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Large language model-empowered technology evolution analysis of remote operation centres of maritime autonomous surface ships

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ABSTRACT

Remote Operation Centres (ROCs) are safety-critical shore infrastructures enabling Maritime Autonomous Surface Ships (MASS) through remote supervision, decision-making, and human-machine cooperation. However, fragmented ROC technologies hinder system-level understanding of their interactions, constraining reliability and safety assurance for fully autonomous maritime operations. This study develops a Large Language Model (LLM)-based patent analytics framework that can systematically enable the identification and mapping of ROC-related technologies from patent data. By integrating LLM-assisted topic modelling, complex network analysis, and temporal trend evaluation, the findings provide a data-driven perspective that captures both the evolutionary dynamics and structural interrelations among ROC technologies. An analysis of 973 relevant patents reveals 22 technology domains, with maritime data communication, remote control and teleoperation, remote condition monitoring, human-machine interface, and maritime positioning and navigation emerging as central and highly interconnected clusters. The results indicate that communication and teleoperation form the structural backbone of remote operation development. Temporal analysis shows technology development increased quickly after 2018, reflecting growing integration across sensing, communication, and control systems. The findings provide an evidence base for prioritising safety- and reliability-critical ROC technology development and for informing harmonised standards, operator competency requirements, and targeted investment to support safe, scalable MASS operations.

1. Introduction

Maritime transport forms the backbone of global logistics, facilitating the movement of vast quantities of goods across international supply chains [1]. As of early 2024, the global fleet comprised approximately 109,000 vessels of 100 gross tonnes or more, with maritime trade volumes reaching 12.3 billion tonnes in 2023 [2]. The scale and complexity of maritime operations make safety a critical priority for reliable, sustainable global logistics. In recent years, with the advancement of technologies such as Artificial Intelligence (AI) and big data, Maritime Autonomous Surface Ships (MASS) have increasingly been recognised as a transformative innovation that enhances both safety and operational efficiency by reshaping how vessels are monitored, controlled, and supported [3–5]. In 2018, the International Maritime Organization (IMO) introduced a four-level classification system for ship autonomy, which has since guided both industrial development and academic research [6]. Although the field still faces technical and human-centred challenges, such as multi-ship collision avoidance [7] and Remote Operators (ROs) competency, recent projects such as the Mayflower [8] and YARA Birkeland [9] have demonstrated the technical feasibility of autonomous ships and contributed valuable operational insights. As ships progress towards higher levels of autonomy across the four levels defined by the IMO [6], they require robust shore-based support infrastructure to ensure safe and scalable deployment. In particular, the availability and reliability of Remote Operation Centres (ROCs) are critical, as they provide continuous monitoring, supervisory control, and timely human intervention when required [10].

According to the IMO classification, at Level 3 autonomy and above, ships rely heavily on support from ROCs. To achieve these functions, they must integrate a wide range of technologies, including advanced communication and sensing systems, autonomous navigation, and decision-support mechanisms [11]. Together, these capabilities enable ships to operate with a high degree of autonomy while human operators maintain oversight and intervene when necessary through the ROC.

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From a system-safety perspective, these technologies should not be viewed as isolated components. Communication, monitoring, control, navigation, decision-support and Human-Machine Interface (HMI) functions are mutually dependent, and failure in one function may influence the performance of others. Therefore, systematically identifying ROC technologies and their interdependencies is important not only for describing technology evolution, but also for recognising safety-critical dependencies, potential failure-propagation pathways and resilience requirements in ROC-based MASS operations.

While previous studies have investigated specific elements of ROCs, such as HMIs, remote navigation, or condition monitoring [12,13], these analyses remain fragmented. Consequently, they do not capture the interdependencies among technologies that are essential for building safe, reliable, and scalable MASS operations. Moreover, existing approaches are predominantly qualitative, relying on case studies and questionnaire-based surveys, and thus provide limited empirical grounding [14]. Although regulatory and classification-society guidance for autonomous and remotely operated ships is emerging, current guidance still requires a stronger evidence base on the technological architecture of ROCs, including how key enabling technologies interact, co-evolve and jointly support remote supervision and control. As a result, current research provides limited evidence on how ROC technologies operate as an interconnected system and how such interactions may affect safety, reliability and operational resilience. This absence of a systematic, data-driven perspective constrains both the development of a comprehensive understanding of the ROC technology landscape and the formulation of practical guidance for regulators and industry stakeholders. Accordingly, there is a pressing need to establish a comprehensive mapping of ROC-related technologies that reveals their interactions and co-evolution, thereby supporting the progression towards higher levels of autonomy in MASS.

Analysing the technology evolution of ROCs is methodologically challenging because ROC capabilities are enabled not by a single technology, but by the interaction of multiple interdependent technological domains. This requires an analytical approach capable of capturing both the diversity of technologies and their interrelationships using large-scale technical evidence. Patent documents provide detailed technical descriptions and public disclosures across multiple technological domains over time. However, patents are typically long and technically dense, with core technological functions often embedded within extensive descriptions, while similar functions may be expressed using different terminology across documents [15]. In addition, analysing technology evolution requires patent data spanning multiple years, which further increases the scale and heterogeneity of the corpus. These characteristics pose significant challenges for analysing ROC technology synergies using manual review or conventional topic-modelling methods such as Latent Dirichlet Allocation (LDA) [16,17]. LLMs, built on transformer architectures and trained on massive datasets, excel at processing long texts and capturing semantic patterns across complex descriptions. Unlike conventional topic-modelling approaches that rely mainly on word co-occurrence, LLMs can interpret full patent texts contextually and recognise common technological functions even when different patents use divergent terminology [18]. Considering the limitations of traditional topic-modelling methods and building on these LLM capabilities, the present study develops an LLM-based topic modelling framework that applies LLMs to full patent texts to identify ROC technologies and their interrelations, thereby providing a structured and interpretable view of the ROC technology landscape.

Specifically, the framework identifies technology topics that support ROC functions in autonomous ships and generates both a technology topic list and a patent-to-topic mapping file. These topics are then represented as nodes in a technology topic network, with co-occurrences in the mapping file forming the edges. Complex network theory is subsequently employed to analyse the network's structural properties and temporal evolution. This integrated approach not only offers a comprehensive and data-driven understanding of ROC technologies and their role in advancing MASS autonomy but also yields insights into their development trajectories and provides guidance for future deployment. To the best of the authors' knowledge, this study represents a pioneering attempt at the systematic application of LLM-based topic modelling to extract a comprehensive technology topic list from patent data and to map ROC technologies for MASS.

The contributions of this research can be summarised as follows:

(1) This study proposes an LLM-based patent analytics method for identifying ROC-related technology topics from full patent texts. The methodological innovation lies in converting long, unstructured patent documents into structured, interpretable, and network-ready technology-topic data. This enables patent texts to be used for subsequent quantitative analysis of technological interconnections.
(2) This study develops a weighted technology-topic co-occurrence network that converts patent-based technology topics into a structured representation of ROC technological interdependencies. Unlike conventional topic-identification approaches that treat technologies as isolated entities, the proposed network framework captures how different ROC technologies are functionally connected and co-developed, thereby enabling systematic analysis of technology interaction patterns.
(3) This study applies complex network theory to quantitatively examine the interdependencies and structural organisation of ROC technology topics using advanced network metrics. By identifying central, bridging and peripheral technologies, the analysis provides a quantitative basis for recognising safety-critical technology dependencies and potential pathways through which technological degradation may affect ROC system performance.
(4) Building on the technology topic identification and network analysis, this study clarifies how the ROC technology network can inform risk-informed design, resilience engineering, policy and regulatory frameworks, and operator competency and training development. This integration of data-driven analysis with stakeholder-oriented insights ensures that the research outcomes are both theoretically significant and practically applicable to the safe and scalable implementation of MASS.

The rest of the paper is structured as follows. Section 2 reviews the relevant research work on MASS, ROCs, and the application of LLMs in the maritime domain. Section 3 outlines the methodology, including patent data processing, topic modelling, and the construction and analysis of the technology topic network. Section 4 presents the results of the technology identification and network analysis based on patent data. The discussion of the findings and implications of this study is presented in Section 5. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Literature review

To situate this study within the existing body of research, this section reviews prior work across three closely related strands: the development of MASS, enabling technologies and operational concepts of ROCs, and the application of LLMs in maritime and transportation research. By synthesising these streams, this review highlights how current studies remain fragmented and lack a systematic, data-driven perspective on the co-evolution and interdependencies of ROC technologies, thereby motivating the methodological approach adopted in this paper.

2.1. Development of MASS

In recent years, advances in technology have driven MASS development through a series of pioneering demonstration projects. The MUNIN (Maritime Unmanned Navigation through Intelligence in

Networks) project, initiated in 2012, was among the first to explore autonomous ship operations concepts [19]. More recent initiatives, such as the Yara Birkeland and IBM Mayflower, have demonstrated that vessels can operate with minimal or no direct human intervention [8,9]. These projects highlight that the implementation of MASS relies on a range of enabling technologies.

The development and implementation of MASS are enabled by integrating perception, communication, autonomous navigation, and control technologies [20–24]. Perception and sensing systems provide essential environmental data to support autonomous navigation [25,26], while advanced communication networks enable real-time transmission of this information between ships and ROCs [27]. Autonomous navigation and control technologies further ensure compliance with maritime regulations through data-driven decision-support and collision-avoidance mechanisms [28,29]. Within this domain, path-following navigation [30,31], and complex situational decision-making [32] remain key research areas that drive the advancement of MASS and enhance the role of ROCs in maintaining operational safety. In parallel, the development of realistic maritime traffic scenarios and robust risk assessment methods is essential for testing and validating MASS technologies to ensure their reliability before large-scale deployment [33,34]. As ships progress towards high levels of autonomy, robust shore-based support becomes critical. ROCs provide continuous monitoring, supervisory control, and timely human intervention, ensuring the safe operation of autonomous ships.

2.2. ROC and topicmodelling

ROCs form the operational link between autonomous ships and human operators. Remote Operators (ROs), working in combination with automation systems within ROCs, must ensure a level of safety equivalent to, or higher than, that of conventional onboard operations [35,36]. Human-Centred Design (HCD) has been identified as an important approach for improving Human-Machine Cooperation (HMC) in ROCs [37,38]. Various interface approaches have been developed to enhance ROs' performance, including Human-Computer Interfaces (HCI) [39,40], Graphical User Interfaces (GUI) [23], and Conversational User Interfaces (CUI) [41]. However, the introduction of new technologies also presents challenges for ROs, such as safety concerns [42,43] and issues related to competencies and training [44,45]. To address these, several studies have examined seafarer competency frameworks from a training perspective to improve the competencies required for future remote operators [46,47].

Existing studies on ROCs in autonomous shipping mainly examine individual technological domains, such as communication systems, decision-support tools, or remote monitoring and control mechanisms. Consequently, these studies only provide a partial view of the technological architecture of ROCs, without clarifying how individual components collectively support higher levels of ship autonomy.

To address this limitation, topic modelling offers a valuable analytical approach for uncovering latent semantic structures in large text corpora [48]. In the maritime domain, several studies have applied topic modelling to classify technological domains and forecast research topic trends [49–51], and this method has also been used to support maritime accident analysis [52]. Traditional topic-modelling approaches, such as LDA, represent documents as unordered collections of words and rely on probabilistic inference to estimate topic distributions [53]. These models often struggle with long, complex documents and the need for manual interpretation during topic selection [54]. As a result, conventional topic-modelling methods are limited in their ability to extract semantically coherent technological categories from long text data such as patents. Recent advances in LLMs have begun to address these limitations by enabling contextual interpretation of long and complex texts.

2.3. Patent dataminingand LLMs research

Patent data provides detailed descriptions of inventions, making it a valuable source for analysing technological developments, monitoring innovation trends, and supporting research in emerging domains [55]. Within the maritime sector, patent data has been employed to trace technological progress in areas such as navigation [56], and the development of autonomous ships [50,57]. Patent analysis has also been applied to assess the knowledge economy of transportation systems [58]. Nevertheless, the highly technical language of patents and the long text pose challenges for text processing and interpretation. To overcome these limitations, scholars have advanced a range of analytical methods, evolving from traditional bibliometric and citation-based approaches to contemporary computational techniques such as text mining and topic modelling [18,59]. In recent years, with the introduction of transformer architectures and advances in AI [60], LLMs have emerged as particularly powerful tools for patent data analysis.

Based on information on LLMs and their releasing organisations collected from publicly available online sources, Fig. 1 presents the growth in model scale by comparing the number of parameters across leading LLMs. From the figure, leading organisations such as OpenAI and Google continue to dominate LLM development, while new players have also entered the field.

LLMs possess architectural characteristics that make them highly effective for analysing complex and structured textual data. Their capacity for contextual interpretation has been demonstrated in various transportation and maritime applications, such as analysing survey responses to assess passenger satisfaction in public transport systems [61]. In the autonomous-shipping domain, LLMs have shown potential to enhance operators' situational understanding in complex and dynamic environments, thereby reducing misunderstandings within ROCs [62]. They have also been integrated into CUIs to support mission planning and execution in response to remote-operator commands [41,63]. Further applications include vessel-trajectory prediction [64], maritime mission planning [65], and risk information extraction from textual data to improve maritime safety analysis [66].

2.4. Research gapsand contributions

A synthesis of the literature reviewed reveals several unresolved gaps in the current understanding of ROC technologies for MASS. First, existing ROC-related studies predominantly examine individual technologies or functional components in isolation, resulting in a fragmented understanding that does not capture how ROC technologies interact, co-develop, and collectively support higher levels of autonomy. Second, although bibliometric and topic-modelling approaches have been applied in maritime research, current methods offer limited capability to systematically identify and structure complex technological domains from long and technically detailed documents such as patents. Third, while patent data and LLMs each demonstrate strong potential for technology analysis, their integrated application to systematically map and analyse ROC technologies in the autonomous shipping domain remains limited.

To address these gaps, this study contributes a data-driven and system-level perspective on ROC technology development. It introduces a framework that enables the systematic identification of ROC-related technologies from patent data and supports the analysis of their structural interdependencies and temporal evolution. The methodological novelty of the proposed LLM-based method lies in its ability to convert unstructured patent documents into a structured and analysable representation of ROC technologies. The resulting technology-topic identification outputs provide the basis for constructing a co-occurrence network among technology topics based on their co-occurrence within patents. Through this network, the structural relationships and temporal evolution of ROC technologies can be analysed, thereby linking LLM-based semantic extraction with quantitative technology evolution

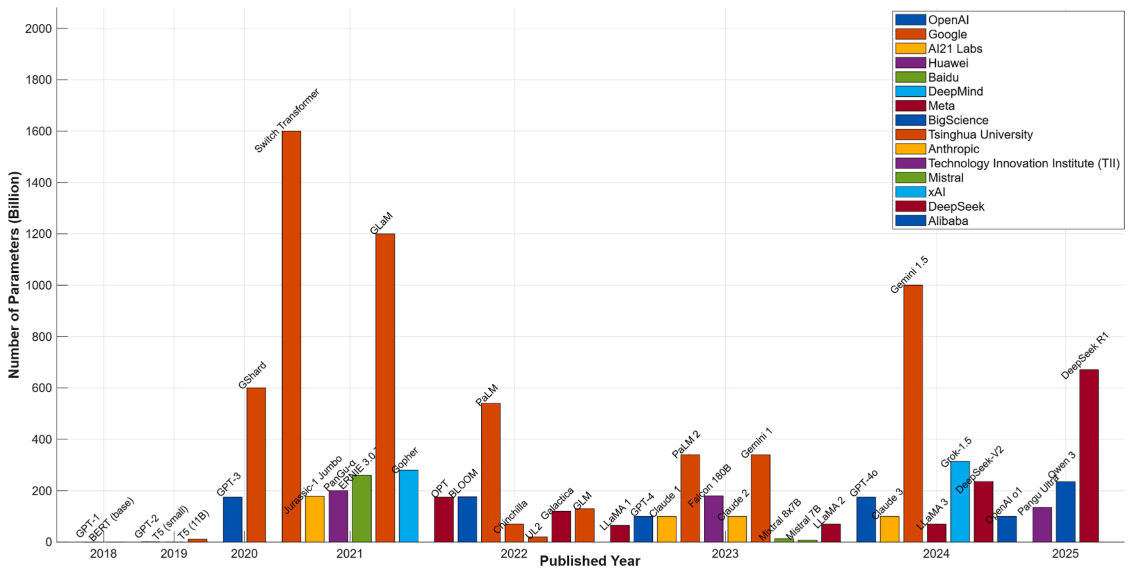

Fig. 1. Parameter sizes and releasing companies of LLMs.

analysis. By combining LLM-assisted topic modelling with network-based analysis, the study provides an integrated view of the ROC technological landscape, establishing a foundation for subsequent research on system design, policy development, and human-machine collaboration in MASS. Furthermore, it extends emerging studies on use of LLM to assist in risk and reliability analysis from accident reports [67,68] to patent context and opens a new direction on associating new technological maturity level with reliability of safety-sensitive products.

3. Methodology

Fig. 2 presents the framework for applying an LLM to identify technology topics from patent data and to construct a technology network capturing technological evolution in the ROC domain. The framework comprises three stages. First, patent records are retrieved and filtered by keywords and publication dates, followed by LLM-based screening of titles and abstracts to retain ROC-relevant patents. Second, an LLM-based topic modelling approach extracts semantically coherent technology topics from full patent texts, removes non-meaningful or low-frequency topics, and generates a structured topic list and a patent-to-topic mapping file. Third, these outputs are used to build a co-occurrence network in which nodes represent technologies and edges represent their co-occurrence within patents. Complex network metrics, including degree, betweenness, and closeness centrality, are then applied for quantitative analysis. The novelty of this framework lies in connecting LLM-based semantic extraction with network-based technology evolution analysis, in which full patent texts are first converted into structured technology-topic data and then used to construct and analyse the ROC technology co-occurrence network. Detailed procedures are described in the following subsections.

3.1. Patent dataselection

The data were collected from Google BigQuery [50] and refined through selection and cleaning to retain only patents related to ROCs in the autonomous ship domain for analysis. As the dataset contains various types of information for each patent, the first step was to determine the relevant data fields. Based on the research objectives, the

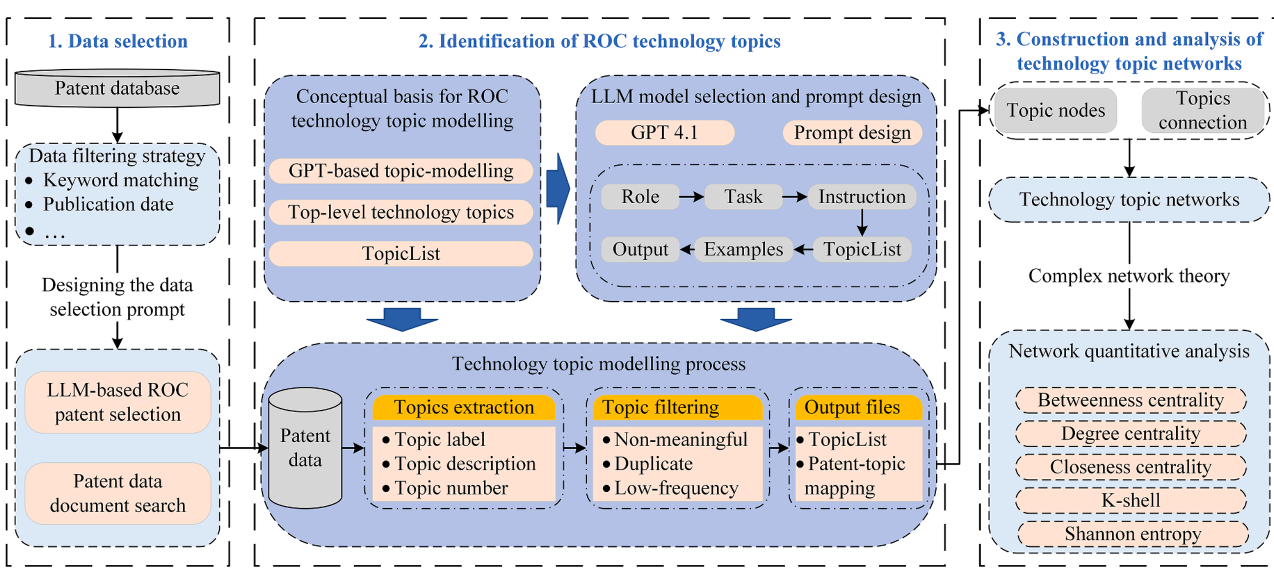

Fig. 2. Framework for identifying and analysing ROC technology topics.

selected fields included publication number, Cooperative Patent Classification (CPC) and International Patent Classification (IPC) code, filing and publication dates, country and kind codes, as well as titles and abstracts. To retrieve relevant records, SQL queries and a keyword-based search strategy were implemented to identify patents related to ROCs and MASS. The keywords were organised into two sets: one targeting ROC-specific terms (e.g., "remote control", "operation centre" and "teleoperation"), and the other focusing on broader maritime and autonomous system concepts (e.g., "autonomous ship", "unmanned ship", "intelligent vessel"). After keyword retrieval, additional filtering was conducted using CPC and IPC classifications to ensure that only patents relevant to remote control and autonomous ships were retained [50]. Publication dates were also used as a filter, with the dataset limited to patents published in or after 2015.

After the initial keyword-based query and filtering, the resulting database still contained patents not directly related to ROCs and MASS. To further refine the dataset, an LLM-based selection process was applied to the titles and abstracts of each patent. In this step, the LLM was instructed to act as a patent analysis expert, tasked with identifying patents relevant to ROC and MASS research and excluding unrelated records. This ensured that the retained patents were not only matched by keywords but also semantically aligned with the actual research focus described in their content. Finally, the selected patents were cross-checked in Google Patents using their publication numbers, and the corresponding full-text documents were downloaded for subsequent technology topic identification.

3.2. Identification of ROC technologytopics

3.2.1. Conceptual basis for ROC technology topic modelling

Patent documents are typically long, unstructured, and filled with specialised terminology, which makes it challenging to apply standard topic extraction techniques effectively. Traditional models such as LDA generally operate at the sentence or paragraph level and rely on word co-occurrence patterns. In contrast, LLMs such as GPT can process the full text of a patent as a single input and use contextual embeddings to recognise semantic relationships that go beyond simple word co-occurrence. This enables the extraction of coherent, domain-relevant themes even when terminology varies across patents.

This study applies an LLM-based topic-modelling approach to identify broad technological themes related to ROCs in MASS. Rather than extracting highly detailed or patent-specific functions, the method distils a set of consistent topics that can be compared across the dataset. Focusing on this high level prevents fragmentation, enables meaningful patent aggregation, and lays the foundation for analysing relationships among technology topics. A technology topic is defined here as an abstracted and generalisable technology category extracted from patent texts. It represents a recurring technical function, method or system capability that supports ROC operations, rather than a specific product, component, implementation, or patent claim. In this study, an ROC operational function refers to a role or capability associated with remote operation tasks, such as communication, monitoring, control, navigation, decision support, human-machine interaction, diagnosis, training, or security. Building on prior work on GPT-based topic modelling of (Pham et al. [18] and tailored to the technological characteristics of ROCs, four criteria are adopted to ensure that the extracted topics are both conceptually meaningful and structural relevant to the ROCs technology landscape.

(1) **Generalisability:** The topic should be applicable across multiple patents within the same technical domain.
(2) **Distinctiveness:** The topic should represent a single, clear technological function or concept, without conflating multiple unrelated components.
(3) **Hierarchical position:** The topic should be positioned at the top of a conceptual hierarchy so that related subtopics can logically fall beneath it.
(4) **Core functionality:** The topic should represent a fundamental technological capability, rather than a specific implementation or use-case.

The criteria of "generalisability" and "distinctiveness" ensure that each topic is coherent, interpretable, and applicable across multiple patents rather than confined to a single document. Building on this basis, "core functionality" and "hierarchical position" are introduced to capture the principal technological functions within ROCs. Each patent is analysed in full by the LLM, which identifies one or more candidate topics and provides concise semantic descriptions of their relevance to ROC operations. To maintain focus, the prompts are carefully structured to limit outputs to broad themes and include an explicit "None" option when no ROC-related technology is found. As topics are extracted, validated ones are added to a dynamic TopicList. The TopicList file stores validated technology topics and is continuously updated to ensure that the set of topics remains coherent and avoids redundancy. The details of model selection, prompt design, full-text parsing, topic extraction, and TopicList management are described in Sections 3.2.2 and 3.2.3.

3.2.2. LLM model selection and prompt design

Selecting an appropriate LLM is an important step in applying LLM-based topic modelling. For this study, GPT-4.1 was chosen because it delivers strong performance on natural language tasks and provides detailed guidance on prompt design, helping ensure reliable, reproducible outputs. As outlined in Section 3.1, this study uses the full text of each patent document as input data for topic modelling. For the model to perform effectively, it must first receive clear instructions about the specific analytical task and how the input should be interpreted. This instruction is provided through a prompt, a textual guide that defines and constrains the model's behaviour.

The first component involves defining a specific role, which specifies the perspective the model should adopt during the task. Here, the model is instructed to act as a technology analysis expert specialising in patent classification. Clearly defining the model's role helps anchor its reasoning process within the intended analytical context, ensuring that the input text is interpreted through a domain-relevant lens. For example, a typical role definition is given as follows:

"You are an expert in patent classification. You will be provided with the full text of patent documents. Your task is to identify the core technology topics described in each patent."

The second component of the prompt includes detailed task instructions that guide the model in generating responses. In this study, the instructions emphasise careful analysis of patent information and require the model to produce accurate and verifiable classifications of technology topics. A key objective of this design is to reduce the risk of hallucination, a known issue in which LLMs may generate content that is factually incorrect or unsupported by the input [69]. To mitigate this, the model is explicitly directed to identify only clear, distinct, and generalisable technologies directly relevant to ROCs in autonomous shipping. When uncertainty arises, the prompt instructs the model to rely on the provided information or tools rather than speculate.

The third component of the prompt design is the use of reference examples, which help clarify the task objectives, the expected input format, and the desired output structure. These examples show how the model should interpret a patent document to express the corresponding technology topics. Including illustrative examples in the prompt enables the model to generalise more effectively across new patent analysis, resulting in more consistent and relevant topic classifications. During this process, each technology topic generated by the LLM includes both a topic label and a one-sentence description explaining the corresponding technology.

The prompt further includes a placeholder variable ("topic"), which supplies the model with a reference list of established technology topics from previous topic modelling. This list serves as a contextual guide, prompting the model to reference existing topics during topic modelling and to use them when a relevant topic has already been identified in the list. By referencing this list, the prompt prevents the creation of irrelevant or redundant topics, reduces semantic noise, and lowers the risk of hallucinated or inconsistent outputs. The detailed structure of this reference list is introduced in the following subsection.

3.2.3. Technology topic modelling process

Building on the conceptual basis and prompt design described in Sections 3.2.1 and 3.2.2, this subsection outlines the workflow implemented to generate ROC technology topics from the pre-processed patent dataset. The overall process is illustrated in Fig. 3.

Before identifying technology topics, each patent document in PDF format requires pre-processing, as LLMs cannot directly interpret PDF files. The PDFs are therefore converted into machine-readable text files using the PyMuPDF library. The extracted text is then used as input for LLM analysis, following the prompt design described in Section 3.2.2. This prompt instructs the model to act as a patent analysis expert and to identify one or more technology topics from each patent, each accompanied by a concise semantic description. During the inference stage, the model is configured with a temperature setting of 0.0 and the token limit is set to 128,000 tokens [70]. The temperature controls how much randomness is allowed when the LLM selects the next word in its output. Setting it to zero ensures deterministic behaviour, meaning that identical inputs always produce identical outputs, thereby eliminating random variation and making the topic-modelling results more consistent and reliable. The token limit allows long patent documents to be processed as complete inputs. In the final topic-modelling run, each of the 973 patent documents is analysed once in a sequential process.

In the topic identification stage, each patent is analysed using a task-specific prompt. At the start, the TopicList file, which stores validated technology topics, is empty. When the first patent is analysed, the model generates an initial set of technology topics, which are subsequently added to the TopicList. Each entry in the TopicList contains a topic label and a one-sentence description of the technology within the context of autonomous shipping. As subsequent patents are processed, GPT-4.1 analyses each full patent text and checks whether the identified technologies match any topics already listed in the TopicList. If a match is found, the corresponding topic is assigned; if not, the model creates a new topic based on the technology described in the patent and the prompt instructions, and then appends it to the TopicList.

For each analysed patent, the model generates an output file containing the identified technology topics and their corresponding descriptions. After all patents have been processed, two finalised outputs are produced: (1) the TopicList file, which contains all unique technology topics with their descriptions; and (2) the patent-to-topic mapping file, which links each patent to its assigned technology topics based on the LLM's responses.

After identifying technology topics from patent data, the validation step is conducted to assess the reasonableness of the extracted topics. Following the premise established by Hain et al. [71] that patents belonging to the same technological category tend to exhibit higher semantic similarity than randomly paired patents, this study evaluates the validity of topic identification by comparing patent-level semantic similarity within and across topics. The underlying rationale is that, if a

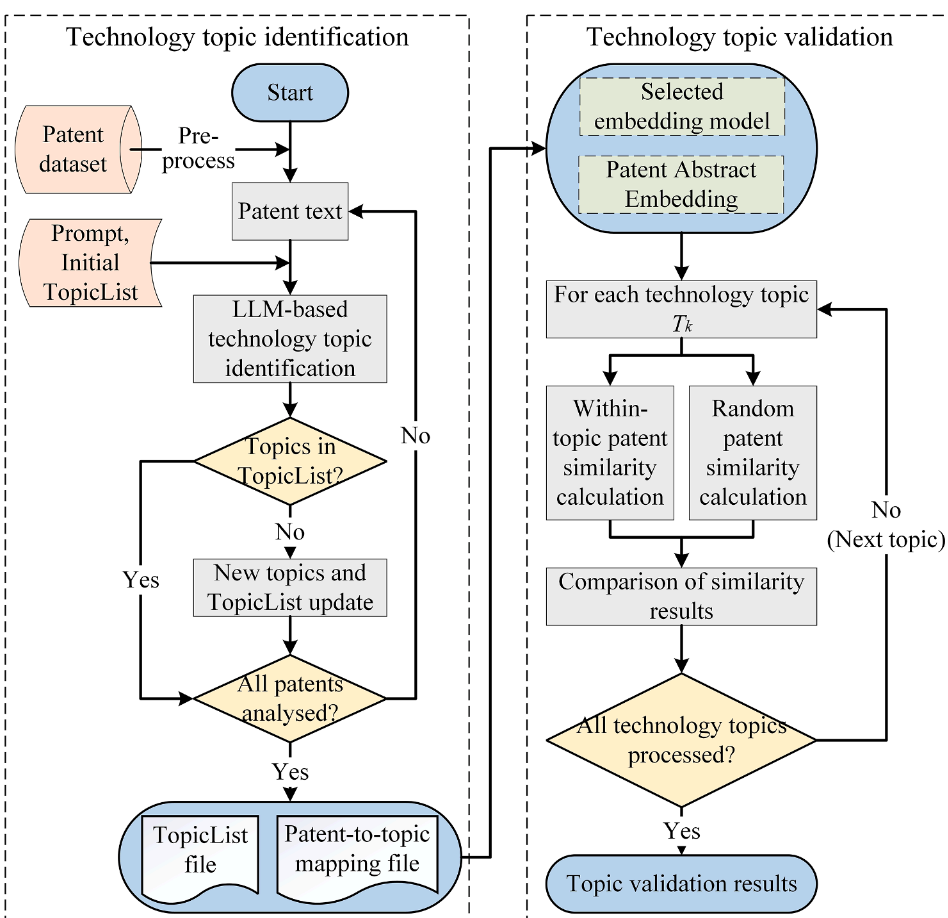

Fig. 3. Process of technology topic modelling using LLM.

topic represents a meaningful technological category and the technology identification is reasonable, patents assigned to the same topic should, on average, be more semantically similar to each other than to patents outside the topic. Accordingly, semantic similarity measures are compared between within-topic patent pairs and randomly sampled patent pairs, providing a relational validation of the topic identification results.

The validation procedure is implemented as follows. Let T_k denote a technology topic k, and let $P_k = \{p_1,\ p_2, \dots,\ p_n\}$ represent the set of n patents assigned to this topic. Semantic similarity between patents is measured using cosine similarity based on their embedding vectors. First, the abstracts of all patents in the dataset are converted into vector representations using a selected natural language processing embedding model. Each patent $p_i \in P_k$ is thus represented by a corresponding embedding vector V_i. Second, pairwise semantic similarities are computed for all patent pairs $\left(p_i,\ p_j\right) \in P_k$ based on their embedding vectors, and the average within topic semantic similarity $\overline{S}_k^{in}$ is calculated. Third, a random set of n patents is sampled from the full patent dataset, and the average semantic similarity among these randomly selected patents $\overline{S}_k^{r}$ is computed using the same procedure. The semantic coherence of the identified technology topic is then evaluated by comparing $\overline{S}_k^{in}$ and $\overline{S}_k^{r}$ using hypothesis testing. The detailed results are presented in Section 4.2.

3.3. Construction and analysisof technologytopicnetworks

As shown in Fig. 4, this subsection uses the technology identification results generated in Section 3.2 to construct a weighted technology topic network that represents the interdependencies among ROC technologies. Complex network theory is then applied to evaluate the network from both node-level and network-level perspectives.

3.3.1. Construction of the technology topic network

Section 3.2 presents the method for extracting technology topics from patent data. This process produces two key output files that contain the information needed to construct the technology topic network. The first is the TopicList file, defined as the set T, where each unique technology topic is represented as an element $t_i \subseteq T$. The second is the patent-to-topic mapping file, for each patent p, this file records the subset of technology topics T_p identified by the LLM. While each patent may focus on a core technical innovation, it often references additional technologies relevant to the broader context of the invention. Patents that span multiple technical domains frequently yield multiple topic labels in the LLM-generated responses. These co-occurring topics, captured in the patent-to-topic mapping file, reflect the multifaceted nature of technological development. Formally, for each patent p, the set of assigned topics is defined as:

$$T_p = \{t_1,\ t_2, \cdots, t_k\},\ T_p \subseteq T,\ k \geq 1 \tag{1}$$

where k denotes the number of topics identified for patent p.

Each element $t_i \subseteq T$ is treated as a node in the technology topic network. It should be noted that a node does not represent a physical ROC component or a specific patent, but an abstracted technology topic corresponding to a recurring ROC operational function. The size of each node reflects the frequency of that topic across the dataset, measured by the number of patents in which t_i appears.

To construct the network, edges are defined based on the co-occurrence of technology topics within individual patents [56]. For each patent p, every unordered pair of topics $\left(t_i, t_j\right)$ with $t_i, t_j \in T_p$ indicates a linkage between those two topics. By aggregating these relationships across all patents, a co-occurrence matrix M is obtained. Each element M_{ij} represents the number of patents in which topics t_i and t_j appear together, calculated as:

$$M_{ij} = \sum_{p=1}^{P} \delta\left(t_i \in T_p\ \right)\delta\left(t_j \in T_p\ \right) \tag{2}$$

where P denotes the total number of patents, and $\delta(\cdot)$ is an indicator function that equals 1 when the condition inside is true and 0 otherwise.

M_{ij} captures how frequently the two topics co-occur across all patents. Using this matrix, an undirected weighted network of technology topics can be constructed and expressed as:

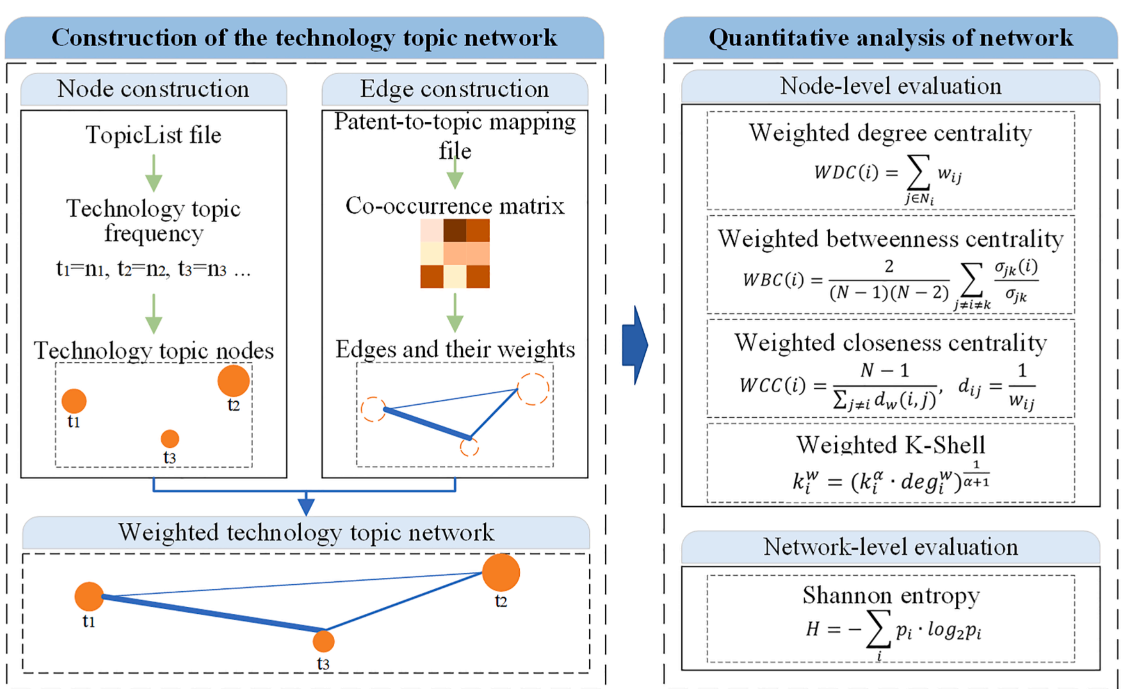

Fig. 4. Workflow for constructing and analysing the technology topic network.

$$\begin{gathered} G = (T, E, W) \\ E = \{(t_i, t_j),\ M_{ij} > 0\} \\ W_{ij} = M_{ij} \end{gathered} \tag{3}$$

where T is the set of topic nodes, E is the set of edges connecting co-occurring topics, and W assigns a weight to each edge based on the number of co-occurrences.

The edge weight reflects the strength of the functional or semantic association between two technology topics across the patent dataset. This weighted network not only captures the diversity of co-development pathways among ROC technologies but also provides the structural foundation for subsequent network analyses.

3.3.2. Quantitative analysis of network properties

To understand the roles, relationships, and overall influence of different technologies in the development of ROCs for autonomous ships, complex network theory is applied to the weighted and undirected technology topic network constructed in Section 3.3.1. This analysis quantifies both the importance of individual technology topics and the overall network structure, revealing how topics are interconnected and how technological development has evolved across the system. Through this approach, the study provides a systematic and data-driven understanding of technology co-development patterns and thematic relationships within the ROC innovation landscape.

Numerous centrality and structural measures have been proposed in complex network analysis, each capturing different aspects of node importance and network organisation [72]. Five complementary metrics are selected to capture different dimensions of technological importance. Specifically, these metrics collectively reflect (i) the extent to which a technology is locally integrated with other domains, (ii) its accessibility and influence across the overall network, (iii) its potential role in connecting otherwise weakly related technology clusters, (iv) its embeddedness within the hierarchical core-periphery structure of the system, and (v) the overall diversity and balance of technological interconnections. As the technology topic network is weighted, all metrics are calculated using their weighted forms.

1) Weighted Degree Centrality (WDC):

In this study, for a technology topic node t_i, the WDC is defined as follows:

$$WDC(i) = \sum_{j \in N_i} w_{ij} \tag{4}$$

where N_i is the set of topics directly connected to t_i; and w_{ij} is the edge weight between nodes t_i and t_j.

The WDC quantifies the overall strength of a topic's connections within the ROC technology system. A higher WDC value indicates that the topic frequently co-occurs with many others and with greater intensity, suggesting that it plays a central, integrative, or general-purpose role in ROC system development. Conversely, a low WDC value implies that the topic is more specialised or isolated, appearing mainly in narrowly focused technological contexts.

2) Weighted Betweenness Centrality (WBC):

For a given technology topic node t_i, the normalised WBC is calculated as [43]:

$$WBC(i) = \frac{2}{(N-1)(N-2)} \sum_{j \neq i \neq k} \frac{\sigma_{jk}(i)}{\sigma_{jk}} \tag{5}$$

where σ_{jk} represents the total number of shortest paths between topics j and k, and $\sigma_{jk}(i)$ denotes the number of those paths that pass-through topic t_i. In the weighted network, shortest paths are determined using edge distances $d_{ij} = 1/w_{ij}$, ensuring that stronger co-occurrence links correspond to shorter distances. This metric captures how often a node lies on the shortest paths between all other pairs of topics in the network.

In the weighted technology topic network, shorter paths between different topic nodes correspond to stronger co-occurrence links between them. A high WBC value indicates that the topic functions as a bridge or conduit between otherwise disconnected or weakly linked clusters of technologies. Conversely, a low WBC value suggests that the topic is embedded mainly within a single, well-defined cluster and plays a limited role in inter-cluster connectivity.

3) Weighted Closeness Centrality (WCC):

For node t_i, the WCC are defined as the reciprocal of the average shortest-path length from that node to all other nodes in the network [73]:

$$WCC(i) = \frac{N-1}{\sum_{j \neq i} d_w(i,j)},\ d_{ij} = \frac{1}{w_{ij}} \tag{6}$$

where N is total number of technology topics in the network, and $d(i,j)$ is the shortest path distance between topics t_i and t_j. In the weighted case, $d_w(i,j)$ corresponds to the weighted shortest-path distance, with d_{ij} defined as the inverse of the co-occurrence weight w_{ij}. This formulation ensures that stronger connections correspond to shorter effective distances.

Technology topics with high WCC are positioned near the structural centre of the network, meaning it can reach other topics through relatively short paths and thus serves as a globally influential element in the technological landscape.

4) K-Shell:

K-shell decomposition is a method used to uncover the hierarchical structure of a network and to determine the relative position and importance of nodes based on their connectivity [74]. Each node is assigned a k-shell index (k_s), which indicates its level of embeddedness or structural depth within the network. In the weighted technology-topic network, the weighted k-shell (k_s^w) is calculated using the weighted degree deg_i^w of each node, which is defined as:

$$\begin{gathered} k_i^w = \left(k_i^\alpha \cdot deg_i^w\right)^{\frac{1}{\alpha+1}} \\ deg_i^w = WDC(i) = \sum_{j \in N_i} w_{ij} \end{gathered} \tag{7}$$

where α is a tuning parameter controlling the relative influence of connectivity and weight, In this study, α is set to 1 following Garas et al. [75], k_i^α is the number of neighbours of node t_i.

Instead of removing technology topics solely based on their number of connections, the weighted approach considers both the number and strength of connections for each topic. Topics with the smallest k_i^w values are iteratively removed and assigned to the outermost shell ($k_i^w = 1$). After each removal, the weighted degrees of the remaining nodes are recalculated to update their k_i^wvalues. Topics that newly fall below the current threshold are also removed. This procedure is repeated for increasing shell indices until all nodes have been assigned a weighted k-shell index (k_s^w).

5) Shannon Entropy:

In complex networks, Shannon entropy quantifies the randomness, uncertainty, or diversity within a probability distribution [76]. In this study, the weighted Shannon entropy captures the degree of balance or imbalance in the distribution of co-occurrence links across technology topics. It is calculated as:

$$H = -\sum_i p_i \cdot log_2 p_i \tag{8}$$

where $p_i = s_i / \sum_j s_j$ and $s_i = \sum_k w_{ik}$, with p_i representing the proportion of the total co-occurrence link in the network associated with topic t_i, and the w_{ik} the edge weight representing the co-occurrence frequency between nodes t_i and t_k.

A high global Shannon entropy indicates that co-occurrence relationships are evenly distributed across many technology topics. This means that multiple technologies are actively connected and contribute similarly to the network, suggesting a diverse and balanced research landscape.

4. Results and findings

4.1. Patent dataselectionresults

By applying the predefined search filters and strategies, approximately 239.11 GB of patent data, comprising 94,515 potentially relevant records, were initially extracted from the BigQuery database. A subsequent data-cleaning process was conducted to refine this dataset, as a substantial number of irrelevant records remained despite the keyword-based filtering. The first step was to remove duplicate records based on publication numbers. For patents with duplicate entries, only the earliest publication was retained. In total, 7362 duplicate records were removed to ensure that each patent appeared only once in the dataset. Then, the CPC and IPC codes for each patent were used to select records related to ROC research initially. A total of 11,398 records were identified; however, many of them were unrelated to the maritime domain, covering technologies such as land vehicles, aviation, and nuclear systems. As described in Section 3.1, an LLM-based patent selection method was then applied to review the titles and abstracts and verify their relevance to ROC technologies in autonomous ships. As a result, 10,291 records were found to contain relevant keywords but were unrelated to the maritime domain, including land vehicles, aviation, and other non-maritime systems. These records were excluded to improve the thematic precision of the dataset, leaving 1017 relevant records retained for subsequent analysis.

Because the initial BigQuery output contained only titles and abstracts, the available information for each patent was limited. Therefore, the full patent documents were retrieved via publication numbers from Google Patents to provide richer textual input for the LLM-based topic modelling. Out of the 1017 patents, 973 full documents were successfully downloaded and used for the technology topic modelling. The results of each data selection and cleaning step are summarised in Table 1.

4.2. Results of ROC technologytopicidentification

4.2.1. Results of technology topic identification

This subsection presents the results of the LLM-based topic modelling process described in Section 3.2, which produced the set of identified technology topics related to ROCs. Following the procedure outlined previously, prompts were specifically designed for topic identification, with full prompt templates provided in Appendix A. The prompt ensured that the LLM correctly understood its analytical task while constraining its outputs to meet predefined standards of accuracy and relevance. To ensure the accuracy of the technology topics identification, the model was instructed to return "None" if it determined that a patent contained no technologies related to ROCs after analysis.

During testing, different versions of the prompt were trialled, and it was found that overly detailed instructions or positive examples (i.e., examples considered as good technology topics) led the model to overfit these cases, reducing its ability to identify more generalisable categories. To mitigate this issue, the final prompt was designed using negative examples, which illustrate what should not be considered valid technology topics.

Another important challenge was that the initial batch of patent analyses strongly influenced the entire process, as it established the initial TopicList for the remainder of the process. Any errors in these early classifications may propagate throughout subsequent analyses. To minimise this risk, the first analysis focuses on patents demonstrating clear and direct relevance to ROCs, ensuring the generation of a high-quality initial TopicList. It is important to note that LLMs operate as "black boxes": while their inputs and outputs are observable, the internal reasoning behind specific responses remains not transparent, and small variations in input can lead to different outputs. In this research, the prompts were therefore iteratively tested and refined. The outputs of each trial were assessed against the research aims and requirements, and the instructions and design of the prompts were revised accordingly. This iterative optimisation ensured that the final prompts were precisely aligned with the objectives of ROC technology topic identification based on patent analysis.

Following this process, the 973 patent documents obtained during the data selection were used as input for the technology topic modelling analysis. Following the procedure described in Section 3.2, 757 patents were assigned at least one technology topic. Among these 757 valid responses, a total of 24 technology topics were initially identified. However, two topics appeared only once across all patents and were therefore considered outliers and removed from the final dataset. Consequently, 22 technology topics were retained, their frequencies of occurrence and corresponding labels are summarised in Table 2.

From Table 2, it can be observed that Maritime Data Communication (MDC) and Remote Control and Teleoperation (RCT) are the two most prevalent topics, appearing in 507 and 496 patents, respectively. Other frequently occurring topics include Remote Condition Monitoring (RCM), HMI, and Maritime Positioning and Navigation (MPN). This distribution highlights the central importance of reliable communication, control, and monitoring systems for enabling remote and autonomous operations in ships. In contrast, several topics such as Human Reliability Analysis (HRA), Decision Support and Automated Task Planning (DSATP), and Power Management and Energy Control (PMEC) appear only occasionally, suggesting that these areas remain in the

Table 1
Patent data selection and cleaning.

		Records
Total		94,515
Duplicate removal		7362
ROC	Unrelated to maritime domain	10,291
	Related to autonomous ships	1017
Successfully downloaded documents		973

Table 2
Identified ROC technology topics.

Technology topic	Count	Label	Technology topic	Count	Label
Maritime Data Communication	507	MDC	Remote Access Security	23	RAS
Remote Control and Teleoperation	496	RCT	Fault-Tolerant Control	18	FTC
Remote Condition Monitoring	270	RCM	Virtual Reality-based Visualisation	12	VRV
Human-Machine Interface	162	HMI	Simulation and Training Systems	9	STS
Maritime Positioning and Navigation	162	MPN	Digital Twin	9	DT
Autonomous Navigation and Collision Avoidance	119	ANCA	Remote Diagnosis and Maintenance	7	RDM
Video-based Monitoring and Surveillance	82	VMS	Distributed System Architecture	7	DSA
Information Fusion	64	IF	Power Management and Energy Control	6	PMEC
Feature Extraction and Signal Processing	58	FESP	Time Synchronisation and Clock Management	5	TSCM
Data Analytics and Predictive Modelling	37	DAPM	Human Reliability Analysis	3	HRA
Optimisation and Decision Support	34	ODS	Decision Support and Automated Task Planning	2	DSATP

earlier stages of research and technological development.

To further examine the robustness of the LLM-based topic identification process, two additional independent topic-identification runs were conducted using the same patent dataset and prompt-based procedure. Together with the original run, this produced three sets of topic-identification results. The comparison focused on topic-number stability, consistency of major technology themes, and variation in topic labels and low-frequency topics. Before low-frequency filtering, the three runs produced 24, 22, and 23 topics, respectively. After applying the same filtering rule, 22, 22, and 20 topics were retained. This indicates that the number of identified technology topics was relatively stable across repeated runs, with variation mainly arising from low-frequency topics. The comparison results are summarised in Table 3.

The results in Table 3 indicate that the overall number of identified topics remained within a relatively similar range across the three repeated runs. The main ROC technology areas identified by the LLM were also broadly consistent, although the exact topic labels differed. Communication-related technologies ranked first in all three outputs, appearing as "Maritime Data Communication" in the first run and "Data Communication and Networking" in the second and third runs. Remote control and teleoperation-related technologies, remote monitoring-related technologies, human-machine interface-related technologies, and sensing or positioning-related technologies were also repeatedly identified among the most frequent topic areas.

These results suggest that the LLM-based topic identification process is relatively stable at the level of broad technology themes. However, some variation exists in the wording of individual topic labels.

4.2.2. Validation of topic identification results

Using the validation method described in Section 3.2.3, the semantic coherence of the identified technology topics is evaluated by comparing the average semantic similarity of patents assigned to each topic with that of randomly sampled patent pairs. Hypothesis testing is then conducted to examine whether the observed differences are statistically significant. A subset of the validation results is presented in Table 4.

As shown in Table 4, the average within-topic semantic similarity is higher than the corresponding random baseline for all reported technology topics, resulting in positive values of Δ. For several topics, such as MDC, RCM, and Information Fusion (IF) the differences are statistically significant, indicating that patents assigned to these topics are semantically more similar to one another than would be expected by chance, as further supported by the associated p-values.

To complement the quantitative validation, a manual verification was conducted to assess the validity of the LLM-generated technology topic assignments. A simple random sample of 50 patents produced 142 technology topic assignments for review. Three evaluators with maritime traffic research experience and maritime-domain expertise independently reviewed each assignment by comparing the assigned technology topic and its description with the corresponding patent text. Each LLM-generated technology topic assignment was coded as supported if the evaluator judged that the patent text provided explicit evidence that the assigned topic reflected the patent's core technological contribution. Assignments were coded as unsupported if the evaluator judged that the topic was not clearly supported by the patent text, was only mentioned in background or contextual discussion, or did not reflect the patent's main technological content. The evaluation results from the three evaluators are presented in Table 5.

Of the 142 evaluated topic assignments, 129 were supported by majority agreement, defined as support from at least two of the three evaluators. This corresponds to a majority-supported assignment rate of 90.8%, whereas 13 assignments were not supported by majority agreement. Most assignments were supported by the evaluators, as reflected in the majority-supported assignment rate, the unanimous agreement rate, and the individual validation rates of 81.0–88.7%. These results indicate that the technology-topic assignments generated by the LLMs are broadly consistent with human judgement and expert interpretation. Together, these quantitative and qualitative checks support the use of the LLM-generated topic assignments as the basis for the network and temporal analyses in Section 4.3.

Although conventional topic-modelling methods such as LDA and BERTopic can reveal latent thematic structures within a text corpus, their outputs are commonly represented by groups of keywords or representative terms. Trial applications of LDA and BERTopic to the collected patent dataset showed that both methods produced topic outputs required further manual interpretation before they could be converted into meaningful ROC technology topics. In addition, conventional topic-modelling approaches usually require substantial text preprocessing, such as tokenisation, stop-word removal, and parameter selection, and these preprocessing decisions may influence the resulting topics. By contrast, the proposed LLM-based approach analyses full patent texts through prompt-based semantic interpretation and directly generates technology-topic labels, concise descriptions, and patent-to-topic assignments. These outputs are better aligned with the aim of this study, which is not only to identify technology topics, but also to construct co-occurrence relationships among technology topics within patents, thereby supporting a deeper understanding of technology interaction patterns, structural evolution, and emerging development pathways within ROCs.

Table 3
Technology topic identification across repeated LLM runs.

Run	Number of topics	Number of retained topics	Top five technology topics by occurrence frequency
1	24	22	Maritime Data Communication; Remote Control and Teleoperation; Remote Condition Monitoring; Human-Machine Interface; Maritime Positioning and Navigation
2	22	22	Data Communication and Networking; Sensing and Positioning; Remote Control and Teleoperation; Remote Monitoring and Diagnostics; Human-Machine Interface / Information Processing
3	23	20	Data Communication and Networking; Sensing and Positioning; Remote Control and Teleoperation; Human-Machine Interface; Remote Monitoring and Diagnostics

4.3. Results of the technologytopicnetworkanalysis

4.3.1. Structure analysis of the network

Building on the identification of technology topics, a ROC technology topics network was constructed to analyse their structural roles and interdependencies. Using the patent-to-topic mapping file, co-occurrence relationships between these technology topics were extracted from the LLM-generated outputs to create a co-occurrence matrix. This matrix forms the basis of the network, where nodes represent individual technology topics and edges indicate their co-occurrence within individual patents. The resulting technology topic network is shown in Fig. 5.

In this network, node size represents the frequency of each technology topic across the analysed patents, while edge thickness reflects the strength of co-occurrence between two topics. The visualisation reveals a strongly interconnected structure centred around MDC and RCT, which exhibit the thickest and most numerous connections. Surrounding these nodes are several closely related technologies, such as RCM, HMI, and MPN, which also exhibit high connectivity. The relatively thick edges connecting MDC, RCT, RCM, and HMI highlight a tight coupling between communication, control, monitoring, and operator interaction. In contrast, topics such as DSATP, HRA, and PMEC have smaller node sizes and display thinner, less frequent connections. Their limited linkages may indicate that these technologies are still in the early stages of

Table 4
Validation results of technology topic identification (partial).

Technology Topic	Patent count	Within-topic similarity (mean)	Random baseline similarity (mean)	Δ	*z* score	*p* value
MDC	507	0.575	0.541	0.034	184.231	0.0005
RCT	496	0.578	0.538	0.039	70.604	0.0005
RCM	270	0.582	0.549	0.034	7.57	0.0005
HMI	162	0.564	0.555	0.008	1.274	0.1010
MPN	162	0.583	0.551	0.032	5.35	0.0005
ANCA	119	0.587	0.553	0.035	4.435	0.0005
VMS	82	0.588	0.553	0.035	3.898	0.0005
IF	64	0.603	0.554	0.049	4.351	0.0005
FESP	58	0.561	0.556	0.005	0.412	0.3400

Table 5
Evaluation results of LLM-generated technology topic assignments.

Evaluator	Supported	Unsupported	Total	Validation Rate
Evaluator 1	120	22	142	84.5%
Evaluator 2	126	16	142	88.7%
Evaluator 3	115	27	142	81.0%

development or are focused on specialised applications that have not yet been fully integrated into the broader ROC ecosystem.

Using publication-year information from the patent dataset, the annual occurrence frequency of each technology topic was calculated, as shown in Fig. 6. The results reveal a significant increase in patenting activity for ROC technologies after 2018, marking the onset of accelerated innovation in this field. This trend may be associated with the release of the MASS classification framework by the IMO in 2018, which provided regulatory clarity and stimulated further technological development. Among these topics, MDC, RCT, and RCM exhibit the steepest growth trajectories, reflecting the growing emphasis on communication, control, and monitoring systems as core enablers of remote and autonomous ship operations. These topics reached their peaks around 2021–2022, suggesting that they have evolved into relatively mature domains. In contrast, topics such as Digital Twin (DT), HRA, and DSATP remained consistently low throughout the period, indicating that these domains are still emerging and have yet to gain significant traction in patent activity.

To further examine the roles of individual technologies within the ROC innovation landscape from a local perspective, the network metrics described in Section 3.3.2 were calculated for each technology topic. Table 6 summarises the values of these metrics for each identified technology topic.

According to Table 6, the highest degree values were observed for RCM, MDC and RCT, each of which is connected to 21 other topics, followed closely by HMI (19). When the WDC is considered, MDC (1121) and RCT (1022) stand out as the most intensively co-occurring topics, underscoring their foundational roles across multiple patents. The WCC values further confirm the central positions of MDC (7.45), RCT (7.41), RCM (7.23), and HMI (7.06), indicating that these technologies are well positioned to interact efficiently with others within the network. These technologies with high WDC and WCC values reveal that communication, teleoperation and monitoring technologies are strongly coupled with multiple ROC-related functions. From a system-safety perspective, this structural centrality indicates that degradation in these technologies could have wider implications for remote supervision, control execution, condition monitoring, operator information access and fallback operation. In contrast, topics such as DSATP, PMEC, and HRA exhibit the lowest degree and closeness values, reflecting their peripheral and specialised roles in the ROC ecosystem. Their low centrality values indicate weak integration within the current ROC technology network, which may reflect early-stage development, or limited connection with the broader ROC architecture. These technologies may therefore represent underdeveloped areas requiring further validation, regulatory attention and integration in future ROC design.

The analysis of WBC values reveals that most technologies do not act as bridges between distinct topic clusters, even though some of them have high degree values, such as RCM (21) or HMI (19). Overall, WBC values are relatively low across the network, but MDC (0.75) and RCT (0.38) emerge as important bridging nodes, facilitating connections

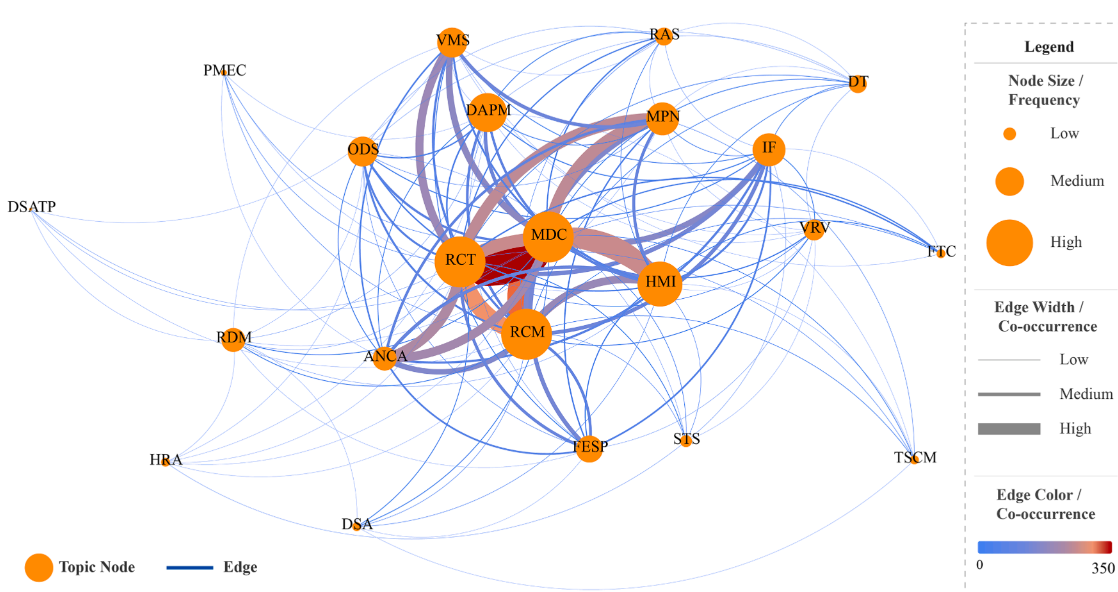

Fig. 5. Co-occurrence network of the ROC technology topics.

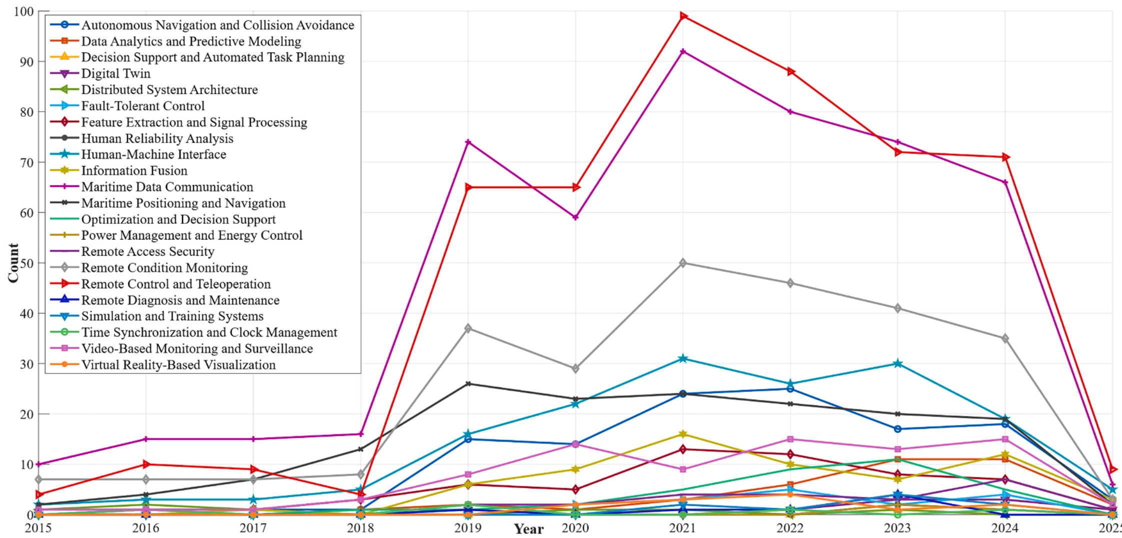

Fig. 6. Annual trends in ROC technology topics.

Table 6
Centrality metrics of the ROC technology topics network.

Topic node	Degree	WDC	WBC	WCC	Topic node	Degree	WDC	WBC	WCC
MDC	21	1121	0.75	7.45	RAS	10	43	0	4.53
RCT	21	1022	0.38	7.41	FTC	7	37	0	4.66
RCM	21	690	0	7.23	VRV	11	35	0	4.16
HMI	19	459	0	7.06	STS	8	23	0.1	3.6
MPN	15	372	0	7.01	DT	10	34	0	3.41
ANCA	12	332	0	6.9	RDM	12	26	0	3.7
VMS	14	227	0	6.75	DSA	7	21	0	3.42
IF	15	218	0	6.57	PMEC	6	12	0	2.22
FESP	13	153	0	6.25	TSCM	7	18	0	3.08
DAPM	17	136	0	6.06	HRA	7	8	0	1.33
ODS	14	106	0	5.5	DSATP	5	7	0	1.64

between otherwise weakly linked technologies. Simulation and Training Systems (STS) also shows a modest bridging role despite its relatively low frequency, suggesting its emerging importance in linking simulation-related developments to the broader ROC technology framework. These bridging technologies represent potential pathways through which disruptions, such as communication failure, control delay, data inconsistency or loss of teleoperation capability, could propagate across dependent ROC functions. Therefore, they warrant further attention in subsequent safety assessment, resilience analysis and ROC design verification, particularly in relation to redundancy, fault tolerance, recovery procedures and fallback control mechanisms.

The weighted k-shell values of the technology topics were calculated to reveal the hierarchical structure of the ROC technology network. As shown in Table 7 and Fig. 7, topics with the high weighted k-shell values, such as MDC (153.43), RCT (146.50), and RCM (120.37), occupy the innermost shells of the network, and topics including HMI, MPN, and Autonomous Navigation and Collision Avoidance (ANCA) also exhibit relatively high values. In contrast, more peripheral topics such as DSATP, HRA, and PMEC have lower weighted k-shell values (below 10). Overall, the concentration of several technologies with high weighted k-shell indices near the network centre, combined with moderate differences among them, indicates that ROC technologies are strongly interconnected. This finding suggests that the ROC technology ecosystem is a highly cohesive structure, where core communication, control, and monitoring technologies are closely integrated with supporting domains such as navigation, data analytics, and human-machine interaction.

By calculating the Shannon entropy of the technology topic network, a value of 3.37 was obtained. For a network comprising 22 topics, the maximum entropy occurs when all categories are equally probable ($p_i = 1/n$). When $n = 22$, the theoretical maximum entropy is approximately 4.46, as defined by the formula in Section 3.3.2. The observed value of 3.37 therefore indicates a moderately high level of diversity in the distribution of co-occurrence links. While a small group of core technologies, such as MDC, RCT, and RCM, remain dominant, many other topics also contribute significantly to the ROC technology network. These results further support the view that the functionality of ROCs depends on the integration and interconnection of diverse technologies, consistent with the k-shell analysis, which also highlights the strong embeddedness of multiple technology domains within the network.

Table 7
The weighted k-shell values of ROC technology topics.

Topic node	Weighted k-shell	Topic node	Weighted k-shell
MDC	153.43	RAS	20.74
RCT	146.50	VRV	19.62
RCM	120.37	DT	18.44
HMI	93.39	RDM	17.66
MPN	74.70	FTC	16.09
ANCA	63.12	STS	13.56
IF	57.18	DSA	12.12
VMS	56.37	TSCM	11.22
DAPM	48.08	PMEC	8.49
FESP	44.60	HRA	7.48
ODS	38.52	DSATP	5.92

4.3.2. *Temporal analysis of the network*

In Section 4.3.1, the structure characteristics of the technology topic network were analysed. In this subsection, the focus shifts to the

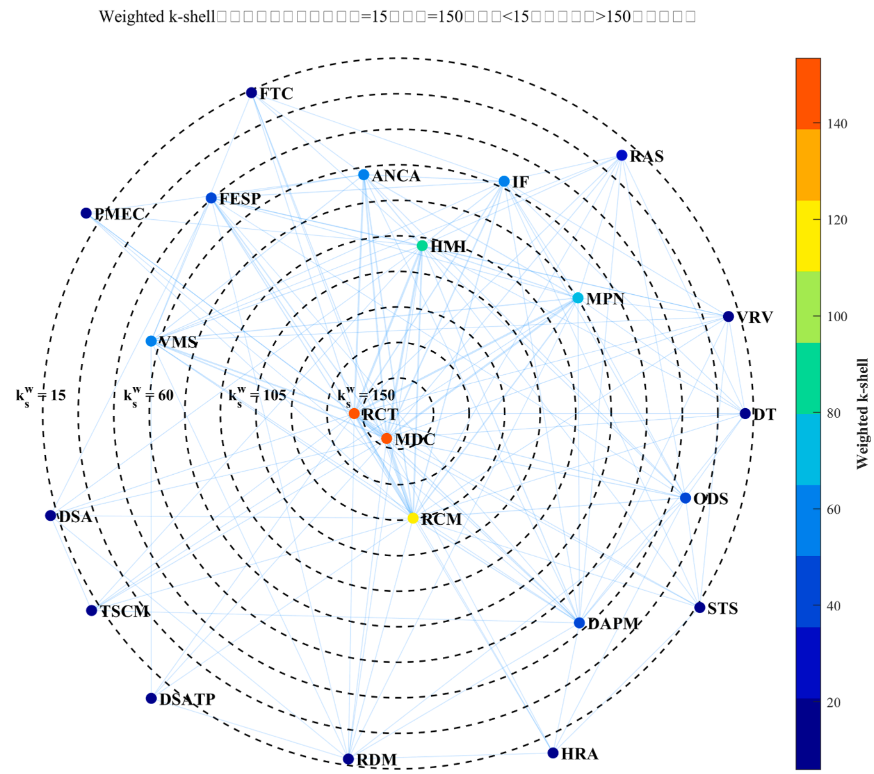

Fig. 7. Weighted k-shell decomposition of the ROC technology topic network.

temporal evolution of ROC technologies and their interconnections. To this end, the dataset was divided into six two-year intervals based on the publication dates of the patents [50]. For each period, a sub-network of technology co-connections was constructed, as shown in Fig. 8. This

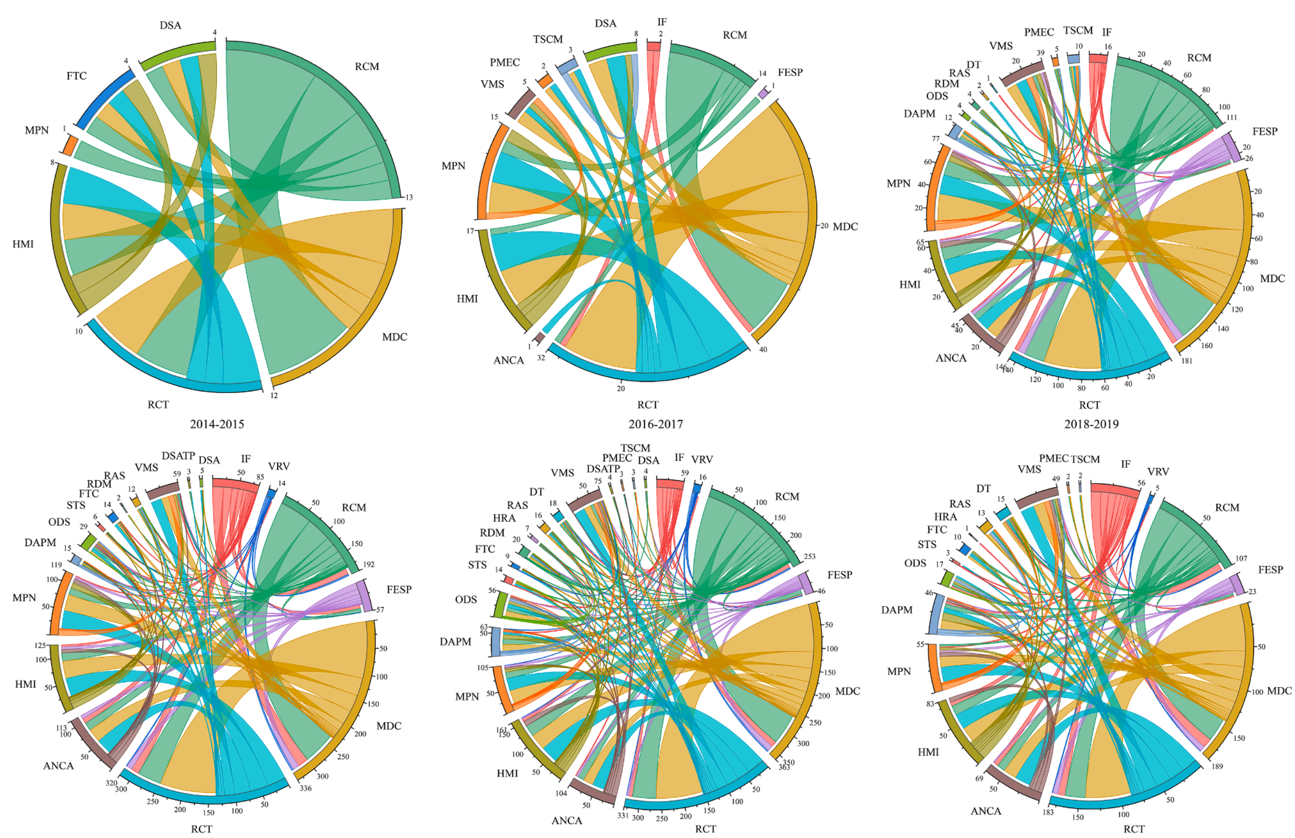

Fig. 8. Temporal evolution of the ROC technology topic sub-network.

enabled the examination of how individual technologies and the strength of their interconnections evolved over time. It should be noted that the period of 2024–2025 includes only patents published up to February 2025; therefore, the results for this may display some fluctuations due to incomplete data coverage.

During the early years (2015–2017), the sub-network was relatively sparse and dominated by core technologies such as MDC, RCT, RCM. From 2018 to 2019, the sub-network expanded, as additional topics, including Feature Extraction and Signal Processing (FESP) and Video-based Monitoring and Surveillance (VMS), became more integrated. The period 2020–2023 marks a peak in overall connectivity, reflecting both rapid growth in patenting activity and increased technological convergence. During this phase, the relationships between different technologies became more complex, indicating stronger functional interdependencies.

Fig. 9 presents the temporal trajectories of WDC, WCC, and WBC values for all technology topics, illustrating how their relative importance and structural roles have evolved over time. MDC, RCT, and RCM consistently exhibit the highest WDC and WCC values, reaching their peaks during 2022–2023, reflecting their dominant and integrative roles in the ROC technology ecosystem. HMI and FESP also maintain comparatively high centrality during this period. In contrast, WBC values remain generally low across the sub-networks, although MDC and RCT demonstrate a gradual increase in betweenness from 2015 to 2023.

Fig. 10 illustrates the temporal evolution of weighted k-shell values for each technology topic. The colour scale represents the weighted k-shell index, with higher values indicating stronger embeddedness in the sub-network core. The results show that, from 2018 onwards, technology topics such as RCM, FESP, RCT, and ANCA show an increase in weighted k-shell values. Other topics, including HMI, Data Analytics and Predictive Modelling (DAPM), Fault-Tolerant Control (FTC), and Remote Access Security (RAS) progressively move toward higher k-shell values with the development. In contrast, emerging technology topics such as DSATP and Distributed System Architecture (DSA) remain positioned in the outer shells throughout the entire period.

The temporal analysis reveals that several ROC technologies have become more structurally embedded within the innovation network, particularly those related to communication, teleoperation, monitoring and autonomous navigation. Meanwhile, the persistently low occurrence and peripheral positions of topics such as DT, HRA, DSATP and DSA suggest that these topics remain emerging or insufficiently integrated, despite their potential relevance for future ROC safety assurance.

Table 8 summarises the Shannon entropy of the technology topic sub-network across six time periods. The results show a clear upward trend, rising from 2.54 in 2015 to a peak of 3.45 in 2022–2023, indicating a steady diversification of ROC technologies over time. In the early stages (2015–2017), the sub-network was highly centralised around a few core technologies. As new topics emerged and became increasingly interconnected, entropy values rose, reflecting a more balanced and varied technological landscape. The slight decline to 3.41 in 2024–2025 is likely attributable to the incomplete patent data for this interval, rather than an actual reduction in diversity.

5. Discussion and implications

5.1. Discussion

5.1.1. Insights of technology topic identification

The application of the LLM-based topic modelling framework enabled the systematic identification of 22 distinct technology topics supporting the development and operation of ROCs for autonomous ships. In contrast to previous maritime patent studies that relied primarily on keyword frequency [50], this framework introduces a semantic-level approach for technology topic identification, capable of capturing contextual relationships embedded in patent texts. By analysing the full text of each patent using a specific prompt, the model extracted coherent and generalisable technology topics while maintaining analytical consistency across a large and diverse dataset.

The resulting TopicList reveals a coherent and interpretable technological structure of ROCs. The distribution of topics indicates that MDC, RCT, and RCM form the technological core of ROC operations. These domains collectively enable real-time data transmission, supervisory control, and continuous system health assessment, which are essential for maintaining safe and effective remote ship operations. Complementary technologies such as HMI and MPN further reinforce this foundation by connecting human operators to ship systems and ensuring spatial awareness in remote environment. In contrast, several

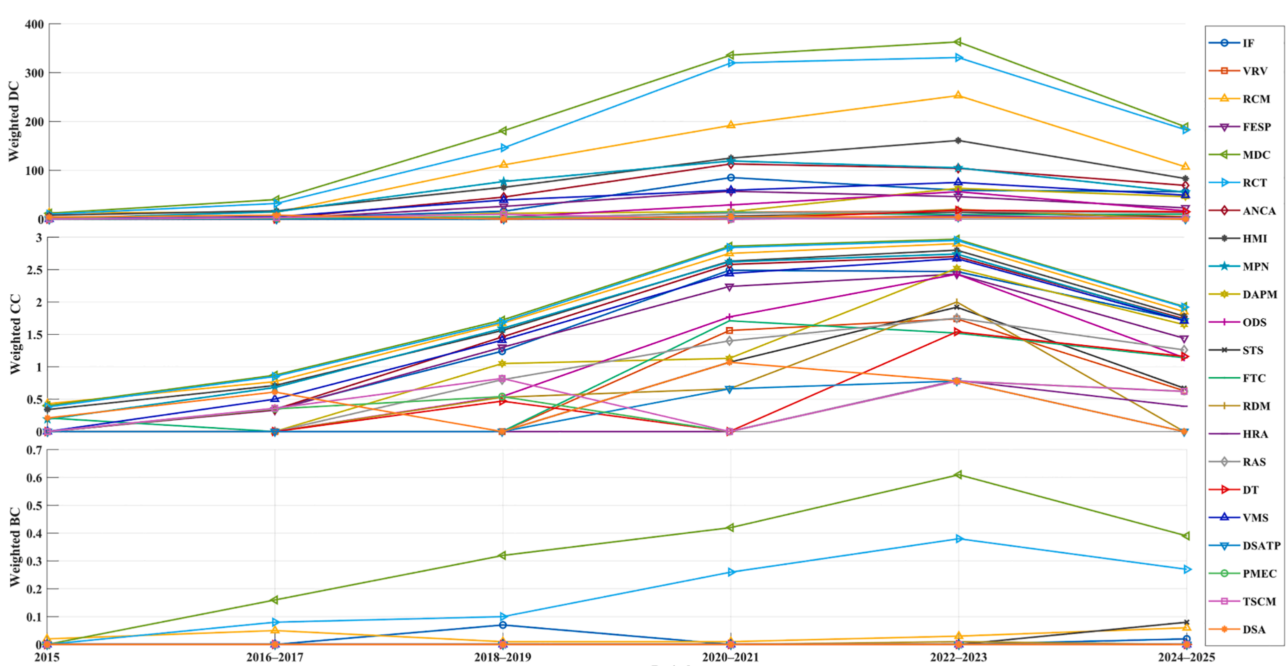

Fig. 9. WDC, WCC, and WBC of the ROC technology topic across different periods.

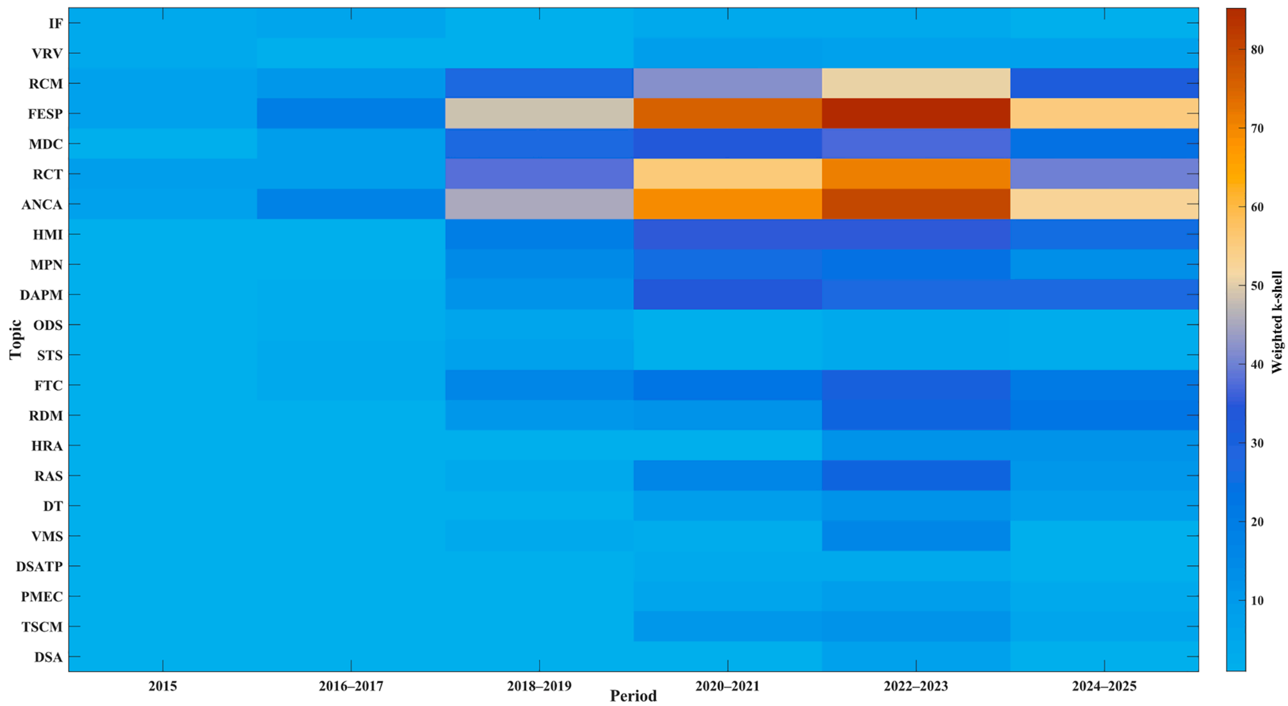

Fig. 10. Temporal evolution of weighted k-shell values for ROC technology topics.

Table 8
Temporal evolution of Shannon entropy in the ROC technology topic sub-networks.

Period	2015	2016–2017	2018–2019	2020–2021	2022–2023	2024–2025
Value	2.54	2.85	3.11	3.25	3.45	3.41

low-frequency topics, including HRA, DSATP, and Power Management and Energy Control (PMEC), appear at the periphery of the dataset. Their limited occurrence suggests that these areas remain at early stages of research and development, possibly reflecting ongoing experimentation or domain-specific application. Nevertheless, these emerging topics signal potential future directions in ROC technological evolution. The presence of topics such as DT and STS also indicates an increasing emphasis on virtual verification, operator training, and situational rehearsal, which may become integral to the next generation of ROC design.

While the LLM operates as a "black-box" model whose internal reasoning cannot be fully observed, several measures were employed to ensure the reliability and validity of topic identification. Iterative prompt testing, manual evaluation of early outputs, and progressive refinement of the TopicList minimised the propagation of initial misclassifications and enhanced topic coherence. The use of negative examples reduced the model's tendency to overfit to pre-defined cases, promoting generalisability across diverse patent descriptions. The technology topic identification framework produced a structured and empirically grounded taxonomy of ROC technologies. By transforming unstructured patent texts into a validated TopicList and patent-to-topic mapping, the results provide a quantitative foundation for analysing technological interconnections. This structured output enables examination of how individual technologies co-occur and interact, offering insights into the underlying architecture of ROC innovation.

5.1.2. *Insights of ROC technology network*

The results from network analysis indicate that ROC technologies have significantly diversified since 2018, with a steady increase in patenting activity and the emergence of new functional areas. Technologies like MDC, RCT, and RCM are highlighted as the structural backbone within the ROC technology landscape. These topics consistently occupy core network positions across different time periods, with high degree and closeness centrality as well as strong k-shell embeddedness. Their prominence underscores that effective communication and teleoperation capabilities, coupled with continuous monitoring, remain the backbone of ROC operations. This finding aligns with the IMO adoption of the MASS autonomy framework in 2018, which represented the first step towards addressing the safety, security, and environmental dimensions of MASS operations [6]. In contrast, topics such as DT and HRA occupy more peripheral positions. While less central, these technologies may provide critical enhancements in simulation, training, and human-system collaboration. Further research is needed to ensure their effective integration into ROC infrastructures.

Furthermore, the temporal analysis reveals that the technological landscape of ROCs has become increasingly diversified over the past decade. This diversification suggests a maturing innovation ecosystem, moving beyond a narrow focus on communication and control towards broader capabilities such as predictive analytics, virtual reality-based interfaces, and simulation. However, the persistence of peripheral technologies such as DT, HRA, and STS indicates that some domains remain underdeveloped or experimental. These emerging topics, although still underrepresented within the network, may become increasingly important as ROCs develop to support higher levels of autonomy and more complex human-machine interactions.

Overall, ROCs rely on a dense and highly interconnected network of technologies, where communication, control, and monitoring form the core technological foundation. This interconnectedness suggests that ROC operational resilience depends not only on the maturity of individual technologies, but also on how sensing, communication, control, navigation and operator-interface functions are coordinated as an integrated system. However, the same interdependence may also increase vulnerability if central or bridging technologies are insufficiently supported by redundancy, fault tolerance and recovery mechanisms. These findings have direct implications for policy making, regulatory development, industry strategies, and operator training.

5.2. Practical implications

5.2.1. Risks and safety in ROCs

As a key technological development driving the maritime sector's transition towards autonomy, MASS has attracted numerous studies that address the safety and risk challenges associated with its development and deployment [77,78]. However, compared with these extensive efforts, studies that explicitly address the safety and risk dimensions of ROCs remain scarce. The results of this study can support ROC safety and reliability assessment by providing a quantitative screening layer for identifying safety-relevant technology dependencies. It should be emphasised that the contribution of the study lies in identifying which ROC technologies are structurally central, strongly connected, or weakly developed, thereby providing evidence for prioritising subsequent risk assessment and safety assurance activities.

In the technology network analysis, technologies with high WDC and high weighted k-shell values, such as MDC, RCT and RCM, represent core technologies that are strongly embedded in the ROC system. Their failure or degradation may affect multiple ROC functions. These technologies should therefore be prioritised in redundancy design, interface verification, cybersecurity assessment, and fallback operation planning. Technologies with high WBC, such as MDC and RCT, may act as bridges between different technology groups. These bridging technologies may represent important pathways through which communication failure, control delay, data inconsistency, or coordination breakdown may propagate across the ROC architecture. These insights contribute to resilience-oriented ROC design for future autonomous ships by supporting efforts to improve system stability and reduce operational risk.

5.2.2. Policies and regulations

Given the central role of technologies such as MDC, RCT, and RCM identified in the above analysis, regulatory bodies should recognise these as critical components within the MASS ecosystem. At the same time, regulators must adopt a forward-looking stance towards emerging but currently peripheral technologies, such as DT and HRA. Early and proactive regulatory engagement is vital to ensure that such technologies are safely and consistently integrated into ROCs, in alignment with internationally harmonised standards.

On the other hand, despite the increasing adoption of automation, human operators remain indispensable as supervisors and decision-makers [79]. A well-defined supervision framework is therefore needed to clarify and guide the role of ROs, ensuring sustained situational awareness and enabling timely intervention in ship navigation when necessary. In parallel, comprehensive liability and accountability frameworks must be established to define and delineate the division of responsibilities between humans and autonomous systems. These frameworks should recognise that the level of autonomy may vary across different operational scenarios and navigational environments, and they must provide clear guidelines for transferring control between autonomous functions and human operators, to ensure that humans continuously remain in the loop throughout cooperation with autonomous systems. The findings of this study contribute to this goal by offering a basis for future research on HMC in ROCs, particularly in evaluating how different technologies require different degrees of human involvement to operate effectively. Building on these insights, regulatory development can shape policies that clearly define HMC in ROCs, thereby strengthening both safety and operational reliability in increasingly autonomous maritime systems.

5.2.3. Competencies and training

As highlighted in Section 4.3.2, technological evolution within ROCs is highly dynamic, with technologies often advancing significantly in the years following their emergence, while new technologies continue to emerge throughout this process. This poses challenges for RO competencies and their ability to continuously interpret, manage, and support autonomous ship navigation decisions. Operators must not only maintain advanced navigation knowledge but also develop a sound understanding of the principles, capabilities, and limitations of AI and autonomous systems. To address this, modernised and adaptive competency training frameworks are required. Although organisations such as Det Norske Veritas (DNV) [80] and UK Maritime & Coastguard Agency (MCA) [81] have proposed initial frameworks for RO training, it must be acknowledged that such frameworks should remain dynamic, with continuous evaluation, updating and adaptation to reflect the integration of emerging ROC technologies. When designing these frameworks, it is also important to consider that learning-related tensions can positively influence operators' willingness to adopt new technologies [82]. Training modules should therefore be designed to strengthen operator competencies without becoming overly complex, thereby increasing ROs' readiness and ability to adapt to new technologies in ROC environments.

The findings and analysis in Section 4 show that numerous technologies, such as VRV and DAPM, are applied in ROCs to support operators in monitoring and remotely controlling autonomous ships. While these technologies enhance supervisory efficiency and situational awareness, experiences from other autonomous vehicle domains, such as cars [83], reveal potential drawbacks, including multitasking tendencies and overreliance on autonomous systems. These behaviours can undermine operators' ability to respond effectively in emergency situations. To address this, training frameworks should include measures that reduce such risks, help operators maintain concentration in ROC environments, and promote an appropriate balance between human oversight and reliance on automation. The outcomes of this research can support maritime organisations in developing tailored training frameworks by identifying specific ROC technologies, thereby minimising training redundancies and addressing potential competency gaps in the preparation of future ROs.

6. Conclusion

Although ROCs play an important role in supporting high levels of maritime autonomy, there remains a significant research gap in systematically identifying the technologies that enable their operation and evaluating their development and interrelationships. To address this gap, this study develops an LLM-based patent analytics framework to examine the technological landscape of ROCs that support MASS and constructs a technology topic network to evaluate the interrelationships among these technologies. This study has made such new contributions as: 1) it develops an LLM-based patent analytics method for identifying ROC-related technology topics from patent data, which, to the best of the authors' knowledge, has not previously been applied in this domain; 2) it constructs a technology topic network by extracting co-occurrence relationships among patents from technology identification outputs, thereby revealing the connections among different technologies within the ROC ecosystem; 3) it applies complex network theory to quantitatively evaluate the structure and temporal evolution of these technological relationships, providing new insights into the development and deployment of ROC technologies. Methodologically, the proposed framework enables the contextual identification of ROC technologies from full patent texts, converts unstructured patent documents into structured technology-topic data, and supports the quantitative analysis of technological interdependencies and temporal evolution through network modelling. It hence extends emerging studies on use of LLM to assist in risk and reliability analysis from accident reports to patent context and opens a new direction on associating new technological maturity level with reliability of safety-sensitive systems. Based on the LLM-based patent analysis and network evaluation, the results reveal that ROC technologies form a tightly connected network, in which sensing, communication, and control technologies are closely integrated to support the role of ROCs in maintaining remote supervision and control functions. The proposed framework provides a systematic and quantitative approach for identifying and evaluating technologies in ROC systems. The findings offer valuable insights to inform future ROC design, regulatory development, and operator competency planning, thereby facilitating the safe and effective deployment of higher levels of autonomous ships.

Several limitations should be acknowledged in this study. The ROC technology identification is based on patent data, which provides rich technical information but may not fully capture industrial know-how, unpublished technologies, commercial system architectures, or regulatory developments. In addition, this study focuses on broad technology topics rather than a detailed multi-level technology taxonomy. Future research can be extended in several directions. First, as additional patent information becomes publicly available, future studies could incorporate a broader range of patent data to provide a more comprehensive picture of ROC technology development. Second, this study identified only board technology topics, further work could focus on identifying different levels of technology topics within these categories. Such efforts would help build a more systematic and hierarchical technology taxonomy for ROCs and reveal deeper connections between related technologies. Third, the relationship between ROC technologies and human operators requires further investigation. Future studies should explore how different levels of human involvement correspond to the operation of various technologies in ROCs. Such analysis could help determine when and how human intervention is most effective, supporting the design of adaptive human-machine collaboration models for different operational scenarios. Ultimately, advancing human-centred ROC development will require bridging technical innovation with human operational perspectives. Linking technology mapping with operator competency, regulatory standards, and training design to ensure that humans-in-the-loop, thereby enhancing both the safety and efficiency of autonomous maritime systems.

CRediT authorship contribution statement

Jiale Xiang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Eddie Blanco-Davis:** Writing – review & editing, Supervision, Project administration, Formal analysis, Conceptualization. **Xuri Xin:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Jin Wang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Zaili Yang:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. LLM-based technology topics identification prompt design.

You are an expert in analysing patent documents related to autonomous maritime systems. You will receive the full text of a patent. Your task is to identify the **technology or method** described in the patent which supports the development or realization of functions in a Remote Operation Centre (ROC) for autonomous ships.

Focus on extracting the **technical approach**, system, or method that plays a role in enabling ROC capabilities.

[Instructions]

When identifying ROC-supported technologies from the patent, follow these rules:

- Each response technology label must be the Level 1 technologies in the technology taxonomy.
- The technology must be general, reusable, and applicable across different patents, avoid implementation-specific or narrow use cases.
- **DO NOT** combine multiple different technologies or functional areas into a single technology topic label. Each label must correspond to one independent and clearly technical concept.
- DO NOT guess, assume, or infer anything beyond what is clearly stated in the patent content.
- If the patent's technologies do not support any ROC function, return "None" instead.
- All technology topic labels must begin with [1] to indicate Level 1 status.
- **AVOID** over-rely on the list of previous technology labels when analysis the new patent data.
- **AVOID** overuse the same technology label across different patents analysis response unless it is clearly and explicitly supported by the current patent.

IMPORTANT: Below is a list of example ROC technologies label from previous patent analyses for you reference.

{Topics}

[Examples]

This is some INVALID examples for you reference:

[1] Real-time Video Streaming of Harbor Operations (too specific).

[1] Tugboat Mission Planning Interface (includes application-specific vessel type).

[1] Control System Using Nvidia GPUs (implementation-specific).

[Input Document]

{Document}

[Output Format]

The response MUST follow this structure, not comments:

[1] Topic Label: Topic Description.

[1] Topic Label: Topic Description.

Data availability

Data will be made available on request.

References

[1] Gu Y, Goez JC, Guajardo M, Wallace SW. Autonomous vessels: state of the art and potential opportunities in logistics. Int Trans Oper Res 2021;28(4):1706–39.
[2] UNCTD. Review of maritime transport 2024: navigating maritime chokepoints. United Nations; 2024.
[3] Negenborn RR, Goerlandt F, Johansen TA, Slaets P, Valdez Banda OA, Vanelslander T, Ventikos NP. Autonomous ships are on the horizon: here's what we need to know. Nature 2023;615(7950):30–3.
[4] Shiokari M, Itoh H, Yuzui T, Ishimura E, Miyake R, Kudo J, Kawashima S. Structure model-based hazard identification method for autonomous ships. Reliab Eng Syst Saf 2024;247:110046.
[5] Song R, Papadimitriou E, Negenborn RR, van Gelder P. Safety and efficiency of human-MASS interactions: towards an integrated framework. J Mar Eng Technol 2024:1–20.
[6] IMO. IMO takes first steps to address autonomous ships. https://www.imo.org/en/mediacentre/pressbriefings/pages/08-msc-99-mass-scoping.aspx; 2018. Online Accessed: 4 September 2025.
[7] Kim TE, Perera LP, Sollid MP, Batalden BM, Sydnes AK. Safety challenges related to autonomous ships in mixed navigational environments. WMU J Marit Aff 2022;21 (2):141–59.
[8] IBM Newsroom. The Mayflower Autonomous Ship Project. https://newsroom.ibm.com/then-and-now; 2025. Online Accessed: 25 April 2025.

[9] Yara Birkeland. Yara Birkeland, two years on. https://www.yara.com/knowledge-grows/yara-birkeland-two-years-on/; 2024. Online Accessed: 26 April 25.
[10] Xiang J, Blanco-Davis E, Xin X, Li H, Hifi N, Wang J, Yang Z. A systematic literature review of human-machine cooperation in maritime autonomous surface ships. Auton Transp Res 2025;1(1):24–43.
[11] Chae CJ, Kim M, Kim HJ. A study on identification of development status of MASS technologies and directions of improvement. Appl sci 2020;10(13):4564.
[12] Alsos OA, Hodne P, Skåden OK, Porathe T. Maritime autonomous surface ships: automation transparency for nearby vessels. J Phys Conf Ser 2022:012027.
[13] Madsen A, Kim TE. A state-of-the-art review of AI decision transparency for autonomous shipping. J Int Marit Saf Env Aff Shipp 2024;8(1–2):2336751.
[14] van de Merwe K, Mallam S, Nazir S, Engelhardtsen Ø. Navigators' Perspective on information requirements for supervisory control of autonomous ships. In: Proceedings of the human factors and ergonomics society. 1 editor. SAGE Publications Inc.; 2024. p. 416–22.
[15] Jiang L, Goetz SM. Natural language processing in the patent domain: a survey. Artif Intell Rev 2025;58(7):214.
[16] Naveed H, Khan AU, Qiu S, Saqib M, Anwar S, Usman M, Akhtar N, Barnes N, Mian A. A comprehensive overview of large language models. ACM Trans Intell Syst Technol 2023.
[17] Wang Z, Pang Y, Lin Y. Large language models are zero-shot text classifiers. arXiv preprint arXiv: 2312.01044.. 2023.
[18] Pham CM, Hoyle A, Sun S, Resnik P, Iyyer M. Topicgpt: a prompt-based topic modeling framework. arXiv preprint arXiv: 2311.01449.. 2023.
[19] Publications Office of the European Union. 2022. Maritime unmanned navigation through intelligence in networks (MUNIN). https://cordis.europa.eu/project/id/314286. Online Accessed: 26 Aug 2025.
[20] Chang C-H, Wijeratne IB, Kontovas C, Yang Z. COLREG and MASS: analytical review to identify research trends and gaps in the development of autonomous collision avoidance. Ocean Eng 2024;302:117652.
[21] Lin J, Diekmann P, Framing C-E, Zweigel R, Abel D. Maritime environment perception based on deep learning. IEEE Trans Intell Transp Syst 2022;23(9):15487–97.
[22] Yu Y, Liu K, Kong W, Xin X. Time-evolving graph-based approach for multi-ship encounter analysis: insights into ship behavior across different scenario complexity levels. Transp Res Policy Pract 2025;194:104427.
[23] Zhao CC, Wu B, Yip TL, Lyu J. A graphical collision alert system of power-driven ship in sight situations considering geometric encounter situations. Ocean Coast Manage 2023;245:106872.
[24] Zolich A, Palma D, Kansanen K, Fjørtoft K, Sousa J, Johansson KH, Jiang Y, Dong H, Johansen TA. Survey on communication and networks for autonomous marine systems. J Intell Robot Syst 2019;95(3):789–813.
[25] Helgesen ØK, Vasstein K, Brekke EF, Stahl A. Heterogeneous multi-sensor tracking for an autonomous surface vehicle in a littoral environment. Ocean Eng 2022;252:111168.
[26] Thombre S, Zhao Z, Ramm-Schmidt H, García JMV, Malkamäki T, Nikolskiy S, Hammarberg T, Nuortie H, Bhuiyan MZH, Särkkä S, Lehtola VV. Sensors and AI techniques for situational awareness in autonomous ships: a review. IEEE Trans Intell Transp Syst 2022;23(1):64–83.
[27] Zhang J, Wang MM, You X. Maritime autonomous surface shipping from a machine-type communication perspective. IEEE Commun Mag 2023;61(10):184–90.
[28] Brandsæter A, Smefjell G, van de Merwe K, Kamsvåg V. Assuring safe implementation of decision support functionality based on data-driven methods for ship navigation. In: Baraldi P, Di Maio F, Zio E, editors. Proceedings of the 30th European safety and reliability conference and the 15th probabilistic safety assessment and management conference. Singapore: Research Publishing; 2020. p. 637–43.
[29] Wang Y, Xu H, Feng H, He J, Yang H, Li F, Yang Z. Deep reinforcement learning based collision avoidance system for autonomous ships. Ocean Eng 2024;292:116527.
[30] Li H, Xing W, Jiao H, Yang Z, Li Y. Deep bi-directional information-empowered ship trajectory prediction for maritime autonomous surface ships. Transp Res Logist Transp Rev 2024;181:103367.
[31] Li H, Yang Z. Incorporation of AIS data-based machine learning into unsupervised route planning for maritime autonomous surface ships. Transp res Logist transp rev 2023;176:103171.
[32] He Z, Liu C, Chu X, Wu W, Zheng M, Zhang D. Dynamic domain-based collision avoidance system for autonomous ships: real experiments in coastal waters. Expert Syst Appl 2024;255:124805.
[33] Xin X, Liu K, Yu Y, Yang Z. Developing robust traffic navigation scenarios for autonomous ship testing: an integrated approach to scenario extraction, characterization, and sampling in complex waters. Transp Res C Emerg Technol 2025;178:105246.
[34] Zhang W, Zhang Y, Zhang C. Research on risk assessment of maritime autonomous surface ships based on catastrophe theory. Reliab Eng Syst Saf 2024;244:109946.
[35] DNV. DNV-CG-0264: autonomous and remotely operated vessels. Det Norske Veritas; 2024.
[36] Dybvik H, Veitch E, Steinert M. Exploring challenges with designing and developing shore control centers (SCC) for autonomous ships. In: Proceedings of the design society: design conference. 1; 2020. p. 847–56.
[37] Li X, Yuen KF. A human-centred review on maritime autonomous surfaces ships: impacts, responses, and future directions. Transp Rev 2024;44(4):791–810.
[38] Veitch E, Alsos OA. Human-centered explainable artificial intelligence for marine autonomous surface vehicles. J Mar Sci Eng 2021;9(11):1227.
[39] Laso PM, Brosset D, Giraud MA, Ieee. In: Monitor and control human-computer interface for unmanned surface vehicle fleets, *OCEANS - marseille conference*. Marseille, France: IEEE; 2019.
[40] Veitch EA, Kaland T, Alsos OA. Design for resilient human-system interaction in autonomy: the case of a shore control centre for unmanned ships. In: Proceedings of the design society. Cambridge University Press; 2021. p. 1023–32.
[41] Hodne P, Skåden OK, Alsos OA, Madsen A, Porathe T. Conversational user interfaces for maritime autonomous surface ships. Ocean Eng 2024;310:118641.
[42] Cheng T, Utne IB, Wu B, Wu Q. A novel system-theoretic approach for human-system collaboration safety: case studies on two degrees of autonomy for autonomous ships. Reliab Eng Syst Saf 2023;237:109388.
[43] Fan SQ, Shi K, Weng JX, Yang ZL. Letting losses be lessons: human-machine cooperation in maritime transport. Reliab Eng Syst Saf 2025;253:110547.
[44] Emad GR, Ghosh S. Identifying essential skills and competencies towards building a training framework for future operators of autonomous ships: a qualitative study. WMU J Marit Aff 2023;22(4):427–45.
[45] Sharma A, Kim TE. Exploring technical and non-technical competencies of navigators for autonomous shipping. Marit Policy Manag 2022;49(6):831–49.
[46] Kim TE, Mallam S. A Delphi-AHP study on STCW leadership competence in the age of autonomous maritime operations. WMU J Marit Aff 2020;19(2):163–81.
[47] Saha R. Mapping competence requirements for future shore control center operators. Marit Policy Manag 2023;50(4):415–27.
[48] Asmussen CB, Møller C. Smart literature review: a practical topic modelling approach to exploratory literature review. J Big Data 2019;6(1):1–18.
[49] Bai X, Zhang X, Li KX, Zhou Y, Yuen KF. Research topics and trends in the maritime transport: a structural topic model. Transp Policy 2021;102:11–24.
[50] Belabyad M, Pyne R, Paraskevadakis D, Chang CH, Kontovas C. Technology evolution in maritime autonomous systems: a patent-based analysis. Ocean Coast Manage 2025;267:107744.
[51] Ma T, Zhe T, Xiao R. Topics and trends in maritime decarbonization: a structural topic model approach. Marit Econ Logist 2025:1–29.
[52] Yan K, Wang Y, Jia L, Wang W, Liu S, Geng Y. A content-aware corpus-based model for analysis of marine accidents. Accid Anal Prev 2023;184:106991.
[53] Bi H, Gao H, Li A, Ye Z. Using topic modeling to unravel the nuanced effects of built environment on bicycle-metro integrated usage. Transp Res Policy Pract 2024;185:104120.
[54] Baden C, Pipal C, Schoonvelde M, van der Velden MAG. Three gaps in computational text analysis methods for social sciences: a research agenda. Commun Methods Meas 2022;16(1):1–18.
[55] Singh A, Triulzi G, Magee CL. Technological improvement rate predictions for all technologies: use of patent data and an extended domain description. Res Policy 2021;50(9):104294.
[56] Sun M, Tong T, Jiang M, Zhu JX. Innovation trends and evolutionary paths of green fuel technologies in maritime field: a global patent review. Int J Hydrog Energy 2024;71:528–40.
[57] Karetnikov V, Ol'Khovik E, Ivanova A, Butsanets A. Technology level and development trends of autonomous shipping means. In: Murgul V, Pukhkal V, editors. International Scientific Conference Energy Management of Municipal Facilities and Sustainable Energy Technologies EMMFT 2019. Cham: Springer International Publishing; 2021. p. 421–32.
[58] Miwa N, Bhatt A, Morikawa S, Kato H. High-speed rail and the knowledge economy: evidence from Japan. Transp Res Policy Pract 2022;159:398–416.
[59] Lin Y, Wang X, Yang J, Wang S. Core technology topic identification and evolution analysis based on patent text mining—a case study of unmanned ship. Appl Sci 2024;14(11):4661.
[60] Wu T, Wang Y, Quach N. Advancements in natural language processing: exploring transformer-based architectures for text understanding. In: 2025 5th international conference on artificial intelligence and industrial technology applications (AIITA). IEEE; 2025. p. 1384–8.
[61] Henriquez-Jara B, Arriagada J, Tirachini A. Impact of real-time information on passenger satisfaction across varying public transport quality levels in 13 Chilean cities. Transp Res Policy Pract 2025;200:104622.
[62] Zheng J, Huang Z, Wang XL, Qi XC, Chen XH. Assessing feasibility of a human-like situation understanding method based on large language models for applying in maritime autonomous surface ships in encounter scenarios. Ocean Eng 2025:341.
[63] Christensen KA, Gusev A, Tufte AG, Alsos OA, Steinert M. AI Captain: conversational mission planning and execution system for autonomous surface vehicles. Ocean Eng 2025:338.
[64] Chen NY, Yang AR, Wu H, Chen L, Xiong W, Jing N. SEMINT: an LLM-empowered long-term vessel trajectory prediction framework. Int J Geogr Inf Sci 2025;39(9):1938–72.
[65] Din MU, Akram W, Bakht AB, Dong Y, Hussain I. Maritime mission planning for unmanned surface vessel using large language model. In: 2025 IEEE international conference on simulation, modeling, and programming for autonomous robots (SIMPAR); 2025. p. 1–6.
[66] Huang D, Fu X, Yin X, Pen H, Wang Z. Automating maritime risk data collection and identification leveraging large language models. In: 2024 IEEE international conference on data mining workshops (ICDMW). IEEE; 2024. p. 433–9.
[67] Crestelo Moreno F, Soto-López V, García Maza JA, Sernaglia M. Fatigue as a latent risk factor in maritime safety systems: a systematic review and implications for reliability analysis. Reliab Eng Syst Saf 2026;267:111930.
[68] Li H, Çelik C, Bashir M, Zou L, Yang Z. Incorporation of a global perspective into data-driven analysis of maritime collision accident risk. Reliab Eng Syst Saf 2024;249:110187.
[69] Farquhar S, Kossen J, Kuhn L, Gal Y. Detecting hallucinations in large language models using semantic entropy. Nature 2024;630(8017):625–30.

[70] Ekin S. Prompt engineering for ChatGPT: a quick guide to techniques, tips, and best practices. Authorea Prepr 2023.
[71] Hain DS, Jurowetzki R, Buchmann T, Wolf P. A text-embedding-based approach to measuring patent-to-patent technological similarity. Technol Forecast Soc Change 2022;177:121559.
[72] Wan Z, Mahajan Y, Kang BW, Moore TJ, Cho JH. A survey on centrality metrics and their network resilience analysis. IEEE Access 2021;9:104773–819.
[73] Yang Z, Zhang W, Yuan F, Islam N. Measuring topic network centrality for identifying technology and technological development in online communities. Technol Forecast Soc Change 2021;167:120673.
[74] Li S, Quan Y, Luo X, Wang J, Tian C, Guan X. Identifying influential nodes in complex networks via weighted k-shell entropy-based approach. Chaos Solit Fractals 2025;199:116909.
[75] Garas A, Schweitzer F, Havlin S. A k-shell decomposition method for weighted networks. New J Phys 2012;14(8):083030.
[76] Zhang Q, Li M. A betweenness structural entropy of complex networks. Chaos Solit Fractals 2022;161:112264.
[77] Chang C-H, Kontovas C, Yu Q, Yang Z. Risk assessment of the operations of maritime autonomous surface ships. Reliab Eng Syst Saf 2021;207:107324.
[78] Li X, Oh P, Zhou Y, Yuen KF. Operational risk identification of maritime surface autonomous ship: a network analysis approach. Transp Policy 2023;130:1–14.
[79] Cheng T, Veitch EA, Utne IB, Ramos MA, Mosleh A, Alsos OA, Wu B. Analysis of human errors in human-autonomy collaboration in autonomous ships operations through shore control experimental data. Reliab Eng Syst Saf 2024;246:110080.
[80] DNV. DNV-RP-0323: certification scheme for remote control centre operators. Det Norske Veritas; 2021.
[81] MCA. Remote operator training and certification pilot framework. UK Maritime and Coastguard Agency; 2025.
[82] Liu X, Zhang D, Nguyen CT, Yuen KF, Wang X. Freedom–enslavement'' paradox in consumers' adoption of smart transportation: a comparative analysis of three technologies. Transp Policy 2025;164:206–16.
[83] Sun S, Wong YD. Drivers' attention economy and adoption to autonomous vehicle. Transp Policy 2023;138:108–18.