based sampling with acceleration-based velocity sampling. This adaptation enables a more realistic representation of the vessel’s motion capabilities. Third, the integration of the SA model with the adapted DWA algorithm, forming the KM-DWA framework, provides a pathway for MASS to interpret situational understanding into decision-making actions.

The next section reviews the recent work in situational awareness and decision-making strategies for autonomous vessels, providing a foundation for the proposed approach.

3.2 Recent work

- **Situation Awareness in the Maritime Domain**

Situational Awareness (SA) is a human cognitive function that is important for strategic decision-making. Its role in human performance has been explored for many years in many domains [56]. In MASS, SA’s role extends to integrating advanced sensor technologies, artificial intelligence, and knowledge maps. Since situational awareness is crucial for the safe navigation of unmanned vessels, the research conducted by [205] focuses on sensor technology and distributed SA, which are the prerequisites for unmanned vessels to sense the environment during navigation accurately and can provide accurate data support for the situational awareness of unmanned vessels.

Recent advancements in MASS navigation, as explored by [246], involve developing sophisticated collision-avoidance systems using SA. These systems predict and mitigate hazards, enhancing maritime safety. Knowledge maps have hereby become integral in MASS for decision-making and navigational accuracy. The integration of general maps and domain knowledge is discussed by [193], illustrating the importance of comprehensive spatial information for navigational systems. The research conducted by [197] applies complex network theory to develop indicators that evaluate marine traffic, significantly contributing to situational awareness and the safety and efficiency of maritime navigation. Additionally, the critical role of these technologies in the realm of maritime education is underscored in [43], highlighting their necessity for preparing the future workforce. Moreover, a quantitative model for situational awareness tailored to address the complexities of maritime scenarios is presented in [255], offering a robust framework for assessing and enhancing navigational decision-making processes.

In the existing body of research on situational awareness for MASS, there is a gap in the deployment of the knowledge map model that is capable of understanding the context of real-time maritime navigation. Such a model is important for the accurate interpretation of situational data, which, in turn, is crucial for making informed navigational decisions. However, most existing implementations rely on fixed-rule logic, which lacks flexibility in handling complex, multi-vessel, and context-dependent scenarios. To overcome these limitations, this study adopts an ontology-based knowledge map model that supports structured representation and semantic reasoning. Compared with procedural logic, this approach offers better scalability and adaptability, enabling MASS to interpret and apply COLREGs dynamically and contextually. The proposed model aims to enhance situational awareness and rule compliance in autonomous collision avoidance.

- **COLREGs-Compliant Decision-Making**

The advent of MASS necessitates a reevaluation of traditional maritime practices, particularly the application of COLREGs. These regulations for ensuring safety and preventing collisions must now be translated into a form comprehensible to autonomous systems. This section explores recent scholarly efforts in embedding COLREGs into the decision-making algorithms of unmanned vessels, as well as the current research needs.

(1) Integration of COLREGs in autonomous navigational systems

Studies conducted by [166] and [41] emphasise the necessity for autonomous systems not only to recognise but also to actively comply with COLREGs. The use of fuzzy logic, as explored in [14], presents an approach to interpreting these rules for autonomous navigation. Collectively, these studies demonstrate steps in integrating human-centric rules into machine-operable directives.

(2) Decision-making in collision avoidance scenarios

The complexity of multi-vessel encounters under COLREGs is a focal point of several studies. Research conducted by [125] delves into decision-making models and cooperative strategies for collision avoidance. The absence of specific COLREGs provisions for such scenarios, as discussed by [221], highlights a significant gap in current regulations, suggesting a need for expansion to accommodate the intricacies of autonomous navigation. The focus of the study conducted by [90] is on collision avoidance systems for autonomous ships, particularly considering uncertainties in ship dynamics. It highlights the challenges in parameter identification for ship dynamics and how these uncertainties can impact collision avoidance.

(3) Control systems and artificial intelligence in COLREGs compliance

A distributed control scheme for autonomous tugboats was proposed in [52] and [53] to ensure collision avoidance in restricted water traffic environments while complying with COLREGs. It contributes to the field by tackling the challenge of collision avoidance in complex, interconnected vessel systems, which is a critical aspect of adhering to COLREGs in modern maritime operations. Furthermore, a multi-agent control scheme for managing the speed and coordination of multiple tugboats during ship towing was introduced in [50], addressing the complexities of multi-vessel operations and the necessity of coordinated actions.

The study conducted in [90] proposes a framework of human-machine interaction for collision avoidance. The framework is tested with respect to its compliance with COLREGs, i.e. the presence of oscillations when the ship is underactuated versus the behaviour of COLREG compliance.

While existing research on integrating the COLREGs into autonomous maritime navigation systems has made great progress, particularly in compliance with power-driven vessels, they have tended to focus on a subset of the regulations, for example, Rules 13, 14 and 15 [52]. Such analyses are less concerned with including COLREGs rules for target vessel manoeuvrability and proactive avoidance rules in collision avoidance, which are pivotal in determining the priority of way and executing explicit and effective evasive manoeuvres. Our research aims to address this limitation by incorporating a more comprehensive interpretation of COLREGs, including consideration of target vessel manoeuvring capabilities, vessel type, and proactive collision avoidance strategies in different encounter scenarios, into the decision-making frameworks.

- **DWA-based Path-Planning in MASS**

DWA, a seminal concept in robotics introduced for robotics navigation by [63], selects the optimal velocity of a robot from a set of feasible velocities within a “dynamic window” based on the robot’s current state and a cost function evaluating safety, efficiency, and goal reachability. The process ensures real-time collision avoidance and goal-oriented movement by continuously updating the robot’s trajectory. Its core advantage lies in its computational efficiency and adaptability to rapid changes, making it very suitable for dynamic environments.

DWA’s journey from theory to wide-ranging applications reflects its robustness and versatility. Its application in high-speed navigation was demonstrated in [18], revealing its capacity for quick adaptation in fast-paced scenarios. Its scope with an adaptive variant was expanded in [46], highlighting its customizability to diverse robotic architectures. Its real-world feasibility through practical application in robotic navigation was underscored in [139] by testing the effectiveness of a proposed collision-checking algorithm combined with the DWA algorithm.

The transition of DWA into maritime domains, particularly in MASS, marks a new chapter in its application. DWA’s role in enhancing navigational safety in autonomous maritime systems was highlighted in [156]. The integration of DWA with a Shark-Inspired Algorithm by [34] and its fusion with the A-Star algorithm by [71] demonstrate its adaptability in maritime environments, blending traditional algorithms with advanced techniques for optimal path planning. Its adaptability to environments with dynamic obstacles was emphasised in [37].

DWA is an efficient algorithm for real-time collision avoidance and path optimisation in robotics, with the advantage of adapting to dynamic changes. However, its application within the maritime domain faces challenges due to the unique kinetics and physical constraints required for MASS movement. This necessitates modifications to the DWA algorithm in order to ensure it aligns with maritime navigation, indicating a gap between its current capabilities and the demands of maritime application.

3.3 Situational awareness modelling

3.3.1 Development of the knowledge maps model

The ontology-based knowledge maps model is developed to enhance the situational awareness of MASS. The map is a semantic graph formed by multiple entities and the relationships among them. The knowledge map model integrates various maritime navigation rules and environmental factors, specifically focusing on COLREGs. The model provides the following three capabilities to support the safe navigation of MASS:

1. **Task awareness** refers to high-level information from maritime regulations, collision avoidance, planned long- and short-term routes, communications with authorities and surrounding ships, etc., which serve as inputs to the ship's KM comprehension module. It is compiled and interpreted in a semantic format to support the MASS's decision-making. See the example presented in Figure 3-1, where MASS is aware of the destination by understanding the route first via "`#MASS`" "`#has_planned_routes`" "`Planned_route`", and then finalise the understanding of its destination via "`#destinationLoc`" as an instance of "`#Planned_route`". The awareness results are organised in an XML format to facilitate knowledge management by MASS.

```xml
<owl:ObjectProperty rdf:about="#has_planned_routes">
  <rdfs:subPropertyOf rdf:resource="http://xxx/owl#topObjectProperty"/>
  <rdfs:domain rdf:resource="#MASS"/>
  <rdfs:range rdf:resource="#Planned_route"/>
</owl:ObjectProperty>
<owl:DatatypeProperty rdf:about="#destinationLoc">
  <rdf:type rdf:resource="http://xxx/owl#FunctionalProperty"/>
  <rdfs:domain rdf:resource="#Planned_route"/>
  <rdfs:range rdf:resource="http://xxx/XMLSchema#string"/>
</owl:DatatypeProperty>
```

Figure 3-1 Representation of task awareness in the knowledge map model using XML format

2. **Control system constraints**: The control system of MASS receives the outputs of the knowledge maps model as constraints, such as the situational information provided by the KM and the decision actions suggested by the COLREGs in the collision avoidance scenarios, where the situational information includes the type of scenario encountered such as crossing, and the suggested actions include turning to the starboard side or going straight ahead. These outputs serve as constraints for the controller or planner, such as the space available for acceleration and turn rate at the next moment, which affects the subsequent decision actions of the ship.

3. **Navigational status synthesis** involves the aggregation of basic navigational and environmental data surrounding the vessel. These two pieces of data are continuously fed into the perception of the KM model for data processing as well as relationship formulation and further fed into the comprehension module to form semantic information that facilitates the real-time construction of situational awareness semantic graphs. The capability of Navigational Status Synthesis supports the representation of the key concepts and relationships related to navigation at the current moment or over a period of time.

An enhanced ontology-based knowledge maps model is presented in this study, building upon a foundational knowledge maps model introduced in [193]. In that prior work, a Situational Awareness-based KM model was developed for MASS, aiming at creating a comprehensive, real-time knowledge base. This base was designed to encapsulate both external information and internal data, including the control system, navigational tasks, and status, with its comprehensive details documented in [193].

The construction of the KM model employs ontology tools grounded in a thorough analysis of situational requirements. This process involved identifying key navigation-related elements of MASS and categorising them into classes, object properties, and data properties. Initially validated through basic scenario tests, the model has now been enhanced to address real-world applications. This enhancement includes the integration of an enriched KM model within the path planner. This model incorporates a broader spectrum of rules for collision avoidance, including the conversion and coordination of multiple COLREGs rules, elements not previously considered in our initial model.

Our aim is to incorporate more COLREGs rules in our model so that MASS can be better adapted to the various navigational environments, especially in those areas full of COLREGs, for example, the harbour area, traffic separation area, etc. In order to incorporate collision rules in the knowledge map, we introduced Semantic Web Rule Language (SWRL) in the model, which provides a convenient way to convert statements into machine-readable language. Specifically, key collision avoidance rules for ships in sight of one another in COLREGs are considered in this chapter, incorporating Rules 11, 13, 14, 15, 16, 17(a(i), a(ii), b, d), 18(a,b,c).

The translation details of COLREGs rules based on SWRL are given in Table 3-2.

3.3.2 Adapted DWA designed for MASS

The classic DWA algorithm is mostly used for two-wheel robot navigation. For MASS, especially for the three degrees of freedom (3DOF) MASS, which has not only the force from the X axis and the moment from the Z axis but also the force from the Y axis, the DWA needs to be adapted.

3.3.2.1 Acceleration-based velocity sampling

To better consider the motion characteristic of MASS, the sampling method proposed in [146], which uses an acceleration-sampling method, is introduced here. The illustration for sampling acceleration in DWA can be seen in Figure 3-2, where $V_s, V_r, and\ V_d$ represent the space of possible velocities, the space of possible velocities constrained by its acceleration, and the intersection of the restricted areas, namely V_s, and V_r. By incorporating the vessel's dynamic capabilities, velocities obtained based on acceleration sampling are computed from the vessel's current velocity: $[a_{u\_min}, a_{u\_max}]$, $[a_{v\_min}, a_{v\_max}]$ and $[a_{\omega\_min}, a_{\omega\_max}]$, where a_{u_min} , a_{v_min}, a_{ω_min} refer to the minimum accelerations from the direction of surge, sway, and yaw axis, respectively, while a_{u_max}, a_{v_max}, a_{ω_max} refer to the maximum accelerations along the directions of surge, sway, and yaw, respectively. Thus, new velocities $u_{t+\Delta t}$, $v_{t+\Delta t}$, and $\omega_{t+\Delta t}$ are derived using: $u_{t+\Delta t} = u_t + a_u \cdot \Delta t$, $v_{t+\Delta t} = v_t + a_v \cdot \Delta t$, and $\omega_{t+\Delta t} = \omega_t + a_\omega \cdot \Delta t$, where Δt is the time step, u_t and a_u are current surge velocity and acceleration, v_t and a_v are current sway velocity and acceleration, ω_t and a_ω are current yaw velocity and acceleration. The velocity space is discretised into potential velocities, constrained within the vessel's maximum and minimum speed limits, forming a cubic space: $V_s = \{[u_{\min}, u_{\max}], [v_{\min}, v_{\max}], [\omega_{\min}, \omega_{\max}]\}$, where $u_{\min}$, $v_{\min}$, and $\omega_{\min}$ refer to the minimum velocities from the direction of surge, sway, and yaw axis, respectively, while $u_{\max}$, $v_{\max}$, $\omega_{\max}$ refer to the maximum velocities along the directions of surge, sway, and yaw, respectively. Additionally, during the vessel's navigation, each velocity pair (u, v, ω) within this space is evaluated for feasibility based on the cubic space constraints, and optimality is evaluated based on the total benefit of cost functions determined by sampling the velocity pairs.

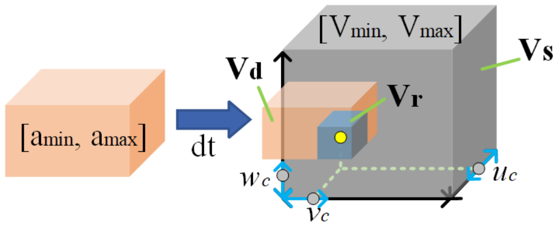


Figure 3-2 The schematic for sampling accelerations in the surge, sway, and yaw directions in the DWA algorithm

Key differences and advantages of acceleration-based sampling over velocity-based sampling in the maritime context include the following:

(1) Acceleration-based sampling aligns with the vessel's current motion state, offering realistic velocity options that reflect the vessel's physical capability for speed and directional changes.
(2) Acceleration-based sampling models more accurately the vessel's motion than the velocity-based sampling method, accounting for realistic acceleration and deceleration rates, which are important in dynamic maritime environments.

3.3.2.2 Prediction of MASS movement in DWA

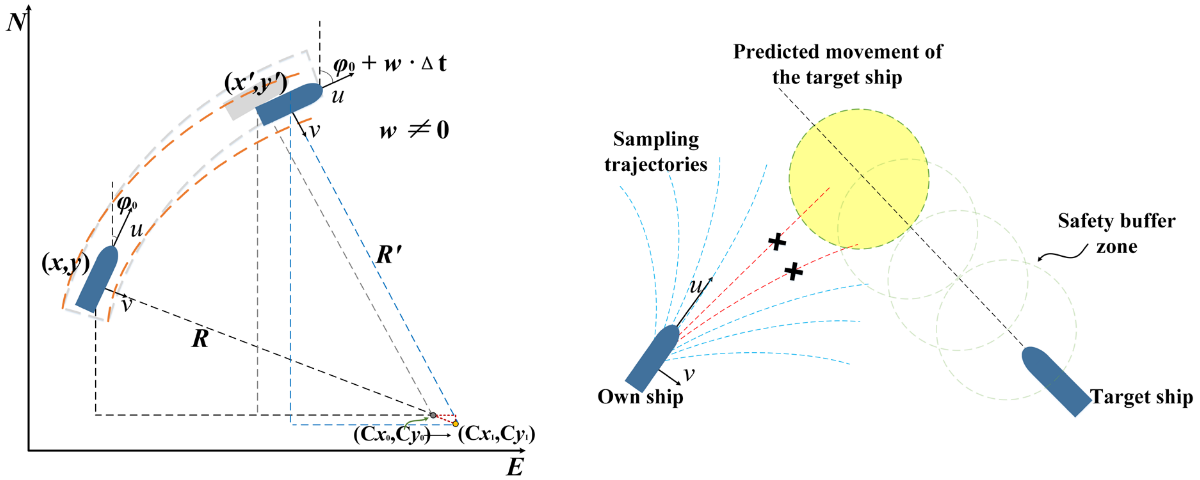
In this part, the focus shifts to predicting the movement of MASS using the DWA. The introduction of a force along the Y-axis adds complexity to the predicted motion trajectory of the object. Unlike the classic DWA algorithm, which primarily relies on linear and angular velocities to predict linear or circular motion, the presence of Y-axis linear velocity introduces additional dimensions to the motion trajectory analysis. This change has resulted in the prediction of vessel motions that will not be conventional linear or circular paths. In order to simplify this problem, assuming the MASS will still do the circular movement during a small period, we revise the algorithm by amending the centre of rotation by moving it from the original point $(C_{t\_x_0}, C_{t\_y_0})$ to the current one $(C_{t\_x_1}, C_{t\_y_1})$ because of the influence of the sway velocity. The scheme diagram is shown in Figure 3-3 - (a) when the yaw velocity ω_t does not equal 0, where (φ_t) and $(\varphi_t + \omega_t \cdot \Delta t)$ represent the original angle at time t and the angle after moving, respectively. u_t and v_t represent the surge and sway velocity at time t, which do not change during the small period. Point $(C_{t\_x_0}, C_{t\_y_0})$ is the original rotation centre, and point $(C_{t\_x_1}, C_{t\_y_1})$ is the new rotation centre, which moves from the former to the current one under the influence of the sway velocity. R_t and R_t' are calculated based on the classic DWA algorithm and simplified extensive DWA tailored for MASS. Additionally, (x_t, y_t) and $(x_{t+\Delta t}, y_{t+\Delta t})$ refer to the start point and the predicted point after Δt, respectively. The equations for calculating them are as follows:

$$R_t = \frac{u_t}{\omega_t}; R_t' = R_t + v_t \cdot \Delta t$$

$$C_{t\_x_0} = x_t - R_t \cdot \sin(\varphi_t); C_{t\_y_0} = y_t + R_t \cdot \cos(\varphi_t)$$

$$C_{t\_x_1} = C_{t\_x_0} + v_t \cdot \Delta t \cdot \cos(\varphi_t); C_{t\_y_1} = C_{t\_y_0} - v_t \cdot \Delta t \cdot \sin(\varphi_t)$$

$$x_{t+\Delta t} = C_{t\_x_1} - R_t' \cdot \cos(\varphi_t + \omega_t \cdot \Delta t); y_{t+\Delta t} = C_{t\_y_1} + R_t' \cdot \sin(\varphi_t + \omega_t \cdot \Delta t)$$



(a) Assumption of MASS for circular motion (b) Extended DWA algorithm with collision avoidance prediction

Figure 3-3: The schematic diagram of the revised DWA algorithm for MASS

Regarding collision avoidance between ships, the collision prevention distance determined according to the classic DWA algorithm is different from the complex motion and longer stopping distances of MASS, influenced by maritime forces and vessel inertia. Thus, we extend the classic algorithm to a predicted collision avoidance algorithm, as seen in Figure 3-3 - (b). The sampling trajectories of the own ship touching the safety buffer of the predicted motion of the surrounding vessel will be removed. The core principle of DWA involves the generation of a velocity space, considering a robot's current velocity and acceleration limits. The following equations define the velocity space:

$$V_s = \{(u, v, \omega) | u_{min} \le u \le u_{max}, v_{min} \le v \le v_{max}, \omega_{min} \le \omega \le \omega_{max}\},$$

$$V_d = \big((u, v, \omega)\big| u \in [u_t - a_u \cdot \Delta t, u_t + a_u \cdot \Delta t], v \in [v_t - a_v \cdot \Delta t, v_t + a_v \cdot \Delta t], \omega \in [\omega_t - a_\omega \cdot \Delta t, \omega_t + a_\omega \cdot \Delta t]\big),$$

where V_s represents the set of all achievable velocities, u is the surge velocity, v is the sway velocity, ω is the yaw velocity, and V_d is the dynamic window, which considers the MASS's acceleration limits.

The algorithm evaluates each acceleration pair (a_u, a_v, a_ω) within the reachable velocity range $(u,\ v,\ \omega)$ using a comprehensive cost function. This cost function incorporates several objectives, including goal-reaching, obstacle avoidance, path-keeping, time to the goal, and compliance with COLREGs compliance. The optimal set of acceleration $(a_u^*, a_v^*, a_\omega^*)$ and optimal velocity (u^*, v^*, ω^*) that minimise this cost function are then chosen for execution; see Equations (3-1) and (3-2). The cost function for each acceleration vector denoted as $C(a_u, a_v, a_\omega)$, is weighted by coefficients α_i, which reflect the importance of various objectives such as safety, efficiency, and rule adherence.

$$(a_u^*, a_v^*, a_\omega^*) = \arg \min_{(a_u, a_v, a_\omega) \in a_d \& a_s} C(a_u, a_v, a_\omega),\ C(a_u, a_v, a_\omega) = \sigma\left(\sum_{i=1} \alpha_i \cdot C_i(a_u, a_v, a_\omega)\right) \tag{3-1}$$

$$(u^*, v^*, \omega^*) = (u_t, v_t, \omega_t) + (a_u^*, a_v^*, a_\omega^*) \cdot \Delta t \tag{3-2}$$

To implement the DWA algorithm on MASS using an acceleration-based sampling technique, the algorithm compares various combinations of accelerations within a discretised sampling space. This procedure entails enumerating potential acceleration vectors that are feasible within the dynamic limitations of the vessel and environmental constraints. For each sampled acceleration vector, the algorithm calculates the resultant velocities.

Subsequently, the acceleration vector $(a_u^*, a_v^*, a_\omega^*)$ that yields the lowest cumulative cost, indicative of the optimal trajectory under current conditions, is selected. This optimal acceleration vector is then utilised to derive the corresponding optimal velocity (u^*, v^*, ω^*), which guides the MASS towards its goal while prioritising safety, efficiency, and regulatory compliance. Furthermore, this selection process is iterative. By systematically analysing the cost associated with each pair of acceleration and velocity, the algorithm ensures that the MASS can adapt its navigation strategy in real time, optimising for the most favourable outcome based on the current situational context.

3.3.3 Integrating the KM model into decision-making

3.3.3.1 System architecture

The KM-DWA architecture consists of three modules: knowledge maps, DWA path planner, and trajectory generator. The formation process of the knowledge maps is presented in Algorithm 3-1. Before processing real-time data, the KM, an XML file used to represent ontology-based KM, needs to be aware of tasks, including route, departure, destination, etc. The XML file contains the concepts and relationships involved in ship navigation, encoded into various classes and properties. **MASS**, **Task**, **Instance**, and **Object Property**, representing the operators of the ontology, namely classes, instance, and objective property, etc., used to instantiate and transform the navigation-related information into the ontology. The own ship $[OS]$, i-th task $[Task_i]$ and the relationship between the own ship and $Task_i$: $\{hasTask_i\}$ are the results of the instantiation. In addition, SWRL is used here to convert COLREGs into machine-understandable rules, that is, the rules that ships need to comply with and the actions recommended by the rules if they satisfy a specific set of conditions. At this point, the generated KM file will be used for real-time situational understanding. First, the KM module continuously receives environmental information EI_t, such as visibility, surrounding vessel information etc., and navigation information NI_t generated by the trajectory generator, such as the *position*, *speed*, *and heading* of the own ship. These data are fed into the Perception module of the KM model, where data processing is performed to generate parameter information used for situation analysis, which will be passed to the Projection module and Comprehension module for further analysis. Specifically, Projection performs the task of risk evaluation, which is to determine whether there is a potential collision risk based on whether DCPA and TCPA reach the pre-set thresholds. Then, the risk estimate generated by Projection is passed into the Comprehension module to update the situational information in the ontology file, including repeating the ontology operation instantiation process as in steps 6 to 7 in Algorithm 3-1 to generate the situational information at time *t*. Then, the Pellet inference engine is called to reason about the parameter information obtained by the Perception module and the risk assessment results of the Projection, the tasks, and the rules that need to be followed to clarify the rules that need to be obeyed, encounter scenarios and other information of $SAInfo_t$, details can be seen in Figure 3-4. Then, situation information and tasks are passed into the planner as constraints, and the planner evaluates the optimal accelerations through sampling. The optimal acceleration obtained will be input into the trajectory generator to update the motion parameters at the next moment, including speed, heading, position and other information. The above process is repeated until the goal is achieved or a collision occurs.

Algorithm 3-1: Formation Of Knowledge Maps For Supporting Safe Navigation Of MASS

Input: *Navigational Rules, Tasks, Environment information* (EI_t)*, Navigational information* (NI_t) *of MASS(OS)*
Output: *Real-time knowledge maps in the form of situational semantic network*

Step 1: Task awareness
1: ***Initialise*** *the Knowledge Maps as an XML file.*
2: *Formulate the Knowledge Maps:* $KM \leftarrow \{\{class, object\ properties\ and\ data\ properties\}, \cdots\}$
3: *Transform and add the task-related information, e.g., planned routes, waypoints, etc.*
4: ***Initialise*** the own ship: $\boldsymbol{Instance}$: $[OS] \leftarrow (\mathbf{MASS}\{OS\}, \mathbf{DataProperties}\{OS\})$
5: ***for*** *each task* $Task_i$ ***do***
6: | **Instance**: $[Task_i] \leftarrow (\mathbf{Task}\{Task_i\}, \mathbf{DataProperties}\{Task_i\})$
7: | **Object Property**$\{hasTask_i\} \leftarrow ([OS], [Task_i])$
8: | Task $= \{[Task_i], \cdots\}$
9: *Interpret navigational rules (COLREGs) as executable orders (turning to port or starboard) and add them to KM.*
10 ***for*** *each rule* $Rule_x$*,* ***do****:*
11 | $Rule_x, RecommendAction_k \leftarrow SWRL(ship, condition_j, condition_{j+1}, \cdots)$
12 | Rule $= \{(Rule_x, RecommendAction_k), \cdots\}$
13 *Store the Knowledge Maps file.*

Step 2: Real-time situation understanding
14 ***While*** *not colliding or reaching the destination,* ***do****:*
| *// Navigational Status Synthesis*
15 | *Obtain navigational information* NI_t *and environment information* EI_t
16 | ***Initialise****:* $NI_t \leftarrow (Position_t, Velocity_t, Heading_t), EI_t \leftarrow (Visibility_t, targetVessels_t, \cdots)$
17 | ***Perception***
18 | $SituationalParameters_t: \{Encounter\ angle, DCPA, TCPA, \cdots\} \leftarrow \mathrm{SA}(NI_t, EI_t)$
19 | ***Projection*** (*risk evaluation*)*:* $Risk_t \leftarrow$ Situational parameters
20 | ***Comprehension****:*
21 | *Update KM:* ***Add*** *Instances, Object Properties, and Data Properties to KM as the steps:* $\mathbf{6} \rightarrow \mathbf{7}$
22: | $SAInfo_t: \{Regulation\ compliance, Encounter\ type, COLREGs\ role, CA\ distance, Recommended\ action\} \leftarrow$ **Reasoning_PelletReasoner**{Situational parameters, $Risk$, Task, Rule}
| *// Navigational Status Synthesis*
23 | *Constraints of the Planner:* $AccelerationSamplingSpace_{t+1} \leftarrow \{SAInfo_t, Task\}$
24 | *Optimise accelerations:* $OptimalAccelerations_{t+1} \leftarrow DWAPlanner(AccelerationSamplingSpace_{t+1})$
25 | *Update velocities and heading:* $Velocity_{t+1}, Heading_t, \leftarrow Velocity_t, OptimalAccelerations_{t+1}$
26 | *Update position:* $Position_{t+1} \leftarrow (Position_t, Velocity_t, Heading_t, Velocity_{t+1}, Heading_t)$
End
27 ***Return*** *Real-time knowledge maps to provide guided information for the planner*

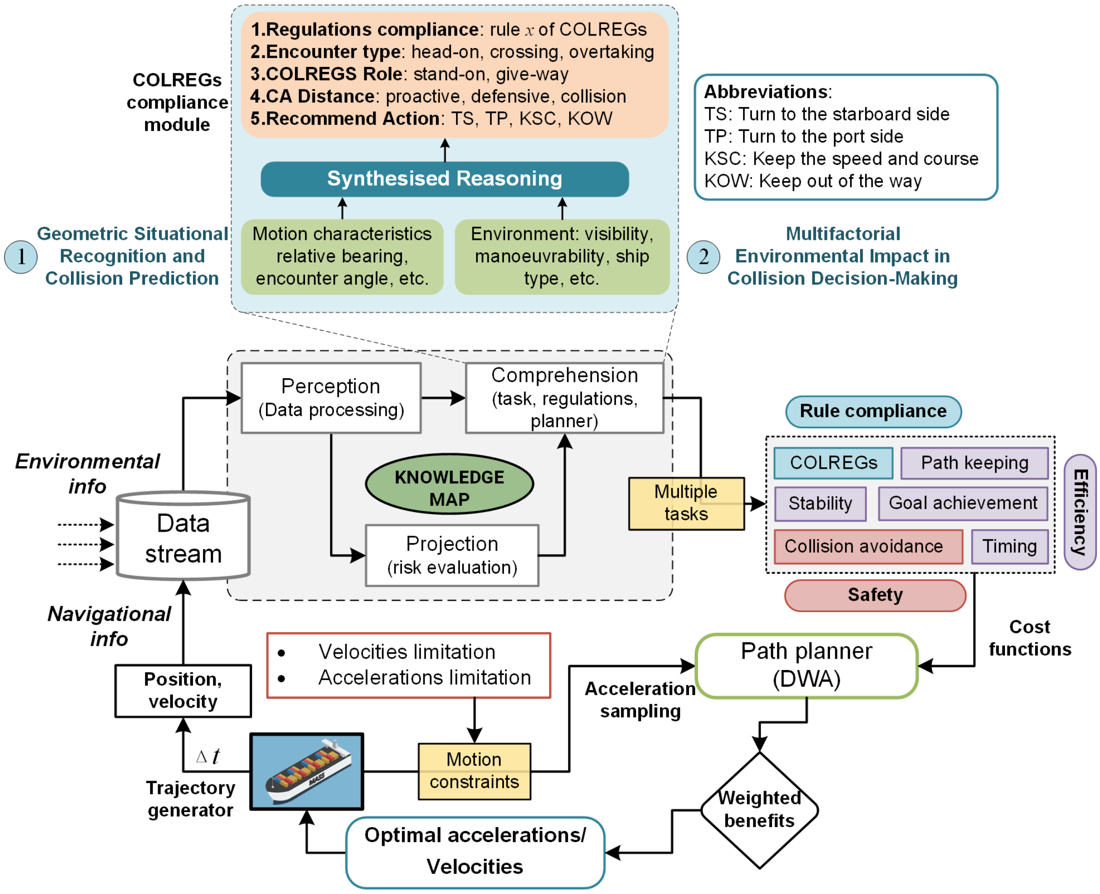


Figure 3-4 The diagram of the KM-DWA decision-making framework based on the knowledge maps and DWA algorithm

3.3.3.2 Integrated collision avoidance scheme

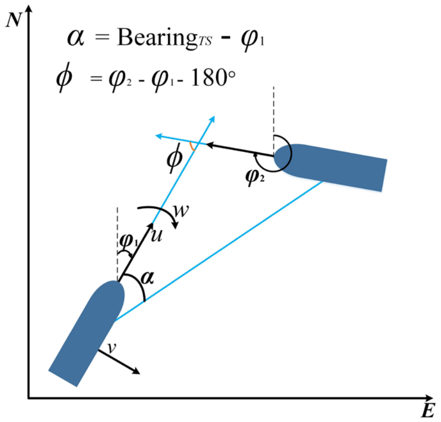
The safe navigation of MASS hinges on their ability to accurately identify current situations and make decisions compliant with the COLREGs. Our methodology, derived from [152], enables MASS to identify encounter scenarios through the calculation of encounter angles and relative bearings when a surrounding vessel enters the detection range. The calculations of the Encounter angle (ϕ) and Relative bearing (α) (see Figure 3-5 (a)) are as follows.

$$\alpha = \frac{\pi}{2} - arctan\left(\frac{(y_{ob} - y_t)}{(x_{ob} - x_t)}\right) - \varphi_t; \qquad \phi = \varphi_{obt} - \varphi_t - \pi$$

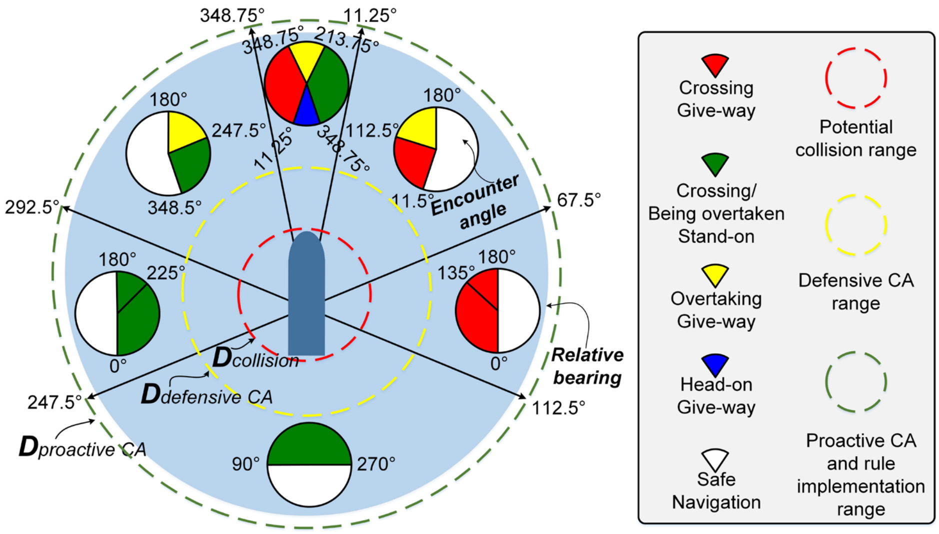
where φ_{obt} represents the heading of the surrounding vessel at time t, $\vec{P}_{ob} = (x_{ob}, y_{ob})$ represents the position of the surrounding vessel at time t.

Based on the six small circles divided into different coloured sections determined by the encounter angle and relative bearing, the type of encounter, such as "crossing", and the navigational priority of my ship, such as "give-way", can be determined, details can be seen in Figure 3-5 (b). The six small circles in the figure are the division of the encounter angle, where different colours indicate different scenarios. The divisions in the blue zone are the sections of the relative bearing of the surrounding vessel relative to the own ship, and the dotted circles indicate three distances for collision avoidance, including proactive distance, defensive, and collision distances. Specifically, the *proactive distance* is the distance at which a "give-way" vessel is required to take collision avoidance action, while the "stand-on" vessel is required to maintain course and speed in accordance with the rules. The *defensive distance* is the distance at which the "stand-on" vessel is required to take evasive action when the "give-way" vessel does not take evasive action from the proactive distance to the defensive distance or when the evasion task cannot be accomplished by the "give-way" ship alone. The *collision distance* is the distance at which a collision between ships occurs.

Additionally, in order to address the need for effective collision avoidance, the three-tier safety buffer, i.e. proactive, defensive, and collision distances, is embedded within the DWA algorithm (see Algorithm 3-2) to satisfy the requirements of Rule 8 of COLREGs, that is *the action taken should be positive, made in ample time, and large enough to be readily apparent to another vessel observing visually or by radar*. COLREGs dictate distinct actions and timings for vessels operating as either the give-way vessel or the stand-on vessel.



(a) Encounter angle and relative bearing



(b) Encounter scenarios determination based on the encounter angle and the relative bearing

Figure 3-5: The illustration of sector division for collision scenario recognition

Distance Closest Point of Approach (DCPA) and Time Closest Point of Approach (TCPA) are further incorporated into the algorithm, ensuring that avoidance manoeuvres are not solely based on physical proximity but also on the timing of potential vessel convergence. Should either DCPA or TCPA fall below their respective thresholds, namely 3 meters for DCPA and 10 seconds for TCPA with respect to our model ship, the algorithm triggers the necessary avoidance manoeuvres, offering a dynamic and responsive framework for collision avoidance.

3.3.3.3 KM-DWA algorithm

The overarching goal of the KM-DWA algorithm is to obtain the best velocities for the action in the next time step. The best velocities can be calculated by the highest cost score by calculating different kinds of cost functions involving safety (collision avoidance), efficiency(Goal achievement, Path keeping, Time to goal, Stability), and rule compliance (COLREGs), as seen in Figure 3-4. The details of the algorithm can be seen in Algorithm 3-3.

Algorithm 3-2: Determination Of Collision Avoidance Distance And Action For MASS

Input: *DCPA_threshold, TCPA_threshold,* $D_{collision}, D_{pro}, D_{def}$
Output: *Distance and recommended action to avoid collision*
Get current distance $d_{current}, DCPA, TCPA$
if $d_{current} < D_{collision}$ ***then***
  | ***Trigger:*** *Imminent collision avoidance, none*
else if $d_{current} < D_{pro}$ ***then***
  | ***if*** *Own_action = "give_way"* ***then***
  | | ***Trigger:*** *Proactive collision avoidance, take evasive action*
  | ***else if*** *Own_action = "stand-on"* ***then***
  | | ***Trigger:*** *Proactive collision avoidance, maintain course and speed*
else if $d_{current} < D_{def}$ ***then***
  | ***if*** *Own_action = "stand-on"* ***and*** *(DCPA < DCPA_threshold and TCPA< TCPA_threshold)* ***then***
  | | ***Trigger:*** *Defensive collision avoidance, initiate independent action*
  | ***else***
  | | ***Continue:*** *Proactive collision avoidance, maintain course and speed*
else
  | ***if*** *DCPA < DCPA_threshold* ***and*** *TCPA< TCPA_threshold* ***then***
  | | ***Trigger:*** *Collision avoidance, none*
  | ***else***
  | | ***Monitor:*** *Normal navigation, none*
Return *Distance and recommended action to avoid collision*

Algorithm 3-3: KM-DWA For Path-Planning Of MASS

Input: (x_t, y_t) (u_t, v_t, ω_t) , φ_t, $\mathbf{ob}$, $T_{horizon}$, $goal, weights, D_{collision}, D_{pro}, D_{def}$
Output: *Optimal path*
Get current distance $d_{current}, DCPA, TCPA$
Function $f_{cost} = (pos, \mathbf{ob}, goal, weights, D_{collision}, D_{pro}, D_{def})$
  | ***return:*** *Total cost*
Function $f_{pred\_ob} = (\mathbf{ob}, time)$
  | ***return:*** *Predicted positions of obstacles after time*
Function $f_{pred\_os} = (pos, velocity, heading, acceleration, T_{horizon})$
  | ***return:*** *The predicted position of the own ship after time*
Function $f_{planning} = (goal, \mathbf{ob}, x_t, y_t, T_{horizon})$
  | ***Initialise*** *Optimal Cost:* $C^* \leftarrow -\infty$,
  | *SampleNum*$\leftarrow 8$ *//Number of samples of each acceleration*
  | ***for*** *each acceleration combination* (a_u, a_v, a_ω) **do**
  | | $a_c \leftarrow (a_u, a_v, a_\omega)$
  | | $(x_{t+\Delta t}, y_{t+\Delta t}) \leftarrow f_{pred\_os}(x_t, y_t , u_t, v_t, \omega_t, \varphi_t, a_c, T_{horizon})$
  | | $(x_{ob_{t+\Delta t}}, y_{ob_{t+\Delta t}}) \leftarrow f_{pred\_ob}(\mathbf{ob}, T_{horizon})$
  | | *Cost* $C \leftarrow f_{cost}(x_{t+\Delta t}, y_{t+\Delta t}, x_{ob_{t+\Delta t}}, y_{ob_{t+\Delta t}}, goal, weights, D_{collision}, D_{pro}, D_{def})$
  | | ***if*** $C > C^*$ ***then***
  | | | $C^* \leftarrow C$
  | | | $a^* \leftarrow a$
  | | | $v^* \leftarrow v$
  | ***Return*** v^*
While the *goal is not true* ***do:***
  | *Optimal velocities* $v^* \leftarrow f_{planning}(goal, \mathbf{ob}, x_t, y_t, T_{horizon})$
  | *Update the next optimal position*
Return *Optimal path*

The mathematical expressions to calculate the total benefit cost at the next time step $t+\Delta t$ in a discrete space are as follows, where the accelerations (a_u, a_v, a_ω) are constant during Δt.

1. Goal achievement cost function:

$$C_{goal}(t+\Delta t) = \|\vec{P}_{pred} - \vec{P}_{goal}\| \tag{3-3}$$

where $\vec{P}_t = (x_t, y_t)$ represents the position of MASS at time t, $\vec{P}_{goal} = (x_{goal}, y_{goal})$ represents the goal position to be reached by MASS, $\vec{P}_{pred} = (x_{t+\Delta t}, y_{t+\Delta t})$ represents the predicted position.

2. Obstacle avoidance cost function:

$$C_{obstacle}(t+\Delta t) = \begin{cases} D_{min} - D_{obs} & if\ D_{min} < D_{obs} \\ 0 & otherwise \end{cases} \tag{3-4}$$

where D_{obs} is the distance to the nearest obstacle on the predicted trajectory at time $t+\Delta t$; D_{min} is the minimum safe distance at time $t+\Delta t$, which is set to be four times the length of the ship hull.

3. Path keeping cost function:

$$C_{pathKeeping}(t+\Delta t) = e_{path} \tag{3-5}$$

where e_{path} is the deviation distance from the candidate point to the planned path.

4. Time to goal cost function:

$$C_{timeToGoal}(t+\Delta t) = \left(\frac{\|\vec{P}_{pred} - \vec{P}_{goal}\|}{\sqrt{u_c^2 + v_c^2} + \varepsilon}\right) \tag{3-6}$$

where u_c *and* v_c are the candidate surge and sway velocities $t+\Delta t$, respectively.

5. Navigation stability cost function:

$$C_{stability}(t+\Delta t) = \left(\varphi_{pred} - \varphi_t\right)^2 \tag{3-7}$$

where φ_{pred} refers to the predicted heading angle after Δt, $\varphi_{pred} - \varphi_t$ is the change in heading angle.

6. COLREGs compliance cost function:

$$C_{colregs}(t+\Delta t) = \begin{cases} min(0, -\omega_c) & if\ Encounter\ type = \text{"}Crossing\text{"}\ and\ Own\ action = \text{"}give - wa \\ |u_c - u_t| + |v_c - v_t| + |\omega_c| & if\ Encounter\ type = \text{"}Crossing\text{"}\ and\ Own\ action = \text{"}stand - o \\ min(0, -\omega_c) & if\ Encounter\ type = \text{"}Head - on\text{"} \\ 0 & otherwise \end{cases} \tag{3-8}$$

where u_c, v_c, ω_c represent candidate surge, sway, and yaw velocities, respectively. u_t *and* v_t denote the current surge and sway velocities, respectively.

The overall benefit function is then defined as a weighted sum of the individual cost functions from Equation (3-3) through to Equation (3-8), which is minimised to select the smallest combination of accelerations, as shown in Equation (3-1).

$$C(t+\Delta t) = \sigma\Big(\alpha \cdot C_{goal}(t+\Delta t) + \beta \cdot C_{obstacle}(t+\Delta t) + \gamma \cdot C_{pathKeeping}(t+\Delta t) + \delta \cdot C_{timeToGoal}(t+\Delta t) + \eta \cdot C_{colregs}(t+\Delta t) + \kappa \cdot C_{stability}(t+\Delta t)\Big) \tag{3-9}$$

where α, β, γ, δ, η, κ are the weighting factors for each cost function. In this chapter, a combination of empirical testing and consideration for the importance of each function in relation to the overall goal of the algorithm was employed.

In adjusting the weighting factors, all weights were initially set to 1 to test if the vessel could successfully avoid collisions. It was observed that the vessel adhered too strictly to its planned route and failed to manoeuvre adequately, leading to collisions. This issue was evident with the weights γ, δ set to 1, causing the vessel to prioritise efficiency over safety. Additionally, the MASS maintained its heading rigidly with κ set to 1, hindering its ability to turn to avoid collisions. Therefore, γ, δ, κ were incrementally reduced from 1, while α and β remained at 1 for efficiency and safety. Through this iterative process, the weights were fine-tuned to α = 1, β = 1, γ = 0.2, δ = 0.1, κ =0.01. This adjustment set a baseline to ensure the MASS maintains its planned route while successfully avoiding collisions without considering COLREGs.

Subsequent fine-tuning focused on the parameter δ, which influences the rule adherence. To isolate the impact of η on the system's ability to conform to COLREGs, we conducted tests with its values varied across a discrete set: 0, 0.3, 0.6, and 1, while other parameters remained unchanged.

3.4 Case study

3.4.1 Simulation environment

The implementation and testing phase of this chapter established a simulation environment featuring the TU Delft-developed *Tito-Neri* model vessel [81]. This model simulates maritime dynamics, coexisting with surrounding vessels that maintain consistent behaviour across scenarios. An interface was designed for simulation, including three proximity levels using concentric circles: proactive avoidance marked in blue (5 times the length of the ship hull), defensive avoidance marked in green (3 times the length of the ship hull), and collision radius marked in red (the length of the ship hull). The details are shown in Figure 3-6.

Moreover, the interface incorporates a situational understanding module in the middle of the right part of the interface, which invokes the designed knowledge maps ontology by calling Python's *owlready2* package for real-time reasoning. This module provides insights into the operational status of the MASS, including the algorithm currently in use, the vessel's mission objectives, and the navigation goal. In scenarios where the MASS encounters another vessel, the module delineates the type of the encounter, assigns roles as defined by the COLREGs, and stipulates the corresponding actions along with their timings. In addition, various performance indicators of the DWA algorithm are shown in the interface, such as distance to goal, obstacles, path keeping, etc. These metrics monitor the parameters of the KM-DWA algorithm.

The computational platform for these simulations was Python 3.10, running on an 11th Gen Intel(R) Core(TM) i7-1185G7 @ 3.00GHz 1.80 GHz system.

3.4.2 Scenario-based testing

Testing was organised into the following scenarios:

(1) Head-on: Assessing the system's course and speed adjustments as guided by COLREGs Rule 14.
(2) Crossing: Evaluating the system's decision-making process in scenarios where surrounding vessels approach from lateral directions, with a focus on varying ship types and manoeuvrability.
(3) Overtaking: Testing the system's ability to safely and efficiently navigate overtaking manoeuvres in compliance with COLREGs Rule 13.

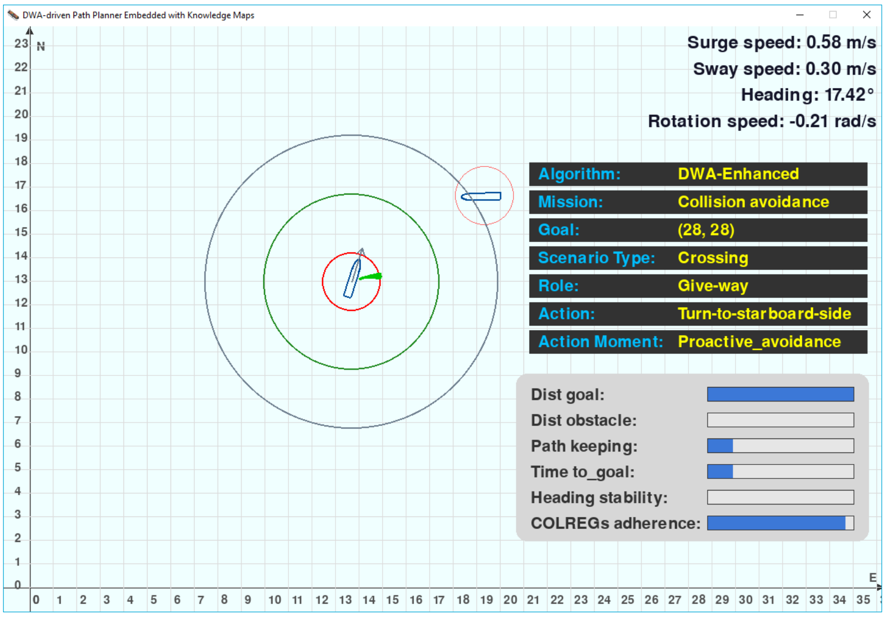


Figure 3-6 The interface designed for simulation in the collision avoidance scenarios.

Specifically, the following experimental control variables were designed in the test scenario, including the *manoeuvrability of the surrounding vessel*, *traffic complexity*, and *the impact of COLREG compliance*. These variables are presented in detail in subsections 4.2.1 through 4.2.3 below.

3.4.2.1 Manoeuvrability of the surrounding vessel

Surrounding vessel types categorised by COLREGs priorities include Power-driven vessels, Type I, Type II, and Type III. Specifically, their corresponding ship type or manoeuvrability is listed below:

- Type I: Sailing vessel;
- Type II: Engaged in fishing;
- Type III: Vessel constrained by her draught, Restricted in her ability to manoeuvre, and Vessel not under command

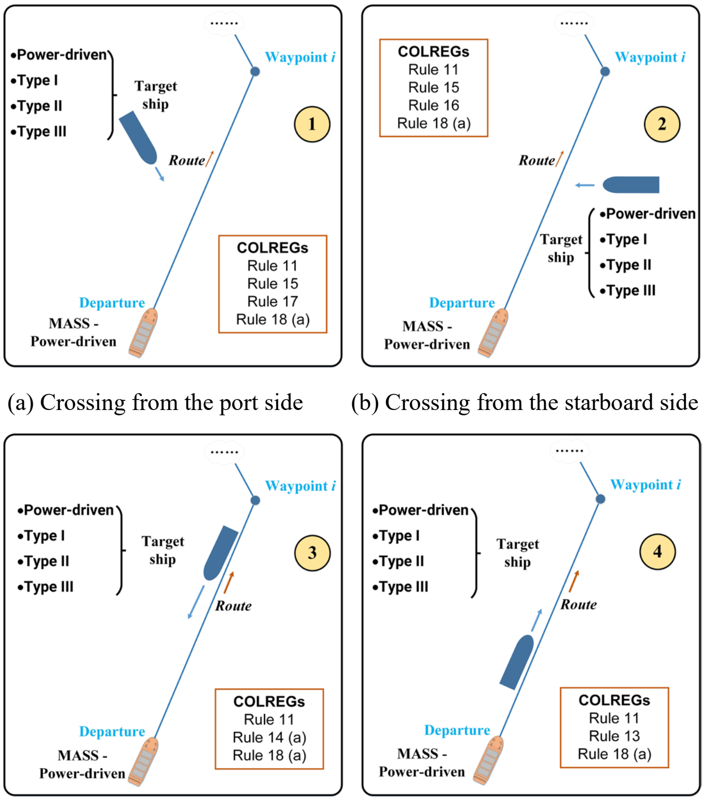
3.4.2.2 Traffic complexity

(1) Individual vessel encounters: These scenarios examine the autonomous system's response to the individual vessel, testing its decision-making process and compliance with the applicable COLREGs rules.
(2) Multi-vessel encounters: This scenario involves multiple vessels considering their manoeuvrability, which requires the MASS to make decisions considering multiple COLREGs rules simultaneously.

Figure 3-7 illustrates four classic scenarios on which our algorithm will be tested to evaluate the system's performance and COLREG compliance. Table **3-1** offers an overview of surrounding vessels' motion characteristics in both individual and multi-vessel encounters.

Table 3-1 Overview of the motion characteristics of surrounding vessels

No.	X_0	Y_0	V_x	V_y	Scenario
1	28	18	-0.4	-0.01	Crossing-starboard side
2	10	10	0.1	0.1	Overtaking
3	6	18	0.3	-0.3	Crossing-port side
4	30	30	-0.1	-0.1	Head-on



(a) Crossing from the port side (b) Crossing from the starboard side

(c) Head-on (d) Overtaking

Figure 3-7: The illustration of scenario setup for experimental verification

3.4.2.3 The Impact of COLREGs Compliance

The algorithm's performance was tested under varying COLREGs compliance weights (0, 0.3, 0.6, 1) to assess how strict or flexible adherence impacts navigation efficiency and safety. This approach allows the evaluation of the KM-DWA algorithm.

3.4.2.4 Performance evaluation metrics

This section outlines the performance outcomes from simulations designed to assess the integrated ontology-based knowledge maps with DWA for path-planning in MASS. The performance of the system was evaluated based on navigation safety, efficiency, and adherence to COLREGs.

- Safety: Whether or not there was a collision, the minimum DCPA, TCPA, and the minimum distances to be maintained from other vessels.
- Efficiency: Assessment of the path efficiency in terms of travel path length and travel time, as well as deviations from the optimal path.
- COLREGs compliance: The distance at which the MASS begins to take proactive or defensive manoeuvres and whether the MASS complies with the rules for taking evasive actions in various scenarios, i.e., the consistency between the action recommended by the COLREGs and the action actually taken.

3.4.3 Results

3.4.3.1 Encountering individual vessels

The simulation results for the basic DWA and KM-DWA algorithms across four scenarios—overtaking, head-on, crossing from starboard, and crossing from port—were analysed. In crossing with overtaking, head-on, and starboard side approaching vessel scenarios, the performance metrics were evaluated for surrounding vessels with power-driven capabilities, and those with restricted manoeuvring were classified as type I, II, and III. The performance curves are shown in

Figure 3-8, Figure 3-11, and Figure 3-12, respectively, and it is found that the algorithmic performance data are the same for the same encounter type. Therefore, we first present here three figures that are representative of the performance of all surrounding vessel types in those encounter scenarios.

In the case of the vessel approaching on the port side, the execution of the algorithm notably differs because COLREGs require different manoeuvring performances depending on the vessel's navigational priorities. Thus, two separate performance graphs were analysed: one where the surrounding vessel was a power-driven vessel, as shown in Figure 3-14**,** and the other where the surrounding vessel's manoeuvring ability was classified as type I, II, or III, as shown in Figure 3-13. More detailed analysis of the performance of algorithms in different scenarios are described below:

(1) **Overtaking**: The basic DWA algorithm collides with the surrounding vessel in the overtaking scenario, as reflected by the broken red curves of the basic DWA algorithm in the subplots in Figure 3-8. This indicates insufficient safety distances, according to the COLREGs, highlighting deficiencies in safety. Conversely, the other curves representing the KM-DWA variants avoid collisions altogether, reflecting a commitment to safety, with longer travel times as a trade-off.
(2) **Head-on**: For head-on encounters, the basic DWA algorithm continued to result in collisions, while KM-DWA variants perform collision-free navigation, reflected by the

broken red curves of the basic DWA and other curves of KM-DWA variants in the subplots in Figure 3-11. As shown in the Heading Difference Comparison subplot of Figure 3-11, the KM-DWA variants execute right-turn manoeuvres as required by COLREGs rules, leading to longer buffering distances, presented in the Distance to Obstacle, DCPA, and TCPA subplots, reducing collision risks and ensuring vessel's successful arrival at the destination, though resulting in a deviation from the optimal path (see Path Deviation Comparison subplot), signalling a strategic shift toward compliance with COLREGs over navigational efficiency.

(3) **Crossing**: In scenarios involving crossing from the starboard and port sides, the KM-DWA variants adhered closely to COLREGs, initiating a right-turn manoeuvre for positive avoidance, unlike the basic DWA algorithm, which performed non-compliant left-turn actions in starboard crossing scenarios (see Heading Difference Comparison subplot of Figure 3-12). In port-side crossings, responses varied with the surrounding vessel's type/manoeuvrability. When encountering power-driven vessels, the own vessel maintained its course and speed for a period as per rule 17 of COLREGs, beginning a right-turn manoeuvre only when the surrounding vessel entered a pre-set defensive avoidance distance. When the surrounding vessel had inferior manoeuvrability, the own vessel took proactive right-turn manoeuvres to avoid the approaching vessel from the port side. Nevertheless, the basic DWA algorithm, while also successfully avoiding collisions, exhibited a gap in compliance (see Figure 3-13 and Figure 3-14)

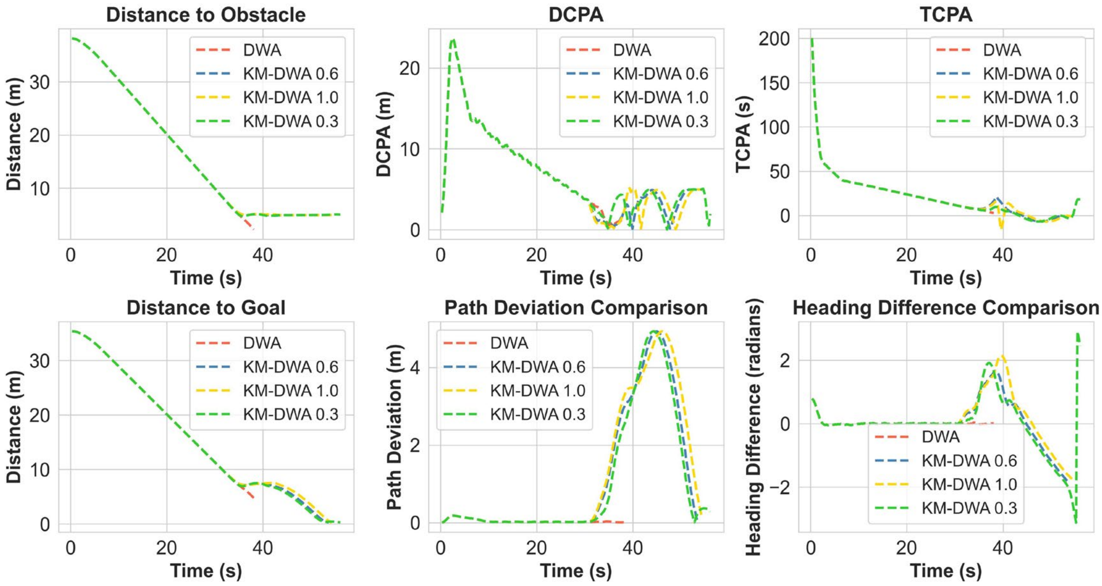


Figure 3-8: Performance comparison when MASS is overtaking the surrounding vessel with manoeuvrability, including power-driven ship type, type I, type II, and type III

(4) **Comparative performance analysis**

1) Proximity to obstacles: While the basic DWA algorithm maintains closer, consistent proximity to obstacles, reflecting a reactive stance, the KM-DWA algorithms demonstrate an evolution towards proactive avoidance. The transition from reactive to proactive is gradual with increasing COLREGs weights, underscoring a strategy that deliberately favours safety over directness towards the goal.

2) Risk assessment (DCPA and TCPA): The riskier navigational choices of the basic DWA are highlighted by its uniformly lower DCPA values. In contrast, the KM-

DWA algorithms, particularly at higher COLREGs weights, reveal a trend of earlier and more decisive manoeuvres to increase the distance of the closest approach, signifying a preference for safety.

3) Navigational path and heading adjustments: The minimal path deviations and heading changes with the basic DWA suggest a preference for efficiency and direct routes. Conversely, the KM-DWA algorithms, especially with higher weights, accepted greater deviations and more significant heading adjustments to enhance collision avoidance and adherence to COLREGs.

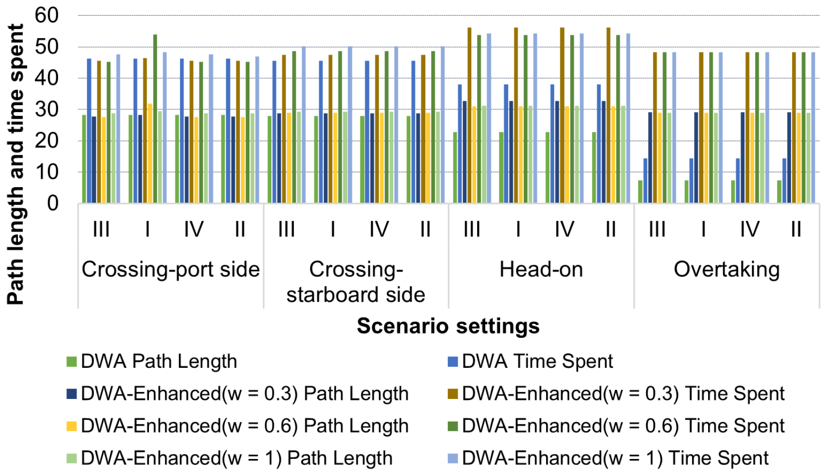


Figure 3-9: The overall performance comparison between DWA and KM-DWA algorithms with different COLREGs weights

(5) **Weighted Performance of KM-DWA**

1) Low COLREGs weight (0.3): The algorithm began integrating COLREGs into decision-making, slightly increasing the distance to obstacles, indicating a proactive approach while maintaining a course relatively direct towards the goal.

2) Medium COLREGs weight (0.6): With a greater emphasis on safety, the vessel initiates avoidance of manoeuvres earlier, increasing path deviation and heading variation to ensure regulatory compliance, signalling a clear preference for safety over directness.

3) High COLREGs weight (1.0): At this setting, the algorithm exhibits a marked preference for safety, significantly altering the vessel's trajectory to avoid potential collisions. The substantial distance maintained from obstacles and the pronounced course corrections reflect the implementation of the principle of "early and broad" in COLREGs.

Additionally, the data representation shown in Figure 3-9 provides a comprehensive overview of the algorithmic performances across various scenarios, illustrating distinct patterns in DWA and KM-DWA algorithms. The analysis of plotted metrics reveals that the KM-DWA algorithms consistently demonstrated longer trajectories than the basic DWA. This trend is evident in the cross-encounter scenarios (short paths in overtaking and head-on scenarios end early due to collisions), where basic DWA has shorter paths but can be more risky, as the 50% collision rate in these overtaking and head-on scenarios suggests. These findings underscore the potential risk of basic DWA, prioritising efficiency over safety.

Conversely, the KM-DWA variants result in longer durations, as they take more cautious routes to ensure full compliance with COLREG, as evidenced by the 100% compliance rate. This planning is evident in scenarios requiring right-crossing manoeuvres, where KM-DWA algorithms comply with COLREGs to avoid collisions, unlike the basic DWA, which made left-turn decisions that may lead to higher navigational risk, achieving only a 25% COLREGs compliance rate. These findings highlight the robustness of KM-DWA in safely navigating collision avoidance scenarios and explain the extended travel times and paths observed.

The experiments indicate that the KM-DWA algorithm adjusts its behaviour to accommodate these vessels' limited manoeuvrability, thus reinforcing a safety-first approach. Fundamentally, while the basic DWA algorithm prioritises path efficiency—reflected in shorter travel times and minimal deviations—it often fails to navigate safely across various scenarios. The improved safety measures of the KM-DWA algorithm, such as increased distances from obstacles and full compliance with COLREGs, are achieved through the acceptance of longer travel times and greater path deviations.

3.4.3.2 Encountering multiple vessels

Considering the good COLREGs compliance of the KM-DWA algorithm in single-vessel encounter scenarios, particularly with encountering power-driven vessels and surrounding vessels with poor manoeuvrabilities, it is demonstrated that KM-DWA variants can account for the manoeuvrabilities of the surrounding vessel during collision avoidance. Therefore, this section focuses on whether the variant algorithms are still capable of achieving COLREGs-compliant multi-vessel collision avoidance when considering the surrounding vessel's manoeuvrabilities and approaching vessels from multiple directions simultaneously.

For this purpose, we selected Type II as the manoeuvrability of surrounding vessels, namely, engaged in fishing, in a multi-vessel encounter scenario to verify whether the MASS driven by the KM-DWA algorithm is able to accomplish autonomous safe collision avoidance in multi-vessel encounters. Error! Reference source not found. visualises the collision avoidance trajectories of MASS driven by the basic DWA algorithm and KM-DWA variants with Type II surrounding vessels. The whole process for collision avoidance of MASS is detailed below:

As shown in Error! Reference source not found., KM-DWA variants demonstrate an early initiation of avoidance manoeuvres compared to the basic DWA algorithm, indicating a proactive approach to collision avoidance. KM-DWA variants differ from the basic DWA algorithm in the timing of manoeuvres for the initial encounter (port side crossing) with the surrounding vessel TS1. KM-DWA algorithms initiate the proactive avoidance manoeuvre earlier than the DWA algorithm and take action at the proactive avoidance distance. This indicates that the KM-DWA variant algorithm accounts for the manoeuvrability of the surrounding vessel and takes proactive actions, while the basic DWA algorithm ignores this situation.

Subsequently, KM-DWA employs a course adjustment to avoid collision as it passes the surrounding vessel TS4, which is informed by a comprehensive evaluation based on criteria including collision avoidance, DCPA, and TCPA metrics. After the adjustment, the KM-DWA algorithm encounters another vessel, the TS2, on its starboard side, necessitating a moderate starboard turn in line with proactive collision avoidance strategies. This action ensures compliance with situational requirements and avoids excessive path deviation. The algorithm then corrects its heading to pass the surrounding vessel safely, the TS3, subsequently resuming its original course towards the destination. These actions adhere to regulations for head-on encounters, including executing a starboard turn to mitigate collision risk. Upon clearing potential collision threats, the vessel returns to a standard navigational state and reaches its destination, guided by various cost functions.

In contrast, the trajectory governed by the basic DWA algorithm exhibits fewer course adjustments, lacking the secondary manoeuvres evident in the KM-DWA's initial and subsequent encounters. While remaining regulatory compliant, the basic DWA algorithm maintains closer proximity to the surrounding vessel, increasing navigation risk. Figure 3-15 demonstrates the performance of the basic DWA algorithm and the KM-DWA variants in accomplishing collision avoidance in the same multi-ship encounter scenario, which is analysed as follows:

(1) Distance to Obstacle and Goal

1) **DWA**: Demonstrates a consistent but risk-tolerant navigational approach towards obstacles, e.g., lower DCPA and TCPA, and disregard when the surrounding vessel's poor manoeuvrability, showing a tendency towards efficiency over safety.

2) **KM-DWA 0.3**: Begins to integrate a proactive collision avoidance strategy, showing a slight increase in the distance to obstacles while still maintaining efficiency.

3) **KM-DWA 0.6 and 1.0**: These settings result in a marked increase in the distance to obstacles, indicating a strong preference for safety. The performance curves for these two weights overlap, suggesting that beyond a certain threshold, increasing the weight assigned to COLREGs compliance does not significantly alter the behaviour of the algorithm under the tested conditions.

(2) DCPA and TCPA

1) **DWA**: Lower DCPA values indicate a riskier, closer approach to obstacles.

2) **KM-DWA 0.3**: Shows improved safety margins with slightly higher DCPA values.

3) **KM-DWA 0.6 and 1.0**: Both exhibit higher DCPA values, with a significant emphasis on safety and compliance, as reflected by the early transition of TCPA from positive to negative. The similarity in their performance curves suggests that both settings prioritise safety to a similar extent.

(3) Path Deviation and Heading Difference

1) **DWA**: Minimal path deviation and heading variation indicate a straightforward but less cautious approach.

2) **KM-DWA 0.3**: Increased path deviation and heading changes indicate a shift towards a more safety-compliant navigation strategy.

3) **KM-DWA 0.6 and 1.0**: Display the highest path deviations and heading changes, showcasing adherence to proactive collision avoidance. The convergence of their performance curves indicates a shared strategy for safety, suggesting a plateau in

the enhancement of safety measures when the COLREGs weight is increased beyond 0.6 under the tested scenarios.

In summary, the above findings emphasise the need for an algorithmic balance between efficiency, safety, and regulatory compliance. The system effectively integrated data from the knowledge maps with the DWA in multi-vessel scenarios, demonstrating: first, the MASS successfully navigated complex multi-vessel encounters by prioritising actions based on safety and COLREGs compliance. Second, in situations with rule conflicts, KM-DWA demonstrated a high capability to resolve conflicts and choose the safest navigational action. Third, KM-DWA, particularly with higher COLREGs weights, consistently maintain safer distances from obstacles, suggesting a prioritisation of collision avoidance over route directness. Finally, KM-DWA exhibit prolonged travel times, likely a reflection of their circuitous routes to ensure compliance with maritime rules.

3.4.4 Discussion

This chapter evaluates DWA against its ontology-based knowledge maps model integrated enhancement for MASS navigation. By embedding a knowledge maps model, the resulting KM-DWA algorithm aims to augment path planning with increased safety, efficiency, and regulatory compliance. Compared to other previous studies, the KM-DWA algorithm demonstrates its capability to avoid collisions while complying with COLREGs in both individual vessel and multi-vessel encounter scenarios.

The trade-off between safety and efficiency: A trade-off between safety and efficiency is evident. As the weight of rule compliance increases, the safety level of a vessel increases while its efficiency decreases relatively, and vice versa. Therefore, it is necessary for MASS to set the weight flexibly to achieve a balance between safety and efficiency in real navigation.

Comparison with existing studies: In this chapter, we build upon the previous studies, such as [193], [205], and [246], which highlighted the importance of situational awareness in MASS navigation. We extend the previous work [193] by constructing structured knowledge maps for MASS navigation that continuously update the situational information with real-time navigational and environmental data, thereby enhancing situational awareness. Additionally, our research broadens the interpretation of COLREGs by extending the scope of earlier studies by [41] to include a broader range of rules, scenarios, and proactive collision avoidance strategies. We also adapt the DWA algorithm for a 3-DOF MASS model, originally proposed for robotics by [63] and further applied in the maritime domain by [18]. By integrating it with our knowledge maps model and extended COLREGs interpretation mechanism, we enhance its capability of scenario recognition and COLREGs compliance.

3-tier collision avoidance distance: The implementation of this concept provides a rule-compliant approach to avoid collisions. The three tiers serve as triggers for initiating collision avoidance manoeuvers, with specific distances set for different roles under COLREGs. The chapter proves that vessels correctly trigger different avoidance distances based on their role—defensive avoidance distance when acting as the stand-on vessel and active avoidance distance when acting as the give-way vessel. This mechanism assists vessels in integrating COLREGs into their collision avoidance behaviour to clarify their intentions to manned ships.

Encountering with surrounding vessels: In individual vessel encounters, the basic DWA tends to prioritise direct routes, potentially compromising safety margins and COLREGs adherence. In contrast, the KM-DWA algorithm variants demonstrate a commitment to safety and regulatory compliance, even if it means accepting longer travel times and paths. Simulations for MASS with Type II surrounding vessels in multi-vessel encounter scenarios demonstrate that KM-DWA algorithms adapt their behaviour to accommodate the constrained manoeuvrability of these vessels (i.e., Type I, Type II, and Type III), reinforcing the safety-first approach. In essence, while the basic DWA algorithm prioritises path efficiency, reflected in shorter travel times and minimal deviation, it frequently fails to navigate safely across various scenarios. The KM-DWA algorithm's safety measures, such as increased distances to obstacles and full compliance with COLREGs, are achieved by accepting a trade-off in the form of longer travel and greater path deviations. Nonetheless, the current local planner remains reactive and short-term in nature. In multi-vessel situations involving sequential or cascading interactions, a more foresighted planning mechanism—integrating global trajectory intent—may be necessary. Future work should consider coupling the local planner with long-horizon predictors to better handle temporally extended COLREGs compliance and reduce cumulative path inefficiencies.

In summary, the KM-DWA algorithm maintains safety and navigational efficiency while complying with COLREGs, suggesting its potential for operational development in autonomous navigation. Its adaptability, allowing for flexible weight configurations to balance efficiency, safety, and rule compliance, is crucial. The 3-tier collision avoidance distance strategy further ensures that vessels can integrate COLREGs effectively, enhancing both proactive and defensive collision avoidance.

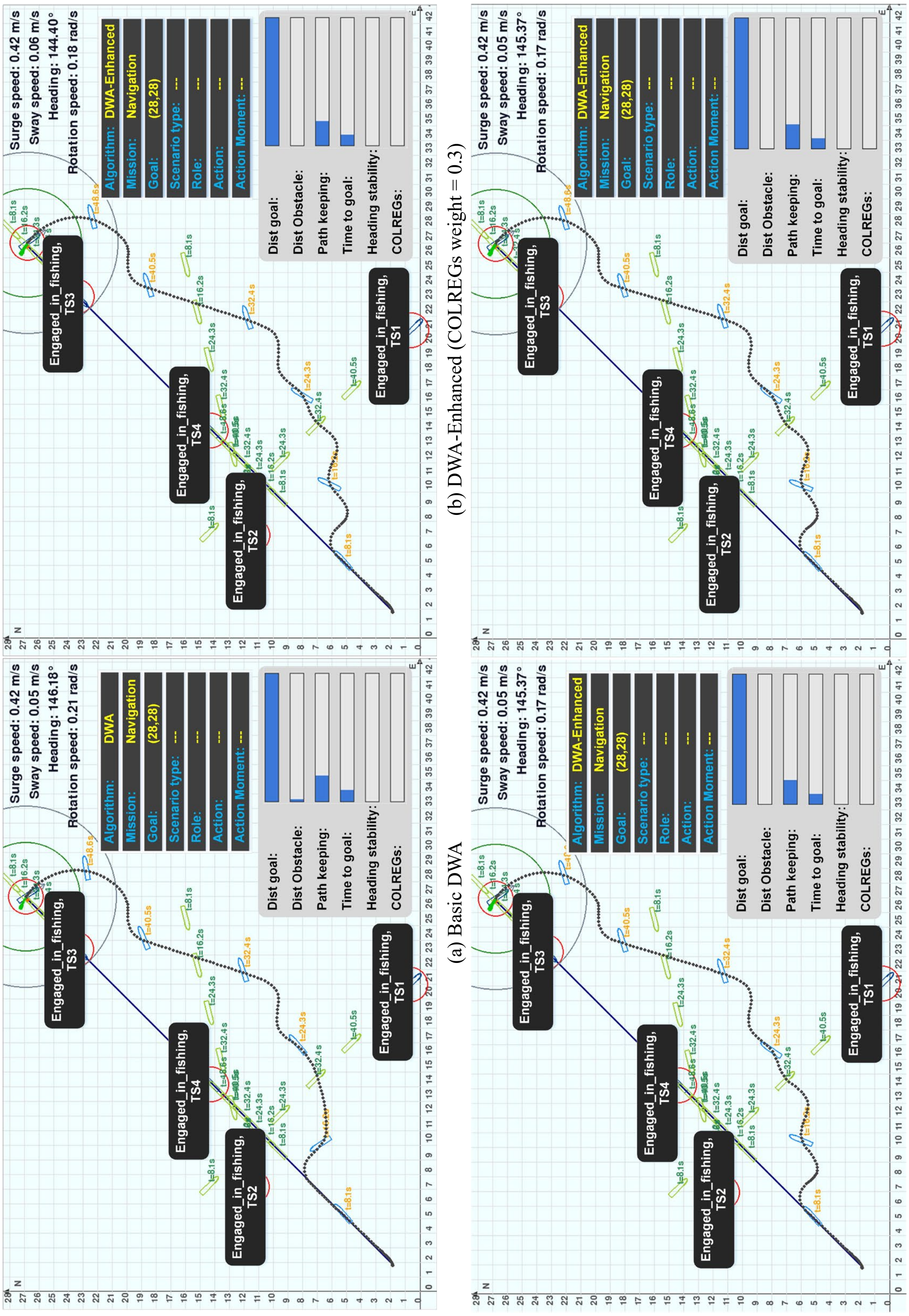
3.5 Conclusions

This chapter introduced the development of a situational awareness model designed for MASS, focusing on the integration of multi-source data into structured decision-making processes. The primary motivation behind this work was to address the challenge of translating situational understanding into actionable navigation strategies in dynamic and various maritime environments. To achieve this, an ontology-based knowledge maps model was developed as a semantic framework for organising and interpreting navigational data. This model provides MASS with enhanced situational understanding by synthesising navigational status, ensuring task awareness, and formulating constraints derived from motion characteristics and regulations such as COLREGs.

Building upon this situational awareness foundation, the KM model was integrated with an adapted DWA, forming the KM-DWA framework. The framework addresses the motion constraints of 3-DOF MASS and replaces traditional velocity-based sampling of DWA with acceleration-based sampling, allowing for a more realistic representation of vessel dynamics. Furthermore, it incorporates 3-tier collision avoidance strategies into real-time path planning. This integration realises the transformation from situational awareness to decision-making, supporting MASS to navigate in a safe, efficient, and rule-compliant way in various contexts.

The contributions of this chapter are twofold: first, the development of the KM model that facilitates the interpretation of multi-source navigational data, and second, the implementation of the KM-DWA path planner, which connects the situational awareness module with a decision-making mechanism for MASS. These efforts directly address the two questions: RQ2-

iii: *How can data from multiple sources be effectively integrated for situational awareness*? and RQ2-iv: *How can a local path-planning algorithm tailored to 3-DOF vessels be developed, integrating the results of situational awareness*? By providing a foundation of situational awareness and its integration into decision-making, this chapter establishes a key component of the thesis framework. The subsequent chapter builds on this framework by introducing human-mimic navigation strategies, leveraging navigational preferences to enhance collision avoidance in mixed waterborne environments.



(a) Basic DWA

(b) DWA-Enhanced (COLREGs weight = 0.3)

(c) DWA-Enhanced (COLREGs weight = 0.6)

(d) DWA-Enhanced (COLREGs weight = 1)

Figure 3-10: Visualisation of the collision avoidance trajectories of MASS with different COLREGs weights in the case of multi-ship encounters.

Table 3-2 Translation of Maritime Collision Regulations into SWRL Rules

COLREGs	Description	SWRL Translation
Rule 11	Application: in sight of one another	MASS(?s1) ^ Surrounding_ships(?s2) ^ involve_risk_of_collision(?s1, ?s2) ^ Scenario(?ss) ^ encounter_scenario(?s1, ?ss) ^ encounter_scenario(?s2, ?ss) ^ has_visibility(?ss, in_Sight_of_One_Another) -> should_obey_regulation(?s1, Rule11) ^ should_obey_regulation(?s2, Rule11)
Rule 13	Overtaking	Scenario(?ss) ^ encounter_scenario(?s1, ?ss) ^ Surrounding_ships(?s2) ^ involve_risk_of_collision(?s1, ?s2) ^ encounter_scenario(?s2, ?ss) ^ has_visibility(?ss, in_Sight_of_One_Another) ^ in_overtaking(?s1, ?s2) ^ MASS(?s1) -> should_obey_regulation(?s1, Rule11) ^ hasCArole(?s1, give_way) ^ should_obey_regulation(?s1, Rule14) ^ should_give_way(?s1, ?s2)
Rule 14	Head-on situation	Scenario(?ss) ^ encounter_scenario(?s1, ?ss) ^ Surrounding_ships(?s2) ^ involve_risk_of_collision(?s1, ?s2) ^ encounter_scenario(?s2, ?ss) ^ has_visibility(?ss, in_Sight_of_One_Another) ^ in_head_on(?s1, ?s2) ^ MASS(?s1) -> should_obey_regulation(?s1, Rule11) ^ hasCArole(?s1, give_way) ^ should_obey_regulation(?s1, Rule14) ^ should_take_action(?s1, turn_to_starboard_side)
Rule 15	Crossing situation	Scenario(?ss) ^ encounter_scenario(?s1, ?ss) ^ Surrounding_ships(?s2) ^ involve_risk_of_collision(?s1, ?s2) ^ encounter_scenario(?s2, ?ss) ^ has_visibility(?ss, in_Sight_of_One_Another) ^ in_crossing(?s1, ?s2) ^ MASS(?s1) -> should_obey_regulation(?s1, Rule11) ^ hasCArole(?s1, should_give_way) ^ should_obey_regulation(?s1, Rule15) ^ should_take_action(?s1, turn_to_starboard_side)
Rule 16	Action by give-way vessel	hasCArole(?s1, give_way) ^ MASS(?s1) -> should_obey_regulation(?s1, Rule16) ^ shouldCAmoment(?s1, Early_proactive)
Rule 17(a)(i)	Stand-on vessel maintaining course and speed	hasCArole(?s2, give_way) ^ hasCArole(?s1, stand_on) ^ Surrounding_ships(?s2) ^ MASS(?s1) -> should_obey_regulation(?s1, Rule17) ^ should_take_action(?s1, keep_course_and_speed) ^ shouldCAmoment(?s1, Early_proactive)
Rule 17(a)(ii) & Rule 17(b)-Rule 17(d)	Stand-on vessel taking action to avoid collision by her manoeuvre alone.	hasCArole(?s2, give_way) ^ hasCArole(?s1, stand_on) ^ Surrounding_ships(?s2) ^ MASS(?s1) ^ performingBehavior(?s2, keep_course_and_speed) -> should_obey_regulation(?s1, Rule17) ^ should_take_action(?s1, turn_to_starboard_side) ^ shouldCAmoment(?s1, Imminent_defensive)
Rule 18-(a)	Power-driven vessel giving way to vessels with restricted manoeuvrability	Surrounding_ships(?s2) ^ has_shiptype(?s1, powerdriven_vessel) ^ has_shiptype(?s2, ?t) ^ I_type(?t) ^ MASS(?s1) -> hasCArole(?s1, give_way) ^ should_obey_regulation(?s1, Rule18) ^ should_take_action(?s1, keep_out_of_the_way) ^ shouldCAmoment(?s1, Early_proactive) ^ should_give_way(?s1, ?s2)
Rule 18-(b)	Sailing vessel giving way under certain conditions	Surrounding_ships(?s2) ^ II_type(?t) ^ has_shiptype(?s2, ?t) ^ MASS(?s1) ^ has_shiptype(?s1, sailing_vessel) -> hasCArole(?s1, give_way) ^ should_obey_regulation(?s1, Rule18) ^ should_take_action(?s1, keep_out_of_the_way) ^ shouldCAmoment(?s1, Early_proactive) ^ should_give_way(?s1, ?s2)
Rule 18-(c)	Vessel engaged in fishing maintaining course and speed.	Surrounding_ships(?s2) ^ has_shiptype(?s2, ?t) ^ has_shiptype(?s1, engaged_in_fishing) ^ MASS(?s1) ^ III_type(?t) -> hasCArole(?s1, give_way) ^ should_obey_regulation(?s1, Rule18) ^ should_take_action(?s1, keep_out_of_the_way) ^ shouldCAmoment(?s1, Early_proactive) ^ should_give_way(?s1, ?s2)

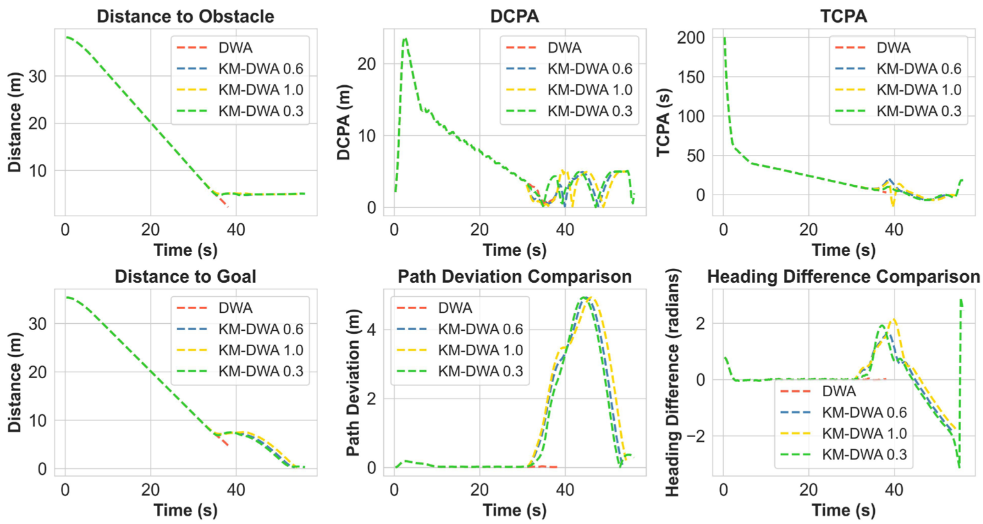


Figure 3-11: Performance comparison when MASS encounters the surrounding vessel with manoeuvrability, including power-driven ship type, type I, type II, and type III and forming the head-on situation

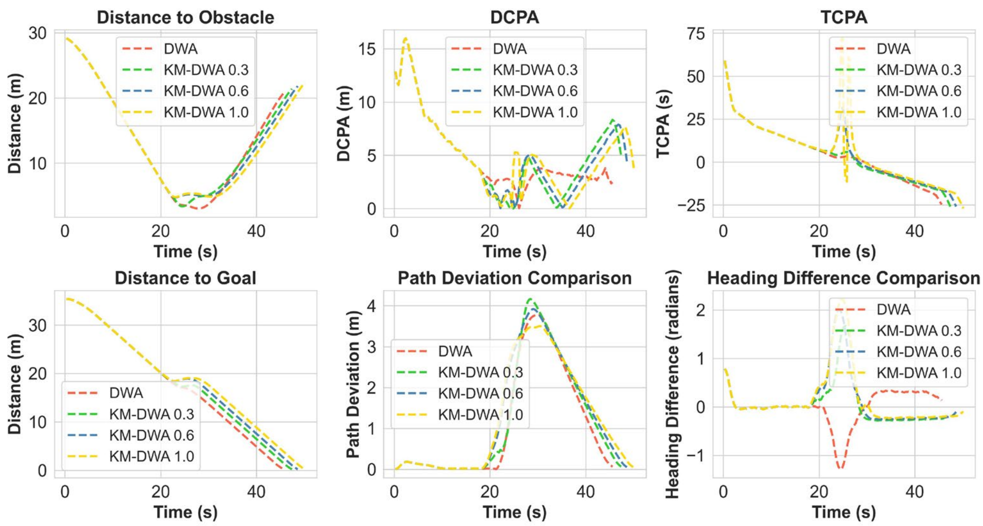


Figure 3-12: Performance comparison when MASS encounters the surrounding vessel with manoeuvrability, including power-driven ship type, type I, type II, and type III approaching from the starboard side

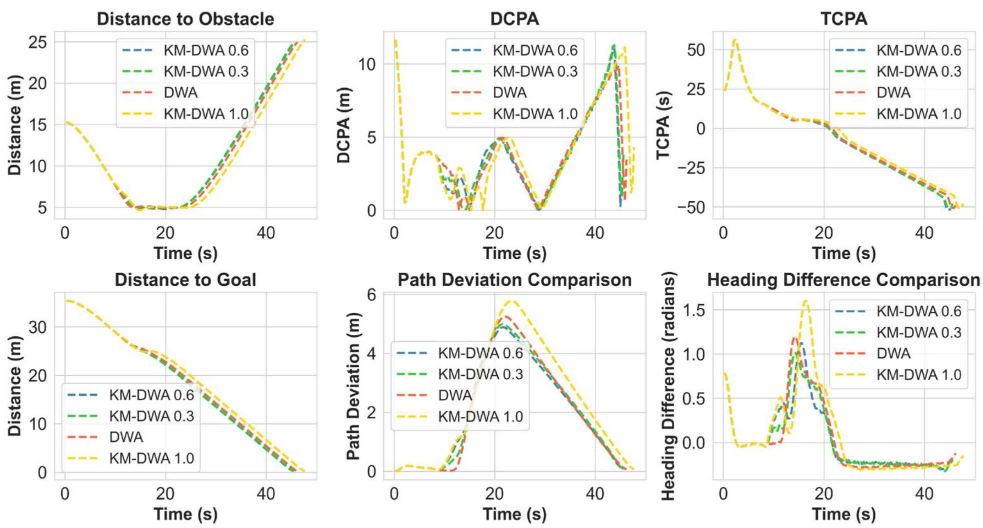


Figure 3-13: Performance comparison when MASS encounters the surrounding vessel with manoeuvrability, including type I, type II, and type III approaching from the port side

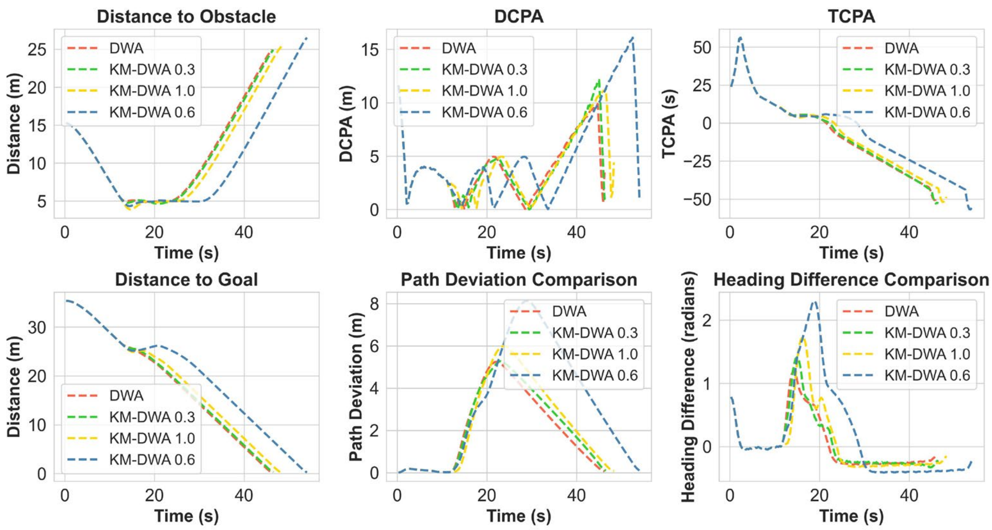


Figure 3-14: Performance comparison when MASS encounters the surrounding vessel with the ship type of power-driven approaching from the port side

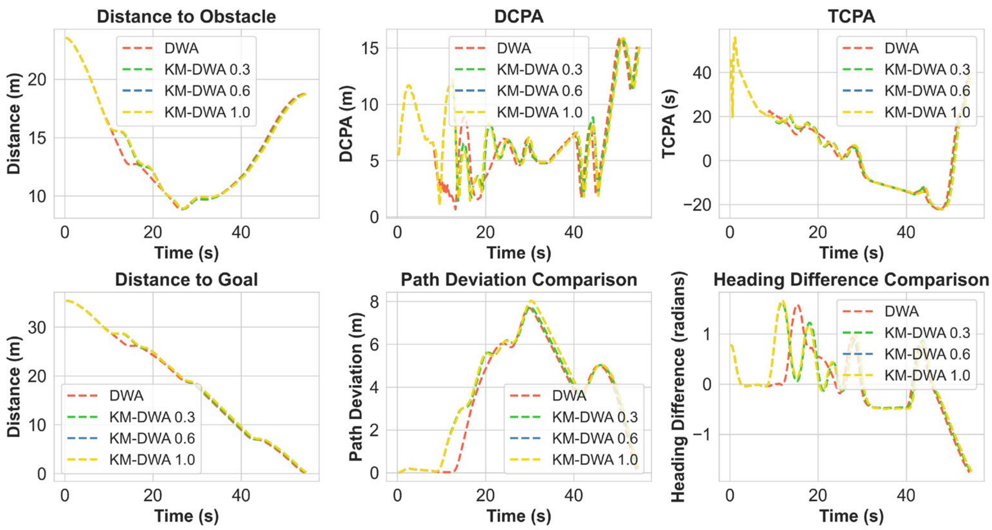


Figure 3-15: Performance comparison between different algorithms in the multi-vessel encounter scenario

Chapter 4. Human-Mimic Navigation and Decision-making by MASS

Building on the decision-making framework proposed in Chapter 2 and enriched with the situational awareness module developed in Chapter 3, this chapter focuses on extending the framework by addressing human-mimic navigation of Maritime Autonomous Surface Ships (MASS) in Mixed Waterborne Transport Systems (MWTS). Incorporating human navigational preferences into autonomous decision-making can help manned vessels better understand the intentions of MASS, thereby supporting smoother interaction and ensuring both safety and operational efficiency. To achieve this, a preference-aware trajectory predictor is developed, using historical movement data to generate recommended routes aligned with human navigational tendencies during vessel encounters. This proactive mechanism improves interaction fluidity by predicting collision-free paths that align with human expectations. Meanwhile, the reactive path-planning method (KM-DWA) from Chapter 3 remains active as a safety guarantee, ensuring local refinement in high-risk scenarios when immediate evasive actions are necessary. By integrating these proactive and reactive strategies, this chapter addresses research questions RQ3-v, RQ3-vi, and RQ3-vii, further enhancing the decision-making framework to support navigational safety, efficiency, and interaction smoothness of autonomous vessels in MWTS.

This chapter is organised as follows: Section 4.1 introduces the research context. Section 4.2 reviews existing methodologies for collision avoidance and highlights the gaps in handling human-MASS interaction dynamics. Section 4.3 describes the development of the preference-aware trajectory prediction model and its integration into the decision-making framework. Section 4.4 evaluates the predictor's performance and validates the proposed framework through simulation experiments. Finally, Section 4.5 concludes this chapter.

4.1 Introduction

Navigating safely and efficiently in mixed waterborne transport systems (MWTS) requires Maritime Autonomous Surface Ships (MASS) to interact seamlessly with human-operated vessels. Current collision avoidance methods primarily focus on algorithmic capabilities such as deterministic path planning and optimisation algorithms that prioritise minimising travel time or fuel consumption [5] while maintaining navigational safety and complying with International Regulations for the Prevention of Collisions at Sea (COLREGs). These methods often use pre-defined rules or optimisation criteria to generate collision-free paths for vessels. However, most of these models typically overlook the dynamic and interactive behaviours of surrounding vessels. Human-operated ships tend to adjust their manoeuvres based on the perceived intentions of neighbouring vessels, a behaviour that is not accounted for in many algorithmic models. This oversight can lead to less accurate and interpretable predictions in real-time collision scenarios.

Additionally, existing models often fail to incorporate dynamic manoeuvres such as high speed with a small starboard side turn and a minor acceleration. These navigational behaviours, typically exhibited by human operators to ensure efficient and safe navigation, highlight the importance of mimicking human-like decision-making behaviours, which will be referred to in the present research as **'human preferences'**. By incorporating such human-mimic behaviours, future models could better capture human operators' adaptive and flexible nature, improving MASS's accuracy and safety in a mixed waterborne environment.

To bridge this gap, it is essential to incorporate human navigational preferences into predictive modelling and decision-making frameworks. By leveraging Automatic Identification System (AIS) data, which captures vessel interactions and manoeuvres, it is possible to extract meaningful insights into human decision-making dynamics in collision avoidance scenarios. Integrating these insights into the decision-making framework enables MASS to predict the intentions and trajectories of human-operated vessels, fostering safer and more efficient interactions.

This chapter addresses the need for preference-aware navigation by developing a predictive trajectory model based on the identification of human navigational preferences. Specifically, a two-step approach is adopted: (1) extracting navigational preferences from AIS data using an LSTM-autoencoder and K-means clustering to model manoeuvring behaviours, and (2) developing a Multi-Task Learning (MTL) Sequence-to-Sequence LSTM model with an attention mechanism (MTL-Seq2Seq-LSTM-Att) to predict the trajectories of both own and neighbouring ships. These preference-aware predictions are integrated into the decision-making framework, proposed in Chapter 2 and enriched with a situational awareness module in Chapter 3, extending its capabilities to enable smoother and more interpretable interactions in MWTS.

4.2 Recent work

In the crucial domain of maritime navigation, the detection of collision conflicts has evolved greatly, incorporating state-of-the-art big data analytics, predictive modelling, and computational techniques to improve the safety navigation of MASS, by enhancing MASS's situational awareness, predictive capabilities, and further decision-making.

- **Collision conflict detection**

A study by [33] utilises AIS data to analyse collision risks dynamically by using a velocity obstacle approach, highlighting the necessity of timely and accurate risk assessments. Similarly, research conducted by [124] applied spatial clustering and analytical methods to manage collision risks. Additionally, an investigation by [231] estimates collision risk among multiple vessels and leverages spatiotemporal patterns and a two-stage Monte Carlo simulation algorithm, thereby enhancing prediction accuracy and efficiency for potential collision scenarios. Research conducted by [120] and [177] focused on identifying high-collision potential areas and analysing ships' reactions in near-collision scenarios. Additionally, the studies by [241] and [67] employed geometric and operational parameter analyses to aid proactive collision avoidance. These studies contributed to improved targeted interventions and collision conflict detection capabilities.

The concept of ship domain and the Collision Threat parameter area method have been extensively studied by [198] and [200]. These approaches integrate environmental factors and ship stability considerations, supporting navigators executing informed collision avoidance manoeuvres.

Studies by [224] and [92] have examined the impact of maritime traffic complexity and the application of Velocity Obstacle algorithms on collision conflict detection, respectively. By addressing the limitations of traditional techniques and introducing methods that consider non-linear and time-dependent ship trajectories, these studies offer more realistic solutions for collision avoidance and reducing false alarms. Furthermore, the application of knowledge graphs has been demonstrated to uncover correlations between critical factors in ship collision scenarios [64], enabling the identification of causal relationships and supporting decision-making in collision avoidance scenarios.

These efforts highlight the evolution of maritime collision avoidance strategies, showcasing innovative methods that integrate dynamic risk assessments, spatial clustering, and simulation algorithms to improve safety and decision-making in complex maritime environments. While these approaches are well-established, our study presents a method aimed at extracting trajectory conflict pairs from AIS data. By focusing on identifying vessel trajectory pairs at risk of collision and defining relevant navigational parameters, this method provides a tailored approach for detecting potential collisions for further navigational preferences extraction.

- **Intention identification**

In maritime navigation, the key task of predicting vessel intentions to enhance safety and prevent collisions has seen great advancements through innovative methodologies.

Research by [149] introduced trajectory prediction for autonomous vessels, emphasising the need for ships to anticipate neighbouring movements for collision avoidance. This foundational work underscores the importance of predictive analytics in autonomous maritime navigation. Expanding on predictive approaches, the investigation by [48] focused on situational awareness by estimating intentions of give-way and stand-on ships, enabling vessels to make informed decisions and enhance proactive safety measures.

The study by [87] applied semantic analysis and topic modelling borrowed from Natural Language Processing to maritime trajectory data. By identifying mobility patterns, this work contributed to route discovery and anomaly detection. The study by [199] utilised the ship domain concept to precisely predict time avoidance manoeuvres and improve decision-making accuracy in critical scenarios. Additionally, environmental factors that influence vessel behaviour are important to be considered in intention identification. For example, the spatio-temporal correlation between tides and ship movements in estuarine ports [187].

In leveraging AIS, the research presented by [240] developed a knowledge-based decision support system using AIS data to guide ship collision avoidance, including encounter identification, behaviour extraction, and scenario matching to generate safe navigation paths. Additionally, research presented by [244] introduced a dynamic system for multi-ship collision avoidance, focusing on predicting vessel intentions through an iterative observation-inference-prediction-decision model.

The approach developed by [30] investigated the cooperative control of autonomous vessels, particularly in the formation and maintenance of a “vessel train.” This study highlights the significance of coordinated behaviour and communication among vessels to improve navigational safety and respond effectively to dynamic maritime environments.

While existing studies have made much progress in intention identification and enhancing situational awareness, many approaches focus on specific scenarios or utilise methods that may not fully capture the sequential features of time-series navigational data. For example, directly applying clustering techniques to high-dimensional trajectory data may be a challenge due to the complexity and temporal dependencies inherent in such data. This suggests a need for methods that can better account for these temporal dynamics, allowing for a more detailed analysis of vessel intentions during the interaction.

- **Trajectory prediction**

LSTM networks are increasingly recognised for their effectiveness in sequence prediction, making them particularly well-suited for forecasting vessel trajectories using AIS data. Research has consistently highlighted LSTM’s capability to handle the sequential nature of AIS data, such as the work by [204] which focuses on dynamically adapting to the most recent known positions.

Building on the foundational strengths of LSTM, recent research has introduced hybrid models that combine LSTM’s predictive capabilities with other computational techniques to better address the particularities of the maritime environment. For example, the study by [122] leveraged the learning capacity of LSTM within an IoT framework to promote smart traffic services, demonstrating high accuracy and robustness in predicting vessel trajectories. Furthermore, the research by [121] proposed an interactive vessel trajectory prediction framework, embedding the Quaternion Ship Domain into LS and addressing dynamic interactions between neighbouring vessels. It has demonstrated better performance than existing methods.

Moreover, integrating LSTM with emerging technologies like graph convolutional networks and context-aware systems underscores a potential trend in maritime traffic management. Research presented by [65] utilised an LSTM within a spatiotemporal edge and node attention graph convolutional network for handling multi-ship encounters. Additionally, research by [245] proposed a Dynamic Spatio-Temporal Graph Attention Network incorporating LSTM for short-term motion pattern perception. Additionally, the study conducted by [220] introduced a deep attention-aware spatiotemporal graph convolutional network, including an LSTM module for motion feature extraction, improving prediction accuracy in complex sea areas. In addition, the incorporation of contextual information into LSTM models has also been shown to enhance prediction outcomes. The study by [142] designed a context-aware LSTM framework that integrates contextual information such as wind, wave size, and current, showing an improvement in accuracy over standard LSTM approaches.

Additionally, the application of LSTM in conjunction with clustering techniques has proven effective in enhancing situational awareness of autonomous ships and aiding proactive collision avoidance strategies. Research by [151] implemented clustering techniques combined with LSTM for extracting trajectory segments from historical AIS data. Another study by [235] developed a model combining the DBSCAN algorithm and LSTM, which cluster vessel tracks before prediction. The study presented by [7] enhanced short-term vessel trajectory prediction by clustering routes and using Random Forest algorithms, demonstrating accuracy improvements for heterogeneous and multi-modal movement patterns.

Seq2seq models have also been introduced into maritime trajectory prediction. A multi-task learning model based on the attentional seq2seq framework was proposed by [97], jointly learning route patterns and future trajectories. The study by [54] employed encoder-decoder architectures for ship trajectory prediction using AIS data and achieved an accurate prediction.

The application of LSTM and its variants in vessel trajectory prediction has demonstrated much progress in accuracy and reliability. By integrating LSTM with clustering techniques, context-aware frameworks, graph convolutional networks, and other models, researchers have developed various methods that address the prediction of ship trajectories. The adaptability of LSTM makes it an essential technology in vessel trajectory prediction.

4.3 Navigational preference modelling and extraction

This section presents the methodological approach to model human navigational preferences in collision avoidance scenarios. We detail the process from navigational preference definition to collision conflict pairs extraction and preference extraction based on an LSTM-autoencoder.

Understanding and predicting the relative dynamic relationship between two vessels is crucial in vessel collision avoidance decision-making, especially in relatively open waters, such as the open sea or port areas. In these environments, geographical constraints on vessel movement are minimal, and collision avoidance decisions primarily depend on relative motion parameters. This study examines navigation preferences in these scenarios with minimal geographical constraints.

Definition: Human Navigational preference refers to the decision-making tendencies and behavioural patterns exhibited by a vessel within the relative motion space based on the dynamic relationship between two vessels. This preference is generally independent of absolute position and heading, reflecting the vessel's operators' choices in collision avoidance through relative motion.

Symbols:

SOG1, SOG2: the speeds over ground of the own and the neighbouring ships, respectively;

ROT1, ROT2: Rates of turn of the own ship and the neighbouring ship, respectively;

ACC1, ACC2: Acceleration of the own ship and the neighbouring ship, respectively;

α, ϕ: Relative bearing and encounter angle ;

DCPA: Distance closest point of approach;

TCPA: Time closest point of approach.

The features presented in Table 4-1 for modelling navigational preferences are selected to identify the preference required for collision avoidance.

Table 4-1 Features selected for preference identification in collision avoidance scenarios

Variables	Explanation of selection
SOG1, SOG2	Indicate the rates at which two vessels are approaching or moving away from each other.
ROT1, ROT2	Indicate the rates at which two vessels change their headings.
ACC1, ACC2	Indicate the rates at which two vessels change their speeds.
α, ϕ	Uniquely determine the encounter situation and navigational priority between vessels.
DCPA, TCPA	Denotes the minimum distance and time until the vessels reach the closest point of approach.

4.3.1 Collision conflict pairs extraction

In order to collect information from ship movement for further investigation, we propose an algorithm to extract collision conflict pairs from raw AIS data (see Algorithm 4-1). The algorithm focuses on identifying instances where vessels come within a pre-defined proximity threshold, thereby filtering out irrelevant data and concentrating on encounters that may call for navigational adjustments. This procedure ensures that only noticeable events are analysed for potential collision risks. This algorithm employs geohashing to facilitate quick spatial comparisons, ensuring the efficiency of detecting potential collisions.

The detection process begins with preprocessing raw AIS data to ensure high-quality and reliable input. This includes interpolating missing data, detecting and removing outliers, and sampling the data for efficient processing. Trajectories are segmented based on a time threshold Δt, set at three minutes, to differentiate continuous from discontinuous vessel movements. Geohashes are then calculated for each segment, converting geographic coordinates into compact alphanumeric strings. This encoding method allows for rapid spatial comparisons within the same geohash bucket [148], identifying potential collision pairs based on spatial proximity and temporal overlap.

Finally, the dataset is prepared and indexed by $\{(mmsi_{m1}, seg_{s1}), (mmsi_{m2}, seg_{s2})\}$ of potentially colliding ship pairs. Here, $mmsi_{m1}$ represents the MMSI number (Maritime Mobile Service Identity) of the first ship in the pair, and seg_{s1} refers to the s_1-th trajectory segment of that ship. Similarly, $mmsi_{m2}$ and seg_{s2} correspond to the MMSI number and trajectory segment of the second ship. Additionally, critical navigational parameters, such as DCPA, TCPA, α, φ, Encountered situations (ES), and navigational priorities (NP), are calculated for each identified potential collision pair. This data provides a foundation for further data-driven preferences investigation.

4.3.2 LSTM-Autoencoder for preference extraction

To capture and represent navigational preferences, we employed an LSTM-based autoencoder architecture, as illustrated in Figure 4-1. The process begins with an input sequence x, which consists of multiple interaction features (SOG1, SOG2, ACC1, ACC2, ROT1, ROT2, DCPA, TCPA, α and ϕ) that characterise the dynamic interaction between vessels over time.

Algorithm 4-1: Potential Collision Conflict Pairs Detection And Contextual Info Annotation

Input: *Raw AIS data*
Output: *List of potential collision pairs*
Step 1: Preprocess the AIS data
Apply interpolation, outlier detection, and sampling on AIS data.
Step 2: Trajectory Segmentation
for *each mmsi* $mmsi_m$ *in AIS data* ***do***
  Segment trajectories based on time intervals exceeding Δt $(e.g., 3\ minutes)$.
  Trajectory segmentation and storage: $Tra\_mmsi_{m,s} \leftarrow (mmsi_m, seg_s)$
Step 3: Compute Geohashes for Trajectory Segments
Initialise dictionary GeohashBuckets.
for *each* $(mmsi_m, seg_s)$ ***do***
  Calculate geohashes for each position $(latitude, longitude)$ *in* $(mmsi_m, seg_s)$
  Store $(mmsi_m, seg_s)$ *in GeohashBuckets under its geohash.*
Step 4: Identify Potential Collision Pairs
Initialise set PotentialCollisions.
for *each bucket in GeohashBuckets* ***do***
  if *length of bucket* > 1 ***then***
    for *all unique pairs* $\{(mmsi_{m1}, seg_{s1}), (mmsi_{m2}, seg_{s2})\}$ *with* $(m1 \neq m2)$ *in bucket* ***do***
      if *time windows of* $\{(mmsi_{m1}, seg_{s1}), (mmsi_{m2}, seg_{s2})\}$ *overlap* ***then***
        Add $\{(mmsi_{m1}, seg_{s1}), (mmsi_{m2}, seg_{s2})\}$ *to PotentialCollisions.*
Step 5: Calculate Navigational Parameters
for *each pair in PotentialCollisions* ***do***
  Compute DCPA, TCPA, Encounter angle, and Relative bearing.
  Identify encounter scenarios and navigational priorities.
Results:
Index: $\{(mmsi_{m1}, seg_{s1}), (mmsi_{m2}, seg_{s2})\}$
Manoeuvring Info: $\{SOG_1, ROT_1, ACC_1, SOG_2, ROT_2, ACC_2, \alpha, \phi\}$
Contextual Info: $\{DCPA, TCPA, ES, NP_1, NP_2\}$
Return *List of potential collision pairs with contextual information*

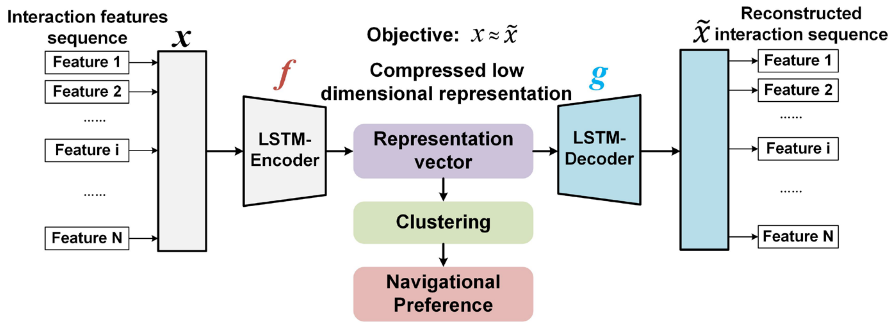


Figure 4-1 The scheme of LSTM-Autoencoder for compressing sequence manoeuvres data.

LSTM-Encoder (*f*): The LSTM-Encoder, represented by the function *f*, processes this input sequence x to generate a compressed low-dimensional representation known as the **Representation Vector**. This vector refers to the latent space representation of the original feature sequence, serving as a compact representation of the vessel's interactive actions.

LSTM-Decoder (g): The latent vector, that is, the representation vector, is then fed into the LSTM-Decoder, denoted by the function g, which attempts to reconstruct the original interaction sequence $\tilde{x}$. The objective of this autoencoder is to minimise the difference between the original input x and the reconstructed output $\tilde{x}$, ensuring that the representation vector accurately captures the relevant features of the interaction sequence. The loss function of the autoencoder is represented by:

$$Loss\_autoencoder = \frac{1}{N}\sum_{i=1}^{N}\|x_i - \tilde{x}_i\|^2 \tag{4-1}$$

Subsequent to the autoencoding process, the **Representation Vector** is subjected to K-means clustering for preference extraction. This step groups similar vectors together, identifying distinct navigational preferences. These preferences are derived from patterns within the interaction sequences and provide valuable insights into the types of interactive manoeuvres in collision avoidance scenarios.

4.4 Preference-based trajectory prediction

4.4.1 Movement predictor design

The movement predictor proposed for trajectory prediction, that is, a multi-task learning Sequence-to-Sequence LSTM model, enhanced with the Luong attention mechanism [129], which aligns and weighs the importance of different input sequence elements, is employed to predict vessels' future movement in collision avoidance scenarios. An LSTM classifier is employed to predict the preference based on the same features as the input features of the LSTM-autoencoder. Furthermore, the navigational preferences serve as the specific tasks to supervise the predictive process, ensuring the prediction accuracy and stability.

The model consists of the following elements, as illustrated in Figure 4-2.

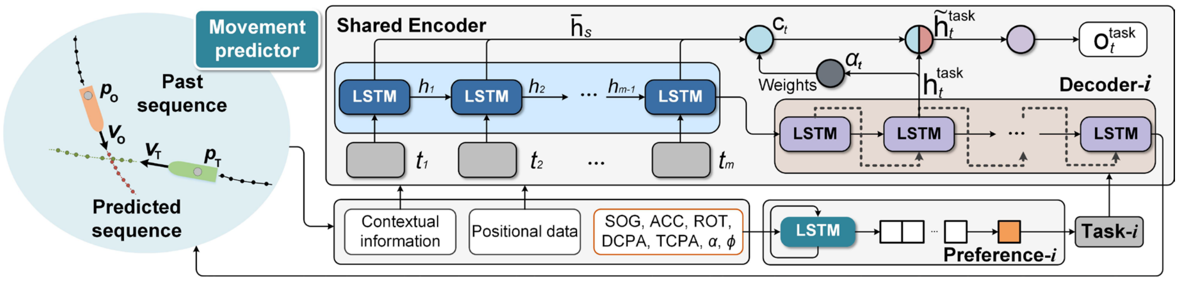


Figure 4-2 The diagram of preference-based movement predictor for trajectory prediction

(1) Encoder

The encoder utilises an LSTM network to process a historical data sequence over a defined time window as the input, including the positions of both the own and the neighbouring ships, the encountered scenario, and navigational priority. The LSTM then generate a series of hidden states that capture temporal dependencies and contextual features of vessel interactions. These representations are essential for the decoder to generate context-aware future trajectories. The mathematical representation of the encoder is given by:

$$(\mathbf{h}_t^{enc}, \mathbf{c}_t^{enc}) = \mathrm{LSTM}(x_t, \mathbf{h}_{t-1}^{enc}, \mathbf{c}_{t-1}^{enc}), (1 \le t \le T_s) \tag{4-2}$$

where x_t is the input feature vector at time *t*, T_s refers to the length of the input sequence, $\mathbf{h}_t^{enc}$ and $\mathbf{c}_t^{enc}$ are the hidden and the cell states of the LSTM at time *t*. $\mathbf{h}_{t-1}^{enc}$ and $\mathbf{c}_{t-1}^{enc}$ represent the hidden and cell states from the previous time step, respectively.

(2) Classifier

The preference is recognised by an LSTM classifier, which receives the same features as the LSTM-autoencoder with the time length of T_s to predict the preference. The representation is given by:

$$y_{\mathrm{pref}} = \mathrm{softmax}\left(\mathbf{W}_{\mathrm{pref}}\mathbf{h}_{T_s}^{enc} + \mathbf{b}_{\mathrm{pref}}\right) \tag{4-3}$$

where y_{pref} represents the navigational preference class of prediction, $\mathbf{W}_{\mathbf{pref}}, \mathbf{b}_{\mathbf{pref}}$ refer to the weights and bias vectors, respectively.

(3) Task-specific decoder

The preference predicted by the classifier is then transmitted into the MTL-Seq2Seq-LSTM-Att model, where the preference is taken as the specific task to decode the input sequences to ensure the alignment between realistic navigational strategies.

$$\mathbf{h}_{t+1}^{task}, \mathbf{c}_{t+1}^{task} = \mathrm{LSTM}\left(\mathbf{y}_t^{task}, \mathbf{h}_t^{task}, \mathbf{c}_t^{task}\right) \tag{4-4}$$

here $\mathbf{y}_t^{task}$ is the input to the decoder at time step t, and $\mathbf{h}_t^{task}$ and $\mathbf{c}_t^{task}$ are the hidden state and cell state of the decoder, respectively.

(4) Attention mechanism

The Luong attention is employed in our model to enhance the relevance and precision of the generated sequences. At each time step t, the decoder utilises a task-oriented attention mechanism to weigh the encoder outputs, producing the corresponding context vector $\mathbf{c}_t$. This process aligns the decoders' focus with the most relevant features of the input sequence, thereby ensuring that subsequent interactive manoeuvres can be captured based on the ship trajectories over a given timeframe.

$$\alpha_t(s) = \mathrm{softmax}\left(\mathrm{score}\left(\mathbf{h}_t^{task}, \bar{\mathbf{h}}_s\right)\right) = \frac{\exp\left(\mathrm{score}\left(\mathbf{h}_t^{task}, \bar{\mathbf{h}}_s\right)\right)}{\sum_{s'} \exp\left(\mathrm{score}\left(\mathbf{h}_t^{task}, \bar{\mathbf{h}}_{s'}\right)\right)} \tag{4-5}$$

$$score\left(\mathbf{h}_t^{task}, \bar{\mathbf{h}}_s\right) = \mathbf{h}_t^{task^T} \boldsymbol{W}_a \bar{\mathbf{h}}_s \tag{4-6}$$

$$\mathbf{c}_t = \sum_s \alpha_t(s) \cdot \bar{\mathbf{h}}_s \tag{4-7}$$

where $\alpha_t(s)$ refers to the attention weight for encoder state s at time t, $\bar{\mathbf{h}}_s$ represents each encoder's hidden state, and the score $\left(\mathbf{h}_t^{task}, \bar{\mathbf{h}}_s\right)$ is the score function that measures the match between the decoder state $\mathbf{h}_t^{task}$ and the encoder state $\bar{\mathbf{h}}_s$ through the trainable weight matrix $\boldsymbol{W}_a$.

The attentional state of the decoder $\tilde{h}_t$ is updated through:

$$\tilde{h}_t = \tanh\left(W_c \cdot \mathrm{concat}(c_t; h_t')\right) = \tanh(W_c \cdot [c_t; h_t'])$$

with W_c being a trainable parameter matrix with the dimension of $[n_h \times 2n_h]$ transforms the context vector c_t and decoder hidden state h_t' into an attentional hidden state.

(5) Output layer

$$(\mathbf{h}_t^{enc}, \mathbf{c}_t^{enc}) = \mathrm{LSTM}(x_t, \mathbf{h}_{t-1}^{enc}, \mathbf{c}_{t-1}^{enc}), (1 \le t \le T_s) \tag{4-8}$$

$$\mathbf{o}_t^{task} = \mathbf{W}_{out}^{task}[\mathbf{c}_t; \mathbf{h}_t^{task}] + \mathbf{b}_{out}^{task} \tag{4-9}$$

where $\mathbf{W}_{out}^{task}$ is the weight matrix for the linear transformation of the specific task, $\mathbf{b}_{out}^{task}$ is the bias vector for a specific task.

4.4.2 Extended KM-DWA decision-making

In order to ensure safe and efficient navigation in mixed waterborne transport environments, this study proposes a decision-making framework for MASS by integrating the predictive model above with previous work. This section details how our framework employs the predictive model introduced in the previous section and integrates it with Knowledge Maps (KM) developed in our previous work [193] and Local Planner Dynamic Window Approach (DWA) proposed in a subsequent study [192]. The framework is illustrated in Figure 4-3.

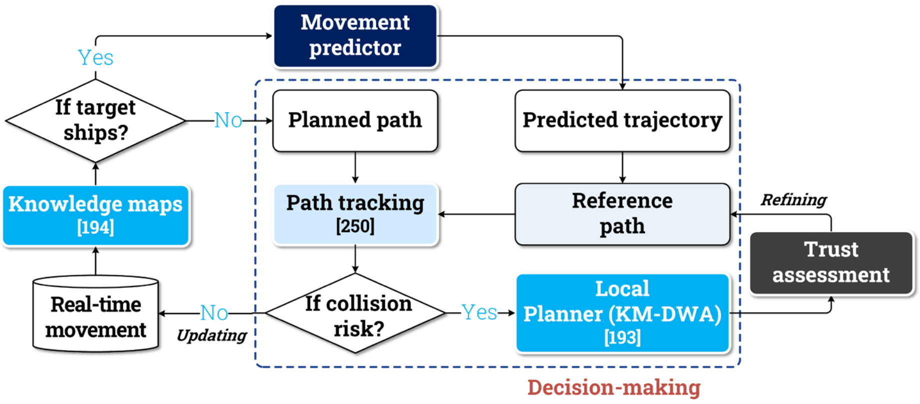


Figure 4-3 The diagram of the decision-making framework based on trajectory prediction

The core components and their interactions are outlined as follows:

(1) **Knowledge Maps (KM)**: The module processes real-time environmental data and historical movement trajectories to support other modules. It provides inputs for the Movement Predictor and decision-making algorithms by transferring relevant requirements to executable actions. This module updates continuously, ensuring the system operates with accurate context-aware information, as detailed in [193].

(2) **Movement Predictor:** When surrounding vessels are detected, this module employs the prediction model to forecast the trajectories of both the own and neighbouring ships. Based on these predicted trajectories, the module constructs the reference path, a human-preferred evasive route for the own ship in the current collision avoidance scenario. This reference path ensures that the MASS behaves in a manner that is predictable and comprehensible to human operators on nearby vessels, reducing the potential for misinterpretation of the MASS's intentions.

(3) **Risk Assessment**: Risk Assessment evaluates potential collision risks based on pre-defined safety thresholds, such as DCPA and TCPA, considering the manoeuvrability of the own ship. As shown in the bottom-right part of Figure 4-3, if any risk is detected, the local planner (KM-DWA) proposed by [192] implements the local planning task for refining the reference path. Conversely, if no risks are detected, the vessel continues to follow the reference path. This mechanism ensures the navigational safety of MASS in dynamic environments.

(4) **Local Planner - KM-DWA:** If a collision risk is detected, the Local Planner module is activated. Using the KM-DWA algorithm, this module refines the reference path by

making localised adjustments to mitigate collision risks. This refinement does not involve generating a completely new path; instead, it focuses on fine-tuning the existing reference path to adhere closely to human navigational preferences. The updated reference path ensures that the MASS avoids collisions while navigating in a manner that remains predictable and understandable to human operators on surrounding vessels.

(5) **Path Tracking**: This module ensures accurate execution of the reference path. A non-linear model predictive control (MPC) algorithm proposed by [250] is employed in this decision-making framework to track the reference path.

4.5 Model parameters

(1) LSTM-autoencoder

1) **Model Structure**: The LSTM-Autoencoder consists of an encoder and a decoder, each comprising two LSTM layers. The encoder compresses the input sequence with a hidden dimension of 128 into a lower-dimensional latent representation with a dimension of 64 while the decoder reconstructs the sequence from this compressed form.

2) **Training**: The training process utilises the AdamW optimiser with a learning rate of 0.001, balancing effective learning and regularisation. Additionally, a ReduceLROnPlateau scheduler is applied, reducing the learning rate when the model's performance plateaus and helping to fine-tune the model over training epochs.

(2) MTL-Seq2Seq-LSTM-Att model

1) **Model Structure:** The encoder and decoder consist of two LSTM layers and a hidden dimension of 128. The encoder processes the input sequence to capture temporal patterns and compresses this information into a context vector, while the decoder outputs the corresponding future trajectories based on the given sequence.

   A custom loss function was implemented to handle the multi-output nature of the task, particularly focusing on the accuracy of predicted trajectories for both the own vessel and the neighbouring vessel.

2) **Loss function**: The primary goal of trajectory prediction is to ensure that the predicted trajectories of each vessel closely match the actual observed trajectories throughout the sequence. Average Displacement Error (ADE) and Final Displacement Error (FDE) are employed together to achieve this alignment. ADE measures the average deviation between the predicted and actual positions over the entire trajectory, ensuring that the model tracks the vessel's movement across all time steps. FDE targets the accuracy at the final position of the trajectory, ensuring that the final point of the predicted trajectory is as close as possible to the actual final one, which is critical for the overall fidelity of the trajectory prediction.

   The total loss is a weighted sum of the ADE and FDE for both the own vessel and the neighbouring vessel, weighed by pre-defined parameters *ade_weight* and *fde_weight*, as shown in Equation (4-10).

$$Total\ loss = ade\_weight \times (ADE\_own + ADE\_tar) + fde\_weight \times (FDE\_own + FDE\_tar) \quad (4\text{-}10)$$

In this study, the weights *ade_weight* = 0.6 to and *fde_weight* = 0.4 are chosen to balance trajectory accuracy and destination precision. The choice of 0.6 for ADE prioritises the accuracy of the entire trajectory, which is critical for real navigation and safety. By assigning 0.4 to FDE, we ensure that destination precision remains essential but without overemphasising the endpoint at the expense of intermediate accuracy. This ratio was chosen based on preliminary experiments, which indicated that a higher weight on FDE could lead to less accurate trajectory predictions, while this balance yielded more reliable overall performance.

3) **Runtime performance:** This module operates as a real-time part of the decision-making framework, predicting vessel trajectories in the next few minutes. Runtime performance is critical for ensuring the system's feasibility in real-time scenarios, which is evaluated by measuring average runtime across multiple trials with an 11th Gen Intel(R) Core(TM) i7-1185G7 @ 3.00GHz processor.

Several metrics were used to assess the model's performance:

(i) Root Mean Squared Error (RMSE): RMSE was calculated to measure the average magnitude of reconstruction errors, with a lower RMSE indicating better model performance.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where, y_i represents the actual value, $\hat{y}_i$ represents the predicted value, and n is the number of data points.

(ii) Mean Squared Error (MSE): MSE was calculated to measure the average magnitude of the squared reconstruction errors, with a lower MSE indicating better model performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

(iii) Mean Absolute Error (MAE): MAE provided another measure of reconstruction accuracy, focusing on the absolute differences between the actual and predicted values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

(iv) R-Squared (R^2): R^2 was used to quantify how well the model captured the variance in the data, with a value closer to 1 indicating better explanatory power.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where, $\bar{y}$ is the mean of the actual values.

(v) Variance: Variance was used to measure the spread of the prediction errors, denoted by Var. It indicates the degree to which the predicted values differ from the mean of the actual values. Lower variance suggests more consistent model predictions.

$$Var = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2$$

(vi) Explained Variance Score (EVS): EVS was calculated to assess the proportion of variance explained by the model and the model's overall effectiveness.

$$EVS = 1 - \frac{Var(y_i - \hat{y}_i)}{Var(y_i)}$$

(3) Decision-making framework

MPC: The MPC framework is designed to ensure trajectory tracking a set of waypoints, with intermediate positions interpolated to generate a smooth trajectory. The prediction horizon is set to N = 15 steps, with a control horizon of Nc = 3 steps and a sampling time (*dt*) of 0.1s. The maximum control inputs are constrained to τ_x, τ_y, and τ_z, as shown in Table 4-2. The vessel's dynamics are modelled using the 3 degrees of freedom model, shown by Equations (4-11) and (4-12). The equations governing the vessel's motion are discretised using the fourth-order Runge-Kutta method during the simulation.

1) 3-DOF ship motion model

The continuous-time state-space representation is given by the following equations:

$$\dot{\boldsymbol{\eta}}=\boldsymbol{R}(\psi(\mathrm{t}))\boldsymbol{v}(\mathrm{t}) \tag{4-11}$$

$$M\dot{\boldsymbol{v}}(t) + C(\boldsymbol{v}(t))\boldsymbol{v}(t) + D(\boldsymbol{v}(t))\boldsymbol{v}(t) = \boldsymbol{\tau}(t) \tag{4-12}$$

where $\eta = [x, y, \psi]^{\mathrm{T}}$ represents the position and heading of the vessel, $\boldsymbol{v} = [u, v, r]^{\mathrm{T}}$ denotes the velocities in surge, sway, and yaw, and $\boldsymbol{\tau} = [\tau_x, \tau_y, N]^{\mathrm{T}}$ corresponds to the control inputs (forces and moment).

The rotation matrix $\boldsymbol{R}(\psi(t))$ that transforms velocities from the body-fixed frame to the inertial frame is expressed by Equation (4-13). Additionally, the state-output relationship is defined by the output Equation (4-14).

$$\boldsymbol{R}(\psi(t)) = \begin{bmatrix} cos(\psi(t)) & -sin(\psi(t)) & 0 \\ sin(\psi(t)) & cos(\psi(t)) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4-13}$$

$$y(t) = \boldsymbol{C} \cdot [\eta(t)^{\mathrm{T}}, v\,(t)^{\mathrm{T}}]^{\mathrm{T}}; \boldsymbol{C} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4-14}$$

In this framework, the MPC optimisation problem seeks to minimise the cost function J, presented by Equation (4-15), penalising deviations from the interpolated reference trajectory and the magnitude of control inputs.

$$J = \sum_{n=1}^{N} \left(\left(y(k+n) - y_{ref}(k+n) \right)^{\mathrm{T}} Q \left(y(k+n) - y_{ref}(k+n) \right) \right) + \sum_{n=0}^{N-1} u(k+n)^{\mathrm{T}} R\, u(k+n) \tag{4-15}$$

$$Q = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}, R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{4-16}$$

where $y_{ref}(k+n)$ represents the interpolated reference trajectory at future time steps, $u(k+n)$ represents the magnitude of control inputs, and Q and R are weighting matrices, see Equation (4-16). These matrices prioritise minimising the tracking error while keeping the control inputs within practical limits.

2) **KM-DWA**: the KM-DWA algorithm uses a set of the same weights as the setting in [192] to balance different objectives during navigation, including obstacle avoidance, pathkeeping, heading stability, etc. The DCPA and TCPA thresholds are set at 10 meters and 50 seconds to trigger evasive actions when necessary.

4.6 Experiment

4.6.1 Dataset preparation and simulation setting

The dataset used in this study is derived from Dutch maritime traffic data within the Rotterdam port area, covering the period from 00:00 UTC on 1 October 2023 to 00:00 UTC on 15 October 2023. The data was collected through VesselFinder and includes detailed vessel movement information within the geographical coordinates of 51.833° to 52.167° latitude and 3.167° to 4° longitude. This dataset specifically focuses on three high-risk areas within the Rotterdam port region, selected for their higher potential for navigational conflicts, as illustrated in Figure 4-4.

Through the conflict pairs extraction algorithm, Algorithm 4-1, proposed in Section 4.3.2, we identified and extracted 1,587 potential conflict pair sequences from the original dataset. These sequences were subsequently used for preference extraction and trajectory prediction model training and validation. During the preprocessing phase, numerical features were normalised and categorical features were encoded to ensure consistency and facilitate their utilisation by the models.

Specifically, the preference extraction was conducted on the entire dataset, using the LSTM-Autoencoder for feature compression and clustering to identify the full spectrum of the navigational preferences. Furthermore, to ensure the generalisability of the trajectory prediction model, the data was divided into a training set and a test set using an 80/20 split. In this case,1,269 conflict pairs were allocated for training, while the remaining 318 conflict pairs were reserved for further testing and validation.

A simulation was implemented in Area 1 of Rotterdam Port to validate the proposed decision-making framework. The goal of the simulation was to evaluate the ability of a tugboat to navigate safely along predetermined routes while avoiding collisions with neighbouring vessels. For this purpose, we utilised *Tito-Neri,* a 1:30 scale model of a tug boat developed by TU Delft [78]. The parameters of *Tito-Neri* are provided in Table 4-2. These parameters can be converted according to the Froude scaling of various physical quantities [147].

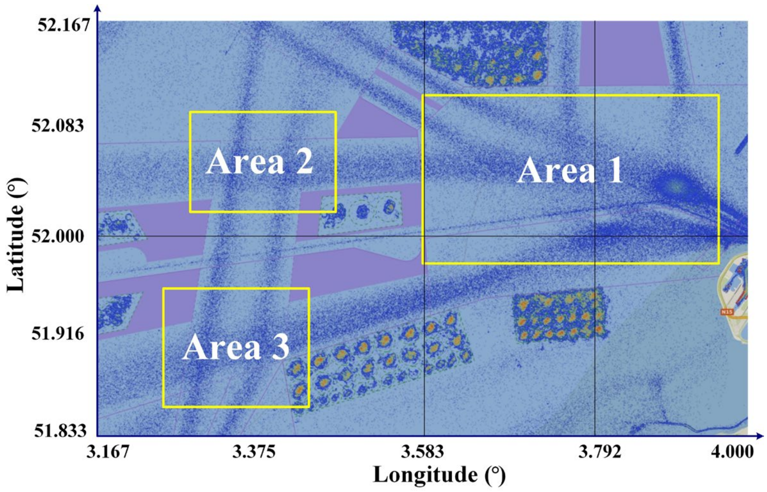


Figure 4-4 The focused areas in the port of Rotterdam in the experiment

Table 4-2 The parameters of the *Tito-Neri* ship model

Quantity	Length	Width	Thruster forces	Mass	Actuators
	0.97 m	0.30 m	τ_x = [-5, 5], (N) τ_y = [-5, 5], (N) τ_z = [-2.5, 2.5] (N·m)	16.9 kg	1) Two stern azimuth thrusters 2) One bow thruster

In this experiment, we selected a navigational scenario from real AIS data where the own ship acts as the stand-on vessel, while the neighbouring vessel is the give-way vessel. Figure 4-5 presents not only the predicted and actual trajectories for both the own and the neighbouring ships on the left side but also DCPA and TCPA variation during this interaction on the right side. In this case, the own ship (represented by red and blue markers) acts as the stand-on vessel, while the neighbouring ship (represented by green and cyan markers) is the give-way vessel. The predicted trajectories for the own ship and neighbouring ship are shown in blue and purple, respectively. Additionally, the variation of motion characteristics, including SOG, COG, DCPA and TCPA, are given in the right panel. As shown in Figure 4-5. DCPA decreases as the vessels approach each other, reaching their lowest point near zero before increasing as they move apart. The TCPA similarly decreases, hitting zero at the closest point of approach, and becomes negative as the vessels begin to separate. This situation requires the own ship to be vigilant for imminent evasive actions.

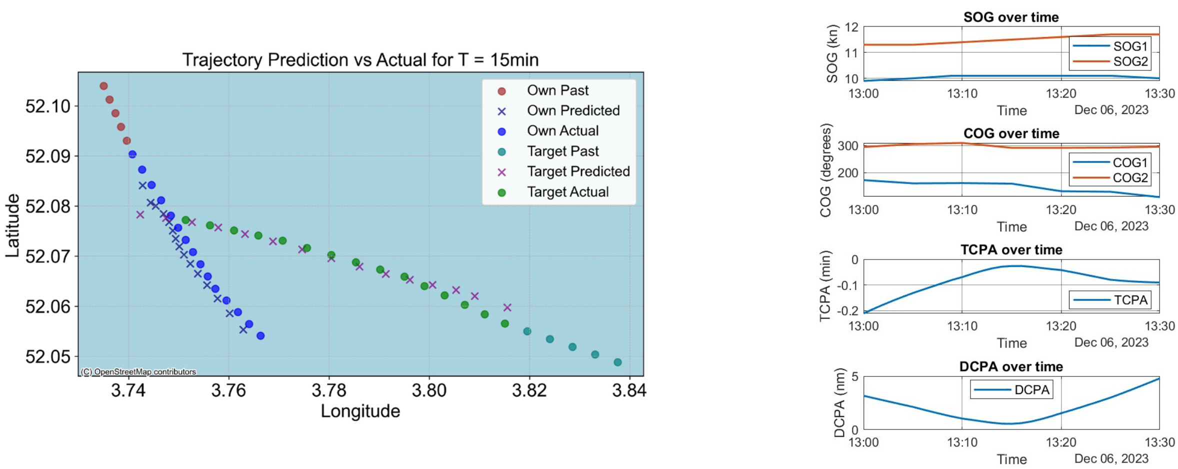


Figure 4-5 Trajectory prediction vs actual trajectory for ships in a crossing scenario

4.6.2 Results

4.6.2.1 Preference extraction results

The performance of the LSTM-autoencoder model was evaluated by several key metrics: the RMSE of 0.048 and the MAE of 0.0284, indicating a high degree of accuracy in the model's reconstruction capabilities. Additionally, the model achieved an R^2 value of 0.936 and an EVS of 0.936, reflecting its effectiveness in capturing the underlying variance in the data.

Furthermore, we applied K-means to the encoded data produced by the LSTM-autoencoder model to identify the optimal number of clusters with identified manoeuvring preferences. The evaluation was based on three key metrics: Sum of Squared Errors (SSE), Silhouette Score, and Davies-Bouldin Index, as illustrated in Figure 4-6. The selection of 4 clusters reflects a balanced consideration of these metrics. While the SSE curve shows diminishing improvements beyond 4 clusters, suggesting limited benefits from additional clusters. Additionally, although the Silhouette Score does not reach its maximum at 4 clusters, it remains relatively high, indicating a balance between intra-cluster cohesion and inter-cluster separation. Furthermore, while the lowest value of the Davies-Bouldin Index occurs at 2, the index at 4 clusters is relatively low compared to other numbers, further supporting this as the most effective configuration.

Based on this cluster selection, Figure 4-7 and Figure 4-8 illustrate the results of our collision avoidance experiment in port water areas, showing vessel interaction trends across the four identified manoeuvring preferences. Each trend represents specific behaviours in terms of the features of navigational preferences, including SOG, ACC, ROT, and other variables. The four clusters represent distinct vessel interaction preferences, summarised in Table 4-3.

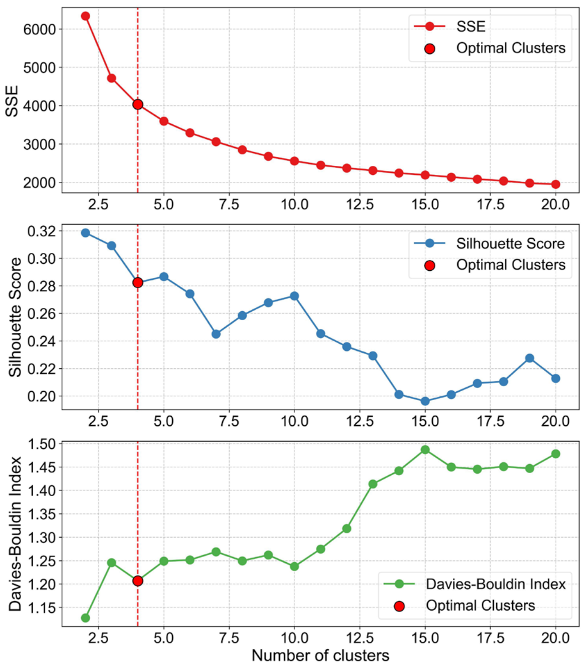


Figure 4-6 The illustration of optimal clustering number investigation

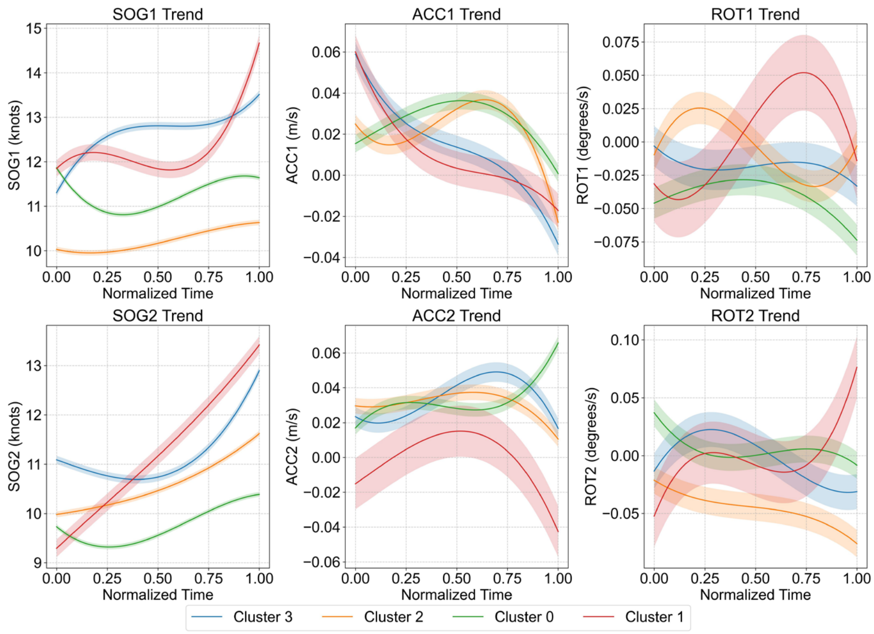


Figure 4-7 Experiment of MASS in port water areas

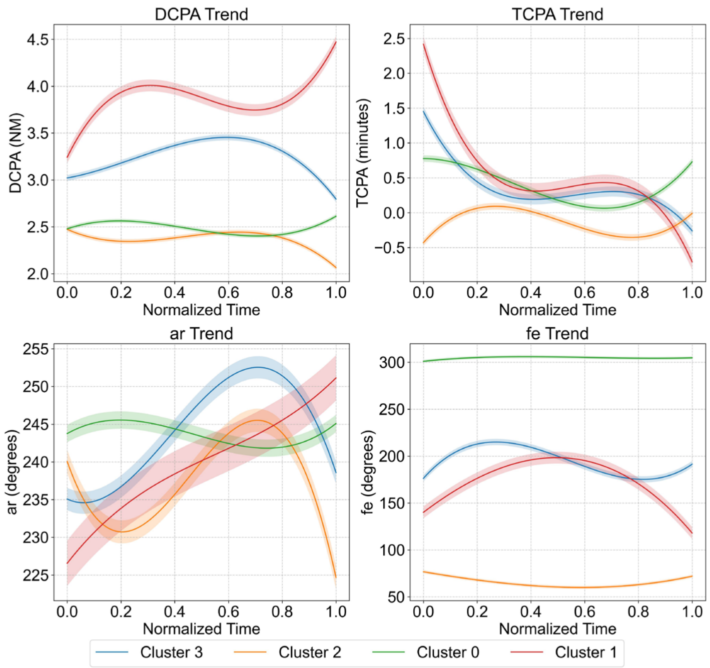


Figure 4-8 Experiment of MASS in port water areas

Each cluster represents a different manoeuvring pattern in collision avoidance: **Cluster 0** exhibits a cautious and stable interaction pattern, where vessels maintain low speeds and straight courses with minimal adjustments. **Cluster 1** reflects a proactive strategy of accelerating through encounter points, with vessels making significant speed and course adjustments near the encounter, indicating a preference for rapid passage through potential collision areas. **Cluster 2** represents a gradual adjustment strategy, with slow changes in speed and heading, indicating a preference for steady navigation in low-risk scenarios. **Cluster 3** demonstrates a response to potentially hazardous situations, with vessels significantly increasing speed and making large course adjustments near the encounter point, suggesting a reactive strategy to avoid imminent collisions.

4.6.2.2 Trajectory prediction results

(1) Preference prediction

An LSTM classifier was trained and evaluated to predict navigational preferences. As shown in Figure 4-9, the model achieved strong performance on the training set, with accuracy at 0.9179, precision at 0.9163, recall at 0.9179, and an F1 score of 0.9165. The slightly lower validation metrics—accuracy of 0.8460, precision of 0.8614, recall of 0.8460, and an F1 score of 0.8498—indicate minor overfitting. Nevertheless, the model demonstrates reasonable generalisation capability, which forms a solid foundation for subsequent trajectory prediction tasks.

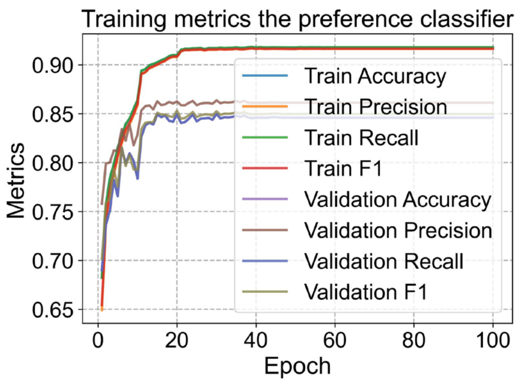


Figure 4-9 Training metrics of the preference prediction classifier

(2) Trajectory prediction

The proposed movement predictor, utilising the MTL-Seq2Seq-LSTM-Att model, was designed to integrate the results of preference prediction into the trajectory prediction process. Figure 4-10 shows the training and validation loss curves for the trajectory prediction model over three prediction horizons: 10 minutes, 15 minutes, and 20 minutes. The validation loss follows a similar trend, stabilizing slightly above the training loss, which suggests good generalisation. In terms of runtime performance, the module completed each trajectory prediction in an average of 12.8 ms, meeting real-time requirements in dynamic collision avoidance scenarios.

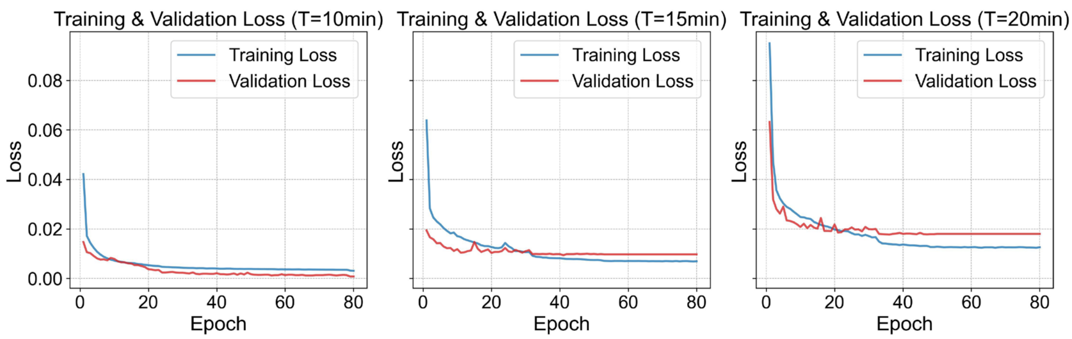


Figure 4-10 Training loss of the MTL-Seq2Seq-LSTM-Att model for prediction of future length

Table 4-3 Characteristics of the Four Identified Vessel Interaction Preferences

Cluster	0	1	2	3
SOG1	Slight drop then recovery, with low speed throughout.	Stable at first, then accelerates; wider interval early on.	The lowest overall speed, with a slight upward trend during the interaction.	Steady increase, with fast initial rise, stable middle, and slower end.
SOG2	Slight initial decrease, then steady acceleration.	Continuous speed increase; wider confidence interval.	Slow and steady acceleration, maintaining a relatively low speed.	Slight drop, then stable, followed by late acceleration.
ACC1	High initial acceleration, then declines.	Gradual decrease, mostly accelerating; widest interval early.	Acceleration with slight dip, rebound, then negative at end.	Consistent drop from positive to negative; interval widens mid-phase.
ACC2	Gradually increases; stable in the middle.	Increases initially, then decreases, with a wide confidence interval.	Stable in positive zone, indicating consistent acceleration.	Slow rise then decline, transitioning to deceleration.
ROT1	Left-turn trend with high variability.	Left turn shifts to right; turning rate decreases; widest interval.	Initially increases, then decreases, followed by a slow rise back to 0, indicating a fluctuating turning behaviour.	Maintains a slightly negative rate (indicating a slow left turn), with a wider confidence interval.
ROT2	Minor right turn, decreases then stabilises at 0.	Continuous right turn; stabilises near 0, then increases; widest interval.	Steady decline into left turn; high variability.	Rises, then falls below 0 and stabilises; right–left turn pattern.
DCPA	Remains stable around 2.5 nm.	Increases initially, then decreases slightly before increasing again, with the largest overall DCPA among the clusters.	Remains stable at around 2.5 nm, then decreases slightly toward the end.	Initially increases by about 0.5 nm, then decreases to approximately 2.8 nm, indicating an overall larger DCPA but lower than Cluster 1.
TCPA	Decreases toward 0, then increases.	Decreases to about 0.5 minutes, stabilises, and then decreases further below 0, showing the ships passing the closest point.	Mostly negative, exhibiting fluctuations, suggesting consistent proximity during the interaction.	Decreases to about 0.2 minutes, stabilizes, then decreases below 0, similar to Cluster 1.
$\boldsymbol{\phi}$	Stable near 245°.	Maintains a steady increase with a large range of variability.	Exhibits fluctuations, initially decreasing, then increasing, and decreasing again.	Displays significant fluctuations, initially increasing and then decreasing.
$\boldsymbol{\alpha}$	Stable around 300°.	Rises and then returns to the initial level.	Lowest and most stable value.	Minor fluctuations: slight rise, then steady fall.

(3) Comparative performance analysis

We compared the performance of the proposed predictive model with the following baseline methods over different forecasting horizons (10min, 15min, and 20min): (1) Basic Seq2Seq RNN (2) Basic Seq2seq attention LSTM (3) Basic Seq2Seq LSTM (4) Bi-LSTM, see Table 4-4 for details. These baseline models were selected because they represent different levels of complexity commonly used in sequence-to-sequence prediction. The Basic Seq2Seq RNN serves as a basic model for comparison, while the Basic Seq2Seq LSTM improve upon it by handling long-term dependencies, and the Basic Seq2seq attention LSTM and the Bi-LSTM further enhance the ability to focus on important parts of the sequence or process data in both directions. The metrics used include MSE, MAE, R^2, variance, evaluating the models' ability to predict future trajectories of the own ship and a neighbouring ship based on initial five-minute trajectory data.

Table 4-4 The prediction results of the proposed method and other baseline predictive methods

T	Metrics	Predictive models				
		MTL-Seq2Seq-LSTM-Att	Basic Seq 2 Seq RNN	Basic Seq2seq attention LSTM	Basic Seq2Seq LSTM	Bi-LSTM
10min	*MSE*	0.0003	0.0003	0.0004	**0.0002**	0.0005
	MAE	0.0113	0.0106	0.0129	**0.0097**	0.0156
	R^2	**99.2%**	**99.2%**	98.6%	**99.2%**	98.5%
	var	0.0003	0.0003	0.0004	**0.0002**	0.0005
15min	*MSE*	**0.0036**	0.0042	0.0046	0.0048	0.0039
	MAE	0.0389	0.0414	0.0435	0.0408	**0.0381**
	R^2	**89.4%**	87.8%	86.7%	86.19%	88.7%
	var	**0.0036**	0.0042	0.0045	0.0048	0.0039
20min	*MSE*	**0.0060**	0.0117	0.0105	0.0103	0.0100
	MAE	**0.0488**	0.0754	0.0612	0.0564	0.0566
	R^2	**85.2%**	71.0%	74.23%	74.5%	75.4%
	var	**0.0060**	0.0116	0.0102	0.0102	0.0098

1) **10-Minute Forecasting Horizon:** The Basic Seq2Seq LSTM model shows the lowest MSE (0.0002) and MAE (0.0097), indicating slightly better short-term prediction accuracy. However, the proposed MTL-Seq2Seq-LSTM-Att model also demonstrates acceptable performance with an MSE of 0.0003 and a high R^2 of 99.2%, comparable to the best-performing models.

2) **15-Minute Forecasting Horizon:** Extending the horizon to 15 minutes, the proposed model continues to perform competitively with an MSE of 0.0036 and an R^2 of 89.4%. These results suggest that the model retains a good balance between accuracy and variance explanation. Although the Bi-LSTM model exhibits a lower MAE, the proposed model maintains robust overall performance. Notably, the Basic Seq2seq LSTM with Attention and without attention models show a reduction in R^2 to 86.7% and 86.19%, respectively, along with higher MSEs and MAEs, indicating a decrease in predictive accuracy over longer horizons.

3) **20-Minute Forecasting Horizon:** For the 20-minute horizon, the performance of the models diverges more noticeably. The proposed model achieves the lowest

MSE of 0.0060 and a relatively high R^2 of 85.2%, suggesting it remains effective for longer-term predictions compared to other models.

The proposed MTL-Seq2Seq-LSTM-Att model demonstrates consistent performance across different prediction horizons. While some baseline models exhibit strengths in specific metrics at certain horizons, the proposed model provides a reliable balance between accuracy and variance explanation, particularly in long-term prediction scenarios.

(4) Visual analysis of prediction results

The prediction results are further visualised in Figure 4-13, Figure 4-14, and Figure 4-15, showcasing the model's performance over 10-minute, 15-minute, and 20-minute horizons, respectively.

For the 10-minute horizon, the model generally captures the trajectory trends but exhibits deviations in certain cases, such as case 3 and case 4, indicating difficulties in handling short-term dynamics. In contrast, the 15-minute horizon provides the most accurate predictions, with a close alignment between predicted and actual trajectories, demonstrating the model's ability to balance global trends with local details. At the 20-minute horizon, while overall trends are still captured, slight distortions and deviations appear, particularly in more complex scenarios, reflecting a decrease in prediction precision as the forecast period extends.

The visualisation results suggest that the model performs best at the 15-minute horizon, where it achieves an optimal balance between accuracy and stability. The 10-minute predictions, though capturing general trends, reveal shortages in capturing fine-grained and foreseeable predictions. The 20-minute horizon, on the other hand, shows the model's reduced precision over longer periods, likely due to increased uncertainty and cumulative errors. Overall, the 15-minute horizon is the most suitable for practical decision-making, balancing immediate accuracy and longer-term trend stability.

4.6.2.3 Decision-making results

To anticipate the future positions of the vessels involved in the scenario, we employed the developed movement predictor in the decision-making framework, shown in Figure 4-3. This model leverages historical 5-minute AIS data to forecast the future paths of the vessels over the selected horizon of 15 minutes. By predicting the future trajectories, we could determine the optimal waypoints for safe navigation of the own ship. Based on the predicted trajectories, we established a series of turning points that the vessel should follow to avoid collisions based on human-preference-aware paths. These turning points were then fed into the MPC framework, which was tasked with tracking the desired trajectory while performing local collision avoidance. The MPC was configured to optimise the vessel's control inputs, ensuring that it adhered to the reference path while dynamically adjusting to any emerging threats.

While in many studies – including our previous work [192], it is assumed that neighbouring vessels maintain their speed or course during interactions, this study focuses on validating the proposed predictive model in a situation where the own ship's trajectory tracking is performed based on the future trajectory points of both the own ship and the neighbouring vessels, as predicted by our model. Moreover, we also address situations where the predicted reference path of a neighbouring vessel poses a collision risk to the own ship. In such cases, we validated the intervention of the KM-DWA local planner to facilitate decision-making throughout the collision avoidance process. This approach was integral in demonstrating the effectiveness of our proposed model in handling dynamic maritime scenarios involving potential collision risks.

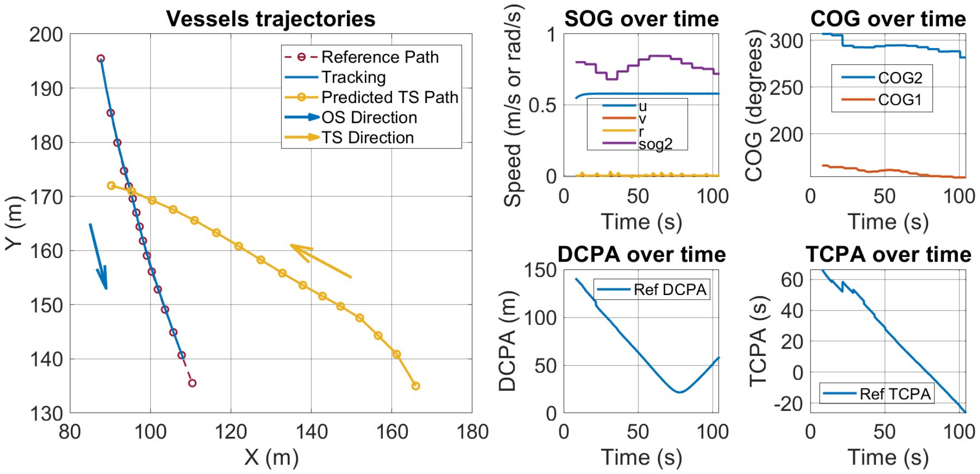


Figure 4-11 Demonstration of path tracking based on predictive trajectory results

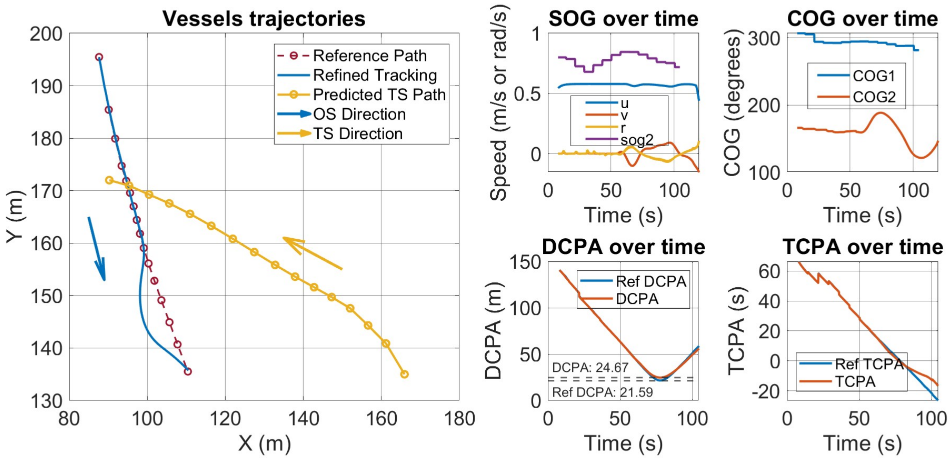


Figure 4-12 Demonstration of path tracking based on refined path results

The simulation results are illustrated in Figure 4-11 and Figure 4-12, where the blue arrows indicate the moving direction of the own vessel, while the yellow arrows indicate the moving direction of the neighbouring vessel. Figure 4-11 illustrates the path-tracking results without the local KM-DWA intervention, while Figure 4-12 shows the path-tracking results with KM-DWA intervention. In the left panel of the two figures, the reference path is depicted as a red dashed line, the path generated by the MPC controller is represented as a solid blue line, and the yellow line illustrates the predicted trajectory of the neighbouring vessel. A close alignment between the reference path and the MPC tracking path demonstrates effective path-following control, ensuring the vessel adheres closely to the desired trajectory. The right panel presents the ship motion parameters during the avoidance process, such as speed, heading, and relative motion characteristics between the vessels, with a focus on DCPA and TCPA. The own vessel maintains stability by controlling the surge speed throughout the tracking process. Meanwhile, the sway and yaw speeds remain near zero as the ship adjusts its heading to follow the desired trajectory. The observed trend of DCPA initially decreasing and then increasing, along with TCPA continuously decreasing, reflects the scenario where the two vessels approached each other before reaching the closest point of approach and then diverged in opposite directions.

Figure 4-12 presents the path-tracking results where the knowledge maps-based DWA path planner is applied. In this case, the DWA was triggered upon the DCPA and TCPA values reaching the set thresholds of 50 meters and 20 seconds, respectively. As shown in the blue tracking path in the left panel, the vessel makes an early right turn at t = 61s in response to the detected risk. This manoeuvre, reflected in changes to sway and yaw speeds, adjusts the COG1 and gradually increases the DCPA. As shown in the right panel, the minimum DCPA improves from 21.59 to 24.67 after intervention, indicating a safer distance between the vessels.

The results from these simulations underscore the importance of the proposed decision-making framework for autonomous vessel navigation. While the MPC is capable of tracking the reference path well, the inclusion of KM-DWA enhances the safety of the navigation by responding dynamically to emerging collision risks by taking account of the ship's manoeuvrability. This approach underscores the potential of combining MPC and KM-DWA to ensure precise path following, collision avoidance, and operational efficiency in real-world maritime navigation.

4.6.3 Discussion

This study aimed to develop a human-preferences-aware trajectory prediction model, which serves as the foundation for a decision-making framework aimed at enabling autonomous vessels to perform human-mimic navigation during collision avoidance in a mixed waterborne environment. The results demonstrated that the proposed framework successfully extracted navigational preferences from AIS data, predicted future trajectories with high accuracy, and enhanced collision avoidance strategies by incorporating these predictions into the decision-making process.

4.6.3.1 Interpretation of Results

The extraction of navigational preferences using the LSTM-autoencoder and K-means clustering revealed four distinct clusters representing different manoeuvring patterns during vessel encounters. Each cluster provided insights into how vessels adjust their speed, acceleration, and rate of turn in response to potential collision scenarios. For instance, Cluster 0 reflected a cautious and stable interaction pattern, while Cluster 3 demonstrated a more reactive strategy involving significant course adjustments and speed variations. These human preference patterns were critical in improving the accuracy and interpretability of the trajectory predictions, allowing the MTL-Seq2Seq-LSTM-Att model to capture the dynamic interactions between vessels more effectively. Additionally, with an average prediction time of 12.8 ms on a standard computation platform, the module ensures the real-time requirement for collision avoidance.

The predictive performance of the trajectory prediction model is related to the roles of its components. The encoder captures temporal dependencies by transforming historical trajectory data into latent representations, which preserve critical information for accurate predictions. The decoder integrates navigational preferences to generate future trajectories that align with specific manoeuvring patterns, while the attention mechanism dynamically weighs input features to focus on relevant aspects of vessel interactions. These components collectively contribute to reducing prediction errors and exhibit good performance across various time horizons, particularly at the 15-minute horizon. The model effectively balanced global trend capture with local detail fidelity, demonstrating that the inclusion of human navigational preferences enhances the credibility and accuracy of trajectory predictions. This improved accuracy is crucial for the subsequent decision-making processes, where these predictions inform both the own ship's and the neighbouring ship's future paths.

The extension of the decision-making framework with the predicted trajectories allowed for more context-aware navigation. Unlike previous approaches, which assumed constant speed and course for neighbouring vessels, this study leveraged the trajectory prediction model to proactively anticipate and react to potential collision risks. By integrating real-time human-preference-aware predictions into the decision-making framework, the framework facilitated avoidance manoeuvres and enabled local path-planning adjustments based on real-time DCPA and TCPA evaluations. This dual approach ensures that both navigational preferences and safety considerations are addressed.

The primary innovation lies in the predictor model, which integrates navigational preferences extracted from AIS data to predict future trajectories. The decision-making framework, designed around this prediction model, incorporates the KM-DWA module for local path refinement and the MPC module for trajectory tracking. The integration demonstrates the feasibility of combining human-preference-aware trajectory predictions with established decision-making methods, serving as the practical foundation for achieving human-mimic navigation during the interactive collision avoidance process in a mixed waterborne environment.

4.6.3.2 Practical Implications

By providing a more accurate prediction of both the own ship's and the neighbouring vessel's trajectories, the framework supports safer and more human-friendly navigation in mixed waterborne environments. This approach allows for more proactive collision avoidance strategies that account for the movement of surrounding vessels rather than relying on static assumptions.

Furthermore, maintaining mutual trust between autonomous vessels and human-operated ships becomes critical in environments where direct communication between vessels is limited or nonexistent. This study acknowledges that autonomous ships while making independent navigational decisions, must also act in predictable and trustworthy ways to human operators—both those on neighbouring vessels and those supervising the autonomous ships. By adhering to predictable navigational patterns and demonstrating an understanding of navigational preferences, autonomous vessels can foster trust [164], reduce uncertainty, and improve safety in mixed waterborne scenarios.

While the study successfully demonstrates the integration of a trajectory prediction model with established decision-making methods, several limitations must be acknowledged.

(1) **Data limitations**: The dataset, while detailed, was limited to the Rotterdam port area and a specific timeframe. This geographic and temporal restriction may limit the generalisability of the findings to other maritime navigational environments.
(2) **Scope of vessel interactions**: The study primarily focused on two-vessel interactions, simplifying the real-world complexity of maritime navigation where multiple vessels often interact simultaneously. While the KM-DWA provides local path refinement to ensure safety, it is designed for pairwise interactions and does not address the interactive

effects of the movements of multiple vessels in congested environments. In multi-vessel scenarios, the interdependence of vessels' trajectories requires dynamic conflict modelling, which was not explored in this work.

(3) **Consideration of environmental factors**: The current simulations do not consider environmental factors such as wind, waves, currents, or restricted visibility, which directly affect vessel manoeuvring and collision avoidance.

(4) **Computational complexity**: The integration of multiple predictive and decision-making models increases the computational complexity, which may affect real-time performance in high-density traffic scenarios or when deployed on vessels with limited processing capabilities.

(5) **Human-mimic navigation patterns:** While incorporating human-mimic navigation is important for coordination in the mixed waterborne transport, such patterns may contain suboptimal decisions. Therefore, further behavioural filtering and evaluation are needed to ensure safety and consistency when mimicking real-world behaviours.

(6) **Human trust dynamics:** While the framework accounts for the navigational preferences of both the own ship and the neighbouring ship, it does not fully model the dynamics of trust between human operators/supervisors and MASS. In scenarios where direct communication is limited, autonomous ships must behave in a way that earns and maintains the trust of human operators. This aspect of human-autonomous interaction is crucial for ensuring safe and coordinated manoeuvres in mixed environments.

4.7 Conclusions

This chapter contributes to enhancing the proposed decision-making framework for MASS by integrating a trajectory predictor based on the identification of human navigational preferences. This integration enhances the ability of MASS to interact safely, efficiently and smoothly with human-operated vessels in the MWTS. By addressing key challenges in modelling and predicting human-preference-based manoeuvres, this study bridges the gap between conventional path planning and adaptive, context-aware collision avoidance.

The primary contributions of this chapter are threefold:

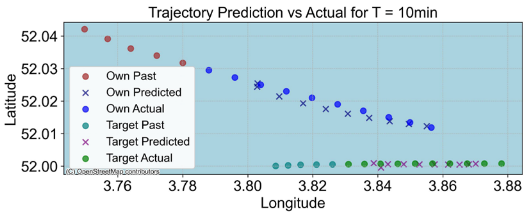
(1) *Human navigational preference extraction*: Developed a methodology to extract navigational preferences based on ship conflict pairs extracted from AIS data through an LSTM-autoencoder and K-means clustering.

(2) *Trajectory prediction model*: Designed and validated an MTL-Seq2Seq-LSTM-Att model to predict ship trajectories considering extracted human navigational preferences for improved accuracy.

(3) *Framework enhancement*: Enhanced the decision-making framework with the trajectory predictor, extending its capabilities to generate preference-aware trajectories. This framework, modularised with the previously developed KM-DWA and trajectory predictor in this chapter, demonstrates its potential to support proactive, seamless, and safe interaction in collision avoidance scenarios.

This chapter directly addresses RQ3-v: *How can AIS data be utilised to extract the navigational preferences of conventional vessels for collision avoidance*? RQ3-vi: *How can past vessels' trajectories be used to develop a real-time movement prediction model with improved accuracy and interpretability based on human navigational preferences*? and RQ3-

vii: *How does the prediction result support the interactive collision avoidance of MASS in a mixed waterborne environment*? By integrating a trajectory predictor module into the proposed decision-making framework, this chapter facilitates a safer, more efficient, and seamless interaction in collision avoidance in the MWTS. In the subsequent chapter, experimental human trust in the decision-making of MASS in collision avoidance is investigated and discussed.



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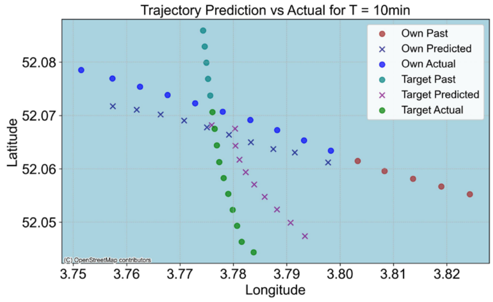

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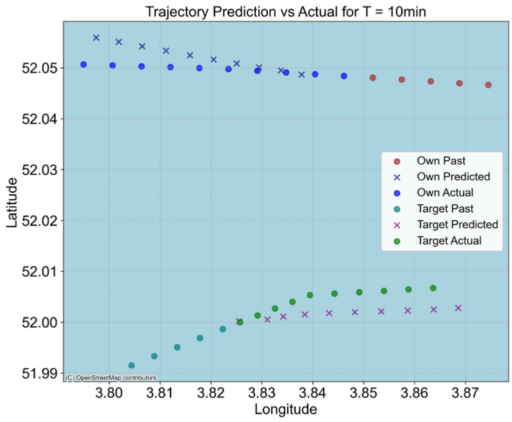

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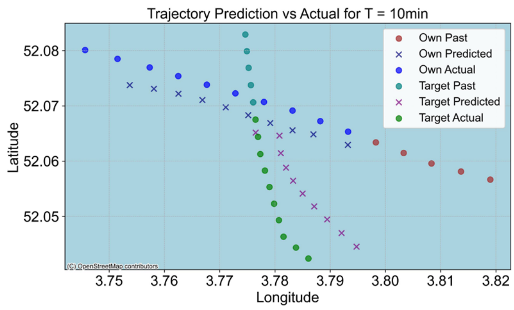

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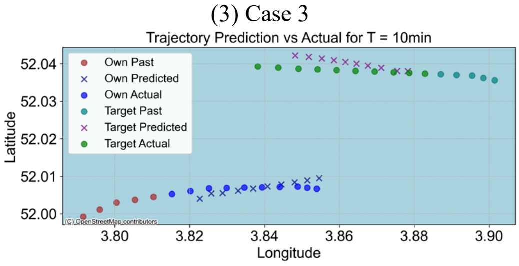

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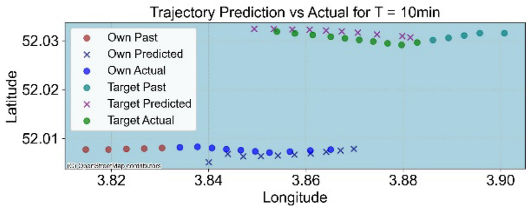

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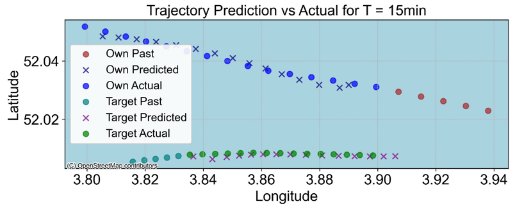
Figure 4-13The visualisation results for the prediction horizon of 10min



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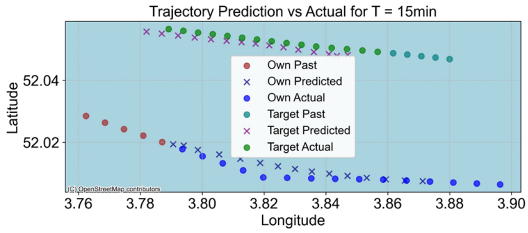

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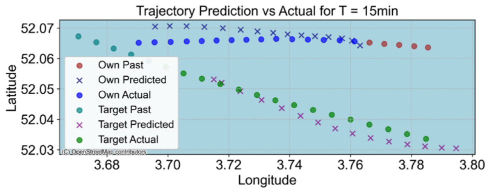

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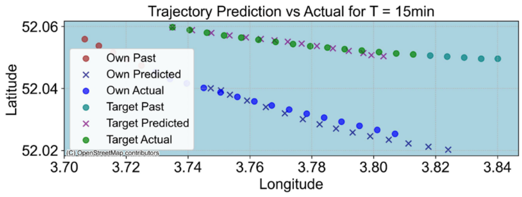

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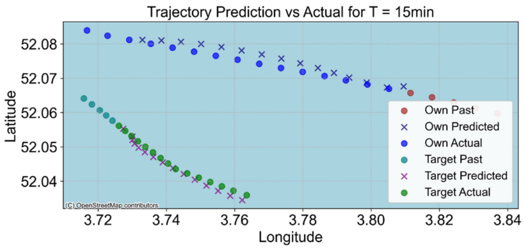

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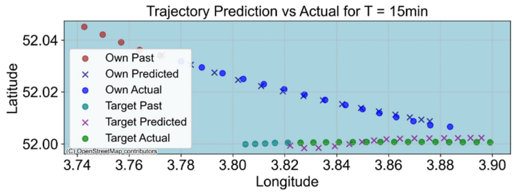

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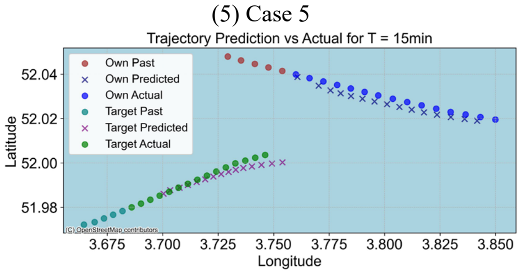

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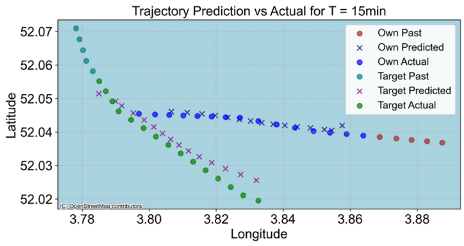

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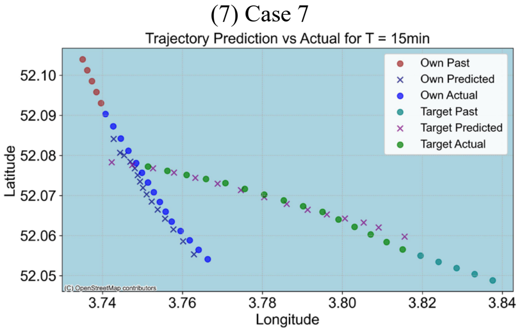

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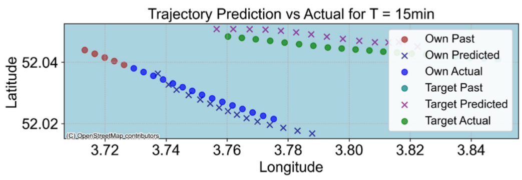
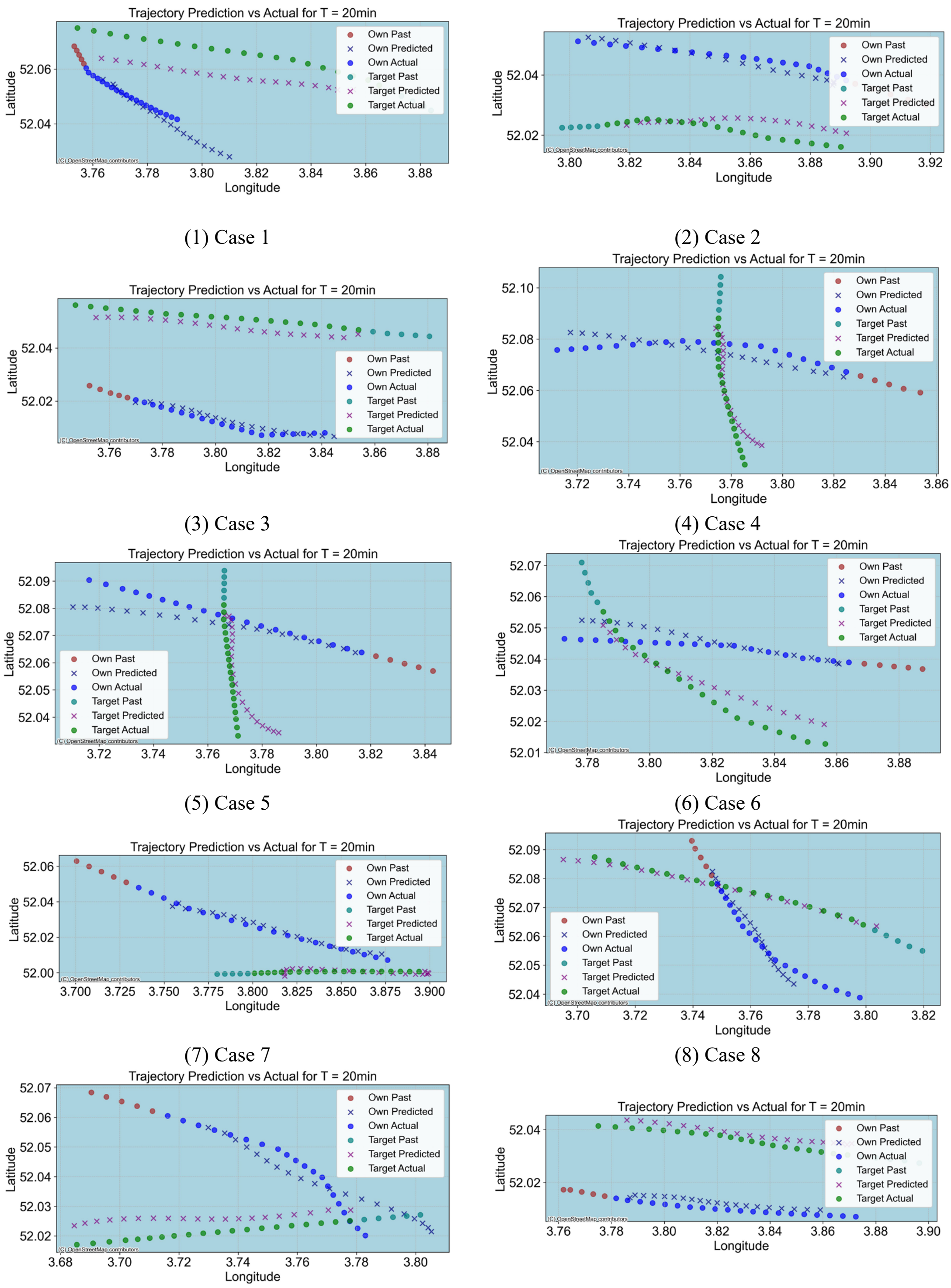


(10) Case 10

Figure 4-14 The visualisation results for the prediction horizon of 15min



(1) Case 1

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(10) Case 10

Figure 4-15 The visualisation results for the prediction horizon of 20min

Chapter 5. Experimental Trust Dynamics Modelling in Autonomous Ship Navigation

The previous chapters established the foundational elements of the integrated decision-making framework for Maritime Autonomous Surface Ships (MASS) in Mixed Waterborne Transport Systems (MWTS). Chapter 2 identified situational awareness, navigation preferences, and human trust as key components for ensuring safe and efficient navigation. Chapters 3 and 4 addressed the module development on situational awareness and human-preference-aware navigation, ensuring a safe, efficient, and seamless interaction between autonomous and manned vessels. This chapter addresses the trust module investigation by focusing on the dynamics of human trust in MASS during collision avoidance scenarios, a critical aspect for ensuring safe and efficient human-system interaction. By addressing research question RQ3-viii, this chapter investigates trust dynamics across navigation stages in collision avoidance (CA) scenarios and identifies key impact factors. Through this, this chapter aims to support the design of MASS systems that foster human trust and optimise decision-making in high-risk maritime contexts.

This chapter is structured as follows: Section 5.1 introduces the research context. Section 5.2 reviews prior research on human-autonomy trust and its significance in maritime operations. Section 5.3 outlines the experimental design and presents the findings of influencing factors through a linear mixed model (LMM) method. Section 5.4 employs a Bayesian Network method to model and investigate trust dynamics. Finally, Section 5.5 concludes this chapter.

5.1 Introduction

Maritime Autonomous Surface Ships (MASS) are being increasingly recognised for their potential to enhance operational efficiency and safety within the maritime industry. Advances in automation technology enable ships to perform navigation tasks autonomously, reducing the need for constant human control. However, human supervision will remain important in the near future [155], as autonomous systems may require monitoring and necessary intervention to ensure safe operations, especially in complicated navigational environments, e.g., for collision avoidance (CA) scenarios. In such situations, human supervisors are important in overseeing the system's actions and intervening when necessary.

Trust in autonomous systems is a key factor in ensuring safe and efficient collaboration between autonomous systems of MASS and human operators [191]. A proper level of trust facilitates human operators to confidently delegate navigational tasks to these systems in specific scenarios. Trust affects how operators perceive the system's actions, their willingness to rely on the system, and their readiness to intervene when required. In addition, trust is not static [106]; it fluctuates based on factors such as system performance, environmental conditions, and operator characteristics [164]. Understanding the dynamics of trust in MASS operations, particularly with CA scenarios, is foundational for developing systems that maintain suitable trust levels.

Despite advances in automation, the dynamics of trust in human-supervised autonomous ship navigation, especially in CA contexts, remain underexplored. In CA scenarios, compliance with the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) is legally required for safe navigation. Human trust in autonomous systems likely depends on how consistently the system adheres to these regulations, particularly in terms of its **evasion strategies** and the **timing of evasive actions**. Studying these dynamics, however, is challenging due to the limited availability of real-world interaction data between MASS and manned vessels, which restricts empirical insights and limits data-driven model development.

Given these constraints, this chapter addresses RQ4 - viii: *How can human trust in MASS be measured, analysed, and modelled within controlled experimental settings*? Addressing this problem is important for understanding how operators interact with MASS, as trust dynamics directly influence operator confidence, intervention likelihood, and overall system performance.

This study makes the following contributions:

(1) Design simulator-based experiments to simulate CA scenarios between MASS and conventional ships, enabling the controlled collection of trust-related data.
(2) Explore how human trust varies over time in CA situations through a linear mixed model (LMM), identifying and quantifying the influence of key factors, such as evasion strategies and timings, on trust dynamics.
(3) Develop a Trust Bayesian Network (TBN) model to further analyse and predict human trust dynamics in CA scenarios, focusing on diagnostic analysis informed by sensitivity analysis and predictive reasoning.

The following section reviews recent work in trust modelling and experimental approaches, providing the context for the methodologies employed in this study.

5.2 Recent work

In recent years, the study of human trust in human-autonomy interaction has gained much attention, particularly in critical domains such as autonomous navigation [15]. The reason is that trust influences the safety and efficiency of these interactions through its effect on operator behaviour: appropriate trust reduces unnecessary intervention while maintaining adequate oversight. In this section, we will explore the nature of trust in the human-autonomy interaction, the methods used to measure and investigate trust, and various approaches to modelling trust.

5.2.1 Trust in human-autonomy interaction

5.2.1.1 Nature of trust

In human-autonomy interaction, trust is commonly defined as a user's willingness to be vulnerable to the actions of an autonomous system based on positive expectations of its performance. A widely referenced conceptualisation of trust was proposed in [141], which characterises trustworthiness through three critical dimensions: ability, benevolence, and integrity. In this model, ability refers to the system's competence in fulfilling tasks, benevolence captures the alignment of the system's goals with those of the user, and integrity reflects the system's adherence to acceptable standards.

In [116], a definition of trust drawn from previous studies is the attitude that an agent will help achieve an individual's goals in a situation characterised by uncertainty and vulnerability. It is pointed out that proper trust calibration prevents overtrust (misuse) and undertrust (disuse) by ensuring that user trust corresponds to the system's real-world performance. Furthermore, this definition was used by [72] to investigate the evolution of trust within human-computer interaction, categorising users into Bayesian decision-makers, oscillators, and disbelievers, each reflecting unique patterns of trust adjustment.

Expanding further, focusing on the factors that may have an impact on trust, a meta-analytic framework is presented by [74], which provides an empirical perspective by examining human, robot, and environmental factors affecting trust in human-robot interaction. Their meta-analysis concludes that robot performance and attribute-based factors are significant contributors to trust development, while environmental factors play a moderate role.

Trust is dynamic and responsive to changes in the operational environment [161] and system performance [9]. Moreover, dynamic models, such as OPTIMo proposed by [232], conceptualise trust as a probabilistic and context-sensitive belief that adapts in real-time to fluctuations in system performance. Trust is viewed as continually updated based on system behaviour, contrasting with static measures that provide only a momentary view.

A three-layered trust model comprising dispositional, situational, and learned trust was proposed by [84] to better understand trust in human-automation interactions. In this model, dispositional trust is an individual's inherent tendency to trust or distrust automation, situational trust arises from contextual elements like task complexity and perceived risk, and learned trust builds through prior experiences with the system. This layered approach integrates individual, contextual, and experiential factors, illustrating that trust varies independently across these layers and is influenced by the dynamic interplay between user expectations and real-time system feedback.

Recently, frameworks like IMPACTS proposed by [86] have extended these trust considerations to encompass practical characteristics essential for building trust in autonomous systems. The model identifies seven characteristics, including intention, measurability, performance, adaptivity, communication, transparency, and security, as crucial for establishing and sustaining trust in autonomy. This model emphasises adaptability and real-time feedback mechanisms, aligning with dynamic models while providing actionable insights for designing trust-supportive systems. Its practical relevance is notable in high-stakes domains, where decision-making must be precise, transparent, and adaptive to changing conditions, underscoring trust as a dynamic, context-sensitive construct.

Additionally, key factors that may influence trust evolvement were investigated by [8], including reliability, predictability, and dependability. Further, studies by [9] focused on the accumulation and decay of trust, identifying that trust can be asymmetrical in response to system performance: while reliability is crucial in building trust, its erosion is more pronounced when systems fail, particularly in high-risk environments.

In summary, while existing studies provide insights into the nature, dimensions, and dynamics of trust in human-autonomy interaction, their application to MASS remains limited, particularly during critical operational scenarios like collision avoidance. In this chapter, we address this gap by incorporating both the dynamic and its multidimensional characteristics, such as reliability, predictability, and safety. Building on established theories, we aim to understand trust dynamics and characteristics in MASS in CA scenarios.

5.2.1.2 Trust measurement and investigation

In the study of trust dynamics within human-autonomy interaction, researchers utilise a diverse array of measurement methods, including subjective, objective, and hybrid techniques.

Subjective methods, such as self-report questionnaires [136], allow operators to directly express their perceived trust levels. For instance, frequent trust measurement intervals have been used to observe how trust levels shift in response to interaction quality and timing [96]. A subjective trust measurement scale tailored to human-robot interaction was developed and validated by [234], exploring how dispositional and history-based trust components influence user trust in varying contexts.

In contrast, objective methods provide physiological indicators of trust fluctuations during task execution. For instance, using psychophysiological data, such as heart rate variability, electrodermal activity, and Electroencephalography (EEG), offers insights into trust dynamics within virtual environments by identifying immediate physiological responses associated with trust levels [29]. Among these, EEG signals capture the brain's immediate response under conditions of trust and thus have been used as a more objective physiological indicator [218][233]. In addition, eye tracking, another measurement method, has been employed to infer trust levels. For example, it was combined with Bayesian models to be used to estimate the workload of operators in real time [128].

To provide a more comprehensive view of trust, hybrid measurements have emerged, integrating both subjective and objective data. The study [110] proposed a toolkit for trust measurement in human-autonomy teams, combining self-report, behavioural indicators (e.g., reliance, compliance, eye-tracking), and physiological data (e.g., heart rate variability) to capture dynamic trust levels. Furthermore, the study [85] examined how cognitive fatigue, robot reliability, and operator gender impact trust in collaborative robots, where both physiological (performance, heart rate variability) and subjective measures (surveys) were employed.

In exploring trust dynamics, statistical methods are commonly employed to analyse how trust varies under different conditions. Techniques like ANOVA and Signal Temporal Logic (STL) are utilised to assess environmental impacts on trust, examining factors such as alarm types or task conditions [186]. Multi-factor analysis, including t-tests and correlation, further reveals how interaction levels and workspace settings impact trust, supporting a nuanced understanding of trust fluctuations [29]. In addition, Linear Mixed Models have been instrumental in capturing trust dynamics over time. For example, exploring specific EEG frequencies (Delta and Gamma) associated with trust fluctuations [218] and investigating the variables of time and frequency, showing the accumulation effect of the frequency of positive interactions on trust [96].

Overall, trust measurement methods include subjective, objective, and hybrid approaches, each with advantages and limitations. Subjective methods are straightforward but are prone to bias. Objective methods provide real-time insights but require complex tools. Hybrid methods are comprehensive but costly. Among statistical approaches, LMM excels at capturing dynamics while accounting for individual differences, whereas traditional methods like ANOVA are limited in handling repeated measures and complex hierarchical data. This chapter uses subjective measurements to gather trust data and apply LMM to analyse its dynamic evolution in MASS collision avoidance scenarios.

5.2.1.3 Trust computational models

In the field of trust modelling for human-autonomy interaction, research has developed multiple approaches to address the dynamic nature of human trust in autonomous systems, each categorised by distinct modelling techniques. Probabilistic models are widely applied in trust modelling. Bayesian inference with a Beta distribution was employed in [72] to capture trust adjustments following successful or unsuccessful robotic tasks, emphasising time dependency and the impact of negative experiences. Their findings categorised users into types (e.g., rational, oscillating, disbeliever), enabling real-time trust updates tailored to individual preferences. The OPTIMo model by [232] combines dynamic Bayesian networks (DBNs) with feedback to estimate trust continuously in high-risk, multi-task settings. In multi-robot environments, Bayesian optimisation and state-space equations are used for trust modelling [251], applying Markov Chain Monte Carlo and Bayesian Optimization Experimental Design to enhance task allocation. Additionally, a DBN-based model with Boltzmann machines was used in [62] to explore trust in multi-robot settings, parameterised by an Expectation-Maximization (EM) algorithm, which aids operators in trust allocation across multiple autonomous agents. These probabilistic models provide high interpretability and adaptability, making them ideal for the real-time demands of human-autonomy interaction operations.

Time-series models further deepen trust modelling by analysing historical trust trends, enabling accurate predictions of future trust levels in sustained human-robot collaboration. Time-series data is leveraged to study trust's self-reinforcing effects and sensitivity to negative feedback [72]. The time-series method is combined with neural networks to dynamically adjust robot speed in response to human feedback [181].

Decision-theoretic models apply structured frameworks, such as Markov Decision Processes (MDP) and Partially Observable MDPs (POMDP), to manage trust by integrating trust as a decision variable in task optimisation. An MDP-based trust model is developed to optimise trust through dynamic task allocation [228], which aligns with the safety-critical needs of MASS operations. Treating trust as a hidden variable within a POMDP enables trust inference and decision optimisation [31] [32].

Machine learning and hybrid models offer enhanced predictive power and flexibility for managing complex, nonlinear trust dynamics. Recurrent Neural Networks are combined with Gaussian processes to capture trust shifts across tasks [189], providing adaptability for multi-task contexts. In the customer experience domain, Partial Least Squares Structural Equation Modelling is integrated with Artificial Neural Networks to analyse trust's nonlinear effects [179], highlighting trust's role in complex and interactive settings. Sparse Gaussian processes and deep neural networks are employed to estimate uncertainty in trust [115], making their model suitable for decision-making in complex environments. Together, machine learning models address the need for precision and responsiveness in trust modelling, enabling autonomous systems to adjust to diverse operator requirements effectively.

Trust modelling methods, including probabilistic models, time-series analyses, and machine-learning techniques, offer different strengths for capturing trust dynamics. Among these, Bayesian networks excel in representing trust evolution and real-time updates. In this chapter, a Bayesian network-based approach is used to model trust dynamics in MASS collision avoidance scenarios, enabling the integration of trust changes with system performance across navigation stages.

5.2.2 Trust consideration in MASS navigation

Following general theories of human-robot interaction, trust in MASS demands particular consideration of the multi-stakeholder context and the dynamic nature of maritime environments. In both Remote Control Centres (RCCs) for fully autonomous ships and in human-autonomy collaborative navigation scenarios, trust is essential for operators who must rely on indirect data transmission and operational feedback without direct physical control [145] [191].

It is emphasised by [145] that in RCC settings, trust is closely linked to the reliability of data transmission and cybersecurity, both of which are critical for maintaining the situational awareness needed for safe supervision. Therefore, it is crucial to maintain network security and ensure the reliability of information transmission. Additionally, the study conducted by [70] observed that high levels of VR immersion may introduce complexities, such as increased motion sickness and slower situational awareness response times, which, if left unchecked, could impact operator trust and decision-making.

Furthermore, a Schema World Action Research Method (SWARM) was employed by [130] and [132] to explore the decision-making process of MASS operators in a remote monitoring centre and to analyse the impact of trust on their operations in conjunction with the Trust Module, revealing that trust in high-automation settings relies heavily on precise feedback and transparent system behaviour.

By combining both quantitative and qualitative methods (questionnaires, interviews, and technician logs), a mixed-methods approach was used by [10] to triangulate findings on public trust and system performance, showing that trust can fluctuate based on perceived system reliability and interaction context.

A decision-making framework designed for MASS was given by [191], where human trust was considered a key element that influences situational awareness and safe navigation of the decisions made by autonomous systems. The trust module of this framework can be modulated by taking human reactions as input during the interaction between human operators and MASS.

Trust within MASS is also recognised as extending beyond individual operators, encompassing collective trust across a mixed waterborne system in which autonomous and conventional ships co-exist [135]. In such an environment, trust among stakeholders becomes essential to facilitate safe and coordinated operations. Additionally, research conducted by [134] examined the changing role of human operators in autonomous maritime systems, noting that trust is influenced by operators' understanding and control over system decisions. Trust is presented as vital for system predictability and reliability, especially as traditional seafaring skills become less relevant.

While progress has been made in exploring trust within MASS systems, critical gaps remain, particularly regarding trust dynamics in collision avoidance scenarios. To address these gaps, this chapter employs an empirical approach to investigate trust dynamics and develops a Bayesian network-based model to capture the evolution of trust across different navigation stages. By incorporating trust's multidimensional characteristics into the dynamic model, this chapter seeks to provide insights into the understanding of trust in MASS decision-making in CA scenarios.

5.3 Trust data collection and dynamics analysis

Definitions: Human trust in the context of MASS's autonomous navigation systems can be narrowly defined as the belief that humans hold to the autonomous system's capability of situational awareness and appropriate task implementation [191]. The trust is dynamic, evolving across different stages of navigation and influenced by factors such as compliance with COLREGs, decision-making strategies, and the timing of evasive actions. Furthermore, trust levels and evasion timings are defined as follows:

(1) Trust levels: human trust in MASS reflects their confidence in the system's autonomous performance. Higher trust means a stronger observer's confidence in MASS's abilities to perform tasks successfully, while lower trust refers to more frequent manual checks and doubts about the capabilities of MASS's decision-making system.
(2) Evasion timings: This refers to the latency between the identification of a potential collision object and the initiation of an evasive manoeuvre by MASS. It is categorised into three key timing windows in this chapter, listed below:
    1) *Standard*: a range where manoeuvres are typically expected to take place based on conventional practices and safety standards. This is a dynamic window that adjusts based on the operational context, allowing for sufficient time to assess the situation and respond appropriately.

2) *Early*: initiating manoeuvres earlier than typically expected, providing additional safety margin. This timing anticipates potential risks and acts before the standard window.

3) *Imminent*: the very last feasible moment when collision avoidance must be executed. This timing is used as a last resort when all prior opportunities to mitigate the situation have passed.

Building on the foundational concepts of trust levels and evasion timing, this chapter formulates three hypotheses to examine the dynamics of human trust in MASS during CA scenarios:

(1) Hypothesis 1 (H1): Human trust in MASS will fluctuate, including trust accumulation and dissipation, depending on the system's compliance with COLREGs rules, in particular Rules 15, 16, and 17, and the timing of evasive manoeuvres such as early and imminent moments.
(2) Hypothesis 2 (H2): Right-turn evasion strategies will lead to a higher trust of the participant than left-turn strategies in the scenario where a vessel approaches from the starboard side, assuming the importance of COLREGs compliance.
(3) Hypothesis 3 (H3): Early evasion actions and imminent action in general risk situations for the COLREGs-aware MASS with a "give-way" role will lead to lower trust levels of human observers, assuming the importance of proper evasive timing.

5.3.1 Experiment design

This chapter investigates the dynamics of observer trust in MASS during collision avoidance scenarios. The experiment was conducted in two phases to examine both the evolution of trust and the impact of different factors influencing trust, such as compliance with COLREGs and timing of evasive actions. Participants observed simulated scenarios and evaluated their trust levels in a controlled environment where MASS executed various collision avoidance strategies in response to an approaching vessel from the starboard side.

Participants: The experiment engaged 26 participants recruited through maritime channels, including captains and officers, ensuring diverse professional experience levels. Each participant voluntarily took part in the experiment, and all had prior experience with ship navigation but with various experiences ranging from <5 years to >8 years. The experiment took place over two phases, lasting approximately 30 minutes per participant.

Apparatus: The experiment was conducted using the NT-PRO 5000 ship manoeuvring simulator, a full-task ship navigation simulator that provides a realistic maritime environment. The simulator was designed to replicate a standard open-sea navigation scenario where an autonomous vessel encounters a conventional vessel from the starboard side. Table 5-1 presents the initial parameters of both the own and surrounding ships. The ships were set to start each scenario with identical positions, speeds, and headings, with the surrounding ship serving as a constant movement while the own ship executing predefined CA strategies.

To simulate the decision-making capabilities of MASS, an experienced ship operator controlled the vessel behind the scenes, following predetermined decision-making logic that emulated the behaviour of an autonomous system. As shown in Figure 1, the logic included two key strategies: (1) *Left-turn and right-turn manoeuvres performed at standard timing*, representing compliance and deviation from COLREGs. (2) *In the right-turn condition, additional strategies involving early and imminent evasive actions were implemented* to examine the effect of manoeuvre timing. Figure 5-1 illustrates the vessel trajectories under all experimental conditions, demonstrating the behaviours of the own ship in response to the behaviours of the surrounding ship, as defined by the initial conditions in Table 5-1.

Participants' task in the experiment was to **observe** the scenarios and **evaluate** their trust levels in the MASS at various navigation and collision avoidance stages. They were instructed to focus on the system's decision-making behaviour, including evasive actions and timing. This approach ensured consistent and reproducible implementation of CA strategies, including compliance with or deviation from COLREGs, while the target vessel maintained course and speed as required by the regulations.

Table 5-1 Initial parameters of the own and surrounding ships in the experimental scenarios

Vessel	Ship type	Ship length	Width	Speed	Heading
The own vessel	Bulk carrier	225 m	32.3 m	10.5kn	090°
The surrounding vessel	Container ship	190 m	30.0 m	12.0 kn	000°

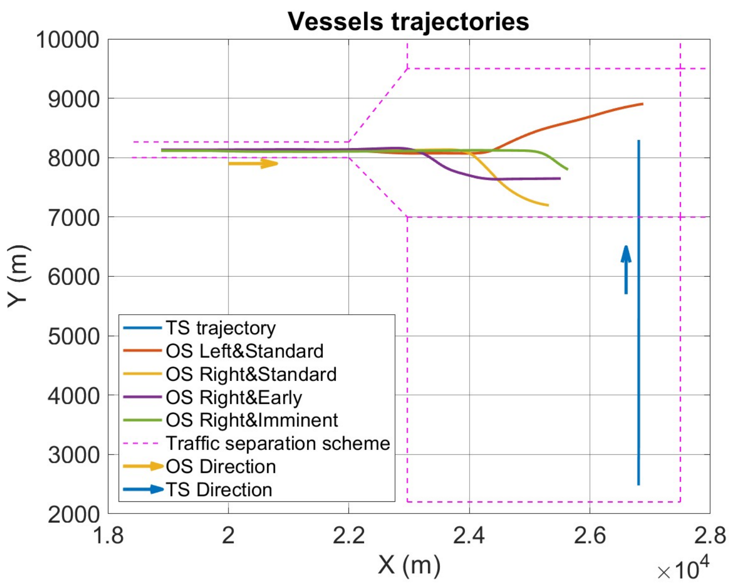


Figure 5-1 Trajectories of the own and surrounding ships under varying conditions.

Experimental Design and Conditions: The experiment followed a two-phase structure, as shown in Figure 5-2. The condition setting is presented in Table 5-2. The experiment consisted of two distinct phases: **Phase 1**, which explored trust levels associated with left-turn and right-turn strategies, and **Phase 2**, which examined trust differences between early and imminent manoeuvre responses in the right-turn condition. Participants were divided into two groups within each phase, experiencing the scenarios in reverse order.

To ensure experimental consistency and operational realism, the evasive manoeuvre timings were defined using fixed-distance thresholds, based on expert consultations and navigational practices. Specifically, right-turn evasive actions were initiated at three distances: 2 nm (early), 1 nm (standard), and 0.5 nm (imminent). A left-turn strategy was also applied at 1 nm to represent a COLREGs-deviating yet safe manoeuvre. These conditions reflect typical judgment points in the current scenario and were validated by experienced mariners.

Phase 1 – COLREGs compliance consideration: Participants observed the MASS navigating under two conditions: one in which the autonomous vessel complied with COLREGs by altering course to the starboard side to avoid the collision, and another where it neglected COLREGs with a left-turn strategy but still successfully avoided a collision. In both scenarios, MASS takes CA manoeuvres at standard timings, as previously defined, where manoeuvres are typically expected to take place based on conventional practices and safety standards.

Phase 2 – Evasion timing consideration: In the second phase, the focus was on the timing of CA strategies. Participants were exposed to two conditions: one where the MASS took early evasive action and another where it took an imminent strategy.

In the two phases, trust dynamics were captured through post-scenario questionnaires after each run and were evaluated across five key stages, details presented below:

- ***Initial Trust***: At the beginning of the navigation process.
- ***Trust During Regular Navigation***: Before any collision-avoidance decisions are made.
- ***Trust During Decision-Making for Collision Avoidance***: As the ship initiates avoidance strategies.
- ***Trust During Collision-Avoidance Execution***: When the ship performs the manoeuvre after deciding on the CA strategy.
- ***Final Trust***: At the conclusion of the scenario, after the whole CA process has been completed.

Hereafter, these five stages are denoted as **Trust1** (Initial Trust), **Trust2** (Trust During Regular Navigation), **Trust3** (Trust During Collision-Avoidance Execution), **Trust4** (Trust During Collision-Avoidance Execution), and **Trust5** (Final Trust) for brevity and consistency in the subsequent analysis.

In addition to the stage-based trust assessments, trust was also measured across five key dimensions after each scenario, using specific questions designed to capture different aspects of trust. These dimensions were as follows:

- ***Dependability***: Assessed by asking participants to rate how confident they were in the MASS's ability to avoid collisions (e.g., "To what extent can you count on the MASS to avoid collisions in this scenario?").
- ***Predictability***: Evaluated based on how predictable the autonomous vessel's behaviour was according to standard maritime practices (e.g., "To what extent did you think the behaviour of the MASS was predictable based on standard maritime practices?").
- ***Anthropomorphism***: Related to the interpretation of non-human things or events in terms of human characteristics and measured by comparing the MASS's behaviour to that of a well-trained human operator (e.g., "How consistent was the MASS's behaviour with how a well-trained human operator would have acted?").
- ***Faith*****:** Captured by asking participants about their belief in the MASS's ability to handle future collision scenarios (e.g., "To what extent do you believe the MASS will be able to cope with all collision situations?").

- ***Safety***: Rated by asking how safe participants felt during the collision avoidance process (e.g., “How much do you feel unsafe in the whole process of autonomous collision avoidance?”).

Data collection: Trust scores were collected through quantitative trust ratings in the post-scenario questionnaires administered via the *Qualtrics* platform, which allowed participants to reflect on their trust levels across various stages after each scenario. Trust scores across both the dynamic stages and dimensions were gathered, enabling further analysis of how trust evolved under different experimental conditions.

Procedure: participants were briefed on the experimental setup and provided with a demonstration of the ship manoeuvring simulator. A pre-experiment survey was administered to collect demographic information. After familiarising themselves with the simulator, participants proceeded with the scenarios in both phases. In each scenario, the participant observed an autonomous ship’s behaviour varied according to the experimental conditions as the autonomous vessel encountered an approaching conventional vessel from the starboard side. The participants’ views on engaging in simulator experiments are shown in Figure 5-3.

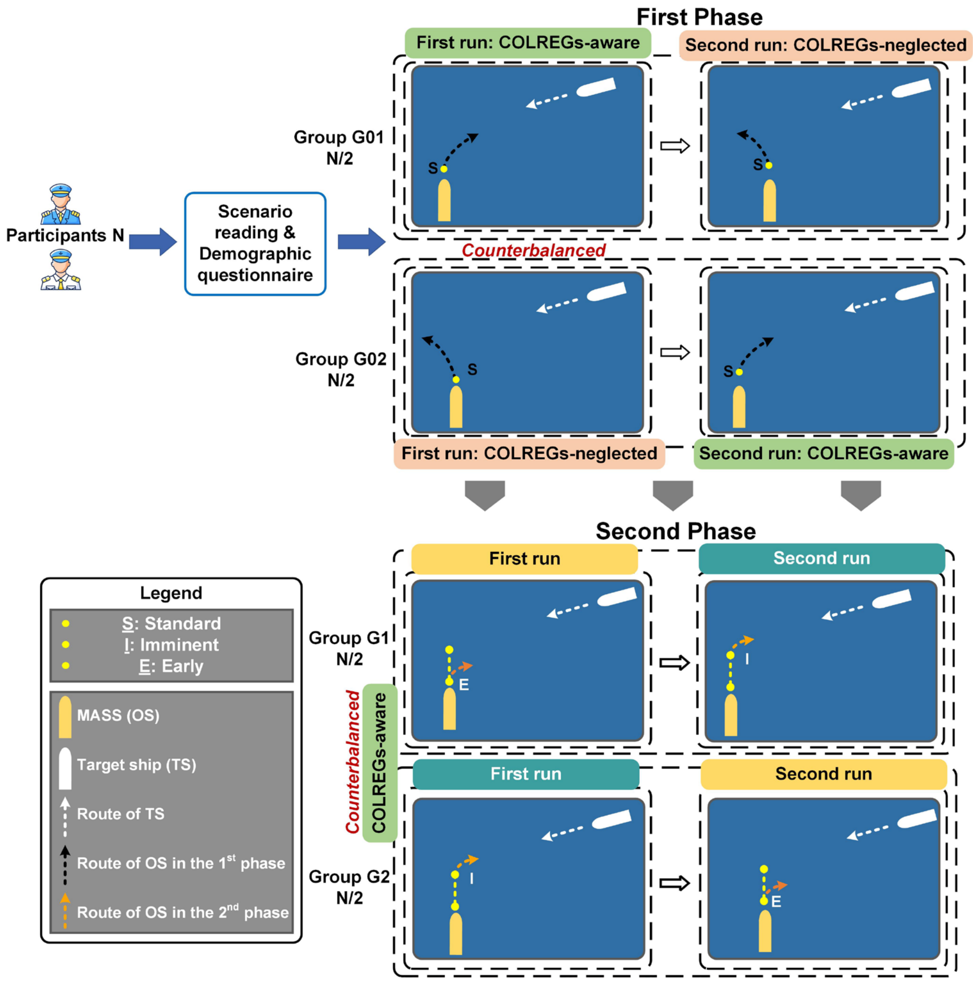


Figure 5-2 Illustration of experimental procedure for collecting observers’ trust in CA scenarios

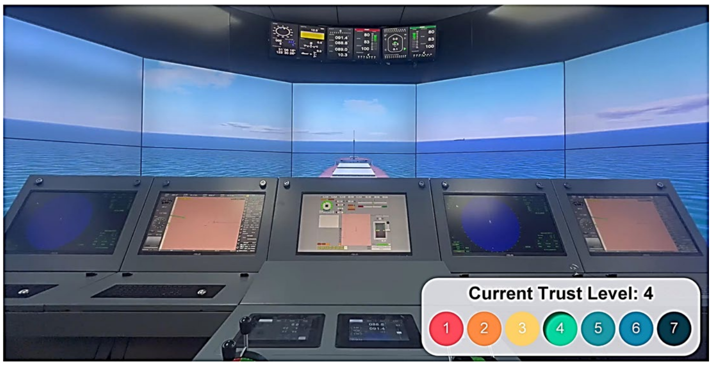


Figure 5-3 Participants' view on engaging in simulator experiments

Table 5-2 Experimental groups and conditions. COLREGs-aware: succeeds with collision avoidance while complying with COLREGs. COLREGs-neglected: succeeds with collision avoidance but neglects COLREGs. Early: taking actions earlier than at the standard time that the corresponding action occurs. Imminent: taking imminent actions.

First phase – COLREGs compliance			**Break & randomisation**	**Second phase – Timings**		
Group No.	Trust dynamics			Group No.	Trust dynamics	
	First run	Second run			First run	Second run
G01 (N = 20)	COLREGs-aware	COLREGs-neglected		Group G1 (N = 20)	Early	Imminent
G02 (N = 20)	COLREGs-neglected	COLREGs-aware		Group G2 (N = 20)	Imminent	Early

After data collection, statistical analysis was performed to compare trust dynamics across the different experimental conditions, focusing on how trust evolved over time and how collision avoidance strategies and timings impact human trust.

5.3.2 Exploratory Analysis

Data were collected via *Qualtrics* from a sample of 26 seafarers (hereafter referred to as "observers") with diverse backgrounds in terms of navigation experience, vessel types, positions, and age groups, enabling exploratory analysis of trust dynamics in autonomous navigation. The participants ranged from 29 to 55, with a majority falling between 30 and 35. In terms of position, the sample included captains (15.4%), first officers (30.8%), second officers (30.8%), third officers (7.7%), and pilots (15.4%). Experience levels varied, with 50% of participants reporting over eight years of maritime experience, 30.8% between five to eight years, and 19.2% with less than five years of experience. The types of vessels that the observer was familiar with were also diverse, including general vessels (65.4%), tankers (23.1%), and special-purpose vessels (11.5%). Trust ratings were measured across five stages, with mean scores ranging from 3.62 to 3.94 (standard deviations of approximately 1.4 to 1.6).

Furthermore, a repeated measures analysis was conducted to investigate the dynamics of trust ratings across experimental stages. The result revealed significant variability in trust levels between participants, as indicated by the significant main effect of individual differences ($p<0.001$). This result underscores the presence of underlying factors contributing to differences in trust across individuals. To further investigate the trust dynamics and account for both fixed effects (e.g., experimental conditions) and random effects (e.g., variability across participants), LMM was employed. This method is suitable for analysing repeated measures data while capturing individual differences.

5.3.2.1 LMM model development

Mann-Whitney U tests were first employed to evaluate trust differences across experimental orders within each phase to determine whether the order influenced participants' trust. The results indicated that for both the left-right strategy comparison and the early-imminent timing comparison, there were no significant differences in trust levels across any of the five measured trust dimensions (trust1 through trust5). Specifically, the p-values were 0.604 (Trust1), 0.672 (Trust2), 0.765 (Trust3), 0.443 (Trust4), and 0.852 (Trust5), all above the 0.05 threshold, suggesting that the sequence of presentation had no significant impact on trust ratings. Thus, the sequence of scenario presentation was considered to have a negligible impact on trust ratings. Consequently, sequence effects were excluded from the LMM to concentrate on primary factors of interest.

Given these findings, the LMM model includes the condition, trust moment (defined by the five key stages in Sec. 5.3.1), and demographic variables (e.g., experience, vessel type, position, age) as fixed effects, while individual participant differences were treated as random effects to account for variability in trust responses. Model performance was evaluated using multiple metrics. The model's marginal R^2 of 0.338 indicated that fixed effects alone explained 33.8% of the variance, while the conditional R^2 reached 0.771, signifying that the combined influence of fixed and random effects accounted for 77.1% of the overall variance. Subsequent analyses focus on significant main and interaction effects, providing insights into trust dynamics across various factors.

The statistical results of the main and interaction effects for trust are presented in Table 5-3, highlighting key factors influencing trust dynamics. The analysis reveals that trust moment and condition are significant predictors of trust, indicating that both the stages of navigation and the conditions influenced participants' trust in the autonomous system. Additionally, interaction effects between age, vessel type, and experience with trust moment suggest that trust evolved differently based on participants' maritime backgrounds and professional experience. These findings underscore the importance of operational context and individual characteristics in shaping trust, setting the stage for a more detailed examination of how these factors influence trust in autonomous navigation.

Table 5-3 Type III Tests of Fixed Effects Dependent Variable

Factors	Source	F	Sig.
Main effects	Intercept	137.462	<0.001
	Position	0.421	0.826
	Experience	1.558	0.245
	Vessel type	2.736	0.099
	Trust moment	2.840	**0.024**
	Condition	5.117	**0.002**
	Age	0.654	0.535
Interaction effects	Trust moment * age	5.723	**<0.001**
	Trust moment * condition	0.728	0.725
	Vessel type * trust moment	2.075	**0.037**
	Experience * trust moment	2.102	**0.034**
	Position * trust moment	0.653	0.872

5.3.2.2 Main effects analysis

Figure 5-4 presents the mean trust scores across five distinct stages of the navigation process, illustrating how trust levels evolve as the MASS progresses through various CA stages. Stage 1 (Initial Trust): Trust is measured at the outset, representing baseline confidence in the system before any navigation manoeuvres. Participants' trust at this stage serves as a reference level and shows relatively high stability. Stage 2 (Trust During Regular Navigation): Trust is assessed during standard navigation, prior to any collision-avoidance decisions. Here, trust levels remain close, with a slight increase to the initial levels, indicating that participants maintain a relatively steady trust during routine navigation without imminent risks. Stage 3 (Trust During Decision-Making for Collision Avoidance): Trust is recorded as the autonomous system initiates collision-avoidance strategies and timings. This stage shows a shape decline in trust compared to both Stage 1 (p=0.01) and Stage 2 (p=0.035), suggesting that participants' confidence diminishes when the system shifts from routine navigation to making critical decisions. Stage 4 (Trust During Collision-Avoidance Execution): Trust is further evaluated as the system performs the avoidance strategies. Another decline in trust is observed, with significant differences between Stage 1 and Stage 4 (p=0.036) and Stage 2 and Stage 4 (p=0.01), indicating increased participant uncertainty or caution during the strategy execution. Finally, at Stage 5 (Final Trust), Trust is assessed at the conclusion of the scenario after all manoeuvres have been executed. Trust levels partially recover at this stage but do not fully return to initial levels, suggesting residual caution even after observing the system's successful task completion.

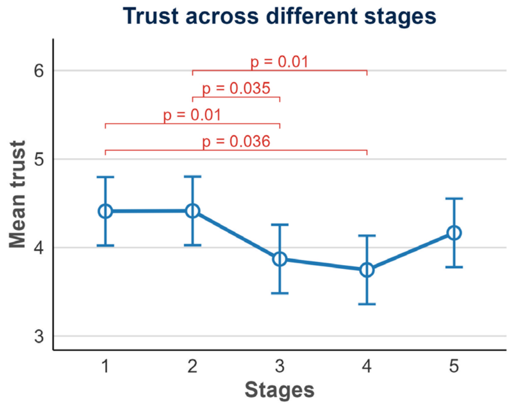


Figure 5-4 The illustration of trust scores across all stages based on linear mixed models

Figure 5-5 displays the mean trust levels across four conditions: Early/Starboard, Imminent/Starboard, Standard/Port, and Standard/Starboard. This comparison highlights how variations in collision-avoidance timing (early vs. imminent) and direction (starboard vs. port) affect trust in the autonomous system. A statistically significant difference between conditions is noted, with Standard/Starboard showing a higher mean trust than Standard/Port (p <0.001).

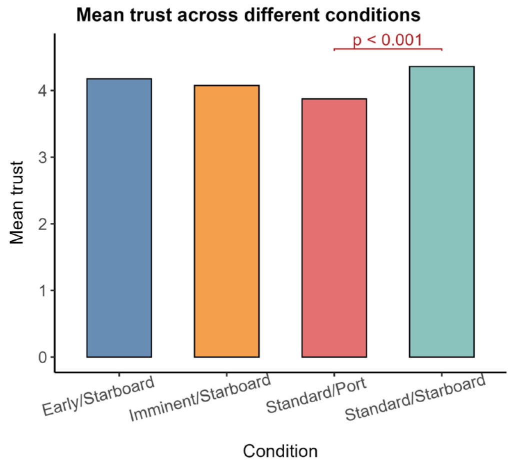
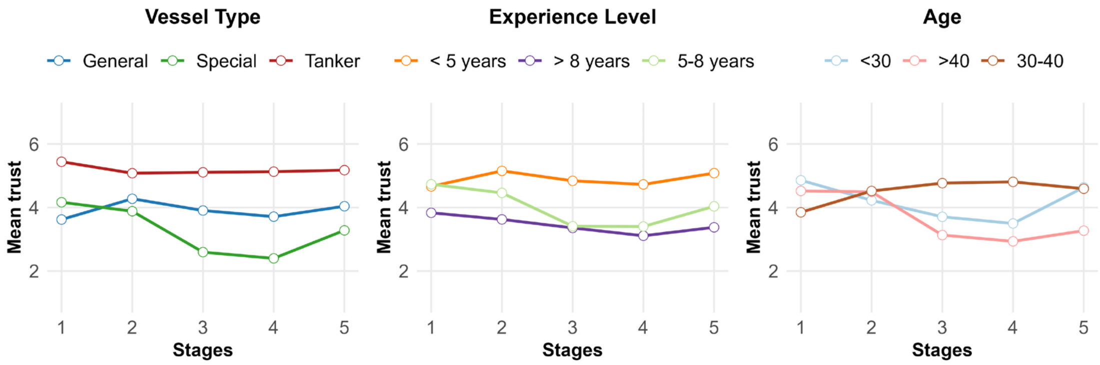


Figure 5-5 The illustration of trust scores comparison between different conditions based on linear mixed models

5.3.2.3 Interaction effects analysis



(a) Trust scores across 5 stages under different vessel types

(b) Trust scores across 5 stages under different experience levels

(c) Trust scores across 5 stages under different ages

Figure 5-6 Trust dynamics across five navigation stages in relation to vessel type, experience level, and age.

As presented in Table 5-3, the significance test results indicate that trust dynamics vary significantly across navigation stages depending on observers' *Vessel Type* (p = 0.037), *Experience Level* (p = 0.034), and *Age* (p < 0.001). Given the lack of significance for other interactions, such as trust moment with *condition* (p = 0.725) and *position* (p = 0.872), the subsequent analysis focuses on these significant effects to provide a targeted exploration of trust dynamics across various stages. Thus, we analysed how trust scores varied across the five navigation stages (from initial to final trust) under specific demographic factors that have significant impacts. Figure 5-6 illustrates these variations concerning three demographic variables: *Vessel Type*, *Experience Level*, and *Age*. Each subplot provides a focused view of how these demographic factors interact with trust dynamics, revealing distinct trends and potential influences at each stage.

For vessel type, as shown in Figure 5-6(a), participants navigating tankers generally exhibited higher trust levels across all stages, while those associated with special-purpose ships showed a notable decline in trust from Stages 2 to 4.

In terms of experience level, as shown in Figure 5-6(b), participants with less than 5 years of experience displayed consistently high and relatively stable trust levels across stages.

Participants with 5-8 years of experience displayed more variability, with trust peaking at the beginning and decreasing notably by the collision-avoidance stages. Conversely, those observers with over 8 years of experience started lower and exhibited a slight downward trend.

Finally, the age-based interaction highlights that participants over 40 years old exhibited relatively stable and higher trust scores (see Figure 5-6(c)), while those younger than 30 had more pronounced declines, particularly from Stages 2 to 4. Together, these interaction effects emphasise that trust is not only influenced by system actions but also by demographic characteristics.

5.3.2.4 Five dimensions of trust

To gain insight into the key dimensions shaping observers' trust in MASS's navigation, we conducted a factor analysis on five trust-related metrics: *Dependability*, *Predictability*, *Anthropomorphism*, *Faith*, and *Safety*. Preliminary tests confirmed that the dataset was suitable for factor analysis, with a Kaiser-Meyer-Olkin (KMO) value of 0.843 (indicating sampling adequacy) and a significant Bartlett's Test of Sphericity was significant (χ^2 = 365.757, p < 0.001). The factor analysis yielded a two-factor solution, explaining 88.16% of the variance, indicating a stable structure in trust assessments (see Figure 5-7). Factor 1 accounts for 67.6% of the variance and includes *Dependability*, *Predictability*, *Anthropomorphism*, and *Faith*, while Factor 2 explains an additional 20.6% and is represented solely by *Safety*. The extracted factors reveal that observers assess trust along two distinct dimensions: general System Competence and Situational Safety.

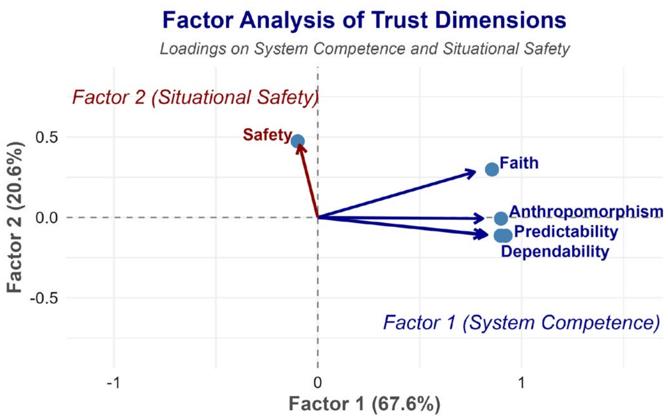


Figure 5-7: The illustration of the factor analysis on five trust-related dimensions

Specifically, the first factor, which we labelled "System Competence", aggregates four dimensions: Dependability, Predictability, Anthropomorphism, and Faith. As shown in Figure 5-7, each of these dimensions has a strong loading on Factor 1. *Dependability* and *Predictability* capture the reliability and consistency of the MASS' navigation, while *Anthropomorphism* and *Faith* add human likeness and forward-looking trust, respectively. The second factor, labelled "Situational Safety", is defined exclusively by the safety-related dimension, which loads solely on this factor. Unlike the broad reliability-based attributes found in Factor 1, *Safety* reflects observers' perceptions of safety during collision avoidance.

5.3.2.5 Correlation analysis of trust dimensions and two related factors

Following the factor analysis, a correlation analysis was conducted to further investigate the relationships between the two key factors of trust and trust levels across different operational stages. This analysis aimed to understand how perceptions of trust evolve during the stages of navigation and how they correlate with the two identified trust factors.

Using Pearson's correlation coefficients, we assessed the strength and direction of relationships between the five trust stages and the two factors identified in the factor analysis. Only significant correlations were visualised in the matrix, with non-significant cells left blank to emphasise meaningful associations. As illustrated in Figure 5-8, The correlation matrix presents a series of moderate to strong positive correlations among trust scores across various stages. Additionally, trust scores between adjacent stages show the highest correlations, such as Trust1 and Trust2 (0.69) and Trust3 and Trust4 (0.90), indicating that trust levels evolve sequentially as participants progress through the stages.

System competence exhibited moderate positive correlations with trust scores across various stages (ranging from 0.51 to 0.64), underscoring the consistent influence of perceived competence on participants' trust. In contrast, *Situational safety* displayed no significant correlations with the trust scores at stages other than the trust at stage 1. This result aligns with the earlier factor analysis, where *Situational safety* emerged as a distinct factor.

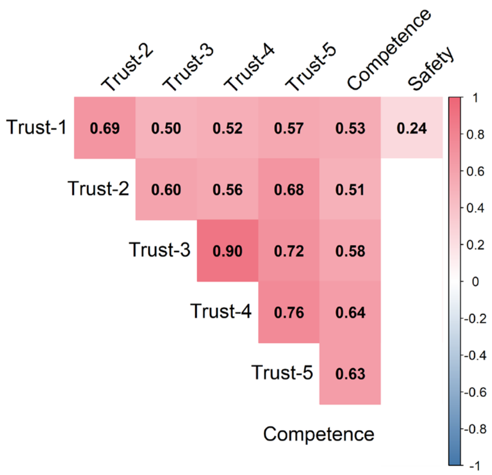


Figure 5-8: The correlation analysis between trust scores across each stage and the two identified components

Building on the insights from our exploratory analysis, which highlighted key demographic and experimental conditions influencing trust, we propose a Bayesian network model for trust to capture these complex dynamics. This model formalises the relationships among System Competence, Situational Safety, stage-specific trust levels, and demographic and situational variables (strategies and timings), allowing us to quantify the influence of each factor on trust formation and development.

5.4 Trust model design

5.4.1 Bayesian network construction for trust

The exploratory analysis revealed that trust in the autonomous system of MASS evolves dynamically across various stages in the CA process. Additionally, trust is influenced by condition, demographic characteristics, system competence, and situational safety. Therefore, the objective of constructing this Bayesian network is to capture the progression of trust by modelling the probabilistic relationships among trust stages while integrating various factors that shape trust outcomes.

5.4.1.1 Node definition and network structure

The Bayesian network incorporates five sequential trust nodes, each representing trust at a specific stage, from *InitialTrust* to *FinalTrust*. This structure leverages the Markov property, as was considered in [107], where each trust stage depends solely on the trust level of its immediate predecessor. By adopting this assumption, the model focuses on the local dependencies in trust evolution, simplifying the structure while preserving the temporal dynamics of trust development. *FinalTrust* serves as the node that represents the cumulative confidence built throughout the CA process. It reflects how trust, as it propagates through the stages, aggregates into an overall assessment of the navigational performance of the autonomous system.

In addition to temporal dependency, trust varies among participants across various backgrounds, such as age, experience, and vessel types. Thus, this model integrates demographics that were identified as key factors, including age, experience, and vessel type, as parent nodes to InitialTrust, reflecting their role in shaping baseline trust levels. These factors account for inherent individual differences in trust propensity, as indicated by the exploratory findings. Furthermore, situational factors such as Strategies and Timings are introduced as parent nodes to Trust 3, representing the influence of CA decisions on trust in the decision-making stage. This structure ensures that the model captures both individual propensity and situational factors on trust transitions.

To capture the multidimensional evaluation of trust, the model incorporates two extracted components: *System competence* and *Situational Safety*. *System Competence* reflects perceptions of dependability, predictability, human likeness, and forward-looking beliefs, while *Situational Safety* focuses on safety evaluations during collision avoidance. These dimensions are linked directly to *FinalTrust*, representing their role in shaping the overall trust in the autonomous system. This framework lays the groundwork for further analysis, including diagnostic analysis informed by sensitivity analysis, predictive reasoning, and causal inference, to explore trust mechanisms in depth.

Figure 5-9 illustrates the staged trust formation process of MASS in the CA process, showing the interaction between performance, real-time beliefs, and stage-specific trust across navigation phases. Trust evolves sequentially, starting with *initial* trust (T_0) and baseline beliefs (B_0), and progressing through key stages, including T_1 (routine navigation), T_s (strategy and timing decisions), T_2 (CA execution), and final trust T_e. At each stage, real-time beliefs (B_k) are updated dynamically based on ongoing system performance P_k, which directly shape staged trust. During CA execution, the system's manoeuvres (e.g., CA strategies and timing) are captured in performance nodes (P_S), which influence T_S via updated beliefs (B_S). Throughout the process, observer evaluations of System Competence (SC) and Situational Safety (SS) are integrated into final trust judgments. These two dimensions are critical to linking specific system performance to comprehensive trust evaluations at the final stage. This framework highlights the interplay of system performance, real-time beliefs, stage trust, and trust-related factors assessment in trust formation. Given the uniformity of vessel performance and the controlled nature of the experimental scenarios, performance variability was minimal. As such, the model excludes explicit *performance* nodes, focusing instead on Strategy and Timing as key situational factors of trust.

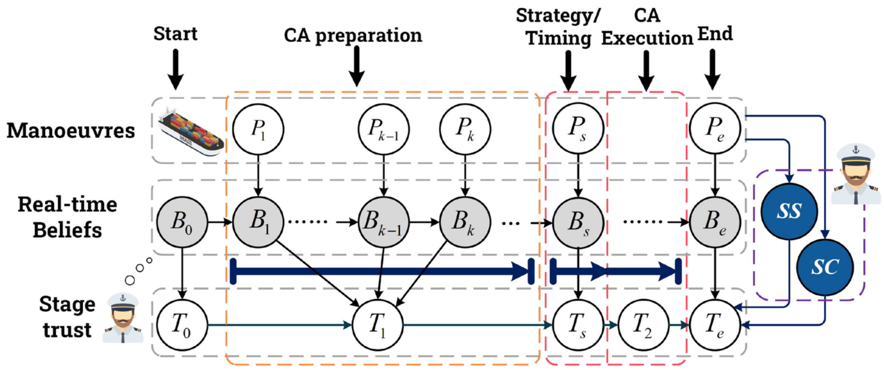


Figure 5-9 Development of a human trust model with Bayesian Networks for MASS operation

5.4.1.2 Parameter setting and model training

The constructed trust Bayesian network is shown in Figure 5-10, where InitialTrust serves as the baseline trust level influenced by demographic factors, including age and vessel type, which were derived from maritime industry reports[1,2]. For example, age distributions (below 30: 16%, 30–40: 29%, above 40: 55%) and vessel type (General: 63%, Tanker: 13%, and Special-purpose ships: 25%). For factors lacking statistical support, such as Strategy and Timing, prior probabilities were estimated based on domain expertise. For instance, left-turns (25%) and right-turns (75%) were assigned probabilities reflecting standard maritime practices under COLREGs, while collision-avoidance timing was set as standard (70%), early (15%) and imminent (15%). Additionally, System Competence and Situational Safety were discretised into low, medium, and high categories using tertile thresholds (0.33 and 0.66) derived from factor analysis scores, while trust ratings (1–7) were similarly classified into low (1–2), medium (3–5), and high (6–7). The prior probabilities of other nodes and conditional probabilities were calculated by using the trust data collected from our survey through the GeNIe software.

5.4.2 Application

Following the construction of the TBN model, its utility was evaluated through targeted applications. These included **diagnostic analysis** informed by sensitivity insights and **predictive reasoning**. Diagnostic analysis, built on sensitivity analysis methods, aims to

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[1] https://www.statista.com/statistics/264024/number-of-merchant-ships-worldwide-by-type/

[2] https://www.gov.uk/government/statistical-data-sets/seafarer-statistics-sfr#certificated-officers-and-trainees-sfr02

identify the most influential factors contributing to a specific observed outcome. Predictive inference estimates future trust levels based on current conditions, aiding in proactive management.

5.4.2.1 Diagnostic analysis

To evaluate the robustness and identify critical determinants of the trust model, we conducted a diagnostic analysis informed by sensitivity insights targeting the Trust5=high outcome. A 30% parameter spread, reflecting realistic variability in parameters, was implemented to simulate realistic uncertainties, visualising results using a tornado diagram (see Figure 5-11), where the top ten bars represent the factors contributing most significantly to the variability of the outcome.

As shown in Figure 5-11, the tornado diagram highlights the diagnostic results of Trust5=high to variations in key parameters, demonstrating how trust outcomes respond to changes in the TBN. Competence=high exhibits the most significant positive influence, aligning with its direct pathway to *FinalTrust* and underscoring its central role in trust formation. Sequential trust stages, such as Trust4=high | Trust3=high, reveal cascading effects, emphasising the importance of consistent trust-building across stages. Together, the insights emphasise the interplay between System Competence and sequential trust evolution, offering actionable guidance for enhancing user trust in autonomous navigation systems.

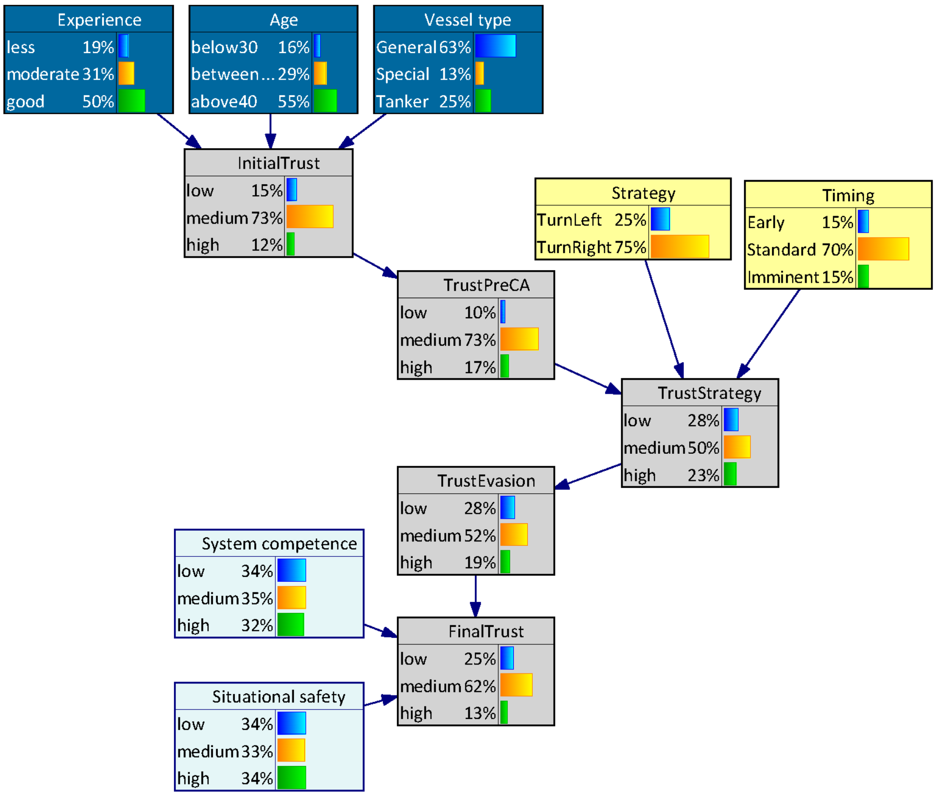


Figure 5-10: Trust model design for autonomous decision-making of MASS in CA scenarios

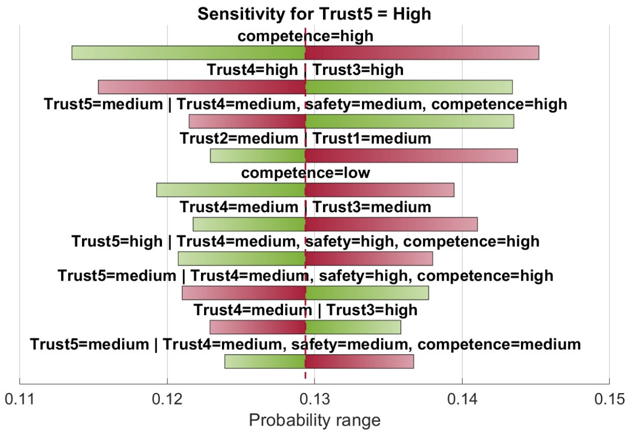


Figure 5-11: Diagnostic analysis visualisation results for Trust5(Final Trust)=high

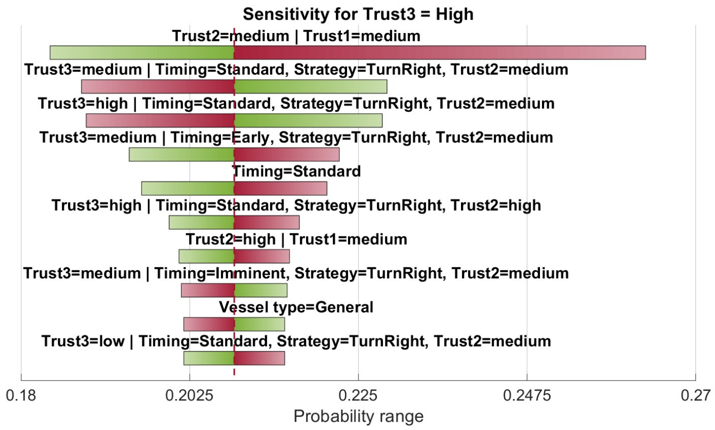


Figure 5-12: Diagnostic analysis visualisation results for Trust3(TrustStrategy)=high

In TBN, Trust 3 represents a critical stage where trust is influenced by the prior trust level, that is, TrustPreCA, and situational factors (e.g., Strategies, Timings). This node is important to explore because it indirectly impacts *FinalTrust*, as identified in Figure 5-11 (The second most important impact factor: Trust4=high|Trust3=high). In addition, it is the key stage in the whole process at which the Strategy and Timing were imposed. Thus, the diagnostic analysis for Trust3=high was conducted further, as shown in Figure 5-12. Specifically, the analysis reveals that Trust2=medium, conditional on Trust1=medium, exerts the strongest influence, with a steep negative derivative (-0.207), indicating that small changes in Trust2 greatly impact Trust3. Similarly, the interaction between Timing=Standard and Strategy=TurnRight demonstrates a marked influence on Trust3=medium, evidenced by its contribution and derivative (-0.133). Notably, the direct influence of Timing=Standard (ranked 5th) compared to its interaction with Strategy (ranked 2nd and 3rd) highlights the compounding effect of navigation strategies on trust. This aligns with the finding that Strategy=TurnRight combined with a higher trust level in Trust2 contributes positively to Trust3=high (derivative: +0.276). Furthermore, while other factors also show the impact on Trust3, such as vessel type = General, their effects are weaker, underscoring the dominance of imminent variables such as situational factors over demographics.

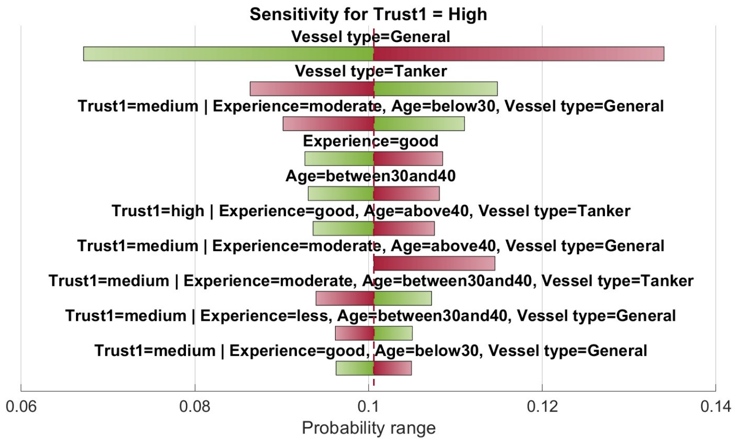


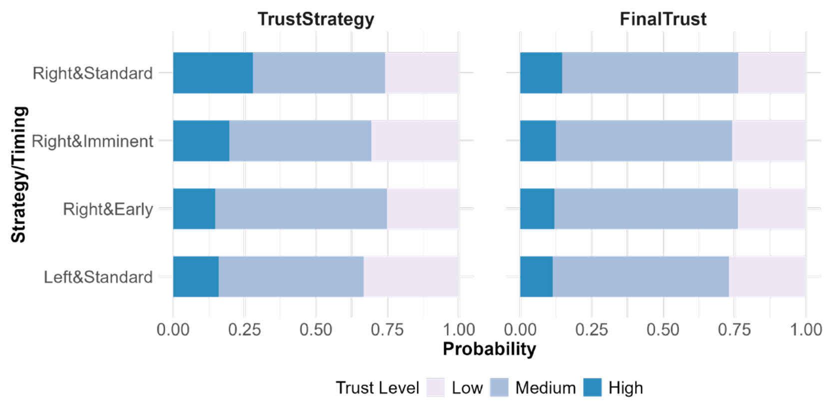
Figure 5-13 Diagnostic analysis visualisation results for Trust1(InitialTrust)=high

Similarly, a diagnostic analysis on Trust1=high was also conducted, as shown in Figure 5-13. The results reveal that Vessel Type exhibits the strongest influence on Trust1, particularly for general vessels showing a negative relationship (derivative: -0.170) and tanker vessels with a positive influence (derivative: +0.206), indicating a higher trust dependency on vessel types. Other demographic factors such as Experience and Age demonstrate moderate but substantial effects, with experienced participants (rated as "good") and those aged 30–40 exhibiting negative impacts on Trust1=high. Conversely, specific combinations of demographic features (e.g., good experience and vessel type "tanker") highlight positive influence, reflecting that senior, experienced personnel on takers enhance *InitialTrust*. This analysis underscores the importance of tailoring strategies to specific observer profiles to foster trust in autonomous systems from the outset.

5.4.2.2 Predictive reasoning

Following the diagnostic analysis, we conducted predictive reasoning to estimate the trust dynamics under the variations in Strategies and Timings, particularly focusing on critical trust nodes, such as *FinalTrust* and *TrustEvasion*, see Figure 5-14. As shown in Figure 5-14 (a), medium trust consistently dominates, with the Right & Early strategy achieving the highest proportion (60%). High trust levels are, although relatively low, peak in Right & Standard (28%), indicating its effectiveness in maintaining trust during the evasive stage. Conversely, low trust is most prevalent in Left & Standard (33%), suggesting its potential drawbacks in trust-sensitive scenarios. Similarly, the FinalTrust subplot, as shown in Figure 5-14 (b), shows medium trust as the dominant outcome across all strategies, with Right & Early achieving the highest proportion (64%) and Left & Standard again exhibiting higher low trust levels (27%).

These findings underscore the diagnostic finding of trust outcomes to operational strategies, highlighting Right & Standard, Right & Early, and Right & Imminent as favourable strategy combinations for sustaining trust during the entire CA process.



(a) Trust Evasion under Different Collision Avoidance Strategies

(b) Final Trust under Different Collision Avoidance Strategies

Figure 5-14 Predictive reasoning on trust evasion and final trust under different CA Strategies

5.4.3 Discussion

Trust was measured using post-scenario evaluations collected via Qualtrics, where participants rated their trust after observing specific collision avoidance manoeuvres. The use of simulated navigation videos embedded within *Qualtrics* ensured that participants evaluated the autonomous system's performance in controlled, consistent scenarios, capturing trust fluctuations across distinct navigation stages. Furthermore, the analysis, conducted using LMM, uncovered trust dynamics across navigation stages. Firstly, consistent with H1, trust in the MASS fluctuated throughout the CA process. Participants' trust varies significantly across several stages (e.g., TrustPreCA vs TrustStrategy) but partially recovered during the final stage, see Figure 5-4. This fluctuation reflects increased scrutiny during high-stakes manoeuvres and a gradual convergence towards a calibrated level of trust as participants gained a deeper understanding of the system. However, the final trust levels did not return to their initial levels, suggesting residual caution or incomplete trust recovery even after successful task completion. Secondly, trust levels exhibit slight increases during the early stages (Trust1 to Trust2), reflecting trust accumulation, but a shapely decrease in Trust3 and Trust4, underscoring the asymmetric nature of trust formation versus erosion, followed by partial recovery at the final stage (Trust5). The initial slight increase may result from the system's adherence to stable navigation practices and predictable behaviour. The abrupt decline likely corresponds to participants' heightened scrutiny during strategies/timings selection and execution stages, where system limitations or perceived inefficiencies become more evident. Trust recovery at the final stage suggests an accumulation effect, where the overall performance in earlier stages is synthesised into a final trust judgment. This pattern aligns with trust accumulation, typically requiring consistent system performance over time, while dissipation can occur rapidly due to a single negative event.

Furthermore, trust in the Right&Standard scenario differs significantly from the Left & Standard scenario, as shown in Figure 5-5, suggesting participants' preference for manoeuvres that align more closely with COLREGs. This result, aligning with H2, may turn out that in CA scenarios, where a vessel is approaching from her starboard side, right-turn strategies may have been perceived as more consistent with standard maritime practices to accumulate trust, while left-turn strategies might have been interpreted as riskier or less conventional to dissipate trust. Finally, aligning with H3, while proactive responses aligned with standard timings were associated with higher trust levels, actions that were “too early” or “too late” demonstrated suboptimal outcomes, see Figure 5-5. The findings imply that MASS systems must balance evasion strategies and proper timings, avoiding evasions that are either too proactive or overly reactive.

Overall, these two factors reveal that observers differentiate between general System Competence and Situational Safety when forming trust in autonomous navigation systems. This insight emphasises the need for MASS designs to address both Competence and Safety to ensure reliability and promote trust in dynamic navigational environments.

In terms of demographic factors consideration, the inclusion of participants with diverse professional backgrounds aimed to ensure the representativeness of trust dynamics across various groups. This diversity allowed to identify the overall trend in trust evolution while also capturing the variability that emerges when demographic factors interact with other factors. The results indicate while the main effects analysis revealed that trust dynamics were primarily influenced by navigational stages and conditions, interaction effects highlighted subtle differences based on experience level, vessel type, and age during specific CA stages, as shown in Figure 5-6. These differences were not the primary focus of this study but provided supplementary insights into how trust responses may vary in certain CA scenarios. Such insights highlight the need for context-specific considerations when evaluating trust in MASS navigation in CA scenarios.

Regarding the dimensional structure of trust, trust was found to encompass two overarching dimensions: System Competence and Situational Safety. The linkage between System Competence and Situational Safety and *FinalTrust* demonstrates the multidimensional nature of trust. This finding highlights that observers evaluate trust both as a comprehensive judgment of the system’s competence and as a context-specific assessment of safety. Additionally, *System competence* exhibited moderate positive correlations with trust scores across various stages (ranging from 0.51 to 0.64), underscoring the consistent influence of perceived competence on participants’ trust. This result suggests that observers’ perceptions of the MASS’s navigational reliability, human likeness, and forward-looking beliefs contribute continuously to their trust across all stages, indicating their foundational role in trust formation. In contrast, situational safety was primarily linked to InitialTrust. Its influence on subsequent trust stages was limited. This may reflect the controlled nature of the experimental design, in which participants were implicitly assured of the system’s safety. In other words, in this context, *Safety* might become a “given” in participants’ minds, leading them to assume that the MASS will handle high-risk scenarios adequately. As a result, Safety ratings might remain stable across different conditions, especially if no unexpected behaviours challenge this expectation. However, this does not imply that situational safety is irrelevant in real-world applications. Instead, it suggests that observers’ perceptions of safety are formed early and remain stable unless disrupted by unexpected system failures or high-risk scenarios.

With respect to TBN, this model captures the staged progression of trust in MASS, integrating temporal dynamics, demographics, and situational factors. This structured approach is essential for understanding how trust evolves and identifying the determinants of trust-building at different stages of the CA process. Firstly, the sequential trust nodes represent a staged process of trust evaluation from *InitialTrust* to *FinalTrust*. The Markov property simplifies the model by assuming that each stage depends primarily on the previous one, which is consistent with the exploratory analysis showing strong correlations between consecutive trust ratings, see Figure 5-8. Secondly, baselined trust levels (InitialTrust) are influenced by demographic variables, such as vessel type, age, and experience (see Figure 5-13 and Figure 5-6(a)).

Focusing on the results of diagnostic analysis informed by sensitivity insights, two aspects of insights can be drawn. (1) The tornado diagram for Trust5=high (Figure 5-11) indicates that System Competence exerts the most significant positive influence on *FinalTrust*. It underscores that perceptions of dependability, predictability, human likeness, and forward-looking beliefs of the autonomous system in the entire CA process are critical for building overall trust. (2) The cascading influence of earlier trust stages on later outcomes (e.g., Trust4=high | Trust3=high) emphasises the cumulative nature of trust (Figure 5-11). The significant impact of *TrustStrategy* (Trust3) on *FinalTrust* highlights the critical role of decision-making strategies and timings in the trust pathway. Furthermore, TrustStrategy (Trust3) was found to be influenced not only by situational factors (e.g., strategy and timing) but also by the trust level in the preceding stage (TrustPreCA). This sequential dependency supports the hypothesis that trust evolves progressively, with earlier stages laying the foundation for subsequent evaluations. The findings support the need for consistent trust-building throughout all stages of interaction.

Finally, the following key takeaways can be derived regarding the results of predictive reasoning: (1) strategies involving Right & Early, Right & Imminent, and Right & Standard manoeuvres consistently achieve higher levels of trust compared to Left strategies, as shown in Figure 5-14, also aligning with the hypothesis of H3. (2) Despite variations during evasive actions, trust partially stabilises at the *FinalTrust* stage. This indicates that the system's overall performance, which affects the system competence of the autonomous system, can mitigate earlier fluctuations, reinforcing the importance of holistic trust-building efforts.

Overall, the results have the following two implications for the design and operation of autonomous navigation systems.

(1) Prioritising competence in system design: System Competence was underscored, comprising reliability, predictability, anthropomorphism, and forward-looking decision-making, as the most critical factor influencing observer overall trust in the entire CA process. MASS systems should prioritise performance consistency and predictability, especially in CA scenarios. To achieve this, developers must enhance the transparency of system behaviour by incorporating real-time feedback mechanisms that clarify decision rationales, particularly during unconventional manoeuvres such as left-turn strategies. Additionally, to maintain trust consistently, MASS systems must focus on early-stage performance to prevent dissipation that could propagate through later evaluations.
(2) Optimising evasion strategies and timing: The study highlights the importance of proper evasive strategy and timing. While proactive responses are generally associated with higher trust levels, actions that are too early or too delayed can dissipate observer trust. To address this, MASS systems should incorporate adaptive algorithms that optimise the timing of evasive manoeuvres with compliance with regulations like COLREGs. Furthermore, autonomous systems should focus on transparency, particularly in explaining the decision logic in scenarios where deviations from observer expectations (e.g., delayed or unconventional manoeuvres) occur. As suggested by [192], observer

trust in autonomous navigational decisions can be strengthened when the regulations are involved in the decision-making mechanism, which can improve the system's transparency.

In terms of comparison with prior research, the findings align with previous studies on trust in automation, particularly the dynamic nature of trust, accumulation and dissipation [9], and its dependence on system performance [232]. In the maritime domain, this research, which is different from [164], investigates observer trust in the autonomous decision-making system of MASS across several stages in a CA process instead of real-time measurement. However, this research expands the understanding of trust in autonomous systems by introducing the dual dimensions of competence and situational safety, providing an in-depth understanding of trust in the autonomous system of MASS in an MWTS.

5.5 Conclusions

This chapter addresses the research question RQ4- viii: *How can human trust in MASS be measured, analysed, and modelled within controlled experimental settings*?, contributing to a deeper understanding of trust dynamics in human-supervised autonomous navigation. The dynamics of observer trust in MASS during CA scenarios are investigated in this chapter, combining quantitative trust measurement, exploratory analysis using LMM, and predictive reasoning via the proposed TBN model.

Trust was measured through post-scenario evaluations collected via Qualtrics, allowing participants to rate their trust in MASS after observing simulated navigation videos. These measurements captured stage-specific fluctuations, which were analysed using LMM to identify key patterns: slight and gradual trust accumulation during routine navigation and sharp dissipation during the CA strategies and timings selection and execution stages. Trust at the final stage, that is, overall trust, is partially recovered, underscoring the cumulative influence of prior stages. Trust dynamics varied significantly by demographic factors, such as experience and vessel type. Moreover, left-turn strategies were associated with lower trust compared to right-turn strategies, reflecting observer preferences for COLREGs-compliant evasion strategies. Factor analysis identified two trust dimensions, including System Competence and Situational Safety, with System Competence strongly correlating with trust across all stages. The Markov-like stage correlations further supported the sequential nature of trust evolution.

Building on these findings, the TBN model quantified trust dynamics, highlighting the dominant role of System Competence in shaping final trust and the cascading influence of intermediate stages. Diagnostic analysis informed by sensitivity analysis emphasised the critical importance of decision-making strategies and timely actions, while predictive reasoning demonstrated the positive impact of proactive right-turn manoeuvres. While the model captures key drivers of trust in controlled scenarios, it does not yet account for continuous operator feedback or real-time trust adaptation, which limits its applicability in dynamic, operational environments. Future extensions could incorporate physiological or behavioural indicators to enable real-time trust calibration. Nevertheless, the results of this chapter provide actionable guidance for designing MASS systems that align with observer expectations, improve transparency, and optimise CA strategies.

Chapter 6. Conclusions and Future Research

This thesis aims to address the challenges posed by integrating Maritime Autonomous Surface Ships (MASS) into Mixed Waterborne Transport Systems (MWTS), with a specific focus on ensuring safety and efficiency in collision avoidance scenarios. To achieve this, we developed a decision-making framework incorporating situational awareness, human-mimic navigation, and human trust as its core components. This framework offers a potential solution to support safer and more effective interactions between autonomous and manned vessels within MWTS.

This chapter concludes the thesis by summarising the findings and addressing each research question in Section 6.1. Section 6.2 outlines potential future research directions to address the limitations and new research opportunities identified in this thesis.

6.1 Conclusions

This section summarises the responses to the sub-questions presented throughout the thesis, demonstrating how each contributes to addressing the main research question:

How can a decision-making framework for collision avoidance, incorporating situational awareness, human preferences, and human trust, be developed to ensure safe and efficient interaction between autonomous and manned vessels in mixed waterborne transport systems?

In order to answer the main research question, we first elaborate on the answers to each sub-question.

(1) Answers to the questions on the state of the art:

(*i*) *What is the state of the art on the safety and efficiency of human-MASS interaction?*

The systematic literature review in Chapter 2 investigated current research on human-MASS interaction, with a focus on safety and efficiency in an MWTS. The review highlighted four key areas: human factors, autonomous system technologies, system analysis and design, and regulatory frameworks. For safety, progress in sensor technologies and collision avoidance algorithms has improved the ability of autonomous vessels to identify and respond to potential hazards. However, situational awareness, a critical component of safe navigation, continues to present challenges, particularly as errors in situational assessment remain a common cause of maritime incidents. Efficiency has primarily been approached through route optimisation and fuel consumption reduction, but existing methods rarely account for the dynamic behaviours of manned vessels in mixed-traffic environments. Trust, identified as a key factor, especially in remote supervision, directly influences how human operators perceive and respond to autonomous decisions. Current systems, however, remain constrained by the need for human oversight, particularly in dynamic and complex navigational environments.

The review results show that despite great progress in this domain, several gaps remain in the state of the art. First, situational awareness models specifically designed for autonomous vessels in MWTS are underdeveloped. Existing models often fail to consider the complexities of mixed traffic environments, where autonomous and manned vessels co-exist and interact. Second, collision avoidance research frequently assumes fixed or constant movement for manned vessels, overlooking their navigational preferences during interactions, which limits the practical applicability of these models. Finally, while trust is widely acknowledged as a critical aspect of human-autonomous interaction, empirical studies examining its evolution and impact factors in human-supervised decision-making, particularly in collision scenarios, are scarce. The absence of trust models for evaluating and maintaining a proper level of trust in existing frameworks represents limitations in supporting safe and efficient human-MASS interaction.

This review established a clear foundation for the research by identifying these gaps and demonstrating the need for an integrated approach. While great progress has been made in individual components, the literature lacks an integrated framework that addresses the interplay between situational awareness, navigational preferences, and human trust. The insights gained from the review informed the development of this thesis, which seeks to enhance safety and efficiency in MWTS by addressing these challenges in a structured and comprehensive manner.

(*ii*) *What factors should be considered in the decision-making framework?*

As discussed in response to the previous question, the decision-making framework for collision avoidance in MWTS should account for three important and interrelated factors identified through the systematic literature review in Chapter 2: situational awareness, human navigational preferences, and trust dynamics**.** Situational awareness involves processing real-time data from sensors, external sources, and domain knowledge to build a comprehensive understanding of the navigational context , including both the surrounding traffic environment and the vessel's own states (e.g., manoeuvrability). This forms the basis for autonomous decision-making and ensures the interpretability of actions for human supervisors. Human navigational preferences are essential to accommodate the behaviours and manoeuvring tendencies of manned vessels, providing cooperative and predictable interactions within MWTS. Finally, trust dynamics emphasise the need to maintain a proper level of human trust in the decision-making system by addressing human supervisors' perceptions of system capabilities during collision avoidance scenarios. The integration of these factors into the decision-making framework ensures that autonomous vessels navigate safely and efficiently in an MWTS by building seamless interactions with human-operated vessels, addressing the identified gaps in current approaches.

(2) Answers to the questions on the situational awareness modelling:

(*iii*) *How can data from multiple sources be effectively integrated for situational awareness?*

Chapter 3 of this thesis examined the integration of multi-source data to enhance situational awareness in MASS operating in MWTS. The chapter proposed an ontology-driven knowledge map model to systematically integrate sensor data, maritime regulations, and contextual information, providing a structured representation of the navigational environment.

Furthermore, the ontology-driven knowledge map was designed to process real-time data from sensors, such as obstacle detection and vessel tracking, and to combine this information with domain knowledge, including COLREGs and behavioural codes. This integration aimed to create a comprehensive understanding of the surrounding maritime environment, enabling MASS to recognise potential risks and evaluate decision-making options. By incorporating such diverse sources of information, the model offered an improved foundation for navigation and collision avoidance. An advantage of this model was its ability to respond dynamically to sensor inputs and changing conditions in real time, providing robust abilities in ensuring navigational safety and rule compliance for MASS in various environments. Simulation studies demonstrated that the model could deal with multi-source data effectively, providing actionable support for real-time decision-making in various environments.

In conclusion, the ontology-driven knowledge map provided a promising approach for integrating multi-source data to support informed decision-making by providing MASS with timely and effective situational awareness. By linking sensor observations with maritime regulations and contextual data, the model contributed to improved safety and operational efficiency. However, further refinements are needed to incorporate environmental factors and to validate the system in real-world contexts, ensuring its readiness for deployment in complex and dynamic maritime environments.

(*iv*) *How can a local path planning algorithm tailored to 3 degrees of freedom vessels be developed, integrating the results of situational awareness?*

Chapter 3 addressed this sub-question by developing and evaluating a local path-planning algorithm tailored to the dynamics of 3-degrees-of-freedom (3-DOF) vessels, which include surge, sway, and yaw motions. The Dynamic Window Approach (DWA), originally designed in robotics, was adapted and integrated with the ontology-based knowledge map model to enable real-time path planning for MASS in the MWTS.

The modified DWA algorithm accounted for the kinematic and dynamic constraints of 3-DOF vessels, such as their limited manoeuvrability. The integration of situational awareness outputs from the ontology-driven knowledge map provided the algorithm with a comprehensive understanding of the surrounding navigational environment. This included proximity to obstacles, COLREGs compliance requirements, and dynamic updates on the positions of other vessels. Simulation results demonstrated the effectiveness of the adapted DWA in handling high-risk navigational contexts. The algorithm consistently generated collision-free paths while maintaining regulatory compliance. It also showed adaptability to congested and dynamic environments, supporting efficient interaction between MASS and manned vessels. However, these achievements came with trade-offs; the algorithm's emphasis on safety occasionally resulted in increased travel distances and longer voyage times.

In conclusion, the tailored DWA, supported by outputs from the ontology-driven situational awareness model, provided a robust framework for local path planning in 3-DOF vessels. By addressing the unique constraints of maritime navigation and incorporating regulatory compliance, the approach contributed to safer and more effective navigation for autonomous vessels in MWTS. However, further validation and refinements are required to ensure the algorithm's performance in real-world maritime operations.

(3) Answers to the questions on the human preferences for human-mimic collision avoidance:

(*v*) *How can AIS data be utilised to extract the navigational preferences of conventional vessels for collision avoidance?*

Chapter 4 addressed this sub-question by developing a methodology to extract navigational preferences from Automatic Identification System (AIS) data, which provided crucial insights into how conventional vessels behave during potential collision scenarios. The process involved analysing ship conflict pairs to identify patterns in speed, acceleration, and course adjustments.

To achieve this, the research developed a methodology to process AIS data using an LSTM-autoencoder combined with K-means clustering. The approach involved detecting ship pairs in potential collision scenarios and analysing their trajectories to categorise behavioural patterns. The LSTM-autoencoder extracted latent features from historical AIS data in Port of Rotterdam, capturing key navigational behaviours, while the K-means clustering algorithm grouped these behaviours into distinct categories. The resulting clusters provided a deep understanding of navigational preferences, such as cautious adjustments, reactive manoeuvres, and standard operational responses.

The results demonstrated the effectiveness of this approach. The model identified four distinct clusters of navigational behaviours, each representing a specific strategy employed by human-operated vessels. For instance, cautious patterns were characterised by minimal course adjustments, while reactive patterns showed significant and rapid changes in heading and speed. These clusters provided interpretable insights into how human-operated vessels navigate during potential collision scenarios. Furthermore, the ability of the model to process large AIS datasets with high computational efficiency ensured its applicability in real-time maritime operations, enhancing the predictive capacity of autonomous decision-making systems.

In summary, the extraction of navigational preferences from AIS data establishes a foundation for integrating human-like navigation into the autonomous decision-making framework. By aligning with the behaviours of manned vessels, this approach promotes safety, predictability, and mutual understanding in mixed waterborne environments. Future research could extend these findings by incorporating broader datasets and exploring the integration of additional behavioural and environmental factors to refine the model further.

(vi) How can past vessels' trajectories be used to develop a real-time movement prediction model with improved accuracy and interpretability based on human navigational preferences?

Understanding and predicting the future movements of vessels in a mixed waterborne environment is important for safe and efficient collision avoidance. Chapter 4 addressed this by developing a movement prediction model that integrates human navigational preferences derived from past movements. By capturing the dynamic interactions and behavioural tendencies of manned vessels, this model offers a predictive capability that not only enhances accuracy but also improves the interpretability of predictions.

The methodology leveraged historical AIS trajectory data, processed using a Multi-Task Learning Sequence-to-Sequence LSTM model with attention mechanisms (MTL-Seq2Seq-LSTM-Att). The model incorporates the navigational preference clusters identified earlier, embedding these preferences into its predictive framework. The encoder-decoder architecture captured temporal dependencies within trajectory data, while the attention mechanism prioritised critical behavioural features relevant to specific navigational scenarios. This multi-task approach allowed simultaneous prediction of the future trajectories of the autonomous vessel and neighbouring manned vessels, ensuring consistency and mutual awareness. Evaluation of the model demonstrated improvements in both prediction accuracy and interpretability. The integration of navigational preferences reduced prediction errors. These results were validated across various time horizons, with particularly strong performance for 15-minute predictions. Limitations included the computational complexity associated with real-time implementation in high-density traffic and the reliance on AIS data, which may not capture all contextual factors such as environmental conditions or operator intent. Additionally, the model's performance in highly congested scenarios involving multiple vessels requires further exploration.

In summary, the movement prediction model presented in this thesis bridges the gap between accuracy and interpretability by embedding human navigational preferences into real-time trajectory prediction. This innovation provides a foundation for autonomous decision-making systems, enabling them to anticipate and respond to various vessel interactions proactively.

(*vii*) *How does the prediction result support the interactive collision avoidance of MASS in a mixed waterborne environment?*

Accurate trajectory predictions are a basis of safe and efficient interaction in collision avoidance scenarios, particularly in an MWTS where autonomous vessels are suggested to proactively respond to the movements of manned vessels to ensure seamless interactions in the presence of limited communication. Chapter 4 explored how integrating prediction results into a decision-making framework enhances collision avoidance strategies. By transforming human-preference-aware trajectory predictions to human-recommended routes, the framework enables MASS to avoid collisions in a human-like manner while keeping navigational safety with the KM-DWA planner in emergency situations, ensuring safe and efficient interactions with surrounding vessels.

The methodology involved embedding the prediction results from the MTL-Seq2Seq-LSTM-Att model into the proposed decision-making framework. These predictions were used to dynamically inform the KM-DWA path-planning module and an MPC trajectory-tracking module. The KM-DWA module utilised predicted trajectories to refine path planning, taking into account dynamic collision scenarios based on the DCPA and TCPA metrics. Simultaneously, the MPC module ensured the vessel could accurately follow its planned trajectory while remaining responsive to real-time updates from the prediction model. This dual integration allowed the framework to prioritise safety and efficiency while maintaining navigational predictability for human-operated vessels. The results demonstrated that the use of prediction results improved the framework's performance in collision avoidance tasks. Autonomous vessels could proactively adjust their paths as "manned vessels recommend" to avoid conflicts, aligning with navigational preferences and behaviours observed in manned vessels. Simulations indicated that the framework reduced the severity of near-collision scenarios. However, limitations were noted, including the computational demands of real-time integration and the reliance on AIS data, which may not fully capture unforeseen navigational behaviours or environmental disruptions. The model also required further validation in high-density traffic scenarios involving multi-vessel interactions to ensure robustness and scalability.

In summary, the integration of prediction results into the collision avoidance framework enhances the decision-making capabilities of MASS in mixed environments. By leveraging trajectory predictions informed by human navigational preferences, the framework fosters safer and more cooperative interactions between autonomous and manned vessels.

(4) Answers to the questions on human trust:

(*viii*) *How can human trust in MASS in collision avoidance be measured, analysed, and modelled within controlled experimental settings?*

Trust plays an important role in ensuring seamless human-MASS interaction, especially during high-risk scenarios where human supervision is necessary, such as collision avoidance. Chapter 5 focused on understanding and evaluating trust dynamics in collision avoidance scenarios involving MASS, with human supervisors acting as observers to evaluate their trust in various navigational stages of collision avoidance scenarios. By investigating trust dynamics across different stages, this chapter aimed to identify factors influencing trust and to develop a trust model that could be integrated into MASS systems to enhance their safety and reliability.

The methodology involved conducting a simulator-based experimental study with participants observing MASS performing collision avoidance manoeuvres. Trust was measured using self-reported questionnaires administered post-scenario, capturing stage-specific trust levels. The trust dynamics were analysed using a linear mixed model (LMM) to identify patterns of trust evolution over time, and factor analysis was conducted to explore the underlying dimensions of trust. Subsequently, a Bayesian network model was developed to capture the sequential dependencies of trust across navigation stages and to quantify the influence of situational and demographic factors on trust levels.

The results revealed that trust is not static but evolves dynamically across different navigation stages. Trust gradually accumulated during routine navigation stages but greatly decreased during the decision-making and execution of collision avoidance strategies regardless of evasive strategies. Trust partially recovered during the final stages of navigation. Factor analysis consolidated trust dimensions into two main components: *System Competence*, representing the system's reliability, predictability, and perceived capabilities, and *Situational Safety*, capturing the observer's perception of safety under specific conditions. The Bayesian network model further quantified the influence of these dimensions on overall trust, highlighting the importance of timely and COLREGs-compliant actions in maintaining trust. Despite its insights, the study faced limitations, including the reliance on simulated scenarios that may not fully replicate real-world complexities and the exclusion of real-time physiological measures of trust.

To sum up, Chapter 5 provided a systematic approach to measure, analyse, and model human trust in MASS during collision avoidance scenarios. By identifying key factors influencing trust dynamics and quantifying their impact through a Bayesian network model, the study offers actionable insights for designing trust-aware decision-making systems for MASS. Future research should explore real-world validation, extend trust modelling to operational contexts with higher complexity, and incorporate real-time trust monitoring techniques, such as physiological data collection, to enhance the robustness and applicability of the findings.

Returning to the main research question of the thesis, it is addressed through the development of an integrated framework that integrates three key elements: situational awareness, human-preference-aware navigation, and trust model. Situational awareness provides the foundation for interpreting the navigational context by integrating sensor data and regulatory knowledge, enabling autonomous vessels to make informed decisions. Human preferences are incorporated to align autonomous navigation with the behaviours of manned vessels, enhancing predictability and cooperation. Trust modelling ensures that human supervisors maintain a proper trust level in autonomous decision-making, especially during high-risk scenarios such as collision avoidance. The framework is designed for MASS to operate within MWTS, fostering safe, efficient, and interpretable interactions between autonomous and manned vessels.

The datasets supporting the findings of this study, including *Qualtrics* data and AIS data from *Vesselfinder*, are available upon request by contacting the author.

6.2 Future research

While this research provides a robust foundation for human-MASS interaction in MWTS, several limitations and future directions merit attention:

1. Expanding the situational awareness model

   Expanding the role of stakeholders: Situational awareness mechanisms should be extended to accommodate the needs of multiple stakeholders, such as port authorities, traffic management centres, and search-and-rescue teams. Future research could explore methods for meeting situational awareness outputs to various stakeholder requirements, enabling efficient communication and coordination. For example, stakeholders may require specific insights into a vessel's operational intentions, compliance with regulations, or situational risks. Developing adaptive information-sharing frameworks will enhance collaboration and improve overall safety and efficiency in MWTS.

2. Enhancing the human-mimic navigation model

(1) *Developing and comparing predictive models developed for various navigational environments for human-mimic navigation considering multiple factors*, such as local regulations, traffic density, and ship static information. Future work should prioritise the development and comparative evaluation of predictive models tailored to a range of navigational environments. This thesis primarily focuses on isolated conditions, neglecting regional variabilities such as local maritime regulations, traffic density, or ship-specific attributes (e.g., size and manoeuvrability). By incorporating these factors into the model design, predictive accuracy can be enhanced across diverse maritime scenarios.

(2) *Preference modelling considering the effects of multi-vessel scenarios*: The current approach to preference modelling primarily addresses pairwise vessel interactions, limiting its utility in real-world multi-vessel environments. Expanding the framework to consider the influence of multiple vessels on navigational decisions is a critical next step. Multi-vessel scenarios inherently introduce higher levels of complexity, requiring the model to dynamically account for interactions between multiple actors. For example, a vessel's decision to turn or adjust speed may not only depend on the closest vessel but also on its relative position and alignment with other nearby ships. Moreover, while preference-based path prediction enhances safety and coordination, it may in some cases result in overly conservative manoeuvres. Future work should incorporate adaptive balancing mechanisms to manage this trade-off, ensuring proportional risk-taking and avoiding unnecessary deviations. By integrating data-driven techniques with dynamic conflict modelling, future studies could enhance the system's capacity to navigate congested or constrained waterways effectively.

3. Further investigation and modelling on human trust

(1) *Real-time evaluation of trust*: Another critical avenue is the development of real-time trust monitoring and adaptive mechanisms. While existing studies have successfully modelled trust dynamics using post-scenario evaluations and Bayesian networks, these approaches are static and retrospective. Future research should explore the integration of real-time physiological and behavioural data, such as heart rate variability, eye-tracking, or EEG, to enable continuous trust assessment. These data streams could inform adaptive system responses, such as adjusting the level of system autonomy or providing additional explanations during critical decision-making stages, ensuring trust remains balanced and appropriate.

(2) *Trust-aware decision-making*: The unidirectional evaluation of trust in existing studies represents a limitation. Operators currently engage as passive observers without opportunities to influence system outputs actively. Future research should focus on developing adaptive situational awareness systems that calibrate trust levels through iterative feedback. This entails transitioning the operator's role from observer to

participant, where trust calibration mechanisms adjust system autonomy based on trust assessments. For example, during high-stakes collision scenarios, an adaptive system might offer more detailed explanations or revert to safer, operator-aligned decisions when trust levels are low. Conversely, higher trust could lead to reduced human involvement, optimising system efficiency. Future research should transition from static trust evaluation to adaptive trust calibration mechanisms. Situational awareness systems must actively respond to trust levels by modifying autonomy or providing explanations in critical scenarios. This shift would involve operators more directly in decision-making processes, fostering balanced trust and optimising system reliability.

(3) *Trust calibration mechanism*: The development of trust-driven decision-making frameworks represents another avenue for research. Current trust studies, including those presented in this thesis, focus primarily on evaluating trust levels through observational methods. However, integrating trust as a core component of decision-making processes could significantly improve the adaptability and reliability of autonomous systems. For instance, decision algorithms could incorporate trust as a dynamic input, modulating actions to align with the operator's trust state. Trust calibration mechanisms would aim to balance human trust with system performance, preventing overtrust or undertrust. By transitioning the operator's role from *observer* to *operator*, the interplay between trust dynamics and operational outcomes should be investigated in greater depth.

4. Strengthing the interrelationship among the three factors

(1) *Establishing dynamic links between trust and situational awareness*: Current situational awareness systems support decision-making but inadequately address their impact on trust dynamics. Future work should develop frameworks where situational awareness actively shapes and adapts to trust levels. For instance, transparent systems could dynamically adjust the detail and frequency of information presented to operators based on real-time trust assessments. This bidirectional feedback loop would ensure the trust is both monitored and leveraged to enhance decision-making.

(2) *Integration of navigational preferences with trust*: While navigational preferences provide an essential basis for human-mimic navigation, integrating these with trust dynamics offers significant potential to improve decision-making transparency and operator confidence. Operators' trust in autonomous vessels often depends on the predictability and consistency of their actions, particularly in complex scenarios. A combined model that incorporates both navigational preferences and trust levels could dynamically adjust the system's behaviour based on operator expectations.

5. System resilience under disruptions

The current framework assumes normal conditions. However, real-world MASS operations are subject to unexpected disruptions such as sensor failure, communication loss, or extreme environmental conditions. Future research should investigate resilience-enhancing mechanisms, including fallback decision modes, partial situational awareness handling, and escalation to human supervision. Integrating robustness metrics and adaptive planning strategies will be essential to ensure safe and continuous operation in uncertain and degraded scenarios.

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Glossary

List of symbols and notations

a_{u_min} , a_{v_min}, a_{ω_min}	Minimum accelerations from the directions of surge, sway, and yaw axis
a_{u_max}, a_{v_max}, a_{ω_max}	Maximum accelerations along the directions of surge, sway, and yaw axis
a_u^*, a_v^*, a_ω^*	Optimal set of acceleration
C_{goal}	Goal achievement cost function
$C_{obstacle}$	Obstacle avoidance cost function
$C_{pathKeeping}$	Path keeping cost function
$C_{timeToGoal}$	Time to goal cost function
$C_{stability}$	Navigation stability cost function
$C_{colregs}$	COLREGs compliance cost function
c_t	Context vector gengerated by LSTM-encoder
f	Function of LSTM-Encoder
g	Function of LSTM-Decoder
$\mathbf{h}_t^{enc}, \mathbf{c}_t^{enc}$	Hidden and cell states of the LSTM at time *t*
$\mathbf{h}_t^{task}$, $\mathbf{c}_t^{task}$	Hidden and cell states of the Task-specific decoder
$\bar{\mathbf{h}}_s$	Each encoder's hidden state
$\tilde{h}_t$	Attentional state of the decoder
J	The cost function of the tracking problem
p-value/p/Sig.	The significance level of a statistic value
$\boldsymbol{R}$	Rotation matrix
T_s	The length of the input sequence of LSTM-Encoder
u_t , a_u	Current surge velocity and acceleration
u^*, v^*, ω^*	Optimal set of velocity
$u_{\max}$, $v_{\max}$, $\omega_{\max}$	Maximum velocities along the directions of surge, sway, and yaw, respectively
$u(k+n)$	The magnitude of control inputs
$\boldsymbol{v} = [u, v, r]^{\mathrm{T}}$	The velocities of a vessel in surge, sway, and yaw
v_t , a_v	Current sway velocity and acceleration
V_s, V_r, V_d	Space of possible velocities, possible velocities constrained by its acceleration, and the intersection of the restricted areas
ω_t , a_ω	Current yaw velocity and acceleration
$\boldsymbol{W}_a$	Trainable weight matrix of the Attention mechanism
$\mathbf{W}_{\mathbf{pref}}, \mathbf{b}_{\mathbf{pref}}$	Weights and bias vectors of the LSTM classifier
$\mathbf{W}_{out}^{task}$, $\mathbf{b}_{out}^{task}$	The weight matrix and the bias vector for the linear transformation of the specific task
x	Input sequence of LSTM-Encoder

$\tilde{x}$	Output sequence of LSTM-Decoder
y_i	The actual value
$\hat{y}_i$	The predicted value
$\bar{y}$	The mean of the actual values
$\mathrm{y}_{\mathrm{pref}}$	The navigational preference class of LSTM classifier
$\mathbf{y}_t^{\boldsymbol{task}}$	The input to the decoder at time step *t*
$y_{ref}(k+n), u(k+n)$	The reference trajectory and control inputs at future *n* time steps
α	Relative bearing
$\alpha_t(s)$	The attention weight for encoder state *s* at time *t*
$\beta, \gamma, \delta, \eta, \kappa$	Weighting factors for each cost function
$\eta = [x, y, \psi]^{\mathrm{T}}$	The position and heading of the vessel
ϕ	Encounter angle
φ	Heading of the own vessel
φ_{obt}	Heading of the surrounding vessel
$\boldsymbol{\tau} = [\tau_x, \tau_y, \tau_z]^{\mathrm{T}}$	The control inputs of a vessel (forces and moment)
Δt	The time step

List of abbreviations

ACC	Acceleration
ADE	Average Displacement Error
ANOVA	Analysis of variance
APF	Artificial Potential Fields
CA	collision avoidance
CAS	collision avoidance systems
COG	Course over ground
COLREGs	Convention on the International Regulations for Preventing Collisions at Sea, 1972
DBNs	Dynamic Bayesian networks
DCPA	Distance closest point of approach
DDQN	Double Deep Q Network
DOF	Degrees-of-freedom
DRL	Deep Reinforcement Learning
DWA	Dynamic Window Approach
EEG	Electroencephalography
EM	Expectation-Maximization
EMCIP	European Marine Casualty Information Platform
EMSA	European Maritime Safety Agency

ES	Encountered situations
EVS	Explained Variance Score
FDE	Final Displacement Error
HRI	Human-robot interaction
IMO	International Maritime Organisation
KM	Knowledge maps
LMM	Linear Mixed Model
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MASS	Maritime Autonomous Surface Ships
MDP	Markov Decision Processes
MMSI	Maritime Mobile Service Identity
MPC	Model predictive control
MSE	Mean Squared Error
MTL	Multi-Task Learning
MTL-Seq2Seq-LSTM-Att	Multi-Task Learning Sequence-to-Sequence LSTM model with an attention mechanism
MWTS	Mixed waterborne transport systems
NP	Navigational priorities
OS	The own ship
POMDP	Partially Observable Markov Decision Process
PPO	Proximal Policy Optimization
R^2	R-Squared
RCC	Remote Control Centres
RMSE	Root Mean Squared Error
RNN	Recurrent neural networks
ROT	Rate of turn
SA	Situational awareness
SC	System Competence
SCC	Shore Control Center
Seg	Segment
SOG	Speed over ground
SS	Situational Safety
SSE	Sum of Squared Errors
SWRL	Semantic Web Rule Language
TBN	Bayesian network-based trust model
TCPA	Time closest point of approach
TS	The surrounding ship
UTC	Coordinated Universal Time
Var	Variance

Summary

This thesis explores the integration of Maritime Autonomous Surface Ships (MASS) into Mixed Waterborne Transport Systems (MWTS), addressing critical challenges in ensuring navigational safety and operational efficiency. Recognising the complexities of interactions in MWTS, especially in scenarios without direct communication between vessels, the research develops a decision-making framework that integrates situational awareness, human-preference-aware navigation, and trust dynamics. These components collectively aim to support seamless interactions between autonomous and manned vessels, ensuring safe and efficient navigation in the MWTS.

The proposed framework builds on a systematic exploration of key challenges in MASS operations. For situational awareness, an ontology-driven knowledge maps model is introduced, enabling MASS to integrate multi-source data and maritime regulations. This model is further combined with a Dynamic Window Approach (DWA) path planner, allowing for real-time compliance with COLREGs and proactive collision avoidance. The research also advances human-preference-aware navigation by extracting and modelling navigational behaviours of manned vessels using AIS data. An LSTM-autoencoder with clustering methods is utilised to identify navigational preferences, which are then incorporated into a trajectory prediction model based on Multi-Task Learning Sequence-to-Sequence LSTM with attention (MTL-Seq2Seq-LSTM-Att) architectures. This integration enhances MASS decision-making by aligning manoeuvring strategies with human operators' expectations, reducing the likelihood of misinterpretation in mixed traffic scenarios.

Additionally, the dynamics of human trust in MASS are explored through experimental studies and modelled using a Bayesian Network. The analysis reveals how trust evolves across navigation stages, influenced by decision-making strategies and timing, and demonstrates the cascading effects of intermediate trust levels on overall operator confidence. The model offers guidance for designing transparent and dependable MASS behaviour to support adoption.

The research underscores the dual priorities of safety and efficiency throughout the framework. Safety is addressed by ensuring effective situational awareness and collision avoidance capabilities, while efficiency is enhanced by optimising travel time, reducing resource consumption, and minimising navigational delays. Together, these contributions offer a foundation for improving MASS operations in MWTS.

Despite its contributions, the research has limitations. The validation primarily relies on simulation-based experiments, which may not fully capture the complexities of real-world maritime conditions, such as varying sea states and traffic densities. Additionally, the geographic scope and vessel types analysed are restricted, and computational challenges in high-density scenarios remain underexplored. Future work should involve field trials, broader operational scenarios, and refinement of trust models with physiological feedback.

In summary, this thesis proposes an integrated decision-making framework that addresses the critical aspects of situational awareness, human preferences, and trust in autonomous navigation. By bridging key gaps in transparency, adaptability, and reliability, the research lays a solid foundation for safe, efficient, and collaborative MASS operations in MWTS, supporting the maritime industry's transition towards more autonomous and intelligent systems.

Samenvatting

Dit proefschrift onderzoekt de integratie van Maritieme Autonome Oppervaartschepen (MASS) in gemengde watertransport systemen (Mixed Waterborne Transport Systems, MWTS) en richt zich op kritieke uitdagingen om navigatieveiligheid en operationele efficiëntie te waarborgen. Rekening houdend met de complexiteit van interacties in MWTS, vooral in scenario's zonder directe communicatie tussen schepen, ontwikkelt het onderzoek een besluitvormingskader dat situationeel bewustzijn, navigatie met oog voor menselijke voorkeuren en vertrouwen dynamiek integreert. Deze componenten ondersteunen naadloze interacties tussen autonome en bemande schepen, en zorgen voor veilige en efficiënte navigatie in MWTS.

Het voorgestelde kader is gebaseerd op een systematische verkenning van belangrijke uitdagingen bij MASS-operaties. Voor situationeel bewustzijn wordt een op ontologie gebaseerd kenniskaartmodel geïntroduceerd, waarmee MASS gegevens uit meerdere bronnen en maritieme regelgeving effectief kan integreren. Dit model wordt gecombineerd met een Dynamic Window Approach (DWA) padplanner, waarmee realtime naleving van de COLREGs wordt bereikt en proactieve aanvaringsvermijding wordt mogelijk gemaakt. Het onderzoek bevordert ook navigatie met oog voor menselijke voorkeuren door het extraheren en modelleren van navigatiegedrag van bemande schepen met behulp van AIS-gegevens. Een LSTM-autoencoder met clusteringmethoden wordt toegepast om navigatievoorkeuren te identificeren, die vervolgens worden geïntegreerd in een trajectvoorspellingsmodel op basis van Multi-Task Learning Sequence-to-Sequence LSTM with attentie (MTL-Seq2Seq-LSTM-Att) architecturen. Deze integratie verbetert de besluitvorming van MASS door manoeuvreerstrategieën af te stemmen op de verwachtingen van menselijke operators, waardoor misinterpretaties in gemengd verkeer worden verminderd.

Bovendien worden de dynamiek van menselijk vertrouwen in MASS onderzocht door middel van experimentele studies en gemodelleerd met een Bayesian Network. De analyse laat zien hoe vertrouwen zich ontwikkelt in verschillende navigatiefasen, beïnvloed door besluitvormingsstrategieën en timing, en toont de cascade-effecten van tussentijdse vertrouwensniveaus op het algehele operatorvertrouwen. Het model biedt richtlijnen voor het ontwerpen van transparant en betrouwbaar gedrag van autonome schepen (MASS) ter ondersteuning van de adoptie.

Het onderzoek benadrukt de dubbele prioriteiten van veiligheid en efficiëntie in het hele kader. Veiligheid wordt gewaarborgd door effectief situationeel bewustzijn en mogelijkheden voor aanvaringsvermijding, terwijl efficiëntie wordt verbeterd door reistijd te optimaliseren, hulpbronnen te besparen en navigatievertragingen te minimaliseren. Samen bieden deze bijdragen een basis voor het verbeteren van MASS-operaties in MWTS.

Ondanks de bijdragen kent het onderzoek beperkingen. De validatie is voornamelijk gebaseerd op simulatie-experimenten, die mogelijk niet volledig de complexiteit van echte maritieme omstandigheden weerspiegelen, zoals wisselende zeestaten en verkeersdichtheden. Daarnaast zijn de geografische reikwijdte en de geanalyseerde scheepstypen beperkt, en blijven computationele uitdagingen in situaties met hoge dichtheid onderbelicht. Toekomstig onderzoek zou veldproeven, bredere operationele scenario's en verfijning van vertrouwensmodellen met fysiologische feedback moeten omvatten.

Samenvattend stelt dit proefschrift een geïntegreerd besluitvormingskader voor dat de kritieke aspecten van situationeel bewustzijn, menselijke voorkeuren en vertrouwen in autonome navigatie aanpakt. Door belangrijke hiaten in transparantie, aanpasbaarheid en betrouwbaarheid te overbruggen, legt het onderzoek een solide basis voor veilige, efficiënte en samenwerkende MASS-operaties in MWTS en ondersteunt het de overgang van de maritieme industrie naar meer autonome en intelligente systemen.

Curriculum vitae

Rongxin Song was born on June 16, 1996, in Lvliang, Shanxi, China. He obtained his B.Sc. degree in Navigation Technology at Wuhan University of Technology, Wuhan, China, in 2018. After this, Rongxin Song obtained an M.Sc. degree in Traffic Information Engineering and Control at Wuhan University of Technology, Wuhan, China, in 2021.

Starting in November 2021, Rongxin Song is sponsored by the China Scholarship Council as a PhD candidate supervised by Prof. dr. ir. Pieter van Gelder, Prof. dr. Rudy R. Negenborn, and Dr. Eleonora Papadimitriou at Delft University of Technology, Delft, Netherlands. He carried out his research in the Section of Safety & Security Science, in close collaboration with the Department of Maritime & Transport Technology and the Researchlab Autonomous Shipping. In his PhD project, Rongxin focused on safe and efficient interaction between autonomous and manned vessels in mixed waterborne transport. His research interests include autonomous vessels, collision avoidance, situational awareness modelling, human-mimic navigation, and human trust dynamics.

Publications

1. Song, R., Papadimitriou, E., Negenborn, R. R., & van Gelder, P. H. A. J. M. (2024). Safety and efficiency of human-MASS interactions: towards an integrated framework. *Journal of Marine Engineering & Technology*, 1–20.
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4. Song, R., Papadimitriou, E., Negenborn, R. R., & van Gelder, P. H. A. J. M. (2022). Constructing Knowledge Maps for Situation Awareness of Maritime Autonomous Surface Ships. In *Proceedings of the International Ship Control Systems Symposium* (Vol. 16, p. 21). Institute of Marine Engineering Science and Technology.

5. Song, R., Papadimitriou, E., Negenborn, R. R., & Van Gelder, P. H. A. J. M. (2023, August). Distributed Situational Awareness for Maritime Autonomous Surface Ships in Mixed Waterborne Transport: An Ontology-based Framework. In *2023 7th International Conference on Transportation Information and Safety (ICTIS)* (pp. 1088-1092). IEEE.

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