Ocean Engineering 302 (2024) 117652

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

COLREG and MASS: Analytical review to identify research trends and gaps in the Development of Autonomous Collision Avoidance

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ARTICLE INFO

Keywords:
COLREG
MASS
Collision avoidance
Ship collision

ABSTRACT

Maritime Autonomous Surface Ships (MASS) face regulatory challenges, with some suggesting that the existing Collision Regulations (COLREG) present linguistic barriers for autonomous vessels' development and implementation. While academic research has focused on developing autonomous collision avoidance (CA), it is producing inconsistent results compared to conventional navigation practices. This study aims to identify trends and weaknesses in recent studies on CA for MASS by conducting a systematic review and analysis of the most relevant literature. The Conventional-Collision-Avoidance-Process (CCAP), which benchmarks manned modern ships' capacity for CA compliance under COLREG and industry requirements, is used to break down a ship's collision avoidance process into 53 CA functions under eight main categories. A total of 32 papers were chosen through filtering based on keywords, publication period, language, and relevance. The content of the recent academic literature was then grouped under appropriate CCAP codes. Statistical and graphical interpretations were generated using the collected literature content data and evaluated statistics of the existing digital contribution of CCAP. The study uncovers significant trends, inconsistencies, and weaknesses that could guide future academic research towards comprehensive CA solutions for MASS.

1. Introduction

The International Maritime Organization (IMO) has introduced the concept of the Maritime Autonomous Surface Ship (MASS), which includes four degrees of autonomy. Since this introduction, numerous organisations within the maritime sector have initiated steps to regulate the integration of autonomy into ships. For instance, through a regulatory scoping exercise in 2021, the IMO, along with classification society guidelines (LR, 2017; DNV.GL, 2018; ABS, 2020), and industry initiatives such as the 'MASS Industry Conduct Principles and Code of Practice' in the United Kingdom (Maritime UK, 2023), have collaborated to update maritime regulations and standards. These updates recognise the potential for instrumentation, design, construction, and operation of MASS. In light of modern technological advancements, it is crucial to consider the benefits that MASS can bring to the shipping industry. These benefits include increased operational efficiency, enhanced safety for personnel and assets, and improved environmental protection (Porathe, 2020; Zhou et al., 2020; Chang et al., 2021).

One of the main challenges of the development of MASS is to ensure safe navigation and avoidance of collision. The International Regulations for Preventing Collisions at Sea (COLREG) introduced by the IMO in 1972, provides the foundation for collision avoidance standards followed by vessels. However, with the advent of MASS, there is a need to reconcile these standards with the new technology. Therefore, it is important to identify regulatory barriers and find means to address them to bridge the gap between conventional and autonomous ship functions.

The IMO, as the global maritime regulator, began working on Maritime Autonomous Surface Ships (MASS) since around 2015. In February 2017, see IMO document MSC 98/20/2, a proposal for a regulatory scoping exercise for MASS was put forward. This exercise concluded in 2021, as noted in IMO document MSC.1. Circ. 1638, with the IMO agreeing that autonomous vessels (MASS) should comply with several existing regulations, including, among others, the COLREG. This IMO Regulatory Scoping Exercise (IMO, 2021) identified the need to address issues related to terminology, lights, shapes, sound signals, and the role of the master (for Degree I autonomy). Additionally, it highlighted the responsibility of the remote operator (under Degree Two autonomy) and distress signals (Degree Three). The expert group noted that Degree One autonomy would be the least disruptive. However, even then it is believed that bridge watchkeeping and other onboard

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https://doi.org/10.1016/j.oceaneng.2024.117652
Received 5 October 2023; Received in revised form 23 March 2024; Accepted 24 March 2024

Abbreviations

AIS	Automatic Identification System
AoC	Alteration of Course
AoS	Alteration of Speed
ARPA	Automatic Radar Plotting Aid
ASR	Available sea-room
BCR	Bow Crossing Range
BCT	Bow Crossing Time
CA	Collision avoidance
CCAP	Conventional collision avoidance process
CDSD	Collision Danger Situation Data
COLREG	International Regulations for Preventing Collisions at Sea
CPA	Closest point of approach
DIP	Danger Identifying Parameters
ECDIS	Electronic Chart Display and Information System
GS	Good seamanship
INS	Integrated Navigation System
Lit. ID	literature identity
MASS	Maritime Autonomous Surface Ship
OS	Own ship
SMD	Ship Manoeuvring Data
SSM	Ship's safety margins
TCPA	Time to CPA
VTS	Vessel traffic service
CO	Course
RB	Relative Bearing
USV	Unmanned Surface Vehicle

operations in autonomous vessels *"will result in distortion or a lack of clarity within COLREG"* (IMO,2021).

While the issue of terminology and other COLREG provisions (e.g., lights and signals) could be addressed straightforwardly, there is an overall clear need to examine the challenges that autonomous vessels will bring to COLREG compliance. This would involve harmonizing the COLREG and other decision-supporting information, such as digital publications and radio broadcasts, with innovative cyber solutions to create a seamless platform (Woerner et al., 2018; Porathe, 2019).

The emergence of MASS has led to a significant number of research studies focused on developing an autonomous collision avoidance system for ships; see Section 2. However, often these academic studies appear to be fragmented and lack an all-encompassing approach to the conventional collision avoidance (CA) process followed by a human navigator. For example, the IMO Collision Regulations (IMO, 1972) outline a sequential process for detecting and avoiding collisions, but these steps are addressed differently in academic studies, impeding the development of complete autonomous systems. To establish a comprehensive decision-making system, various aspects of collision avoidance autonomy must be addressed. It would therefore be advantageous to have a comprehensive overview of recent research trends and potential gaps in the studies related to MASS. Comparing the proposed artificial or digital autonomy with the conventional collision avoidance process (CCAP) followed by a human navigator, would offer the essential understanding of the degree to which human intervention could be replaced and assist in setting goals for the development of safe and conflict-free MASS operations. Assessing recent academic research for its achievements in collision avoidance (CA) autonomy and the level of human involvement required in the CCAP will highlight the trends, strengths, and weaknesses of the scholarly studies. This analysis will aid the research community by providing a deeper understanding of collision avoidance at sea and how to achieve a comprehensive and effective decision-making autonomy that supplants human-centric conventional practices.

Hence, this study aims to examine the recent academic research (2018–2022) focusing on the comprehensive CA autonomy for MASS. This paper first identifies human interventions in each CA function by mapping the Collision Course Avoidance Process (CCAP) and other navigational characteristics. Next, it evaluates the extent to which technological and conceptual advancements can replace human intervention in CCAP, which is highly demanded as revealed in the academic literature. The other new contributions of this paper are (a) a novel method for the mapping of CCAP and (b) identification of the gaps between the existing literature and the practical measures for CA in maritime autonomous systems and ships.

The rest of the paper is structured as follows: Section 2 reviews relevant the literature on ship collision regulations. Section 3 discusses the applied methodology. Section 4 presents the mapping of CCAP and Section 5 the results of the mapping. Discussion is presented in Section 6 and Conclusions are drawn in Section 7.

2. Literature review on ship collision regulations

It is evident from the relevant literature that the emergence of MASS has led to a significant number of research studies focusing on the development of an autonomous collision avoidance system for ships. Even prior to the introduction of MASS at the IMO level, discussions were already taking place, as reflected in academic literature, on the use of technology (i.e., "intelligent navigation systems"); for an early review of autonomous ship collision avoidance, referring to the work of Statheros et al. (2008). For more recent reviews, especially on the use of machine learning and artificial intelligence in collision avoidance applications, the readers can refer to Burmeister and Constapel (2021) and Akdağ et al. (2022). In addition, for a recent survey on the relevant regulations and industry codes, reviews of MASS R&D developments and collision avoidance navigation systems are documented in such studies as X. Zhang et al. (2021).

This section outlines a thorough analysis of the relevant literature. It will show that MASS face regulatory challenges, with some suggesting that the existing Collision Regulations (COLREG) present linguistic barriers for autonomous navigation systems. While academic research has focused on developing autonomous collision avoidance (CA), it has produced inconsistent outcomes compared to conventional navigation practices. This review analysis will reveal the necessity of conducting a new systematic review and analysis of the trends and weaknesses in recent studies on CA for MASS.

2.1. Latent ambiguities of rules

International collision regulations were established in 1972, for the purpose of standardising the rules of the road used at sea by ships (IMO, 1972). These rules are developed with the assumption of human involvement in navigation, but in the context of artificial intelligence, many rules are expressed in linguistic form (Bakdi and Vanem, 2022). However, the lack of quantitative data in these rules (Miyoshi et al., 2022) presents challenges for developing an AI-based platform for collision avoidance. Without a digitally interpretable platform, collision regulations either need to be re-structured for simplification and compatibility with technology, or a common ground needs to be established between MASS and manned ships (Porathe, 2019).

2.2. Technological advancements

Efforts are underway to create a comprehensive AI-powered collision avoidance system, including advances in technology, design, and conceptual approaches (Bakdi and Vanem, 2022). Deconflicting systems have been used during trials on MASS, but there remains the challenge of demonstrating that these systems meet the requirements set by COLREG and can effectively interact with manned ships. Woerner et al. (2018) argue that sensor-based systems, including high-resolution cameras and infrared cameras, are already available to replace the human lookout function through visual and auditory means.

2.3. Quantifiability of good seamanship

The COLREG emphasises the significance of adhering to good seamanship (GS). Cockcroft and Lameijer (2012) present the potential measurement and application of GS through real court case examples. When navigating a vessel in a narrow channel or fairway, GS and prudent navigation dictate that the vessel should "keep to starboard" if it is safe and practical. To allow an adequate passing distance from an overtaking vessel in a fairway, GS recommends "moving away, as safe as practicable, from the side of the fairway in which the overtaking ship intends to pass" and "reducing speed to decrease the period of running closely parallel to each other." In an open sea crossing situation, GS suggests that a stand-on vessel should not allow a give-way vessel to come within approximately twelve times its own length. If the stand-on vessel realises it is too close and the collision cannot be avoided by the give-way vessel alone, it must take evasive action, typically about four times the length of the give-way vessel.

The generally accepted practice of a ship performing GS manoeuvre is to deconflict route and provide more sea-room to another ship or to avoid a potential collision situation, even if not specifically required by the COLREG (Zhou et al., 2020). By examining the examples, GS practices can also be catalogued and digitised to incorporate AI in replicating prudent human decision-making.

2.4. Collision-free traffic management

Porathe (2020) introduced the concept of “Moving Haven” integrated with an e-navigation system to define a virtual but moving safe-navigation-zone for MASS, to provide safe passage with no conflict of traffic. This concept can be adopted to introduce a holistic traffic management model to coastal vessel traffic service (VTS) systems to allocate customised virtual moving slots for ships’ transit within its domain. This, organised and controlled traffic management system could positively address the quest for CA autonomy for MASS by either minimizing or eliminating collision situations from their developments. However, this would require well-organised traffic coordination and management with an extremely localised mechanism for traffic data collection, processing, and exchange.

2.5. Digital interpretation of COLREG, navigation data and e-navigation

The focus on digitally interpreting the COLREG has been a common topic in many research discussions. Modern ships that are navigated by humans are equipped with advanced technologies to improve navigation safety compared to the ships in previous decades. Integrated Navigation System (INS) combines various navigation equipment, including main propulsion controls, and serves as a standalone operability for modern navigators. For a considerable period, navigators have used geometric techniques (i.e., Radar Plotting) to identify dangerous targets in the vicinity. Parameters such as Closest point of approach (CPA), Time to CPA (TCPA), Bow Crossing Range (BCR), Bow Crossing Time (BCT) and Relative Bearing (RB) are widely used in deciding the risk of collisions (Olindersson and Janson, 2015), although they are not defined in COLREG. These parameters are used as decisive metrics by professional navigators, VTSs as well as in Electronic Navigation systems (i.e., Automatic Radar Plotting Aid (ARPA), Automatic Identification System (AIS), Electronic Chart Display and Information System (ECDIS)) to represent the behaviour of targets around the ship and to detect potential collision risks as required by COLREG. With the long-standing usage of these parametric, there is potential to develop a comprehensive AI-based autonomous CA system that integrates with human-oriented functions.

Papageorgiou et al. (2019) made a pragmatic approach to model an autonomous decision support framework for ships by incorporating existing systems and potential innovative advancements. However, some vital elements were overlooked in the decision-making process such as the integration of ship-specific data, manoeuvring characteristics, regional or local restrictions, and good seamanship practices, all of which are critical in avoiding collision. Bakdi and Vanem (2022) applied fuzzy-logic analysis on COLREG linguistics and developed a decision-making model for MASS. Gil et al. (2022) used big data analytics to determine the BCR of a ship. Nonetheless, digital representation of certain COLREG provisions is widely used by navigators and VTS to identify collision risks and plan safe passages. Consequently, developing a universal autonomous CA platform will be essential due to the potential of adopting MASS Degree of Autonomy 1 by a modern manned ship. This approach would eliminate the potential communication gap that could arise in a CA situation between MASS and manned ships.

2.6. Identifying collision avoidance functions

The process of CA as for the requirement of COLREG (IMO, 1972) can be considered a sequential one, highlighting the importance of situation awareness and adapting to the specific sailing area based on the ship’s abilities and limitations. Although it may seem complex, traditional navigators follow a structured procedure as they gain experience and mastery of their skills. Ship’s safety margins (SSM) and Safety Parameters of danger-identification (i.e., DIP) are adapted depending on the limitation of the navigable sea area by the ship for its draught, density of traffic in proximity, navigational dangers, and local sanctions. The surrounding area is continuously monitored through proper lookouts and various means such as RADAR, AIS, etc. (Cockcroft and Lameijer, 2012). The identified targets are then assessed to determine the collision risks. The situation (such as overtaking or crossing or head-on or keep-out-of-the-way) is determined based on Rules 13, 14, 15 and 18 of COLREG, respectively.

Rule 18 provides responsibility between ships having different navigation statuses (i.e., Power-driven vessel, vessel not under command, vessel restricted in her ability to manoeuvre, sailing vessel), encounter each other in a collision-danger situation. Having transmitted the navigation status through AIS or other means, the ship required to keep out of the way (the give-way ship) will be ascertained.

The available sea-room (ASR) for the ship to safely manoeuvre around the position of CPA is assessed. A suitable action, either alteration of course (AoC) or speed (AoS) or by both, is decided considering the general provisions of “Actions to avoid collision” based on COLREG Rule 8 and executed to avoid danger. Monitoring is then carried out until the danger has passed and the situation is safe (IMO, 1972; Cockcroft and Lameijer, 2012; Olindersson and Janson, 2015). The assessment-phase and before-action-phase consist of detection and determination functions. Manoeuvre represents the execution function; after after-action phase resembles the monitoring function and a safe situation is where the danger of collision has passed and is clear.

3. Methodology

The structure of the research is illustrated in Fig. 1 and outlined as follows.

Initially, we conduct a review of literature (see Section 2) using three primary resources: (a) the IMO COLREG regulation (abbreviated as Collision Regulations (CR)), and a widely recognised textbook by Cockcroft and Lameijer (2012) titled “A Guide to the Collision Avoidance Rule - International Regulations for Preventing Collisions at Sea” (which will be referred to as the “Guide” from here on), (b) industry-lead literature (such as derived by Class and other stakeholders) and (c)

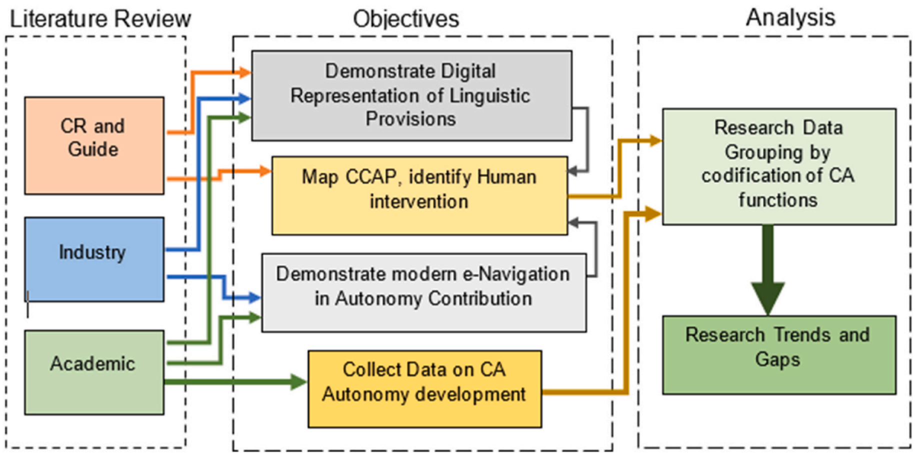

Fig. 1. Research progress Structure.

academic papers.

Based on the literature review, we then obtain a set of objectives such as demonstrating the digital interpretation of the collision regulations and the autonomy contribution of e-navigation, which we addressed in Section 2.5.

More importantly, our methodology aims to map CCAP functions and break them down into, what we refer to as "fragmented" CA functions, to which we assign a code.

3.1. Detailed mapping of CCAP

Collision avoidance regulations (CR) and the 'Guide' (see Cockcroft and Lameijer, 2012) along with industry-led and academic sources are used for the mapping of the various CCAP steps. Individual CCAP functions were scrutinised further using the generic outline illustrated in Fig. 2, which has n number of 'main CA functions" and m number of "fragmented data or functions" under each standard sub-group of Inputs, Evaluation/Processing and Outputs.

3.1.1. Inputs

This section represents the information or data required to process the object of the function to deliver "Outputs". Crucial data for each function is listed and coded as a fragmented function under a main CA function. The input data will be recognised through a close investigation of the CA practice required to be followed by a human navigator.

3.1.2. Evaluation/processing

This element identifies evaluations and/or processes necessary to achieve the objective of the main CA function. These are the first to be considered whilst constructing the CCAP, and the input data is then identified. Depending on the scope of the CA function, one or more evaluations and processes under a main function are recognised and divided into smaller parts. The means or sources of processing are also evaluated to assess the contribution of digital autonomy and human navigators.

3.1.3. Outputs

These are the results (outputs) of the primary CA function, and they serve as inputs for the subsequent CA functions; it's important to recall that we perceive CA as a process that occurs in a sequence. The sources of outputs will also be assessed for the extent of digital contribution. If the output is generated by the navigation system without human involvement by the navigators, the data can be transferred as input data to the next CA function.

In general, the capabilities of existing marine electronic navigation systems and their limitations are investigated, identified, and considered here to recognise and demonstrate the availability of digital contribution to withdraw onboard human intervention when dealing with a CA situation as per CCAP. It mainly focuses on identifying capabilities in data management, such as means of data (or information) collection from available sources, data feed and sharing through the integration of different navigation systems (i.e., INS) and task-oriented processing/evaluating means that can be either sole human-based or digital or blend of both. Whenever there are fragmented CA functions that consist of both human and digital sources, the most predominant source would be taking charge of the function. For instance, if a data input function does solely not involve any on-board human, it will be awarded "Digital Autonomy" status. In case there is human involvement, but digital contribution alone possesses the capability to suffice the objective of the function in general, without exceptional circumstances, then it will be also awarded with "Digital Autonomy" status and vice versa. If the process accomplishment depends on human contribution, it will be awarded as "Human Dependent".

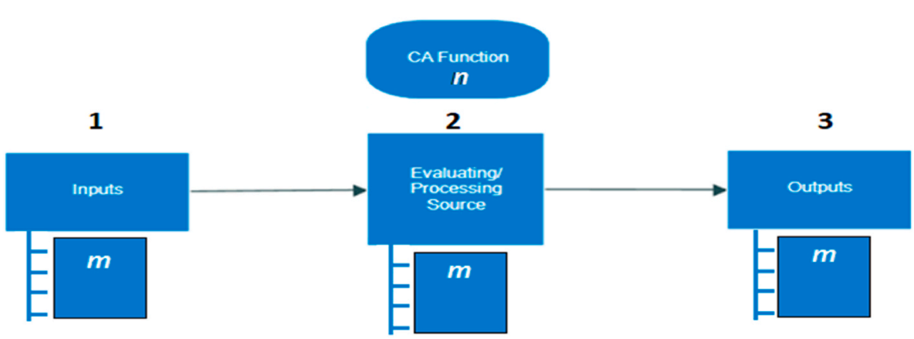

Fig. 2. CCAP coding.

3.2. *Fragmentation and codification of CCAP functions*

The qualitative literature-data collection under CCAP mapping will be streamlined by breaking down each step of the CA process into a simplified functional and data-oriented model and assigning each fragmented CCAP with a code. With these codes, the autonomy-development content of each selected academic paper can be grouped. If an academic study covers all the codes of CCAP, it is expected to have the holistic functionality of CA identified to develop an autonomous CA system.

3.3. *Academic literature selection for data collection*

The search for academic literature is primarily through the Scopus database using keywords {(MASS) OR (Autonomous Ships) AND (COLREG) AND (Collision Avoidance)}. The search is limited to the following selecting criteria, (a) content: title, abstracts, scope of the study, (b) language: literature only published in English is considered, (c) type of publications: only journal and conference papers are included, (4) period of publications: the recent five years from 2018 to June 2022 as to cover the recent MASS developments at an IMO level.

The analysis and categorisation of the linguistic data for each CA function is conducted using NVIVO, a qualitative data analysis software.

4. Outcome of detailed mapping of CCAP

4.1. *Main CA functions*

Based on standard practice and the regulations mentioned above, the following main CA functions are derived from CCAP mapping in the scope of simplifying the complex sequential processes outlined in Fig. 3.

Step 1: Situation Awareness

The main objective of this step is to anticipate and prepare the ship for upcoming traffic conditions, observing all appropriate information (i.e., limitations, restrictions, and special procedures) that is available to conduct safe navigation.

Step 2: Target Detection

This is the first active step of CA functionality, locating targets (vessels in the vicinity). Identification is also enabled with modern navigation systems such as AIS. Overlaying of ARPA target data, as well as AIS target data on ECDIS through data integration, provides better spotting of targets in the vicinity.

Step 3. Determination of Dangerous Targets

Dangerous targets are filtered from the rest of the detected targets. By feeding threshold safety parameters (i.e., DIP values of CPA/TCPA/BCR/BCT) into systems such as ARPA and AIS-based ECDIS target tracking, any potential infringements will trigger automatic warnings or alarms to bring attention to the risk of collision being developed.

Step 4. Determination of Situation and Rule

This step is to identify the development of the ship encounter situation. For instance, it can be one of the following scenarios: Head-on, Overtaking, Crossing or Keep-out-of-the-way. This is crucial for the adoption of a correct COLREG rule and understanding the available options for CA manoeuvring.

Step 5. Determination of Available Sea-Room

This step is to estimate the available safe navigable waters at the location where both ships get dangerously closer (i.e., the location of CPA). If the sea-room is inadequate or restricted in terms of the width and/or depth of the available waters to avoid the risk of collision by AoC alone, an AoS would be necessary to execute the CA manoeuvre

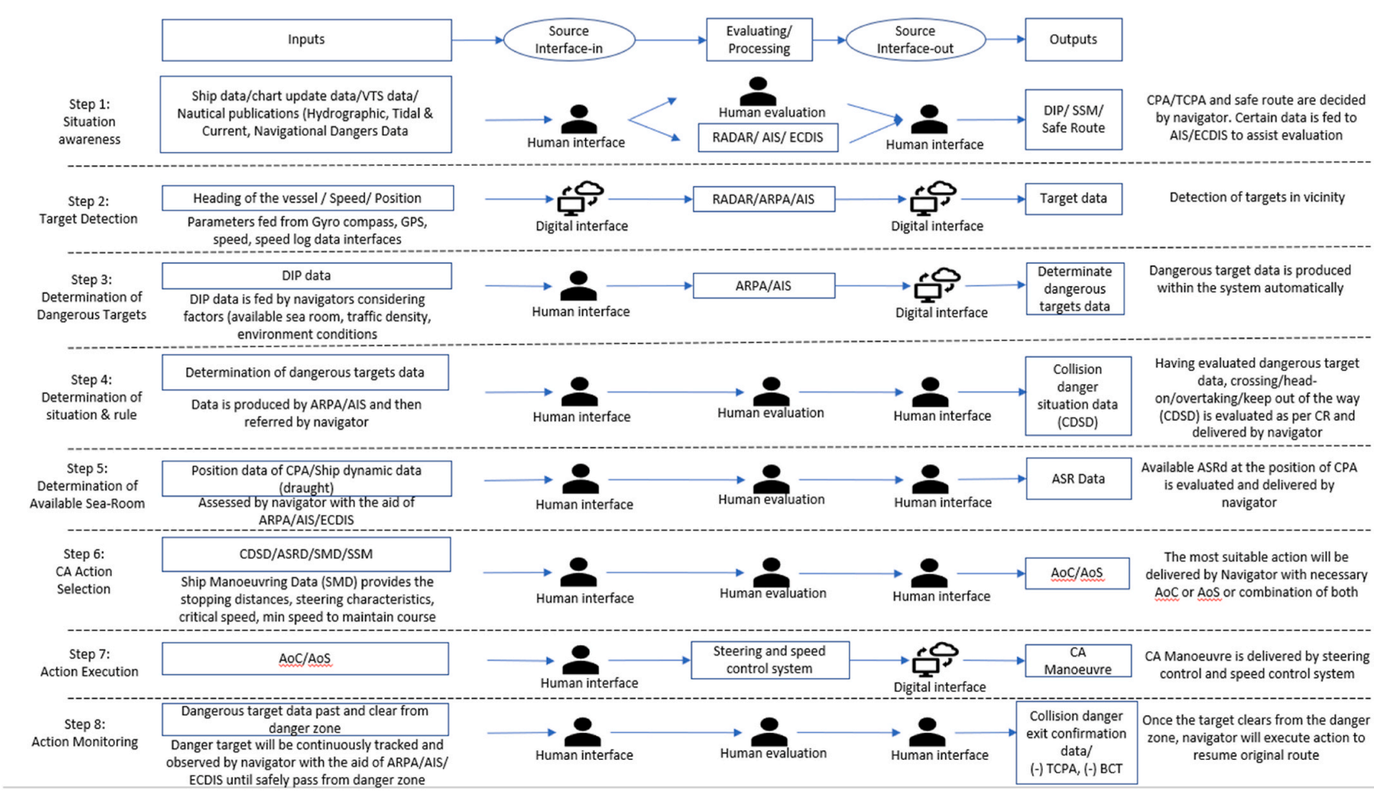

Fig. 3. Mapping of CCAP

effectively and safely without encountering another danger.

Step 6. Collision Avoidance Action Selection

All optional collision evasive actions are evaluated, and the optimal action is selected either by AoC or AoS or both.

Step 7. Action Execution

This step involves the required AoC and/or AoS are applied to evade the danger of collision being developed. These two functions are involved with heavy machinery on a ship such as the main engine for speed control and steering the gear system for course alteration. Sophisticated automation is in place and typically only requires human intervention for selecting the appropriate values through the engine speed controller (i.e., Telegraph or Controllable Pitch Propeller Controller) and wheel-order or course-to-steer in Autopilot. However, in congested waters where large AoC takes place frequently, manual steering is mandatory instead of using the Autopilot.

Step 8. Action Monitoring

This step is to check the effectiveness of the initiated action. This function shall ensure that the dangerous targets are away from the threshold of DIP values and ascertain the safe clearance from ships' domain of safety so that the ship can resume its original route.

4.2. Descriptive classification of fragmented functions

A detailed classification of CCAP mapping is generated and presented in Table 1. The highlighted functions (in bold italic) are identified as 'Human Dependent' and require further digital integration to achieve 'Digital Autonomy'.

4.3. Outcome of an academic literature review

Initially, a total of 168 academic papers were filtered from the Scopus database with the selected keywords mentioned in Section 3.3. However, only 32 papers were selected for the analysis based on the criteria mentioned in Section 3.3. Their details are presented in Table 2.

5. Results

5.1. Function-flow mapping of CCAP

Based on the concept presented in Fig. 1 and Table 1, a code-oriented function-flow-map to give a graphical overview of the CCAP is shown in Fig. 4. The code system helps to show the sequential process and the dependence of a function on the previous one. The map highlights two types of inputs in the CCAP process. Primary inputs (dark blue) are obtained from independent sources such as equipment, sensors, and information from publications and manuals. Secondary inputs (light blue) either rely on primary inputs or the outputs of preceding functions.

This flow map assists readers in understanding the overall CA process in a systematic manner throughout the study and distinguishes the primary and secondary data requirements for each main CA function. For example, 1.1.1 (Ship Dynamic Data) is an input for 1.2.1 (DIP values) and 2.1.1 (Heading of the vessel), this means Ship Dynamic Data is required data to get a DIP value and Heading of the vessel. Output data (orange) is the final data of the CA function at that level (e.g., 2.3.1 is the output data of CA function 2), but it can also be an input of the next level CA function (e.g., 2.3.1 is the input data of 3.1.1). The orange arrows show the sequences of the 8 CA functions.

To achieve autonomous decision-making, it is crucial to develop digital platforms to gather primary input data. Some data can be generated by shipborne instruments (e.g., Gyro compass, speed log, GPS), and is almost fully digitalised. Other data is dependent on the dynamic status of the ship (e.g., ship status, etc.) requiring AI integration to process and recognise the physical status of vessel operability based on COLREG. Informative data (e.g., sailing direction, tidal and current data, VTS data, Meteorological data) is generated externally and conveyed to the ship via different means (e.g., digital publications, radio broadcasts, linguistic data), and would require extreme digitalisation to produce digital platforms that can operate autonomously. An ECDIS platform has made progress in producing a universal means of collecting some primary input data (e.g., chart update data, notices to mariners) with minimal human intervention, where data exchange and application occur automatically.

5.2. Analysis of existing digital contribution to CCAP

This analysis is performed to evaluate the current status of main CA functions and to develop a baseline for further research.

5.2.1. Extent of existing human intervention and digital contribution

The status of human and digital contribution in each fragmented function has been examined based on its modern capabilities (see Section 4.2). Each code is rated either to denote "Human Dependent" or "Digital Autonomy" to provide comprehension of the autonomous functional state at present. Fig. 5 presents the level of human dependence in each main CA function according to the number of codes, reflecting the level of human involvement. Three interesting results (i.e., Situation Awareness, Target detection and CA action selection) are discussed as follows:

Situation Awareness is associated with the highest number of CA functions and therefore with most of the code (i.e. 18 in total). A significant portion of the input data for this function comes from independent sources (e.g., digital publications but not real-time or near real-time data) that are not fully integrated into INS systems due to limited digitisation. Thus, human intervention still requires interpreting these data and evaluating outputs. For instance, DIPs (CPA, TCPA, etc.) are still evaluated by navigators with their judgement and experience supported by the collected data.

Target Detection is the only full Digital Autonomy function of CCAP. This is because the instruments used, such as the Radar and AIS, can detect targets automatically without human involvement. This assumes that these instruments are functioning optimally, and any operational flaws are not considered in this study. In practice, a navigator continuously monitors the equipment, but such elements are not covered in the scope of the study.

CA Action Selection is the only entirely Human Dependent function. Currently, there is no system in place to digitally interpret the COLREG, which impedes its automation. As modern ships still require sea crews at the bridge, there has been limited development of a decision-support system or mechanism. With the development of MASS, finding a solution for digital autonomy in this function may become a priority.

5.3. Academic research interests over fragmented CA functions

By comparing the content references of academic literature to fragmented CA functions, it can aid in providing a state-of-the-art understanding of recent scholarly research trends and shortcomings in maritime CA autonomy. This analysis can help identify dormant functions that have been minimally or not addressed in the literature and highlight areas where future studies could focus on in the CCAP.

5.3.1. Autonomy contribution chart

Table 3 maps individual papers through their identification number (i.e., Lit. ID) to their study outcomes by mapping the codes they addressed. In each row, the X represents the CA functions addressed in the paper, whereas the blank indicates omissions. This provides a clear graphical overview of individual coverage of autonomy development

Table 1
CCAP classification.

No	Code	CA Function	Brief Explanation
	1	Situation Awareness	
	1.1	Inputs	
1	1.1.1	Ship Dynamic Data	Comprises values of Course Over Ground, Speed Over Ground, Heading of the vessel, speed log, position, Rate of Turn, etc., that change with ship motion
2	1.1.2	Ship Static Data	Comprises Ship Dimensions, Unique Identities (i.e., Name, Maritime Mobile Service Identity No, IMO No), etc., inherent to the ship
3	***1.1.3***	***Voyage Data***	Comprises information on Draught, Destination, Estimated Time of Arrival, Type of Cargo, etc., particularly for the current voyage
4	***1.1.4***	***Ship Status***	Contains Navigation status of the ship at present (i.e., Power Driven Vessel / Vessel Not Under Command / Vessel Restricted In her Ability to Manoeuvre / Sailing Vessel)
5	***1.1.5***	***VTS Data***	Provides local communication means, speed limits, Traffic info, mandatory and dynamic traffic requirements
6	***1.1.6***	***Chart Update Data***	Electronic Navigation Chart updates, these are crucial amendments to operating areas for safe navigation
7	***1.1.7***	***Tidal and sea current data***	Crucial for evaluating dynamic effects on ships' manoeuvrability and safe navigable depths
8	***1.1.8***	***Notices to Mariners Data***	Consists of crucial information to adopt, avoid, or consider for safe navigation in the area
9	***1.1.9***	***Sailing Direction Data***	Provides specific vital information including safer routes, and navigational dangers in coastal regions
10	***1.1.10***	***Meteorological and Weather Data***	Provides regional weather prognosis, and surface analysis data. (i.e., Wind force/ direction, sea state, wave height, visibility, precipitation, etc.)
	1.2	Evaluation/ Processing	
11	***1.2.1***	***DIP values***	Predetermining threshold safety parameters (i.e., CPA, TCPA, BCR, BCT to detect dangerous targets)
12	***1.2.2***	***SSM values***	Predetermining safety zones to maintain the ship within, to avoid running into navigational dangers other than traffic. (i.e., channel limits, safety depths, Look-ahead limits, etc.)
13	1.2.3	Safe Navigable Area Identification	Process of screening the operating area on electronic navigation charts for charted dangers and highlighting unsafe regions as per safety depth.
14	***1.2.4***	***Safe Route***	Process of selecting the safe path with respect to existing navigational hazards and avoiding dense traffic
	1.3	Outputs	
15	***1.3.1***	***DIP Data***	Limits of CPA, TCPA, BCR, BCT (Use to detect dangerous targets)

No	Code	CA Function	Brief Explanation
16	***1.3.2***	***SSM Data***	Safety Channel Margins, look ahead zones, Guard Zones, etc., are used to detect charted navigational hazards other than ships. Crucial for dynamic detection of topographical dangers
17	1.3.3	Safe Navigable Area Data	Referred during the selection of avoidance-action in respect to available sea-room for manoeuvre
18	***1.3.4***	***Safe Route Data***	Use to navigate the ship safely with minimal risks to the intended destination
	2	Target Detection	
	2.1	Inputs	
19	2.1.1	Heading of the vessel	Provides Direction of ship motion
20	2.1.2	Speed of Ship	Provides speed of the ship
21	2.1.3	Position of Ship	Provides position of the ship
	2.2	Evaluations/ Processing	
22	2.2.1	Detecting Targets in the Vicinity	Process of locating and identifying the target in the ship's vicinity
23	2.2.2	Evaluating the Status of Targets	Acquiring the navigation status of the targets
24	2.2.3	Evaluating/ Acquiring Target Motion Data	Evaluating the position, ID, true and relative CO, speed, and CPA, TCPA, BCR, BCT, RB of targets
	2.3	Outputs	
25	2.3.1	Target Data	Target ID, position, True/ Rel. CO, speed, CPA, TCPA, BCR, BCT, RB
	3	Determination of Danger targets	
	3.1	Inputs	
26	3.1.1	Target Data	Target ID, position, True/ Rel. CO, speed, CPA, TCPA, BCR, BCT, RB
27	***3.1.2***	***DIP Data***	Limits of CPA, TCPA, BCR, BCT (Use to detect dangerous targets)
28	***3.1.3***	***SSM Data***	Channel Margins, Look ahead zones, Guard Zones, etc.
	3.2	Evaluation/ Processing	
29	3.2.1	Identifying Dangerous targets	Process of identifying targets infringing the safety threshold limits (DIP) of the ship
	3.3	Outputs	
30	3.3.1	dangerous target Data	dangerous targets ID, position, True/ Rel. CO, speed, CPA, TCPA, BCR, BCT, RB
	4	Determination of situation and rule	
	4.1	Inputs	
31	4.1.1	Dangerous targets Data	dangerous targets ID, position, True/ Rel. CO, speed, CPA, TCPA, BCR, BCT, RB
	4.2	Evaluation/ Processing	
32	***4.2.1***	***Identification of Collision Danger Situation***	Process of identifying developing situations according to COLREG or Local regulations
	4.3	Outputs	
33	***4.3.1***	***Collision Danger Situation Data (CDSD)***	Head-on/ Crossing/ Overtaking/ Keep-out-of-the-way

No	Code	CA Function	Brief Explanation
	5	Determination of Available Sea-Room	
	5.1	Inputs	
34	***5.1.1***	***CPA Position Data***	Estimated geographical positions of the own ship and dangerous targets at CPA occurrence
35	5.1.2	Ship Safety Margins Data	Channel Margins, Look ahead zones, Guard Zones, etc.
36	5.1.3	Safe Navigable Area Data	Referred during the selection of avoidance-action in respect to available sea-room for manoeuvre
	5.2	Evaluation/ Processing	
37	***5.2.1***	***Evaluation of ASR at CPA***	Process of evaluating sufficiency of the sea area for CA manoeuvre
	5.3	Outputs	
38	***5.3.1***	***ASR Data***	Extent of available sea area on the chart display
	6	CA Action Selection	
	6.1	Inputs	
39	***6.1.1***	***ASR Data***	Extent of available sea area on the chart display
40	***6.1.2***	***CDSD***	Head-on/ Crossing/ Overtaking/ Keep-out-of-the-way
41	***6.1.3***	***SMD (Ship Manoeuvring Data)***	Max/Min Speed, Critical Revs, stopping distances, turning circles for Laden and Ballast conditions
	6.2	Evaluation/Processing	
42	***6.2.1***	***Selection of Avoiding Action Manoeuvre***	Best option of action determining either AoC or AoS or blend of both
	6.3	Outputs	
43	***6.3.1***	***AoC Data***	Heading of the vessel Value
44	***6.3.2***	***AoS Data***	Speed value
	7	Action Execution	
	7.1	Inputs	
45	7.1.1	AoC Data	required Heading of the vessel Value
46	7.1.2	AoS Data	required speed value
	7.2	Evaluation/Processing	
47	7.2.1	Processing AoC Manoeuvre	Turning of the ship by the steering gear control system
48	7.2.2	Processing of AoS manoeuvre	Adjustment of the speed by ME speed control system
	7.3	Outputs	
49	7.3.1	New Course	New Course Over Ground value
50	7.3.2	New Speed	New Speed Over Ground value
	8	Action Monitoring	
	8.1	Inputs	
51	8.1.1	Dangerous target Data	dangerous target ID, position, True/ Rel. CO, SPD, CPA, TCPA, BCR, BCT, RB
	8.2	Evaluation/Processing	
52	8.2.1	Identify Danger is Past and Clear	Process of confirming the exit from collision danger. For dangerous targets passing astern of the own ship (OS), negative TCPA confirms safe clearance but for dangerous targets passing ahead of the OS consider negative BCT for safe clearance.
	8.3	Outputs	
53	8.3.1	Collision Danger Exit Confirmation Data	TCPA, BCT, and negative time values constitute historical events thus the resembling events (i.e., CPA and BCR) can be confirmed as past and clear.

Table 2
Selected literature.

No	Authors	CA functions	Autonomy development fundamentals
1	Han et al. (2022)	4.2.1, 4.3.1, 6.1.2, 6.2.1, 6.3.1, 6.3.2, 7.1.1, 7.1.2	• The strategy consists of two layers: global path-guided and local reactive layers, which rely on expanded Theta* (ETheta*) and an enhanced artificial potential field approach. • In the global layer, a nominal mapping relation is established by running ETheta* in reverse. Sub-targets derived from the nominal mapping relation are used to guide the unmanned surface vehicle (USV), ensuring it avoids all stationary obstacles and reaches its destination. • The local layer generates a dual-attractive potential for nearby sub-targets and a grid-based repulsive potential for irregularly shaped stationary obstacles. • A repulsive potential aligned with COLREGs is generated when the USV detects a potential collision hazard. • The autonomous obstacle avoidance and navigation of the USV is achieved by computing the gradient of the steepest descent in the overall potential field and employing a PID (Proportional-Integral-Derivative) control method.
2	Miao et al. (2022)	1.1.1, 1.2.4, 1.3.4, 2.2.1, 2.2.2, 2.2.3, 2.3.1, 3.1.1, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1	• Based on the given missions and chart data, the global path planning module generates an initial path. • The autopilot issues precise steering and propulsion commands to ensure the own ship follows the designated path. • The sensor module, including endogenous and exogenous sensors, to collect the present condition of the ship and the status of surrounding obstacles. • In contrast to the global path planning module, the local CA module is designed to adjust the local route based on the dynamic and more detailed environmental context. • The authors assumed the following information is available: o Real-time updates on the OS's position, velocity, and heading o The positions and velocities of the obstacle states o The desired destination of the ship o Kinematic and dynamic models of the ship o A predictive model for estimating the future trajectories of obstacles. o Static environmental information such as shoreline contours, water depths, etc. o Measurements of wind speed and ocean current relative to the sailing area. • A collision pre-check technique (collision velocity check) has been introduced and implemented.
3	Zheng et al. (2022)	1.2.1, 1.3.1, 2.2.3, 2.3.1, 3.1.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.2.1, 6.3.1, 7.1.1	• A predictive control strategy is formulated for dynamic CA and formation trajectory tracking of MASS. • A trajectory-tracking nonlinear controller for MASS was developed in the framework of model predictive control. • A ship collision risk index is introduced as a CA constraint within the controller's framework
4	Zhou et al. (2022)	4.2.1, 4.3.1, 6.1.2, 6.2.1, 6.3.1, 6.3.2, 7.1.1, 7.1.2	• Path generation algorithm that combines Bézier curves integrated with a stream function. • The application of circular theorem within a sink flow context • Vortex flows in the flow field
5	Zhang et al. (2022)	3.1.2, 3.1.3, 3.2.1, 3.3.1, 5.1.1	• Real-time Collision Prediction model combined with AIS data, analyse encounters conflict probability in real-time quantitatively. • Algorithm 1: K-means algorithm.
6	Zhen et al. (2022)	1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1	• AIS databased clustering algorithm DBSCAN (Density-based spatial clustering of applications with noise) to identify DIP and to cluster the real-time navigation ships, Mercator's algorithm to calculate distance, • Collision risk index to prioritise targets by ranking them.
7	He et al. (2022)	1.1.7, 1.1.10, 1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 6.1.3	• The utilisation of VO theory, and dynamic CA algorithm to establish an autonomous manoeuvring mode.
8	Xu et al. (2022)	1.1.7, 1.1.10, 1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.1.3, 8.1.1, 8.2.1, 8.3.1	• A hybrid CA algorithm based on deep reinforcement learning is Introduced.
9	Bakdi and Vanem (2022)	1.1.3, 1.1.7, 1.1.10, 1.2.2, 1.2.3, 1.3.2, 1.3.3, 4.2.1, 4.3.1, 6.1.2	• Implementing algorithmic COLREGs within real-world applications for MASS. • Utilising a fuzzy expert system based on ordinary seamanship practice.
10	Liu et al. (2022)	1.2.3, 1.3.3, 3.2.1, 3.3.1, 4.1.1, 5.1.3, 6.1.3	• An optimisation algorithm considering both global route planning and local CA. • Nonlinear constraint optimisation models are created to address limitations related to obstacles, safe water depth and ship steering. • Potential Energy A* algorithm and a route planning framework are introduced, employing potential energy fields to precisely express the environment.
11	Murray and Perera (2022)	3.2.1	• Historical AIS data are utilised to forecast the future trajectory of a chosen ship. • Employing a system intelligence-driven method that can later be employed to enhance navigators' situation awareness and as well as MASS, facilitating proactive CA. • By assessing historical ship behaviour within a specific geographical area, the approach applies machine learning methods to identify shared characteristics in relevant trajectory segments. • Extracted trajectories are condensed through the Karhunen–Loéve transform, and grouped together by applying a Gaussian Mixture Model
12	Blindheim and Johansen (2021)	1.2.1, 1.2.3, 1.3.3, 4.2.1, 6.1.1	• Electronic Navigation Chart visualisation and manipulation application programming interfaces implemented in Python
13	Zhao and Fu (2021)	3.1.1, 3.2.1, 3.3.1, 4.1.1, 6.2.1	• To improve the accuracy and objectivity of the collision risk index by accounting for dimension-related factors, and to make the index more user-friendly in collision avoidance decision-making, a "margin of projected collision" index has been developed. This index combines dimension data from AIS with the VO approach. (Enhance the identification of dangerous targets and with suitable velocity data to avoid collision CA action selection can be enhanced

(continued on next page)

Table 2 (*continued*)

No	Authors	CA functions	Autonomy development fundamentals
14	Chen et al. (2021a)	1.2.1, 1.2.2, 1.3.1, 1.3.2, 3.1.2, 3.1.3, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.2.1, 6.3.1, 7.1.1	• A collaborative CA method for multiple vessels is devised, employing a multi-agent deep reinforcement learning algorithm. • Neural networks are employed in this context to model actions, observations, and cooperative interactions.
15	Li et al. (2021a)	1.2.1, 1.2.2, 1.3.1, 1.3.2, 3.1.2, 3.1.3, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.2.1, 6.3.1, 7.1.1	• Utilising a Deep Q-learning network, continuous interaction with a visually simulated environment is employed to acquire experience data. This enables the agent to learn optimal action strategies within the visually simulated environment. • To solve the potential CA scenarios during USV navigation, the position of the obstacle ship is categorised into four CA zones in accordance with the COLREGs. • To enhance the Deep Q-learning network algorithm, the artificial potential field algorithm is used to refine both the action space and the reward function. • A simulation experiment is conducted to assess the performance of the proposed method. • The improved deep reinforcement learning effectively facilitates autonomous CA path planning.
16	Li et al. (2021b)	1.2.1, 1.2.2, 1.3.1, 1.3.2, 3.1.2, 3.1.3, 3.2.1, 3.3.1, 4.1.1, 6.2.1, 6.3.1, 7.1.1	• Rule-aware ship domains with parametrically formulated which are inherent to ship • The relative distance between ships considering rule-aware ship domains and ship manoeuvrability- Calculation of Dangerous Actions based on the relative distance between ships • Instead, CPA and TCPA, ship domain is adapted with danger zones to identify dangerous targets. • A Rule-aware Time-varying Conflict Risk (R-TCR) measures the capability to prioritise dangerous targets.
17	Chen et al. (2021b)	2.2.1, 2.2.3, 2.3.1, 4.2.1, 4.3.1	• Utilising deep learning techniques, ships' encounter situation modes are determined through AIS data. • Employing a Semi-Supervised Convolutional Encoder-Decoder Network, ship encounter situations are classified based on AIS data
18	Vestre et al. (2021)	1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 8.1.1, 8.2.1, 8.3.1	• A scalable algorithmic for handling extensive raw AIS data employing the CPA framework.
19	Ni et al. (2021)	1.2.1, 1.3.1, 3.1.2, 3.2.1, 4.2.1, 4.3.1, 6.2.1, 6.3.1, 6.3.2, 7.1.1, 7.1.2	• An anti-collision path planning algorithm is employed, which quantified anti-collision manoeuvre within the algorithm. • The utilisation of Boolean expression technology facilitates the determination of encounter situation types and corresponding action automatically. • Apparent actions are quantified and integrated into the VO algorithm, enabling the calculation of a feasible course region for the give-way ship. Moreover, the introduction of virtual repulsion forces and a predefined parameter for the number of time steps expands the applicability and enhances the practicality and rationality of the optimised solution. • Specifically designed for open sea encounter
20	Zhu et al. (2021)	3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.2.1, 6.3.1, 7.1.1	• An innovative CA algorithm was introduced based on a modified artificial potential field method, to develop a functional MASS CA system. • The CA algorithm is implemented through a path-guided hybrid artificial potential field approach.
21	Liang et al. (2021)	3.2.1, 3.3.1, 4.2.1, 4.3.1, 6.1.2, 6.1.3, 6.2.1, 6.3.1, 7.1.1	• The A* algorithm is improved. It incorporates a safe distance setting and optimisation of the route's roll. Unlike manual configuration of danger zones, this algorithm allows for the direct specification of a safe distance from the shoreline. • Minimum course alteration is introduced to avoid collision with target ships. The algorithm is constrained by COLREGs
22	Kang et al. (2021)	1.2.2, 1.3.2, 1.3.4, 3.2.1, 3.3.1	• A path-planning method was introduced. A ship domain model was adopted to evaluate the collision risk among vessels, utilising both static and dynamic information sourced from onboard monitoring equipment. • Multiple test scenarios were formulated to assess the algorithm. Each scenario represents various combinations of typical encounters in COLREGS
23	He et al. (2021)	1.3.1, 3.1.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.1.3, 6.2.1, 6.3.1, 7.1.1	• Ship course-control system employs a fuzzy adaptive PID control approach to achieve real-time system control. • The ship's automatic course-altering process is forecasted by integrating the ship-motion model with a PID controller. • A scene-identification model is created to identify these situations and the course-altering range of the OS is determined via an enhanced velocity obstacle model
24	Zaccone (2021)	1.2.4, 1.3.4, 2.2.1, 2.2.3, 2.3.1, 3.1.1, 3.1.2, 3.2.1, 3.3.1, 6.1.2, 6.2.1, 6.3.1, 7.1.1, 7.2.1, 7.3.1, 8.1.1, 8.2.1, 8.3.1	• An optimal path-planning algorithm, based on the Rapidly Exploring Random Tree • A system for guidance and control is introduced.
25	Lazarowska (2021)	1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.2.1	• Trajectory Base Algorithm, a deterministic method for real-time path-planning with CA is proposed.
26	Chun et al. (2021)	1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.2.1, 6.3.1, 7.1.1	• A quantitative assessment method for collision risk is proposed according to the ship domains and the CPA. It further generates a path for CA. • Ship domain is presented as an asymmetric shape integrating manoeuvring performance and the COLREGs. • CPA is employed as a quantitative metric for assessing collision risk. • To determine the avoidance time and to generate an avoidance path that aligns with COLREGs for the ship with the highest collision risk, a path generation algorithm applying deep reinforcement learning has been introduced.
27	Lei et al. (2021)	3.2.1, 3.3.1, 6.2.1, 6.3.1, 7.1.1	• Through a machine learning approach, the framework can generate a model of interactive movement behaviour using historical AIS traffic data that includes near-collision scenarios. It can generate several predicted trajectories for ships during encounters.
28	Zhang et al. (2021)	1.3.1, 3.1.2, 6.2.1, 6.3.1, 7.1.1	• A collision avoidance path planning method for ships is proposed according to a heuristic algorithm.

(*continued on next page*)

Table 2 (*continued*)

No	Authors	CA functions	Autonomy development fundamentals
29	Ha et al. (2021)	1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.1.3, 6.2.1, 6.3.1, 7.1.1	• The proposed method assesses collision risk by utilising the CPA and establishes the ship domain as a threshold value for collision risk to ensure dependable CA.
30	Geng et al. (2019)	2.2.1, 2.2.3, 2.3.1, 3.1.1, 3.2.1, 3.3.1, 4.1.1, 6.1.1, 6.1.3, 6.2.1, 6.3.1, 6.3.2, 7.1.1, 7.1.2	• Velocity obstacle models with both dynamic and static obstacles are employed to depict the potential conflict-free areas. • A motion planning algorithm based on the velocity obstacle model is introduced and improved by a way-blocking metric to evaluate the risk of collision. • A dynamic programming approach is proposed to generate an optimal motion plan comprising multiple intervals for MASS. • MASS systems are typically equipped with a variety of sensors, including cameras, Lidar, laser radar, and ultrasound radar.
31	Shi et al. (2019)	1.2.1, 1.2.3, 1.2.4, 1.3.1, 1.3.3, 1.3.4, 3.1.2, 6.2.1	• An initial reference path is generated using a hybrid A* algorithm that incorporates constraints from motion primitives. • Based on the specific types of dynamic obstacles, COLREG rules are applied, and a local threat map is created based on Apollonius circles to facilitate obstacle avoidance.
32	Lyu and Yin (2018)	1.2.2, 1.2.3, 1.2.4, 1.3.3, 1.3.4, 3.2.1, 3.3.1, 4.1.1, 4.3.1, 5.2.1, 5.3.1, 6.1.1, 6.1.2, 6.2.1, 6.3.1, 7.1.1	• A hybrid artificial potential field method guided by a predefined path

attempted over the 53 codes (CA functions). The study's contribution coverage over CCAP codes is charted statistically and graphically using the green scale bars on the right-hand end of Table 3 to show the percentage coverage of the CCAP functions for each paper.

5.3.2. Spectrum analysis for literature density and CCAP code coverage

Table 4 displays the number of academic articles under each CCAP code for each year of publication (2018, 2019, 2021, and 2022) and overall. This highlights the popularity of academic interest in autonomy integration and the overall coverage of CCAP codes.

When analysing the grey scale spectrums, darker regions in the intensity analysis represent the CCAP codes with high concentration for autonomy establishment. Research published in 2021 and 2022 shows concentrated efforts to deliver solutions in the inputs, evaluation/process, and outputs of “Determination of Dangerous Targets” (No.3) and “Determination of Situation & Rule” (No.4), and “CA Action Selection” (No. 6) (i.e., cover from 3.1.2 to 4.3.1 and 6.1.2 to 7.1.1). However, some of these codes (especially No 6) lie within the white zones of the “Existing Digital Contribution” (i.e., green bar chart), indicating a vacuum in existing digital contribution. On the contrary, efforts towards addressing autonomy demand in “Situation Awareness” (No.1) seems minimal, with many codes being white patches. In addition, although “Determination of ASR” (No.5) has three codes covered by existing digital contribution, the rest of two (i.e., 5.2.1 and 5.3.1) have limited research addressing these two codes in the existing literature. This indicates significant lags in recent studies. The only productive endeavour toward prevailing autonomy demand was covered by Lyu and Yin (2018).

a) Highly concentrated CCAP codes

12 codes are observed when considering highly concentrated CCAP codes, including 1.2.1, 1.3.1, 3.1.2, 3.2.1, 3.3.1, 4.1.1, 4.2.1, 4.3.1, 6.1.2, 6.2.1, 6.3.1 and 7.1.1 (see from the overall row in Table 4). After extracting the data, Table 5 shows that the majority (9 out of 12) of the functions are still human-dependent. In contrast, there are three codes indicating mature autonomous operations in modern navigation systems.

b) Analysis of coverage

Fig. 6 helps identify the remaining human-dependent functions that have not been addressed by any of the studies. This gives a clear understanding of how far academic studies have collectively come within the past five years. The human-dependent CA functions that have not yet been addressed by any of the reviewed studies are "1.1.4, 1.1.5, 1.1.6, 1.1.8, and 1.1.9″, which are inputs to “Situation Awareness” and represent "Ship Status Data”, “VTS Data”, “Chart Update Data”, “Notices to Mariners Data”, and “Sailing Direction Data", respectively. It is noteworthy that although 1.1.2, 2.1.1, 2.1.2, 2.1.3, 5.1.2, 7.2.2, and 7.3.2 are also blank, they have already been addressed by existing digital solutions (i.e., the green bar) in practice. This implies that these are not highly expected to be targeted by scholars or, at least, not to the same extent as the ones mentioned earlier as not been addressed.

5.3.3. Distribution of literature over CCAP codes

5.3.3.1. Irregularity under “Situation Awareness”. The relationship between main functions and academic studies' outcomes (in Section 5.2) revealed that the "Situation Awareness" received a high number of references. However, the distribution of references within the "Situation Awareness" shows that more weight was given to "Evaluation/Processing" and "Outputs" and less to "Inputs" (Fig. 6). In CCAP, "Inputs" is crucial in the pursuit of full autonomy in collision avoidance, as it involves referring to various independent information and data sources for subsequent evaluation and processing. This imbalance highlights a gap in the state-of-the-art studies in the field.

5.3.3.2. Noteworthy trends. The CA functions enveloped within the clusters of Fig. 6, demonstrate their popularity among the scholarly studies. Among these clusters, “Determination of dangerous targets (3)”, “Determination of Situation & Rule (4)” and “CA Action Selection (6)” gain the recognition of being noteworthy trends since these three main functions are highly human dependent according to CCAP. Code 3.1.2 “DIP Data input” has been covered by more than 50% of the 32 studies. Code 4.2.1 “Identification of CDS” has also been covered by over 50% of the studies. Code 6.2.1, “Selection of Avoiding Action Manoeuvre” has been covered by more than 60%.

5.4. Base theories, concepts and trialling methods used in research studies

The analysis of the literature content data showed that the baseline theories and concepts used in the individual studies were grouped into 15 categories. Table 6 demonstrates the usage of the 15 theories and concepts in each study. Plotting the categories against each Lit.ID provides an overview of the concepts used in each study. The statistics show that most of the studies focused on algorithmic development and the use of algorithms has increased over time. Other popular theories including AIS data, artificial potential field theory, collision risk assessment based, deep reinforcement learning based, path-planning, and trajectory based, are often used in combination. However, according to the gathered information, most of the studies have been only tested through various simulations. Lazarowska (2021) is the only research that has conducted a preliminary real-life test of the algorithm.

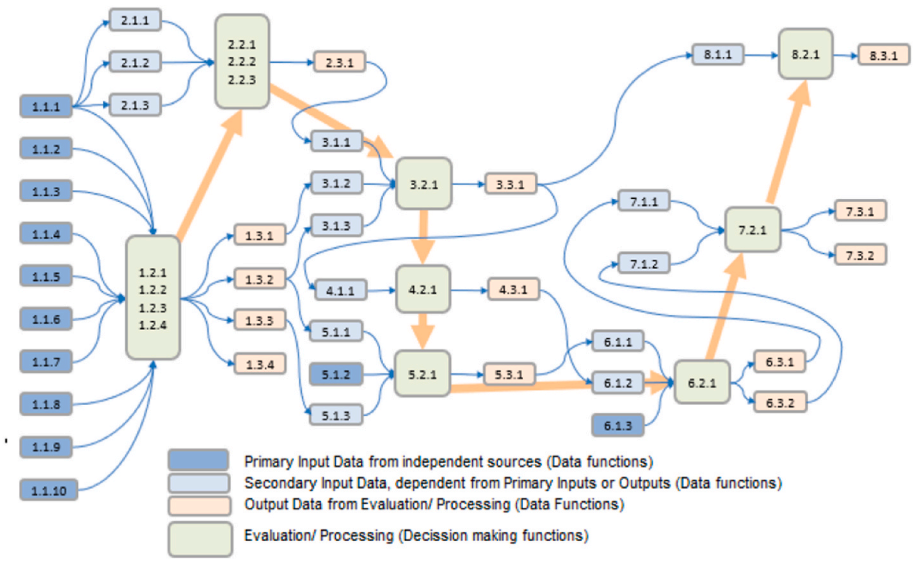

Fig. 4. Data-oriented function – flow map of CCAP.

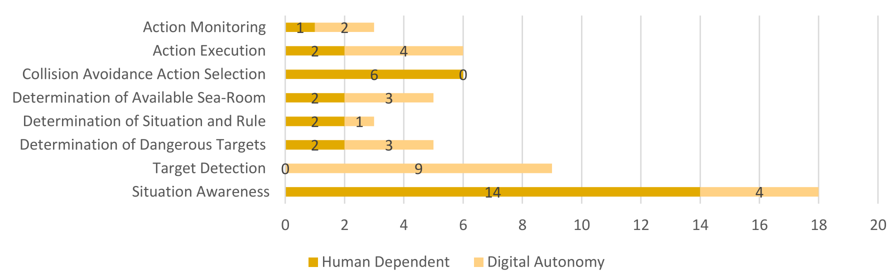

Fig. 5. Analysis of the existing status of fragmented functions of CCAP.

6. Discussion

6.1. Effectiveness of CCAP mapping

The CCAP mapping streamlines the human-centric Collision Avoidance (CA) process by delineating it into 53 fundamental functions across eight primary categories. Through systematic classification and codification, this approach facilitates rapid decoding when necessary. By subdividing each primary function into three sub-functions—inputs, evaluation/processing, and outputs—it aids in organizing literature content (references) related to both data-driven and process-driven advancements. This framework also allows for clear distinctions within each CA function, delineating aspects of autonomy development and facilitating grouping accordingly. While there may be occasional discrepancies in grouping literature content, efforts are made to assign the most appropriate CCAP codes. For example, Li et al. (2021) proposed a novel approach of defining ship-specific dynamic danger zones for identifying hazardous targets, which deviated from traditional methods. Rødseth et al. (2023) analysed the interaction problems between manned vessels and autonomous ships and provided a list of short- and long-term recommendations to address the problems. However, since this approach still pertained to the identification of danger parameters akin to CPA and TCPA parameters (DIP), it was coded under DIP. Thus, the CCAP mapping furnishes a comprehensive yet straightforward framework to advance research in the field. Additionally, it allows for flexible adjustments to address any oversights, offering a scalable structure and guiding insights for subsequent users to analyse and update the process as needed, particularly in light of evolving technologies. This structured approach would be beneficial for researchers unfamiliar with contemporary navigation practices, aiding in their comprehension of Collision Avoidance at sea.

6.2. Efficiency of the analysis and main findings

The examination of academic literature data uncovers valuable insights and gaps in scholarly research concerning CCAP codes. An analysis of literature density (see Section 5.3.2) reveals a notable trend, indicating the necessity for the research community to broaden their exploration into less emphasised CA functions. Furthermore, this analysis identifies a gap in studies concerning certain fragmented functions crucial for autonomy, such as the inputs associated with "Situation Awareness" and the evaluation of ASR. Moreover, there is an observable trend of inconsistent research focus within the "Situation Awareness" function (see Fig. 6), with a disproportionate emphasis on evaluation compared to inputs. Conversely, there exists a satisfactory body of research concerning autonomy-demanding aspects like the determination of situations and rules. Baseline theory analysis identifies common concepts and theories, such as AIS data, artificial potential field, VO, deep reinforcement learning, fuzzy logic, and machine learning. Additionally, potential instrument additions like cameras, LIDAR, laser radar, and ultrasound radar are highlighted (Geng et al., 2019. In recent years, an increasing amount of research has focused on path planning for MASS CA (for example, Zhao et al., 2023a; Zheng et al., 2023; Li et al., 2024; Li and Yang, 2023), incorporating data from sensor technologies (Zhao et al., 2023b), and artificial intelligence applications e.g. deep/-reinforcement learning methods (such as Teitgen et al., 2023; Chun

Table 3
Autonomy contribution chart.

No	CCAP / Lit ID	1.1.1	1.1.2	1.1.3	1.1.4	1.1.5	1.1.6	1.1.7	1.1.8	1.1.9	1.1.10	1.2.1	1.2.2	1.2.3	1.2.4	1.3.1	1.3.2	1.3.3	1.3.4	2.1.1	2.1.2	2.1.3	2.2.1	2.2.2	2.2.3	2.3.1	3.1.1	3.1.2	3.1.3	3.2.1	3.3.1	4.1.1	4.2.1	4.3.1	5.1.1	5.1.2	5.1.3	5.2.1	5.3.1	6.1.1	6.1.2	6.1.3	6.2.1	6.3.1	6.3.2	7.1.1	7.1.2	7.2.1	7.2.2	7.3.1	7.3.2	8.1.1	8.2.1	8.3.1	# Code Ref	Ref %
1	Han et al. (2022)																																X	X							X		X	X	X	X	X								8	15.1%
2	Miao et al. (2022)	X													X				X				X	X	X	X	X			X	X	X	X	X																					13	24.5%
3	Zheng et al. (2022)											X				X									X	X	X	X		X	X	X	X	X							X		X	X		X									15	28.3%
4	Zhou et al. (2022)																																X	X							X		X	X	X	X	X								8	15.1%
5	Zhang et al. (2022)																											X	X	X	X				X																				5	9.4%
6	Zhen et al. (2022)											X				X												X		X	X	X																							6	11.3%
7	He et al. (2022)							X			X	X				X												X		X	X	X										X													9	17.0%
8	Xu et al. (2022)							X			X	X				X												X		X	X	X	X	X							X	X										X	X	X	15	28.3%
9	Bakdi and Vanem (2022)			X				X			X		X	X			X	X															X	X							X														10	18.9%
10	Liu et al. (2022)													X				X												X	X	X					X					X													7	13.2%
11	Murry and Perera (2022)																													X																									1	1.9%
12	Blindheim and Johansen (2021)											X		X				X															X							X															5	9.4%
13	Zhao and Fu (2021)																										X			X	X	X											X												5	9.4%
14	Chen et al. (2021a)											X	X			X	X											X	X	X	X	X	X	X							X		X	X		X									15	28.3%
15	Li et al. (2021a)											X	X			X	X											X	X	X	X	X	X	X							X		X	X		X									15	28.3%
16	Li et al. (2021b)											X	X			X	X											X	X	X	X	X											X	X		X									12	22.6%
17	Chen et al. (2021b)																						X		X	X							X	X																					5	9.4%
18	Vestre et al. (2021)											X				X												X		X	X	X	X	X																		X	X	X	11	20.8%
19	Ni et al. (2021)											X				X												X		X			X	X									X	X	X	X	X								11	20.8%
20	Zhu et al. (2021)																													X	X	X	X	X									X	X		X									8	15.1%
21	Liang et al. (2021)																													X	X		X	X							X	X	X	X		X									9	17.0%
22	Kang et al. (2021)												X				X		X											X	X																								5	9.4%
23	He et al. (2021)															X											X	X		X	X	X	X	X							X	X	X	X		X									13	24.5%
24	Zaccone (2021)														X				X				X		X	X	X	X		X	X										X		X	X		X		X		X		X	X	X	18	34.0%
25	Lazarowska (2021)											X				X												X		X	X	X	X	X							X		X												10	18.9%
26	Chun et al. (2021)											X				X												X		X	X	X	X	X							X		X	X		X									12	22.6%
27	Lei et al. (2021)																													X	X												X	X		X									5	9.4%
28	Zhang et al. (2021)															X												X															X	X		X									5	9.4%
29	Ha et al. (2021)											X				X												X		X	X	X	X	X							X	X	X	X		X									13	24.5%
30	Geng et al. (2019)																						X		X	X	X			X	X	X								X		X	X	X	X	X	X								14	26.4%
31	Shi et al. (2019)											X		X	X	X		X	X									X															X												8	15.1%
32	Lyu and Yin (2018)												X	X	X			X	X											X	X	X		X				X	X	X	X		X	X		X									16	30.2%

Table 4
Literature densities and existing digital contribution.

CCAP / Year	1.1.1	1.1.2	1.1.3	1.1.4	1.1.5	1.1.6	1.1.7	1.1.8	1.1.9	1.1.10	1.2.1	1.2.2	1.2.3	1.2.4	1.3.1	1.3.2	1.3.3	1.3.4	2.1.1	2.1.2	2.1.3	2.2.1	2.2.2	2.2.3	2.3.1	3.1.1	3.1.2	3.1.3	3.2.1	3.3.1	4.1.1	4.2.1	4.3.1	5.1.1	5.1.2	5.1.3	5.2.1	5.3.1	6.1.1	6.1.2	6.1.3	6.2.1	6.3.1	6.3.2	7.1.1	7.1.2	7.2.1	7.2.2	7.3.1	7.3.2	8.1.1	8.2.1	8.3.1	# Code Ref
2022	1		1				3			3	4	1	2	1	4	1	2	1				1	1	2	2	2	5	1	8	7	6	6	6	1		1				5	3	3	3	2	3	2					1	1	1	97
2021											9	4	1	1	10	4	1	2				2		2	2	3	11	3	15	14	10	12	11						1	8	3	14	12	1	12	1	1		1		2	2	2	177
2019											1		1	1	1		1	1				1		1	1	1	1		1	1	1								1		1	2	1	1	1	1								22
2018												1	1	1			1	1											1	1	1		1				1	1	1	1		1	1		1									16
Overall	1		1				3			3	14	6	5	4	15	5	5	5				4	1	5	5	6	17	4	25	23	18	18	18	1		1	1	1	3	14	7	20	17	4	17	4	1		1		3	3	3	312
Existing Digital Contribution																																																						
Missing CA function																																																							
				1.1.4	1.1.5	1.1.6		1.1.8	1.1.9																																													

et al., 2024), among others. These studies represent the emerging trends and themes and are relevant for guiding future research. However, it is noted that a significant portion of studies predominantly concentrates on developing algorithmic solutions for AI-integrated decision-making in CA, potentially overlooking certain data-oriented autonomy developments in the academic research community.

7. Conclusion

In recent years, MASS has received significant attention from the maritime community. Although there have been successful trials (see W. Zhang et al., 2021) for the recent advances), the main barrier to the widespread adoption of MASS is the lack of an adequate regulatory framework and perhaps cost and insurance considerations. To address

Table 5
Highly concentrated CA functions in academic studies.

Human		Digital	
1.2.1	DIP values (evaluation)	3.2.1	Identifying Dangerous target (evaluation)
1.3.1	DIP data (output)	3.3.1	Dangerous target data (output)
3.1.2	DIP data (input)	4.1.1	Dangerous target data (input)
4.2.1	Identification of CDS (evaluation)		
4.3.1	CDSD (output)		
6.1.2	CDSD (input)		
6.2.1	Selection of avoiding action manoeuvre (evaluation)		
6.3.1	AoC Data (output)		
7.1.1	AoC Data (input)		

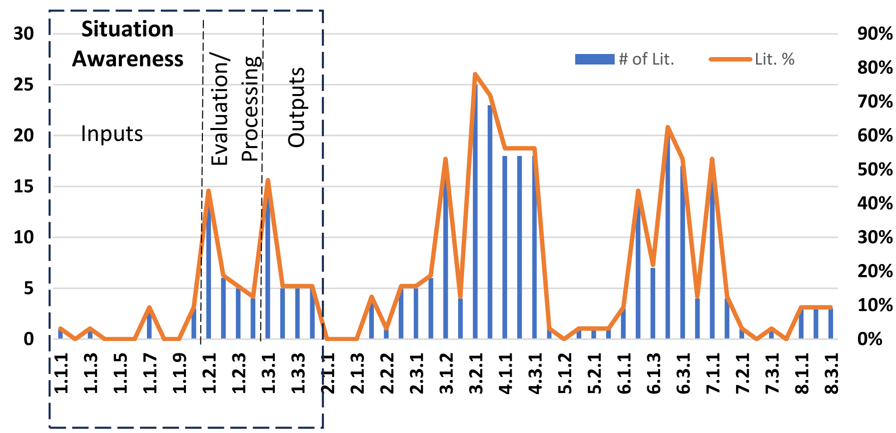

Fig. 6. Distribution of literature over CCAP codes.

this issue, the IMO initiated a regulatory scoping exercise, which highlighted the importance of COLREG among the priority regulations. However, the human-centred language of the provisions in COLREG has led many researchers to call for a digitised representation to enable the development of artificial autonomy. To address these issues, this study analyses the recent studies addressing the CCAP in human-withdrawal solutions.

By using CCAP, eight main functions were identified for future academic research in CA autonomy development that comply with COLREG, including situation awareness, target detection, determination of dangerous targets, determination of situation and rule, determination of available sea-room, collision avoidance action selection, action execution and action monitoring. Dividing the complex human-centred CA process into smaller, manageable parts was crucial, as it allowed for a more thorough examination of the priority-based processes and data flows for each main function. Analysing the existing digital autonomy status for each CCAP breakdown helped to identify the gap in digital autonomy. In addition, the challenge of inconsistent terminology usage in different papers was overcome through the classification.

This research provides guidance to academic researchers in the field of maritime CA by highlighting the trends of recent studies and encouraging the use of practical approaches in future studies on autonomy development. The analysis of recent studies is expected to give an overview of their focus, gaps, and the theories they are based on. The CCAP concept can be further developed to make it more user-friendly and to encourage researchers to carry out more comprehensive and productive studies in the future.

There are a few future research directions identified in this study.

First of all, several gaps for the attention of automatic collision avoidance have been identified from the existing literature, it is suggested that future research can address these gaps with an in-depth discussion on making relevant regulations to foster the development of maritime autonomy, especially for the development of MASS. Secondly, more empirical and primary data can be collected to further develop the findings from this review-based study. More specifically, it is suggested that future research can collect and analyse empirical data to evidentially support the importance and impacts of the CCAP on maritime autonomy from both safety and security perspectives. Thirdly, this research uses Scopus as the database to search the relevant studies from 2018 to 2022. Although an initial analysis of recent literature suggests that our results are valid, given the ever-increasing popularity of MASS research, it is suggested that future research could accommodate a large and comprehensive sample of academic papers, involving different databases and expanding the period covered. Fourthly, this paper mainly addresses the regulation from the CA perspective. There are other aspects that should be academically beneficial such as maritime education and training (MET) and new technologies for CCAP, and/or the relevant risk assessment, etc. Finally, maritime cybersecurity, an increasingly important and new challenge in the MASS sector due to its increasing dependence on IT and ICT, will also affect maritime autonomous systems and further affect CCAP. It is suggested that future research investigates this issue to prevent or mitigate any possible relevant catastrophic consequences.

CRediT authorship contribution statement

Chia-Hsun Chang: Conceptualization, Funding acquisition, Methodology, Supervision, Validation, Visualization, Writing – review & editing. **Isuru Bandara Wijeratne:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. **Christos Kontovas:** Validation, Writing – review & editing. **Zaili Yang:** Validation, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal

Table 6
Fundamental theories and concepts of academic studies.

Year	Lit. ID \ Base theory	AIS Data based	Algorithm	APF theory	CRA based	DRL based	ENC based	Fuzzy Logic	Machine learning	Path-planning	Sensor additions	Ship domain	Trajectory based	VO theory	Other novel concept	Other theory
2022	1			X												X
	2						X			X	X		X			
	3				X								X			
	4		X													X
	5	X	X													
	6	X	X		X											
	7													X		
	8		X			X										
	9		X					X								
	10		X													X
	11	X							X				X			X
2021	12						X									
	13	X												X		
	14		X			X										X
	15		X	X						X					X	X
	16											X			X	
	17	X														X
	18	X	X													
	19		X							X						X
	20		X	X												
	21		X													
	22		X									X				
	23							X						X	X	
	24		X													X
	25		X							X			X			
	26		X		X	X									X	
	27	X							X				X			
	28		X							X						
	29				X							X				
2019	30		X								X			X	X	X
	31		X												X	X
2018	32			X												
Overall		7	19	4	4	3	2	2	2	5	2	3	5	4	6	11

relationships which may be considered as potential competing interests: Chia-Hsun Chang reports financial support was provided by Economic and Social Research Council (ESRC).

Data availability

Data will be made available on request.

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