Ocean and Coastal Management 267 (2025) 107744

Contents lists available at ScienceDirect

Ocean and Coastal Management

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

Technology evolution in maritime autonomous systems: A patent-based analysis

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ARTICLE INFO

Keywords:
Maritime autonomous surface ships
Patent analysis
Technology forecasting
Topic modelling
Network analysis
S-Curve

ABSTRACT

Technology evolution in maritime autonomous systems is moving rapidly, yet the understanding of how different technologies integrate and mature remains limited. This study maps the technological landscape through patent analysis of 5987 patents from 2010 to 2024. The framework combines the following: a) bibliometric analysis, (b) Latent Dirichlet Allocation (LDA) topic modelling for the identification of key topics, c) topic-topic network analysis examining knowledge flows, and d) technology lifecycle analysis and forecasting using comparative growth curve modelling (Bass, Gompertz, and Logistic models). The analysis identifies 20 technological domains organised into seven clusters, with network analysis showing 'Sensor Integration' as the most influential technology through centrality metrics. The technology lifecycle assessment shows distinct maturity patterns: 65 % of domains are in growth phase, with safety technologies best predicted by Bass models and complex infrastructural technologies by Gompertz models. Key findings include predicted technology inflection points during 2025–2030, strong interdependencies between domains and emerging cognitive technologies showing high growth potential despite low current maturity. This research offers evidence-based insights for future research studies, research and development (R&D) prioritisation, and investment timing in the development of autonomous shipping. It also demonstrates the effectiveness of integrated patent analytics for technology forecasting, which has potential applications in several areas.

1. Introduction

Technology is driving the maritime sector through unprecedented transformation. Ships represent complex engineering systems integrating both traditional and cutting-edge technologies. These floating technological hubs, operated by skilled seafarers, must constantly evolve to meet growing demands for safety and efficiency in an increasingly digital maritime landscape (Jovanović et al., 2024). Autonomous shipping has made significant progress from concept to reality in recent years, with milestone projects like YARA Birkeland and DNV GL's ReVolt project (Adams, 2014; Yara, 2024). This progression builds on recent advances in maritime decision-making technologies. Wang et al. (2023) demonstrated a Maritime Autonomous Navigation Decision-making System integrating route keeping, optimisation, collision avoidance, and recovery capabilities in real ship trials. Bahrami and Siadatmousavi (2023) developed environmental-responsive route algorithms reducing fuel consumption by 4.76 % compared to traditional approaches. Hocek et al. (2024) showed that advanced autopilot systems with decision support capabilities significantly enhance energy efficiency while reducing operational errors. These developments show the synchronised advancement necessary for the implementation of autonomous shipping. While the maritime sector might not be leading the overall autonomous revolution, with automotive and aeronautical industries setting the pace, it is rapidly catching up, driven by clear operational and economic benefits (Kurt and Aymelek, 2022).

The discussion of technological innovation often refers to patents, as they represent two sides of the same coin. Patents do more than just protect inventors' rights; they provide a window into the future of technology and how industries are evolving. About 70–90 % of all technological information exists only in patent documents, making them an invaluable resource for understanding technological landscapes (WIPO, n.d.; Asche, 2017). Studying these patents, essentially the DNA of technological innovation, can help map out where autonomous shipping technology is headed and understand the complex web of

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https://doi.org/10.1016/j.ocecoaman.2025.107744
Received 21 February 2025; Received in revised form 17 April 2025; Accepted 9 May 2025
Available online 21 May 2025

innovations making it possible. Patent activity in maritime autonomy is accelerating, with the majority of applications submitted post-2018 indicating that Maritime Autonomous Surface Ships (MASS) are not just a hype, but the industry is actively engaged in bringing the concepts into reality (Karetnikov et al., 2020).

While previous studies have examined maritime autonomous technologies through patent analysis (Lin et al., 2024; Liu et al., 2024), they primarily focus on identifying technological components without quantifying their developmental trajectories or system-level interactions. Additionally, existing research lacks predictive modelling of technology growth patterns, with no studies attempting to forecast the maturation trajectories of different autonomous shipping technologies. This creates a critical knowledge gap in understanding both the current maturity levels and future development paths of these technologies, as well as their system-level interdependencies. Furthermore, the absence of comparative growth curve modelling (Bass, Gompertz, and Logistic) in maritime autonomy research limits the ability to predict when different technologies will reach critical development milestones. This study addresses these gaps by analysing how these technologies evolve and interact through an integrated framework combining patent analytics, network analysis, and lifecycle forecasting, with particular emphasis on predicting development trajectories through 2030. **Thus, this research answers the following questions about autonomous shipping technologies: *What is the current technological landscape and maturity level of autonomous shipping technologies? How do these technologies interact and influence each other within the autonomous shipping ecosystem? What are the predicted growth trajectories of these technologies through 2030?***

This study makes several contributions to the field of autonomous shipping technology research: a) it provides a quantitative assessment of technological interdependencies in maritime autonomy through network analysis, moving beyond the traditional component-level analysis to understand system-wide interactions; b) develops and validates a novel methodological framework that combines topic modelling, network analysis, and comparative growth curve modelling to forecast technology evolution, offering a comprehensive analytical approach than existing single-method studies; c) delivers a systematic maturity assessment of autonomous shipping technologies by quantifying their development stages and growth trajectories, establishing an empirical basis for understanding technological progression in this domains, and d) provides a data-driven framework for strategic Research and Development (R&D) prioritisation by identifying key development windows and technology interdependencies. Finally, the comparative analysis of different growth models (Bass, Gompertz, and Logistic) advances the theoretical understanding of how maritime autonomous technologies evolve, distinguishing between technologies driven by industry adoption versus those constrained by technical complexity.

The rest of this paper is organised as follows. Section 2 reviews relevant literature on autonomous shipping development and patent analysis. Section 3 details the analytical framework. Section 4 presents the findings on technological evolution patterns. Section 5 discusses implications for theory and practice and concludes with recommendations for future research.

2. Literature review

2.1. The developing trend of smart and autonomous shipping technologies

The evolution of autonomous shipping technologies has progressed significantly since the early 2010s, driven initially by the European maritime industry's challenge of seafarer shortage. The first major initiative, the Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) project, established the foundational framework by defining autonomous ships as next-generation modular control systems enabling wireless monitoring and control functions both on and off board (Burmeister et al., 2014). By 2015, the focus expanded beyond crew reduction to include operational efficiency, environmental sustainability, and maritime safety enhancement through technological innovation (Kretschmann et al., 2017). The International Maritime Organisation (IMO) formalised this progression by establishing four distinct degrees of ship autonomy: conventional ships with automated functions (level 1), remote-controlled ships with crews (level 2), remote-controlled unmanned ships (level 3), and fully autonomous vessels (level 4) (IMO, 2021a).

From the literature, it can be observed that technological development has followed three parallel tracks: sensor integration and environmental perception (Lee et al., 2024; Wang et al., 2024), autonomous navigation systems (Woo and Kim, 2020; Wright, 2019), and shore-based control infrastructure (Alsos et al., 2022; Veitch et al., 2021). In sensor technologies, the integration of high-resolution optical and thermal imaging with LiDAR and radar systems has enabled precise object detection and classification even under adverse weather conditions (Yao et al., 2023). The development of autonomous navigation algorithms progressed from basic collision avoidance to sophisticated path planning incorporating real-time environmental data and maritime regulations (Vagale et al., 2021).

The first commercial implementation milestone occurred with Norway's YARA Birkeland project in 2017, representing the world's first fully electric autonomous container vessel. This project demonstrated both technical feasibility and environmental benefits, projecting annual reductions of 40,000 diesel truck journeys and associated emissions (Yara, 2024).

Technical challenges have centred primarily on system reliability and cyber security, with key risks including interactions with manned vessels, object detection, cyber-attacks, human error, and equipment failure, highlighting the vital role of safety and perception technologies (Chang et al., 2021; Misas et al., 2024). Shore Control Centres (SCC) constitute a crucial infrastructure element in MASS development ecosystem, needing advanced communication systems capable of maintaining continuous vessel connectivity. Current systems achieve high reliability in satellite communication links, though maintaining this performance in extreme conditions would need large processing power of data which can be expensive (Zolich et al., 2018).

Previous studies have reviewed technological developments in autonomous shipping. (Wang et al., 2020) established a comprehensive framework of core technologies, identifying critical components from intelligent awareness to edge computing, while emphasising the role of sensor fusion and communication systems. Kim et al. (2024) analysed 3363 MASS-related articles, finding image recognition and deep learning technologies dominating current research trajectories. Jovanović et al. (2024) mapped MASS technologies into clusters, identifying key technological domains including autonomous navigation and collision avoidance systems. These studies used different approaches primarily focused on identifying technological components only.

Looking at MASS from a theory perspective, maritime technological innovation, like other engineering based sectors, follows established patterns of technological evolution theorised by Dosi (1982), where development trajectories are shaped by technological paradigms and selection environments. In autonomous systems, these trajectories often demonstrate what Hughes (1989) called as "reverse salients", critical subsystems lagging behind overall system development. This theoretical viewpoint helps explain the complex evolution of maritime autonomous systems, where advances in different technological domains progress at varying rates influenced by both technical constraints and market demands.

Recent developments have focused on standardisation and regulatory frameworks. The IMO's Regulatory Scoping Exercise (RSE) identified critical areas requiring regulatory adaptation for autonomous vessel operation (IMO, 2021b). The IMO has decided to create a non-required, goal-based code for cargo MASS, which may eventually become mandatory depending on application experience. The code's objective is to offer a foundation for both remote control and autonomous execution of critical functions. The non-mandatory MASS Code is expected to be completed by 2026, with an experience-building period after its implementation. A required code is scheduled to go into effect as early as January 1, 2032 (DNV, 2024).

2.2. The use of patents for technology mapping

Patents, as a form of agreements between governmental bodies/agencies and inventors, provide standardised, detailed technological information while conferring temporary monopoly (exclusive) rights (Hoerner, 1991). As Campbell (1983) described them, they are a form of "*a deed to intellectual property*" where citations serve as "metes and bounds" by referencing related intellectual property, similar to how land boundaries are described by neighbouring landmarks in old English descriptions of deeded land. However, the theoretical significance of patent analysis extends beyond simple innovation documentation. Patents embody technological trajectories as described and explained by the evolutionary economics theory, being structured patterns of innovative activity shaped by scientific paradigms, market forces and technological interdependencies (Nelson and Winter 1982). Through this perspective, patent documents capture not only technical specifications but also the evolutionary pathways of technological development.

Empirically, patents have been widely used to analyse these theorised evolutionary pathways of technology (Lee, 2021). Patent analysis offers different theoretical advantages over other innovation indicators. While scientific literature primarily reflects research activities, patents bridge the gap between scientific discovery and commercial application (Murray and Stern, 2006). Approximately 70–90 % of technological information in patent documents remains exclusive to this medium and not published anywhere else, clearly showing their unique value in technological forecasting (WIPO, n.d.; Asche, 2017). This information asymmetry makes patent analysis particularly advantageous for understanding commercialisation trajectories and market-oriented technological development.

Furthermore, patent analysis allows quantitative analysis as they provide a systematic framework through a standardised classification system and comprehensive technical disclosure requirements. The International Patent Classification (IPC) system is an example of this standardisation through its hierarchical structure (Gomez and Moens, 2014). The IPC system provides a hierarchical framework for organising technological information. This classification comprises eight sections, and approximately 80,000 sub-divisions, offering a standardised taxonomy for technological categorisation. For instance, an IPC code B63B25/08 represents maritime cargo shipping technology where 'B' indicates performing operations/transporting, '63′ denotes ships/waterborne vessels, 'B' specifies ship equipment, '25′ indicates cargo handling capacity/arrangement, and '08′ specifically relates to arrangements for bulk cargo. This detailed classification enables precise technological positioning and trajectory mapping.

Patent analysis methodologies have demonstrated efficacy in various sectors. For example, de Oliveira et al. (2024) applied network analysis on sustainable aviation fuel patents to track biofuel technologies. Cho et al. (2021) used cross-citation analysis and main path analysis which gave technological evolution patterns in autonomous driving systems. In the robotics domain, Qiu and Wang (2022) used topic modelling (using the Latent Dirichlet Allocation (LDA) algorithm) and citation network modelling to discover development trajectory of the robotics technologies.

While patent analysis is being widely applied for technological mapping and forecasting across numerous sectors, its application in maritime research, particularly autonomous shipping technologies, remains surprisingly constrained in both scope and analytical sophistication. Recent studies demonstrate accelerating patent activity in autonomous maritime technologies, with over 70 % of applications submitted post-2018, indicating rapid technological advancement (Karetnikov et al., 2020). The patent landscape in maritime autonomy exhibits unique characteristics of technological clustering, primarily around vessel control systems, navigational intelligence, and operational safety mechanisms. Ivanova et al. (2021) identified three primary patent clusters comprising 14 subgroups (246 patents) in core autonomous technologies, 12 subgroups (164 patents) in supporting systems, and 4 subgroups (26 patents) in specialised applications, demonstrating the hierarchical nature of technological development in this domain. Recent analyses of maritime propulsion technologies through patent data observed significant technological convergence, particularly in green fuel technologies, with only four distinct sub-technologies accounting for 34.6 % of patents and 38.3 % of citations (Sun et al., 2024). Liu et al. (2024) and Lin et al. (2024) employed LDA topic modelling to analyse patent data, with the former identifying emerging technologies in intelligent control systems and ship equipment intelligence, while the latter revealed a pattern of technological fragmentation and integration across 14 distinct topics.

3. Methodology

Fig. 1 shows the research framework employed, constituted of four steps: 1) Patent Data Collection and Bibliometrics, 2) Topic Modelling and Technology Identification, 3) Topic-Topic Network Analysis, and 4) Technology Lifecycle Analysis and forecasting.

The first step involves creating a dataset of patents, which undergoes a bibliometric analysis (distributions by publication year, assignees, countries and patent citations network). Latent Dirichlet Allocation (LDA) topic modelling is then performed on the dataset, which results in topics that help identify and classify technological domains. These identified domains are then subjected to topic-topic network analysis, constructing a directed weighted graph where vertices represent technology topics and edges represent citation relationships. This graph is analysed through network density, clustering coefficient, and PageRank centrality metrics. Finally, building on the previous steps, a technology lifecycle analysis is conducted using comparative growth curve modelling (Bass, Gompertz, and Logistic models), with parameters optimised through training data (2010–2020) and validated against testing data (2021–2023) to assess technology maturity levels and forecast development trajectories. All analyses were conducted using Python 3.11 in the Google Colab Environment.

3.1. Data collection and bibliometrics

Patent data was retrieved from Google Patents through BigQuery due to its comprehensive coverage of global patent documents and ability to efficiently process complex search queries with multiple classification codes and semantic terms (Younes and de Rassenfosse, 2024).

Patent data was retrieved from Google Patents through BigQuery using SQL queries. The search query (Table 1) was structured through a three-layer Boolean logic. The first layer applies a temporal filter (2010–2024). The second layer combines maritime domain classifications (B63 series for ship/vessel construction, marine propulsion, and auxiliaries) with maritime terms (e.g., ship, vessel, marine) to ensure maritime context. The third layer integrates autonomous systems classifications (G05D1 for vehicle control, G06N for computer models) with autonomous technology terms (e.g., autonomous, unmanned, self-navigate) to capture autonomous capabilities. Core CPC codes were selected based on their direct relevance to maritime autonomous systems, covering vessel construction (B63B), propulsion (B63H), traffic control (G08G3), and navigation systems (G01C21). Furthermore, only patents with English titles and abstracts are included.

Logic Structure:

1 **Temporal Filter** AND
2 (**Maritime Domain Classifications** OR **Maritime Domain Terms**) AND

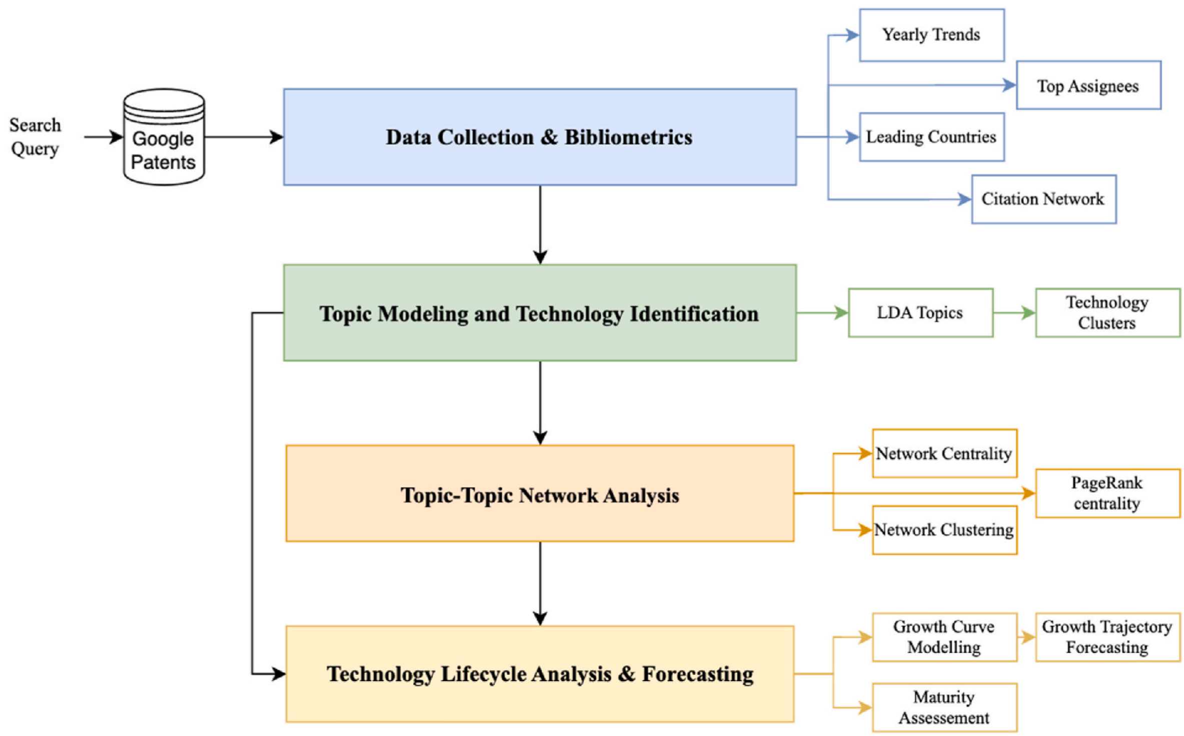

Fig. 1. Research Framework illustrating the four-step methodology: 1)Patent Data Collection and Bibliometrics, 2) Topic Modelling and Technology Identification,3) Topic-Topic Network Analysis, and 4) Technology Lifecycle Analysis and Forecasting.

3 (**Autonomous Systems Classifications** AND **Autonomous Technology Terms**).

Patent screening analysis is conducted using PRISMA process (Fig. 2), which is a set of guidelines for systematic reviews to increase transparency and reproducibility (Page et al., 2021). This process has been widely used and adapted for patent analysis (Arsad et al., 2023; Srivastava and Jain, 2024), as it follows the same core stages: identification, screening, eligibility, and finally including the eligible records.

The search query gave an initial dataset of 6418 patents. The first screening process followed the PRISMA process, removing duplicates and patents with unavailable titles or abstracts. Patent documents were processed at the family level using the INPADOC[1] family definition. Each technological innovation was counted once, regardless of multiple jurisdictional filings. Priority documents (the first patent application filed) were used. This prevents double-counting of patents.

Out of the initial 6418 patents, 6291 were included in the next stage of eligibility checking. Titles and abstracts were reviewed at this stage to confirm alignment with core aspects of autonomous shipping, such as autonomous navigation, propulsion, collision avoidance, fleet management, system integration, etc. Patents were excluded if they focused on unrelated fields. A total of 304 patents were removed because of their irrelevancy, as they fall into categories such as aquaculture (e.g., fish farming systems), offshore wind farm operations (e.g., hydrological monitoring), or niche maritime applications (e.g., yacht docking systems or fishing-specific technologies). The final selection of patents included 5987 patents.

The final dataset contains 5987 patents, with information organised across 13 columns: publication and application numbers, family IDs, filing and publication dates, titles, and abstracts, CPC and IPC codes, assignees, inventors, country identifiers and citation data.

Bibliometric analysis was conducted on the collected patent data, including distribution by year, country and assignees. Furthermore, a citation network analysis tracked knowledge flows across seven two-year periods (2010–2012 through 2022–2024), visualising how the network's structure evolved. Each time window's network was analysed for density and clustering patterns.

3.2. Topic modelling for technology domain identification

This research uses Latent Dirichlet Allocation (LDA), an unsupervised machine learning model, to identify the underlying topic structures based on latent relationships of technological terms and phrases extracted from the patent corpus. The LDA assumes that each document is represented by a mixture of various latent topics, where each topic is characterised by a distribution over words (Jelodar et al., 2019).

Various approaches exist to extract key topics from texts, ranging from classical models like Latent Dirichlet Allocation (LDA) to neural and embedding-based techniques such as neural topic models and transformer-based Large Language Models (LLMs). However, for large and domain-specific corpora like patents, LDA remains one of the most reliable and interpretable methods (Jelodar et al., 2017). Its probabilistic base enables it to represent documents as mixes of latent themes, providing unambiguous distributions across words and documents, which is important for recognising subject patterns across thousands of technical texts (Blei et al., 2003; Sbalchiero and Eder, 2020). In the specific context of patent analysis, LDA has demonstrated superior performance in identifying emerging technological trends and knowledge flows across domains (Vayansky & Kumar, 2020). Unlike LLMs, which often act as black boxes, LDA provides clearer topic-word distributions, making it more suitable for unsupervised analysis (El-Gayar et al., 2024).

LDA models patent documents according to the following generative process. Given a corpus D of M documents, with each document d containing N_d words (Blei et al., 2003):

[1] INPADOC (International Patent Documentation) represents a comprehensive patent family definition system maintained by the European Patent Office (EPO) that groups patent documents sharing at least one common priority application.

Table 1
Search query breakdown.

Category	Components	Description	Examples/Details
Temporal Filter	Publication Date	Patents from 2010 to 2024	20100101 to 20241231
Maritime Domain Classifications	Ship/Vessel Core (B63)	B63B: Ships/ vessel construction	Hull constructions, equipment
		B63H: Marine propulsion	Propulsion elements, steering
		B63J: Marine auxiliaries	Auxiliary vessel equipment
		B63G: Marine attack/defense	Naval equipment, armament
	Marine Traffic	G08G3: Marine traffic control	Vessel traffic management
Autonomous Systems Classifications	Control Systems	G05D1: Vehicle position control	Autonomous navigation control
		G05B: General control systems	Adaptive and automated control
	Intelligence Systems	G06N: Computer models	AI, ML, neural networks
	Navigation Systems	G01C21: Navigation instruments	Navigation guidance systems
		G01S: Radio navigation/radar	Positioning, radar systems
	Communication	H04B: Transmission systems	Basic transmission technology
		H04L67: Network protocols	Real-time control protocols
		H04W4: Wireless services	Wireless network applications
Maritime Domain Terms	Vessel Types	General maritime vessels	ship, vessel, boat, ferry
		Specific vessel types	submarine, barge, tanker
		Commercial vessels	cargo-ship, container-ship
	Maritime Infrastructure	Port facilities	port, harbor, offshore
	Maritime Context	General maritime terms	marine, maritime, nautical, naval
Autonomous Technology Terms	Core Autonomy	Basic autonomous concepts	autonomous, unmanned, uncrewed
	Navigation	Navigation capabilities	self-navigate, path-planning
	Control Systems	Control mechanisms	automatic-control, dynamic-position
	Intelligence	AI/ML terminology	artificial intelligence, neural network
	Safety Systems	Safety features	collision-avoid, obstacle-avoid
	Operational	Operational aspects	autonomous operation, remote-control

1. For each topic $k = 1, \ldots, K$
   o Sample parameters for topic-word distribution $\phi_k \sim \text{Dirichlet}(\beta)$
2. For each document d in corpus D:
   o Sample parameters for document-topic distribution $\theta_d \sim \text{Dirichlet}(\alpha)$
   o For each word position $i = 1, \ldots, N_d$:
      - Draw topic assignment $z_{di} \sim \text{Multinomial}(\theta_d)$
      - Draw word $w_{di} \sim \text{Multinomial}(\phi_{z_{di}})$

Here, α and β are hyperparameters controlling the Dirichlet priors on the document-topic and topic-word distributions respectively. In the above generative process, the words in the document are the only observed variables, while latent variables (ϕ and θ_d) are determined in the inference process, given the values of the hyperparameters. The model learns the latent variables θ_d (document-topic distributions), ϕ_k (topic-word distributions), and z_{di} (word-topic assignments) through collapsed Gibbs sampling (Griffiths and Steyvers, 2004), because of its computational efficiency over other methods like Variational Expectation Maximisation (VEM) (Wang and Hsu, 2020).

Since the abstract often incorporates the invention's technique and primary technical material, it was taken into consideration for this research (Qiu and Wang, 2022; Ghaffari et al., 2023). Therefore, patent titles and abstracts were combined. In order to prepare the combined text and implement LDA, such texts must be pre-processed.

Pre-processing followed similar steps as previous studies applying LDA (Wang and Hsu, 2020; Gupta et al., 2022), and included text normalisation (converting to lowercase and low frequency removing), tokenization (splitting text into individual tokens using spaCy), lemmatisation (reducing tokens to their root forms of grammar "lemma"), and removal of stopwords (using both standard spaCy English stopwords and domain-specific terms like 'method', 'system', 'apparatus'). Additionally, tokens shorter than 3 characters were filtered out. Documents were then represented as term frequency vectors, with terms appearing in fewer than 5 documents or more than 50 % of documents being removed to reduce noise.

The pre-processed corpus then underwent topic modelling using LDA. Model parameters were optimised through grid search: the number of topics was tested in the range of 5–30 in increments of 5. The final model identified K = 20 topics (K = 20 having the highest coherence score), each characterised by a probability distribution over terms P(w|t) and a corresponding document-topic distribution θd. The 20 topics were then thematically organised into technology clusters based on semantic similarity to provide a broader view on the technology landscape.

Unlike supervised methods, LDA topic modelling was trained on the entire corpus of 5987 patent documents to identify latent themes. Hyperparameters were optimised through grid search, including testing topic counts from 5 to 30 in increments of 5 (i.e., 5, 10, 15, 20, 25s, and 30). The optimal number of topics was selected based on the C_v coherence measure, which combines word embeddings with normalised pointwise mutual information (NPMI) to evaluate semantic similarity between high-probability words within each topic (Röder et al., 2015). This approach ensured the model captured meaningful semantic patterns while maintaining topic boundaries.

The topics were then analysed temporally. Topic and cluster evolution was tracked through yearly patent distribution patterns. For each year (y), the prevalence of the topic was calculated using:

$$P\left(\text{topic}_{k,y}\right) = \frac{N_{k,y}}{N_y} \quad \text{Eq 1}$$

where $N_{k,y}$ is the number of patents assigned to topic k in year y, and N_y is the total patents in year y.

In the implementation of LDA, the topic overlap challenge was addressed through hyperparameter optimisation. Following Wallach et al. (2009), asymmetric Dirichlet priors were used for document-topic distributions (α) and symmetric priors for topic-word distributions (β). This allows documents to be represented as mixtures of multiple topics with varying proportions, a core advantage of LDA over earlier clustering methods (Blei et al., 2003). To identify optimal hyperparameters, an extensive grid search was conducted for α and β, selecting final values based on maximising topic coherence scores. Additionally, to further refine the model's handling of topic overlap, a probabilistic threshold approach was implemented where topics were assigned to documents only when their probability exceeded a significance threshold, which was set at 0.3, effectively filtering out minor topic contributions while preserving meaningful semantic relationships (Agrawal et al., 2018). Despite all these approaches, the underlying meanings of the topics are still subject to human interpretation, requiring expertise to infer key semantic coherence to the discovered patterns.

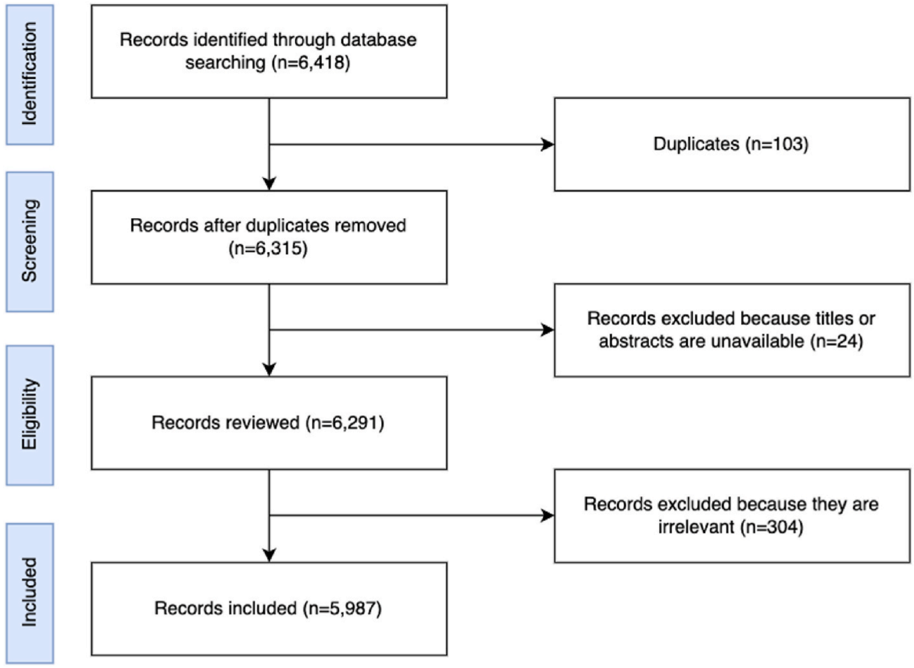

Fig. 2. PRISMA Flow Chart showing the systematic patent screening process.

3.3. Network analysis

In order to understand the knowledge flows and interdependencies between different technological domains in autonomous shipping, a topic-topic citation network analysis was conducted. This network representation enables quantification of how technological domains influence and build upon each other.

Using the topics identified by the LDA, a topic-topic citation network was constructed as a directed weighted graph G = (V, E), where vertices V represent the 20 identified technology topics and edges E represent citation relationships between topics. Edge weights w_{ij} were computed as the sum of citations from patents in topic i to patents in topic j:

$$w_{ij} = \Sigma C_{ij} \quad \text{Eq 2}$$

where C_{ij} represents individual patent citations.

Network characteristics were analysed through several key metrics, which are widely used in network analysis literature (Freeman, 1978; Gupta et al., 2016; Gleich, 2015):

a. **Network density**, indicating the proportion of possible topic connections that exist:

$$D = \frac{E}{N(N-1)} \quad \text{Eq 3}$$

where E is the total number of edges (connections) in the network, N is the total number of nodes (topics).

b. **Clustering coefficient**, measuring topic grouping tendencies:

$$C_i = \frac{L_i}{k_i(k_i-1)} \quad \text{Eq 4}$$

where Li is the number of links between the neighbours of node i and ki is the degree of node i (number of neighbours).

The global clustering coefficient (C) is then:

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i \quad \text{Eq 5}$$

c **PageRank centrality**, quantifying topic influence while accounting for the influence of citing topics:

$$PR(i) = \frac{1-d}{N} + d\sum\nolimits_{j \in M(i)} \frac{PR(j)}{L(j)} \quad \text{Eq 6}$$

where d is the damping factor (typically 0.85), N is the total number of nodes, M(i) is the set of nodes that link to node I, L(j) is the number of outbound links from node j and PR(j) is the PageRank value for node j.

3.4. Technology lifecycle analysis and forecasting

Technological evolution follows a predictable rhythm, mirroring patterns observed in nature and economic cycles. Technological growth tends to follow an S-shaped growth curve (Fig. 3), an assumption that has been theoretically and empirically validated and discussed over the years (Andersen, 1999; Chen et al., 2012; Miwornunyuie et al., 2024). It is a predictable rhythm, mirroring patterns observed in nature and

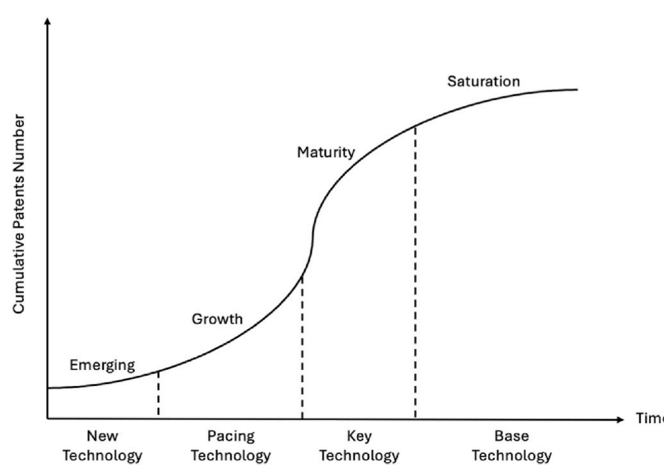

Fig. 3. The S-curve concept (Gao et al., 2013; Hosseini Bamakan et al., 2021).

economic cycles, characterised by different phases: emerging, growth, maturity and saturation. In this step, the aim is to analyse the Lifecyle of each technology (topic), using this assumption. Specifically, the objective is to assess and quantify maturity levels of each technology as well as forecasting their evolution.

Three growth functions are used, the Bass Diffusion, Gompertz and Logistic models, which have been widely used and tested for accuracy and outperforming other models for growth modelling of patents and technology trends (Bengisu and Nekhili, 2006; Sood et al., 2012; Tattershall et al., 2021).

3.4.1. Model specifications and adaptations

First, the Bass diffusion model (Bass, 1969) is a foundational framework for modelling the adoption of innovations, capturing how new technologies spread through market and social networks. According to the Bass model, the cumulative adoption function of an innovation is presented as

$$N(t) = m\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \quad \text{Eq 7}$$

This is an S-shaped function capturing slow initial adoption, rapid growth, and eventual saturation. This equation is used to model the behaviour of patents publications. N(t) represents the cumulative number of adopters at time t, p is the innovation coefficient, describing the rate of adoption due to external effects (e.g., regulatory policies, first-mover incentives), q is the imitation coefficient, capturing the adoption caused by social or network effects (e.g., firms adopting based on competitor actions), and is the total market potential, representing the upper limit of adoption. This model assumes that the likelihood of adoption at any time is driven by both independent decision-making (innovation effect) and social influence (imitation effect), producing the characteristic S-curve observed in many technological diffusion processes (Norton and Bass, 1987; Jeong et al., 2015).

To adapt the Bass model for patent trend forecasting, network-based citation metrics are used to estimate its parameters. Previous studies have argued that patent citations are linked to technology diffusion. For example, Lee et al. (2010, 2018) extended the Bass model for consumer product diffusion, their approach assumes that citation volume alone sufficiently represents technological diffusion. Their approach validates the use of citation metrics as indicators of technological impact, though this study extends beyond their model by incorporating network-based parameters.

For the innovation coefficient (p), estimates are derived from early citation patterns. Early citations indicate rapid recognition and technological impact, mirroring the role of early adopters in consumer diffusion models (Franses, 2003; Fok and Franses, 2007). Patents with higher early citation rates tend to be foundational, serving as technological breakthroughs that influence subsequent innovations (Min et al., 2018). The p coefficient is calculated as the ratio of early citations to total citations ($p = \frac{\text{early citations (3 years)}}{\text{total citations}}$), ensuring that technologies with strong initial influence receive higher innovation coefficients (Hall et al., 2001).

For the imitation coefficient (q), network centrality is used through PageRank values, calculated from step 3 in section 3.3 above. PageRank effectively captures how patents influence future technological development, as highly cited patents in interconnected fields tend to drive adoption in related areas (Min et al., 2018). Unlike simple citation counts, PageRank accounts for indirect influence, making it a stronger measure of knowledge diffusion (Min et al., 2018). The q coefficient is estimated as the mean PageRank value across patents within a given technological domain ($q = mean(PageRank)$). This ensures that technologies with broad influence receive higher imitation coefficients.

Market potential (m) in the traditional Bass diffusion model represents the total number of adopters expected in the long run (Bass, 1969). In the context of consumer products, this is typically a fixed quantity representing the maximum number of units that could be sold. However, applying this concept directly to technology diffusion—particularly patent trends—introduces limitations. Unlike product adoption, where market saturation follows clear demand constraints, technological development is not inherently bounded and evolves through cumulative innovation, cross-industry spillovers, and emergent subfields (Min et al., 2018). Therefore, a static assumption for m does not reflect the dynamic nature of technological progression, necessitating an adaptive estimation approach.

Patents represent knowledge diffusion rather than discrete product sales, meaning their cumulative growth is shaped by interconnected developments rather than a predefined consumer base. Unlike consumer markets, where product adoption is constrained by population size or purchasing power, the number of patents in a given domain is not inherently limited. furthermore, High-impact patents often stimulate further development, as new technologies build upon prior art. This makes traditional saturation assumptions problematic because the emergence of key enabling technologies can reshape the upper limit of market potential (Ding et al., 2021). Also, external factors such as funding availability, policy incentives, and industrial trends influence how many patents are filed in a given domain. A static m ignores these influences, potentially misrepresenting long-term trends.

To address these challenges, m is redefined using a network-driven, dynamic approach. Rather than treating market potential as a fixed number, this study models it as a function of current patent volume, growth trends, and technological influence, ensuring adaptability to real-world innovation dynamics. The proposed formula is:

$$m = \textit{current total patents} \times (1 + \textit{growth rate}) \times (1 + \textit{network influence}) \quad \text{Eq 7}$$

where:

- Current total patents represents the cumulative number of patents in the technology domain, serving as a baseline estimate.
- Growth rate accounts for recent trends in patent filings, ensuring that m reflects expansion dynamics rather than remaining static.
- Network influence is derived from betweenness centrality, as calculated in step 3 in section 3.3, a key graph-theoretic measure that quantifies how critical a patent is in connecting different technological domains. High-centrality patents typically indicate fundamental breakthroughs that influence multiple fields, making this metric an ideal proxy for the expansion potential of a given technology (Min et al., 2018; Ding et al., 2021).

Second, the Logistic model was first introduced by Verhulst in 1845 as a biology growth model. It is symmetric at its peak and describes a growth that is initially exponential and then slow down as a limit is reached (Gatto et al., 1988). The model is expressed mathematically as:

$$\mathrm{Y(t)} = \frac{\mathrm{K}}{1 + e^{(-\mathrm{b(t-t^0)})}} \quad \text{Eq 8}$$

where K represents carrying capacity (maximum potential), b is growth rate, and t_0 is the inflection point which is the point at which the rate of growth is the greatest, or mathematically is when the acceleration calculated by the second derivative moves from positive to negative.

Third, the Gompertz model, another biology growth model, is different than the Logistic model because it allows for asymmetry at its peak. It assumes that the rate of growth is inversely proportional to the current cumulative frequency (as cumulative frequency increases, growth decreases) (Dhar and Bhattacharya, 2018). Mathematically, this presented as:

$$\mathrm{Y(t)} = \mathrm{K} \times e^{\left(-e^{(-\mathrm{b(t-t_0)})}\right)} \quad \text{Eq 9}$$

The parameter estimation employed constrained non-linear least squares optimisation through the Levenberg-Marquardt algorithm.

Initial parameter bounds follows the constraints previous set by Burg and Schachter (2017) and further used by Tattershall et al. (2021):

- Carrying capacity k: $k \in \left[\frac{\max(y)}{2n}; \frac{4\max(y)}{2n}\right]$
- Growth rate r: $r \in \left[\frac{1}{8(\max(t)-\min(t))}; \frac{1}{\max(t)-\min(t)}\right]$
- Inflection point b: $b \in \left[\min(t);\ (\max(t)-\min(t))^2 - \min(t)\right]$

Without bounds, parameter estimation can diverge or produce mathematically invalid solutions, especially that the Levenberg-Marquardt algorithm requires reasonable parameter spaces to efficiently converge to optimal solutions.

3.4.2. Models implementation and forecast

To implement these models, the dataset is structured into two distinct periods: training data (2010–2020) and testing data (2021–2023). This split allows to estimate model parameters using historical patent trends while validating the predictive accuracy of each model on unseen data. Fitting the models on the entire dataset (2010–2023) without reserving a validation period risks overfitting—-where the model performs well on the training data but fails to generalise to future trends. The training-testing split the parameters are evaluated on out-of-sample data, ensuring that they do not produce unrealistic adoption curves or saturation levels.

To determine which model provides the most reliable forecasts for each technology (topic), their performance is evaluated using multiple metrics as followss:

Coefficient of Determination (R-squared) indicates what percentage of variance in the data is explained by the model (Kvalseth, 1985). Values range from 0 to 1, with higher values representing better fit.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \quad \text{Eq 10}$$

Root Mean Squared Error (RMSE) measures the square root of the average of squared differences between predicted and actual values (Chai and Draxler, 2014). Lower values indicate better model fit.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2} \quad \text{Eq 11}$$

Mean Absolute Percentage Error (MAPE) expresses accuracy as a percentage of error, providing a relative measure of prediction accuracy (Hyndman and Koehler, 2006). This metric is particularly useful for comparing performance across different models and datasets

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y}_i}{y_i}\right| \quad \text{Eq 12}$$

Where y_i represents the actual value, $\widehat{y}_i$ represents the predicted value, $\overline{y}$ is the mean of the observed data, and n is the number of observations.

The model having the lowest RMSE and MAPE while maintaining a high R-squared value is selected.

As for the forecasting horizon selected, Meade and Islam, (1998) emphasise that forecasting accuracy declines significantly beyond a reasonable extension of the historical data used for model fitting. Their analysis indicates that reliable forecasts typically extend no more than twice the length of the historical dataset, while accuracy diminishes as projections move further into the future. Given that this study uses patent data from 2010 to 2020 for model estimation and validates against 2021–2023 observations, the 2030 horizon represents a reasonable upper bound, ensuring model stability while minimising excessive extrapolation.

To quantify the uncertainty in the predictions, a parametric bootstrapping approach was followed as described by Nelson (2008) to estimate confidence intervals for all models. After obtaining the optimal parameters for each model (p, q, m for Bass or K, b, t0 for Gompertz/Logistic), bootstrap samples were generated by resampling residuals (differences between actual and fitted values) and adding them to the fitted values. For each of the 1000 bootstrap iterations, the model was re-fitted to obtain a new set of parameters. This iterative process produced a distribution of predictions at each time point. The 95 % confidence intervals were determined by extracting the 2.5th and 97.5th percentiles of these predicted distributions, thereby capturing both parameter uncertainty and model fit variability. This method ensures that confidence bounds are available for the training, testing, and forecast periods, providing a robust measure of prediction reliability.

3.4.3. Maturity classification

To help classify technologies, the progress percentage (P) is used, which represents technology position within its growth trajectory, and calculated as:

$$P = \left(\frac{Ct}{K}\right) \times 100 \quad \text{Eq 13}$$

where Ct denotes cumulative patents at time t, and K is the carrying capacity.

Furthermore more, the growth rate G is calculated through three-year moving averages of annual growth rates:

$$G = \frac{1}{3}\sum_{i=0}^{2} g_{t-i} \quad \text{Eq 14}$$

where the annual growth rates g_t are calculated as follows

$$gt = \left(\frac{N_t - N_{t-1}}{N_{t-1}}\right) \times 100 \quad \text{Eq 15}$$

with Nt being the being the number of patents at year t.

Technologies are then classified into four stages based on the following thresholds:

- **Emerging (P < 25 %) - Initial development phase**: This stage represents technologies in their initial development phase. Technologies at this stage typically demonstrate high technological uncertainty but significant potential for future growth.
- **Growth (25 % ≤ P < 60 %) - Established market presence**: Technologies in this stage have established technical feasibility and demonstrate accelerating adoption patterns. Growth-stage technologies show clear market validation while maintaining substantial potential for further development.
- **Maturity (60 % ≤ P < 80 %) - Approaching saturation**: Mature technologies have achieved established market presence with well-defined technical standards and implementation frameworks. This stage represents technologies that possibly have become standard components but continue to evolve through refinement and optimisation.
- **Saturation (P ≥ 80 %) - Maximum potential reached**: The saturation stage represents technologies that have reached high levels of development maturity and standardisation. It does not indicate technological obsolescence, rather a focus on system integration and efficiency improvements. These technologies form the stable foundation upon which newer innovations build, playing a crucial role in the overall technological ecosystem despite their advanced development state.

To refine classification, additional criteria are applied: (1) A high-growth adjustment (G > 20 %) allows technologies to move up one stage, preventing misclassification of mature technologies with temporary spikes. (2) Maturity confirmation (G < 5 % for 60–80 % progress) ensures technologies experiencing natural slowdowns remain classified as Mature. (3) Early-stage validation (P < 30 % with <15 annual patents) identifies genuinely Emerging technologies. These refinements enhance accuracy while aligning with technology lifecycle dynamics.

Andersen's (1999) seminal study provides strong empirical validation for the classification threshold choices in this study. Through analysing over 100 technological growth cycles using US patent data from 1890 to 1990, she observed consistent development patterns that align remarkably well with this study's defined stages. Her research documented that technologies typically show clear phase transitions at around 25 % development (marking emergence into growth), 50 % (inflection point), and 75–80 % (maturation), with full technical maturity generally achieved around 95 %. Importantly, her study empirically demonstrated that these thresholds are not arbitrary but reflect fundamental dynamics in how technologies evolve - early exponential growth below 25 %, rapid but decelerating growth between 25 and 75 %, and diminishing returns above 75 %. This empirically-based precedent directly supports the classification system of Emerging (<25 %), Growth (25–60 %), Maturity (60–80 %), and Saturation (>80 %) stages.

4. Results

4.1. Bibliometric analysis

The key characteristics of the patent dataset are analysed over the period 2010–2024. As shown in Fig. 4, patents publications grew exponentially, increasing from 71 patents in 2010 to 764 patents in 2023. This gives a Compound Annual Growth Rate (CAGR) of 19.8 %. Three distinct phases in this growth trajectory are noticed: initial slow growth (2010–2015), accelerated development (2016–2020), and stabilisation (2021–2023), with 2024 partial-year data (421 patents) suggesting continued momentum.

China, the United States, and South Korea are the dominant jurisdictions, accounting for 61.4 % of total patents. As shown in Fig. 5, China leads with 1862 patents, followed by the United States (1,250) and South Korea (623), establishing the Asia-Pacific region as a primary innovation hub for technologies related to autonomous shipping. European representation is selective, with contributions from Denmark and Finland.

As for assignees, as shown in Fig. 6, the ecosystem of innovation actors is diverse, comprising academic institutions, maritime technology corporations and traditional shipping companies. Wuhan University of Technology leads with 86 patents, while established marine technology providers like Yamaha Motor Co., Ltd. (69 patents) and Navico Holding (63 patents) are contributing to the innovation output. There is a presence of academic institutions (Dalian Maritime University, Korea Institute of Ocean Science & Tech) which suggest a strong research-industry collaboration patterns.

Beyond the basic bibliometric indicators above, citation network analysis was conducted to assess knowledge flows and understand the evolutionary dynamics of autonomous shipping innovation. The 15-year period (2010–2024) was broken down into 2-year brackets, and for each, a citation network was constructed as shown in Fig. 7. The linkages between the nodes (edges) are the citation intensity between patents. The network structure experiences significant densification through subsequent periods, reaching 895 edges among 1984 nodes in 2022–2024, after it started with only 2 edges among 184 nodes in 2010–2012.

4.2. Topic Modelling and Technology Identification

Using the LDA as outlined in section 3.2., 20 topics were derived from the patent corpus, which are studied further. An example of LDA topic models can be seen in Table 2. The optimal topic count (K = 20) was determined through coherence score optimisation across a range of 5–30 topics.

Different technological domains are identified, which are organised into seven primary clusters, as can be seen in Table 3. The Autonomous Control & Navigation cluster is a foundational technological domain, including remote operations (Topic[2] 0), propulsion control (Topic 17), and motion dynamics (Topic 13). This cluster emphasises on core autonomous capabilities, particularly in vessel control and operational management systems. Perception & Awareness technologies is another cluster focused on environmental sensing and object detection, incorporating visual, radar and sonar-based systems (Topic 6, Topic 19). The Safety & Navigation cluster is composed of collision avoidance (Topic 1) and route optimisation (Topic 18) technologies, indicating significant development in navigational safety systems. Data & Communications forms a separate technological domain, centred on communication infrastructure (Topic 2) and AIS data processing (Topic 10). Lastly, Environmental Monitoring and Infrastructure & Platforms clusters show another form of specialised technological development in marine environment sensing (Topic 5) and underwater operations (Topic 3) respectively. **Examples of patents for each topic are presented in the supplementary material.**

The evolution of these topics, and their correspondent clusters, are tracked over the period 2010–2023 (the year 2024 was excluded because of incomplete year data). Figs. 8 and 9 shows the yearly patent counts by each topic and cluster.

The Safety & Navigation cluster shows intense growth acceleration post-2018, with patent activity increasing from 50 to over 220 annual patents by 2023. This coincides with intensified development in the Perception & Awareness cluster, seen also in the synchronised advancement in Multi-sensor Object Detection (Topic 6) and Sonar & Search Systems (Topic 19) technologies.

Data & Communications exhibits early rapid growth followed by stabilisation at approximately 150 annual patents post-2020, while Perception & Awareness shows sustained growth thereafter. This indicates maturation of foundational communication infrastructure enabling subsequent advances in perception technologies. Autonomous Control & Navigation stabilises around 150 patents annually, inferring transition from basic control systems toward advanced safety capabilities.

At the topic level, Motion Control & Dynamics (Topic 13) shows a clear peak (~90 patents) during 2020–2021 followed by decline, indicating a resolution of key technical challenges. Concurrent steady growth in Collision Avoidance (Topic 1) and Multi-sensor Object Detection indicates ongoing development in safety-critical systems. The temporal correlation between sensor integration technologies (Topic 12) and route planning systems (Topic 18) suggests coordinated advancement in complementary capabilities.

Environmental Monitoring and Maritime Operations clusters maintain consistent innovation rates (~50 annual patents), indicating systematic evolution of supporting technologies. This steady-state development, particularly evident in Hull & Water Sensing (Topic 7) and Environmental Measurement (Topic 9), suggests sustained refinement of fundamental maritime autonomous capabilities. The observed patterns indicate strategic prioritisation of safety and perception technologies while maintaining steady advancement in supporting technological domains.

4.3. Topic-topic network analysis

Using the topics from the LDA model, a topic-topic network graph is constructed to analyse the relationship between technologies as explained in section 3.3. Fig. 10 presents the network visualisation of topic-topic relationships where node size represents topic prevalence, edge weight indicates citation strength between topics, and colour

[2] The LDA output of topic indexing was maintained, beginning at 0 following the standard convention in LDA algorithms and Python-based machine learning libraries.

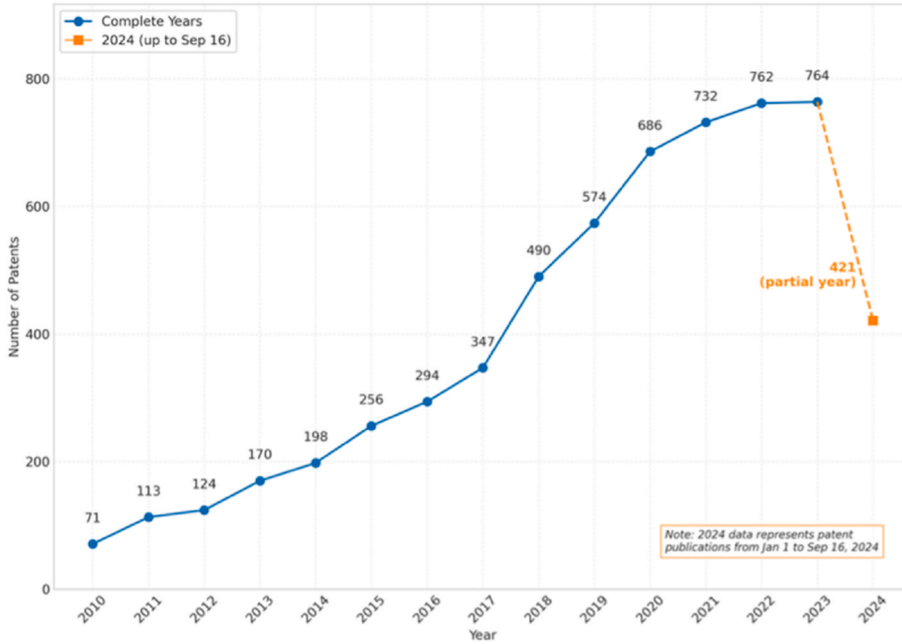

Fig. 4. Annual Patent Publications from 2010 to 2023, with partial-year data in 2024.

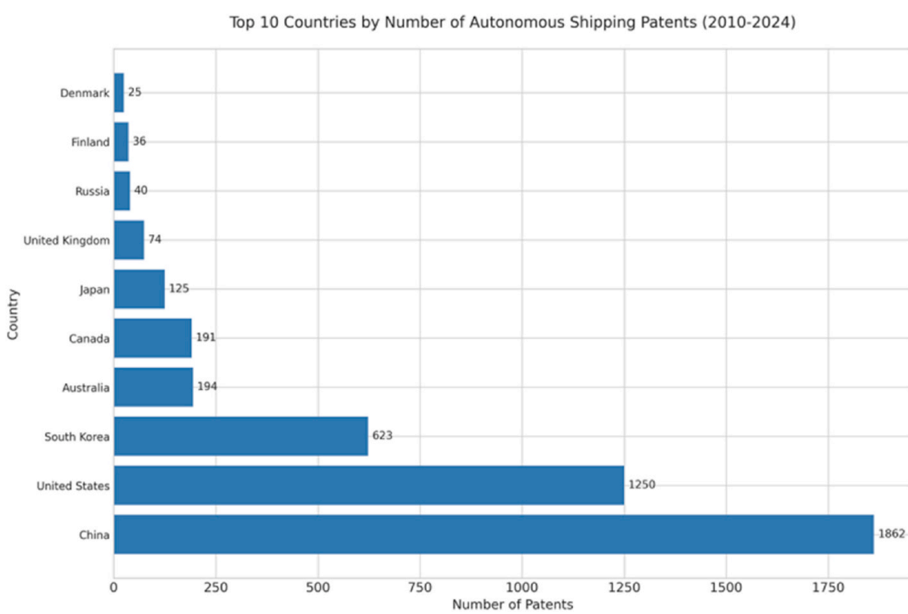

Fig. 5. Top 10 countries by patents' numbers showing the geographic distribution of maritime autonomous technology patenting activity.

intensity corresponds to PageRank centrality values. The network is characterised by high network density (0.6579) and clustering coefficient (0.7650). This densely connected structure, with 20 nodes connected by 250 edges, shows a significant knowledge flow between technological domains, thus forming collaborative technological integration rather than isolated development paths.

Sensor Integration (Topic 12) can be seen as the most influential technological domain with a PageRank value of 0.118, followed by Route Planning & Display (Topic 18, 0.093) and AIS Data Processing (Topic 10, 0.089). The importance of sensor integration technologies in network centrality shows its foundational role in enabling broader autonomous shipping capabilities. This is evidenced by sensor integration patents like US-2022198342-A1 which integrates multiple sensor systems for berthing detection and WO-2022084230-A1 which combines vessel motion sensors with stabiliser systems. The high PageRank values of navigation-related topics (18 and 10) further emphasise the criticality of navigational systems in technological development.

Looking at the node positioning and edge directionality in the network visualisation, it is observed that Remote Control Operations (Topic 0) and Platform & Drive Systems (Topic 11) function as source nodes, exhibiting higher outward edge weights than inward connections. These domains generate foundational technological knowledge that propagates through the network (example patent: WO-2024080879-A1 which describes a hierarchical control system for autonomous vessels with fleet coordination and vessel execution layers). Contrarily, Sensor Integration (Topic 12) and Route Planning & Display (Topic 18) operate as primary pass-through nodes, evidenced by high betweenness centrality and balanced bidirectional edge weights,

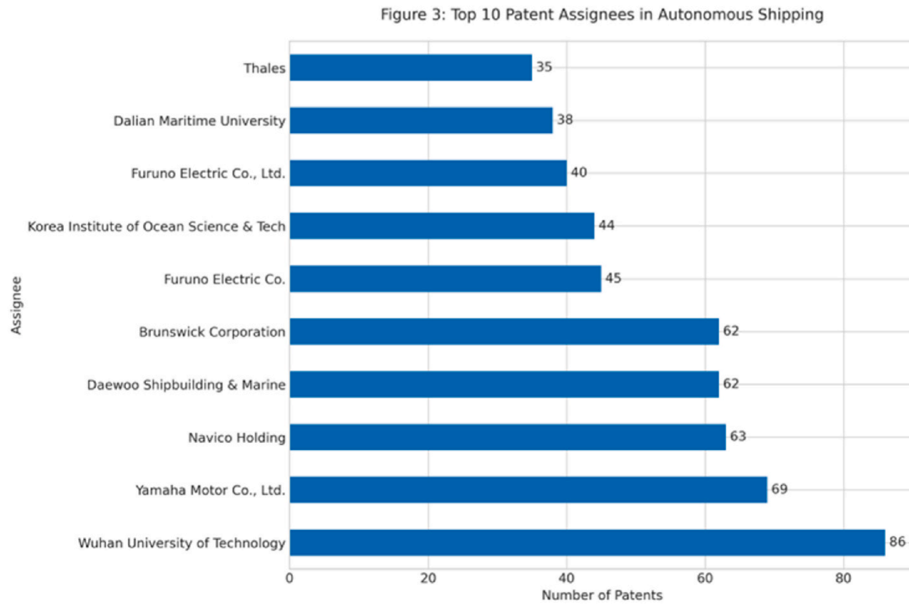

Fig. 6. Top 10 assignees by patents' count showing active organisations in maritime autonomous technology patenting.

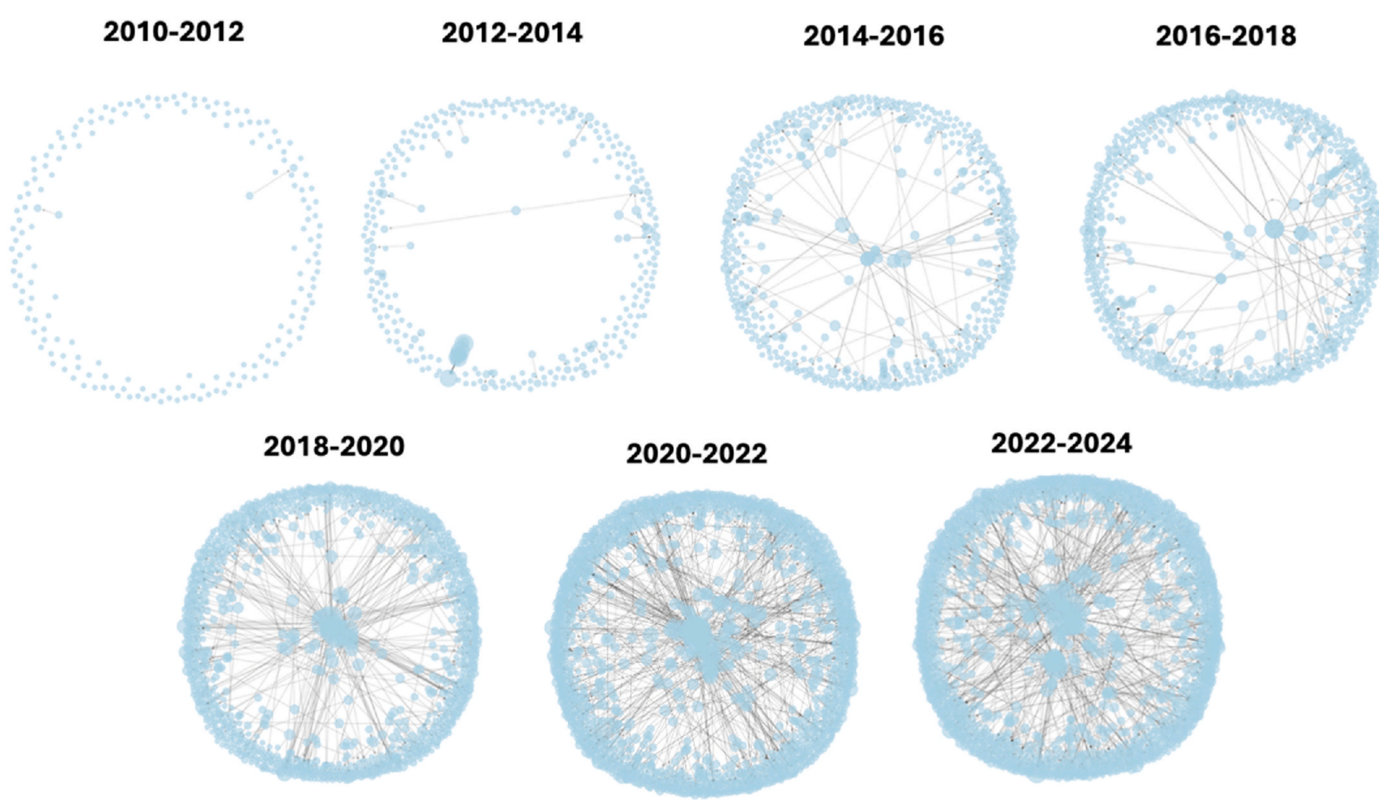

Fig. 7. The evolution of the citation network of autonomous shipping technologies across seven two-year periods (2010–2024).

facilitating critical knowledge transfer between perception systems and operational control domains. Key patents include EP-3984878-A1 for vessel stabilisation systems and US-2022364867-A1 for nautical chart processing.

Terminal nodes, particularly Maritime Activity Management (Topic 14) and Environmental Measurement (Topic 9), show higher inward edge weights, as exemplified by WO-2021211627-A1 for anchoring operations monitoring and KR-20180137819-A for water-depth measurement systems. The central positioning of sensor integration and route planning nodes, marked by larger node sizes and higher colour intensity, establishes their function as technological bridges. Strong edge weights connecting these central nodes to perception-focused topics show strong dependencies in environmental awareness capabilities.

4.4. Technology lifecycle analysis and forecasting

The final step presents the analysis of technology evolution in

Table 2
LDA raw results example.

Topic	Keywords and Weights
Topic 1: Collision Avoidance	collision (0.0435), navigation (0.0236), track (0.0227), area (0.0219), risk (0.0217), datum (0.0198), information (0.0197), time (0.0160), accord (0.0160), obstacle (0.0159)
Topic 17: Propulsion Control Systems	control (0.1075), power (0.0630), steering (0.0234), propulsion (0.0234), controller (0.0202), engine (0.0170), drive (0.0169), mode (0.0160), propeller (0.0150), energy (0.0146)

autonomous shipping, via forecasting growth trajectories and assess maturity levels across all technology domains derived from step 2. The Bass, Gompertz, and Logistic models were applied, each validated through training (2010–2020) and testing (2021–2023) phases as explained in section 3.4, and identified the optimal forecasting model for each technology, with the Bass model emerging as the most robust across multiple topics. These models were assessed based on multiple performance indicators: R^2, RMSE, and MAPE across both training and testing datasets (Table 4).

All models exhibited strong fit to the training data, with R^2 values exceeding 0.95 across all technologies, indicating that each model was capable of replicating historical patent trends with high precision. This result confirms that the Bass, Gompertz, and Logistic models effectively capture the underlying structure of past technology diffusion and growth patterns. However, when applied to test data, the performance diverged significantly, showing differences in each model's ability to generalise beyond the training period. The variability in test R^2, RMSE, and MAPE suggests that some models overfitted past trends, while others provided more stable forecasts.

The **Bass model** showed superior performance in nine technologies. Its strongest predictive performance was observed in Collision Avoidance (test $R^2 = 0.943$, RMSE = 17.143, MAPE = 5.617) and Multi-sensor Object Detection (test $R^2 = 0.950$, RMSE = 10.232, MAPE = 2.662), where it maintained strong accuracy from training to testing phases. However, the model showed significant volatility in test performance for certain technologies: Communication Modules (test $R^2 = -0.179$, RMSE = 63.368, MAPE = 11.110) and Sensor Integration (test $R^2 = -2.293$, RMSE = 74.033, MAPE = 14.006).

The **Gompertz model** was the optimal choice for eight technologies. Its highest predictive accuracy was achieved in Underwater Vehicle Systems (test $R^2 = 0.985$, RMSE = 2.634, MAPE = 0.233) and Hull & Water Sensing (test $R^2 = 0.970$, RMSE = 3.911, MAPE = 1.151), where testing phase metrics remained consistent with training performance.

Lastly, the **Logistics model** was selected as optimal for three technologies. Its most reliable predictions were observed in Intelligent Navigation (test $R^2 = 0.971$, RMSE = 13.28, MAPE = 3.624) and Collision Avoidance (test $R^2 = 0.997$, RMSE = 29.534, MAPE = 5.731).

Each technology was classified into Emerging, Growth, Maturity, and Saturation stages based on progress percentage, growth rate, and annual patent activity (Table 5). Furthermore, using the optimal model for each technology, patent numbers were forecasted up to 2030 and forecasting plots were visualised for each technology, using all models

Table 3
LDA Topic results and derived technologies and clusters.

Technology Cluster	Topic ID	Topic Name	Primary Keywords	Technical Domain/Technological Focus
AUTONOMOUS CONTROL and NAVIGATION	0	Remote Control Operations	unmanned (0.1012), control (0.0800), unit (0.0489), remote (0.0306)	Primary vessel control and remote operation systems
	17	Propulsion Control Systems	control (0.1075), power (0.0630), steering (0.0234), propulsion (0.0234)	Advanced propulsion and power management
	13	Motion Control & Dynamics	speed (0.0454), motion (0.0254), control (0.0234), parameter (0.0207)	Vessel dynamics and motion control
PERCEPTION and AWARENESS	6	Multi-sensor Object Detection	image (0.0666), target (0.0555), radar (0.0218), camera (0.0157)	Visual and radar-based detection systems
	19	Sonar & Search Systems	sonar (0.0878), rescue (0.0378), detection (0.0248), tracking (0.0272)	Underwater detection and search operations
	16	Acoustic Positioning	acoustic (0.0406), position (0.0207), surface (0.0218), drone (0.0244)	Acoustic-based positioning and tracking
SAFETY and NAVIGATION	1	Collision Avoidance	collision (0.0435), navigation (0.0236), risk (0.0217), obstacle (0.0159)	Safety and risk management
	18	Route Planning & Display	information (0.0381), position (0.0371), route (0.0283), navigation (0.0178)	Navigation and route optimisation
	8	Intelligent Navigation	equipment (0.0262), navigation (0.0163), intelligent (0.0136), positioning (0.0134)	Smart navigation systems
DATA and COMMUNICATIONS	2	Communication Modules	module (0.0819), communication (0.0428), information (0.0388), terminal (0.0166)	Communication infrastructure
	10	AIS Data Processing	datum (0.1172), ais (0.0317), signal (0.0223), network (0.0195)	Maritime traffic data systems
	12	Sensor Integration	control (0.0542), signal (0.0352), sensor (0.0230), configure (0.0311)	Sensor fusion and control
ENVIRONMENTAL MONITORING	5	Marine Environment Monitoring	water (0.0391), ocean (0.0367), depth (0.0300), seabed (0.0181)	Environmental sensing
	9	Environmental Measurement	measurement (0.0214), wind (0.0153), pressure (0.0128), draft (0.0181)	Environmental parameter monitoring
	7	Hull & Water Sensing	sensor (0.0379), water (0.0258), hull (0.0227), seismic (0.0187)	Hull monitoring and water sensing
INFRASTRUCTURE and PLATFORMS	3	Underwater Vehicle Systems	underwater (0.1053), vehicle (0.0973), buoy (0.0444), surface (0.0171)	Underwater operations
	11	Platform & Drive Systems	platform (0.0293), submarine (0.0288), motor (0.0233), drive (0.0179)	Platform infrastructure
	4	Structural Systems	structure (0.0763), force (0.0382), maintenance (0.0128), optical (0.0190)	Structural monitoring
MARITIME OPERATIONS	14	Maritime Activity Management	anchor (0.0543), aquatic (0.0465), fishing (0.0373), watercraft (0.0221)	Specialised maritime operations
	15	Surface Operations	body (0.0528), water (0.0451), surface (0.0197), unmanned (0.0169)	Surface vessel operations

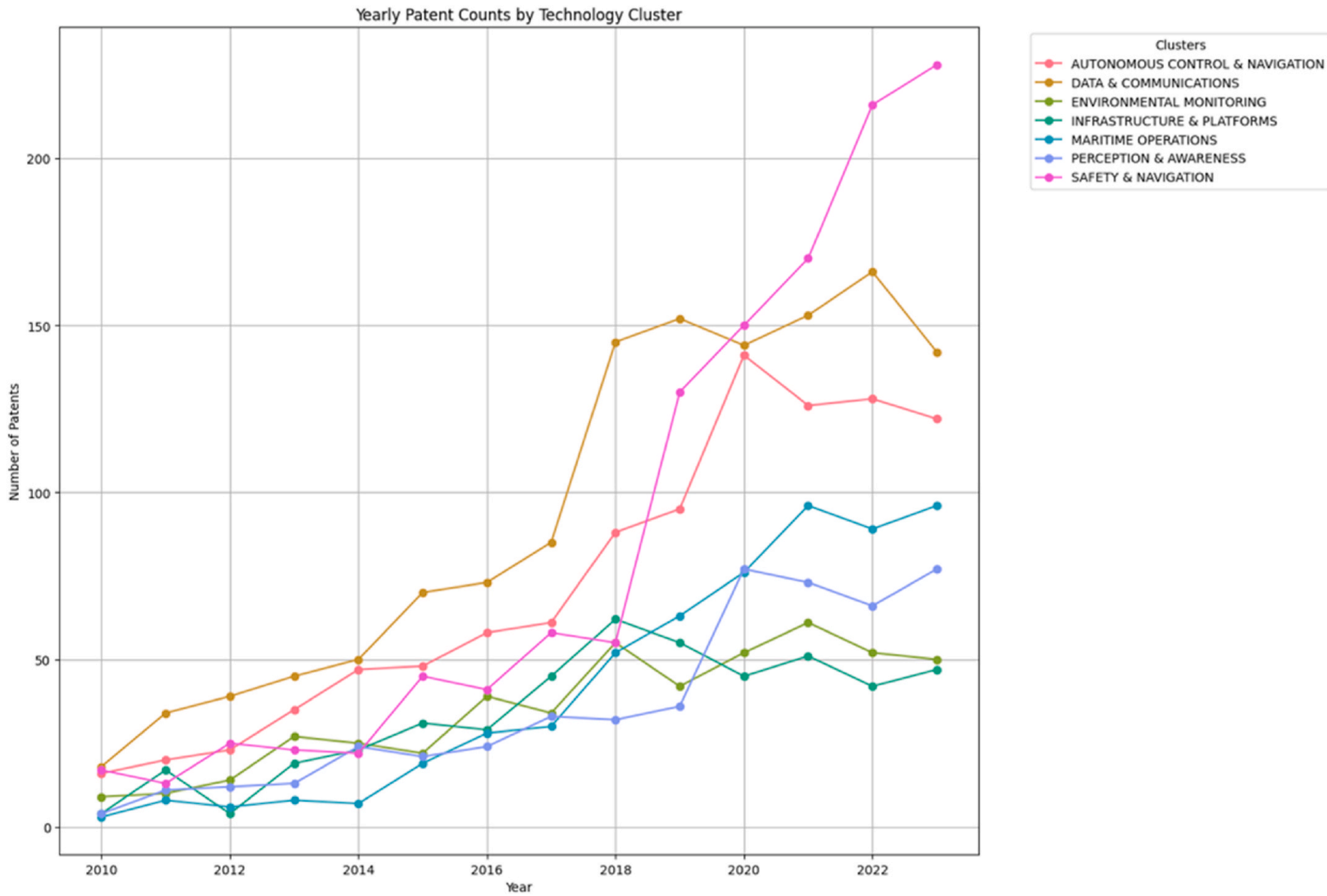

Fig. 8. Technology clusters evolution by time showing the annual patent counts for each of the seven identified technology clusters from 2010 to 2023.

with their confidence intervals, while highlighting the best model for each (Table 5 and Fig. 12).

One technology (5 %) is identified as emerging, thirteen technologies (65 %) in growth phase, four technologies (20 %) in maturity, and two technologies (10 %) reaching saturation, indicating an industry predominantly in its growth phase. The mapping of Growth Rate versus Progress Percentage (Fig. 11) shows a negative correlation between progress percentage and growth rate, with technologies generally showing lower growth rates as they advance in maturity. Overall, technologies clustered in the 20–40 % progress range show the highest variability in growth rates (ranging from 14 % to 30 %). Topic 8 (Intelligent Navigation) stands out as an outlier, maintaining an exceptionally high growth rate (30 %) despite its advanced progress (63 %), possibly indicating potential technological breakthroughs or renewed innovation momentum in this domain despite high progress.

Route Planning & Display emerges as the sole technology in the **emerging stage**, with 18.92 % progress and a moderate growth rate of 17.37 %. Despite its early progress percentage, the technology demonstrates substantial annual patent activity (57.87 patents). The Gompertz model was the most accurate forecasting approach for this emerging technology, supporting its validity in modelling uncertain early-stage growth trajectories. This is expected, as Gompertz assumes initial slow adoption followed by an acceleration phase, before eventually decelerating as technologies mature. The forecasting trajectory shows significant expected growth: from 423.97 (current value) to 615.46 by 2026 and reaching 891.51 by 2030. This represents a projected growth of approximately 110 % over the seven-year forecast period, suggesting rapid anticipated development. The emergence of Route Planning & Display as the only technology in the emerging stage, despite being fundamental to autonomous shipping, suggests it represents a new generation of development focusing on advanced capabilities. Its high patent activity despite low progress percentage indicates intensive current research and development efforts, possibly focusing on integrating advanced algorithms, intelligent capabilities or new safety features (Example: **patent EP-3918553-A1** demonstrating advanced voyage optimisation through dynamic integration of design parameters, weather conditions, and user preferences for automated route planning).

Growth-stage technologies comprise 65 % of the analysed technologies. It can be observed that three sub-groups based on progress percentages: Early Growth Cluster (P = 16–21 %); Mid Growth Cluster (P = 30–45 %); Late Growth Cluster (P = 50–65 %):

- First, Remote Control Operations (P = 16.37 %), Communication Modules (P = 17.99 %), and Surface Operations (P = 20.85 %) form the early-growth cluster characterised by unusually high patent activity (39.85–95.87 patents annually) relative to their progress percentages. These technologies share late inflection years (2027–2030) and high carrying capacities (1580–2870), suggesting extensive future development potential. The Gompertz model dominates this cluster, indicating development patterns characterised by gradual initial growth followed by accelerated development phases. These early-growth technologies show the most aggressive projected expansions, with Communication Modules forecasted to increase from 516.44 to 1219.83 (136.2 % growth), Surface Operations from 487.95 to 1248.41 (155.8 % growth), and Remote Control Operations from 258.57 to 596.22 (130.6 % growth) by 2030.
- Second, the largest subgroup includes six technologies, from AIS Data Processing (P = 30.96 %) to Collision Avoidance (P = 44.05 %).

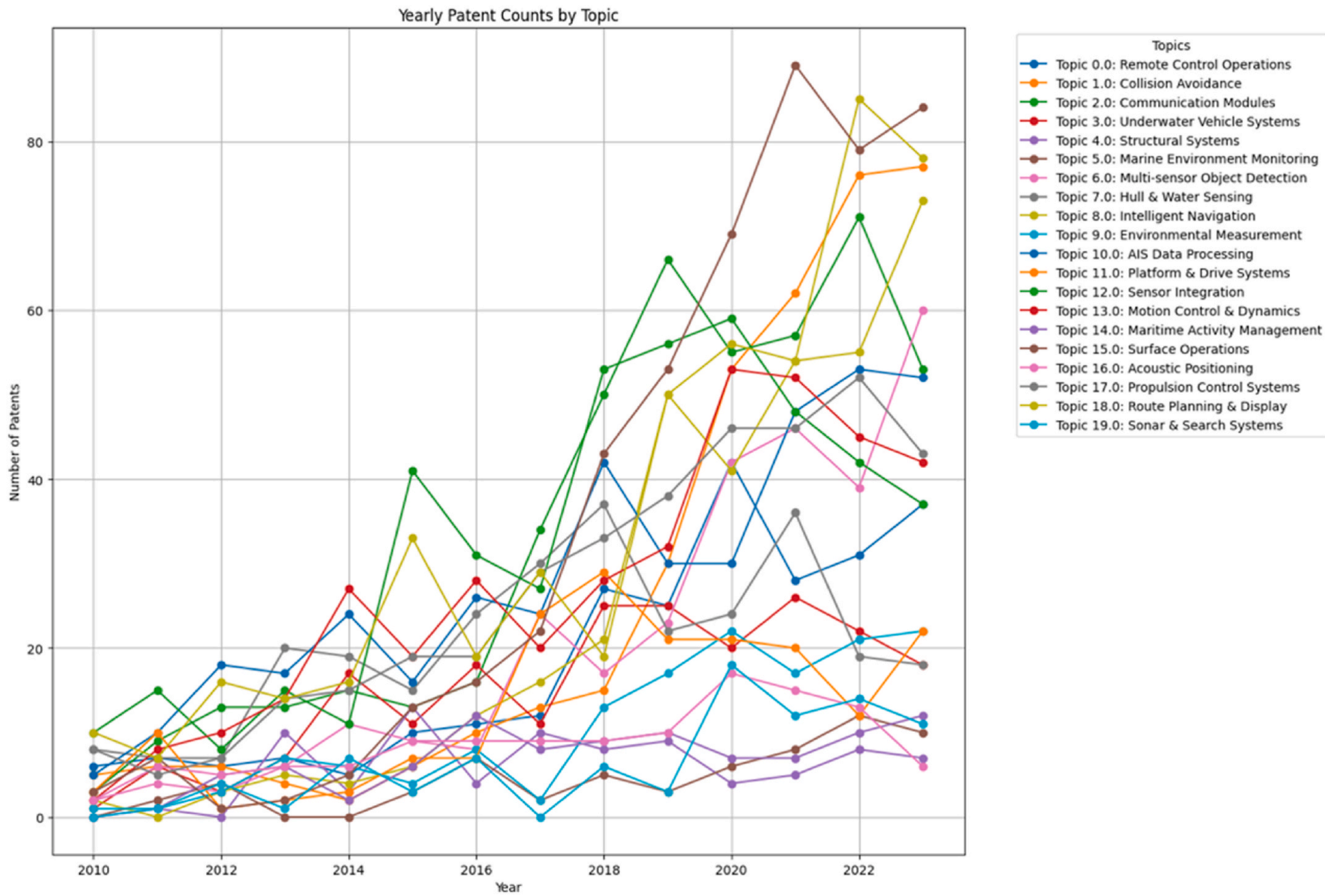

Fig. 9. Technology topics evolution by time displaying annual patent counts for all 20 technology topics from 2010 to 2023.

This cluster shows consistency in growth rates (P = 13.93–27.79 %) despite varying patent volumes (12.41–64.80 patents annually). The Bass model is the optimal one for most technologies in this group, suggesting development patterns driven by industry adoption dynamics. These technologies show mid-range inflection years (2025–2028) and moderate carrying capacities (250-1210). These technologies demonstrate more moderate but still significant projected growth. Collision Avoidance is forecasted to reach 717.61 by 2030 (117.2 % growth), Multi-sensor Object Detection 621.32 (117.3 % growth), and Propulsion Control Systems 819.66 (109.1 % growth).

- Third, Acoustic Positioning (P = 50.32 %), Underwater Vehicle Systems (P = 54.17 %), and Intelligent Navigation (P = 63.18 %) compose the late growth cluster. These technologies demonstrate lower but stable growth rates (11.79–30.02 %) and varied patent activity (11.03–65.71 patents annually). The cluster shows a mix of optimal models (Gompertz and Logistics), reflecting different development patterns as technologies approach maturity. Earlier inflection years (2020–2022) suggest these technologies are nearing their next development phase. They show more conservative growth projections, reflecting their advanced progress percentages. Underwater Vehicle Systems is projected to reach 315.97 by 2030 (50.8 % growth), Acoustic Positioning 180.52 (51.4 % growth), and Intelligent Navigation 550.08 (55.2 % growth).

Three technologies show **maturity** characteristics: Hull & Water Sensing (P = 65.16 % progress), Structural Systems (P = 69.81 %), Sensor Integration (P = 76.05 %). These technologies show more moderate growth rates between 8.57 % and 14.00 %, consistent with their advanced development stage. The annual patent volumes for mature technologies average 20.71 patents, significantly lower than technologies in the growth phase.

In terms of forecast, Hull & Water Sensing shows the most conservative growth projection among the three, with the Gompertz model forecasting an increase from 289.09 (current) to 344.00 by 2026 (19.0 % growth) and reaching 390.73 by 2030 (35.2 % total growth). Structural Systems, modelled by Bass, demonstrates the most restrained growth trajectory, projecting from 80.19 to 92.99 by 2026 (16.0 % growth) and 103.98 by 2030 (29.7 % total growth). Moreover, Sensor Integration, despite its high progress percentage (76.05 %), shows slightly more robust growth projections through the Logistics model: from 480.83 to 572.28 by 2026 (19.0 % growth) and 617.32 by 2030 (28.4 % total growth). These forecasting patterns stand in contrast to those of growth-stage technologies, which average 109.1 % projected growth through 2030. The mature technologies' projected growth rates (28.4–35.2 % through 2030) show their advanced development status and suggest a focus on refinement rather than fundamental advancement.

Two technologies have reached the **saturation stage**: Platform & Drive Systems (P = 80.92 % progress) and Maritime Activity Management (P = 86.82 % progress). These technologies exhibit the highest progress percentages in the dataset, coupled with characteristically moderate growth rates: Platform & Drive Systems at 14.71 % and Maritime Activity Management at 12.38 %. This combination of high progress and moderated growth indicates technologies that have largely realised their development potential. Their annual patent volumes (18.41 and 8.71 patents respectively) are significantly lower than both growth-stage (average 57.82) and mature-stage technologies (average 20.71), suggesting a shift from innovation to maintenance and

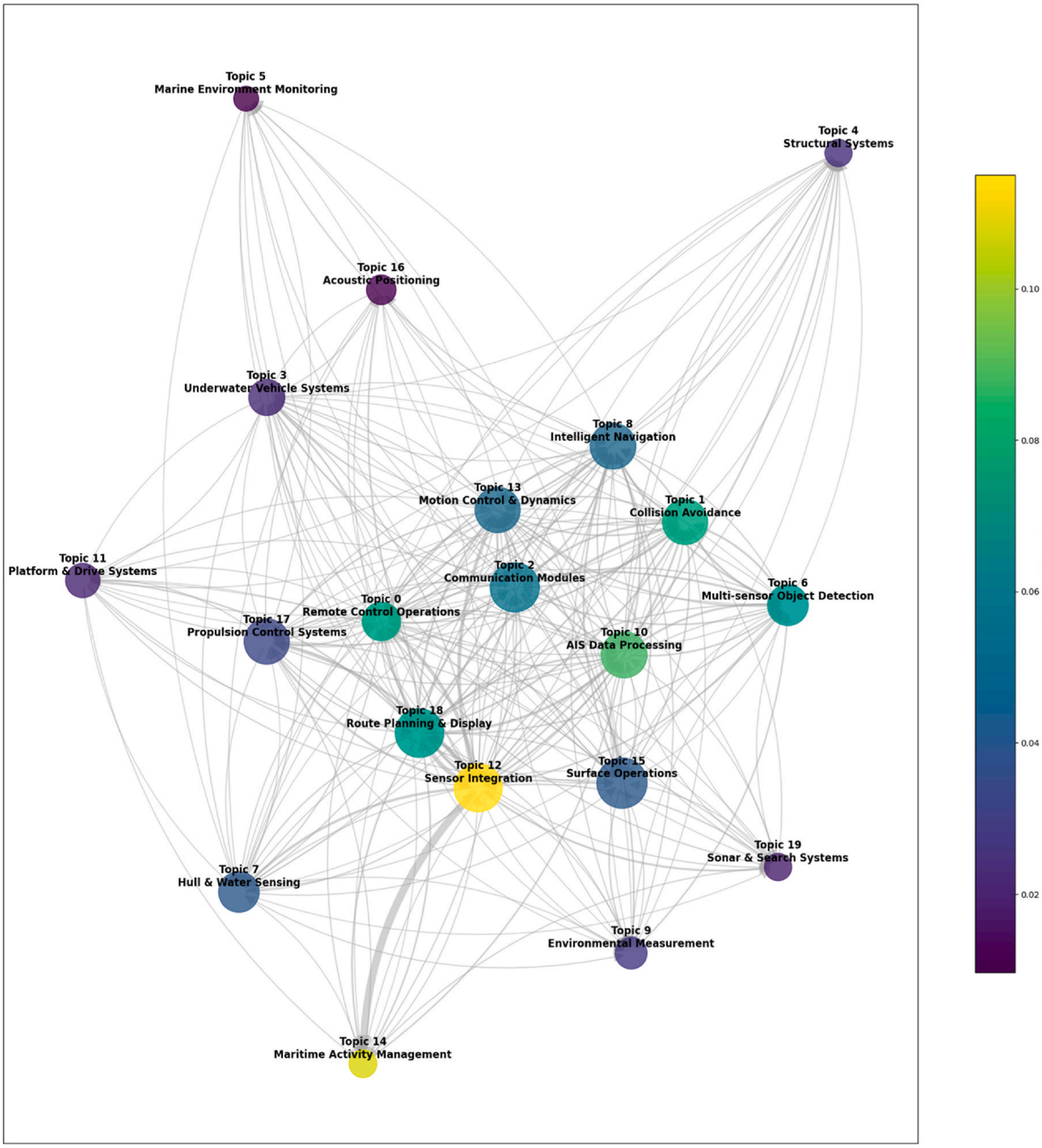

Fig. 10. Network of topics visualising interdependencies between 20 technological domains Node size represents topic prevalence, edge weight indicates citation strength, and colour intensity corresponds to PageRank centrality. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

optimisation. Platform & Drive Systems projects growth from 196.88 to 228.56 by 2026 (16.1 % growth) and 240.54 by 2030 (22.2 % total growth). Maritime Activity Management shows even more restrained projections: from 91.48 to 114.18 by 2026 (24.8 % growth) and 134.56 by 2030 (47.1 % total growth). For instance, Platform & Drive Systems patents like CN-111559511-B concentrate on enhancing existing deck extension systems through improved control methods and modular mechanisms, rather than introducing fundamental new capabilities. Similarly, in Maritime Activity Management, patent WO-2021211627-A1 introduces monitoring and measurement methods to existing anchoring operations through computer vision and real-time sensing, rather than reinventing core operational principles. This saturation of these technologies suggests an optimisation-focused advancement. These patents exemplify how saturated technologies continue to evolve through the refinement of established functionalities and the integration of advanced monitoring capabilities within well-defined technological boundaries, rather than through revolutionary changes to fundamental operating principles.

The findings indicate that autonomous shipping technologies are predominantly in the growth phase, with a clear trajectory toward maturity and saturation. Bass-dominant technologies exhibit rapid, industry-driven adoption, while Gompertz-dominant ones follow gradual expansion, constrained by early-stage barriers. Saturation-stage technologies show declining patent activity, signalling a shift from innovation to optimisation. Inflection years confirm that most growth-phase technologies will peak between 2025 and 2030, while mature ones have already stabilised. This highlights a critical window for investment in high-growth technologies, while mature and saturated fields will likely focus on incremental efficiency improvements rather than disruptive advancements.

Table 4
Comparative robustness results of growth models fitting (Best mode highlighted in bold).

Topic		BASS				Gompertz				Logistics			
ID	Name	train_R2	test_R2	test_RMSE	test_MAPE	train_R2	test_R2	test_RMSE	test_MAPE	train_R2	test_R2	test_RMSE	test_MAPE
0	Remote Control Operations	0.991	0.758	16.024	4.71	**0.987**	**0.779**	**15.504**	**3.965**	0.997	−4.926	80.244	26.347
1	Collision Avoidance	**0.984**	**0.943**	**17.143**	**5.617**	0.962	−0.349	86.992	25.275	0.984	0.875	26.511	8.407
2	Communication Modules	0.997	−0.179	63.368	11.11	**0.993**	**−0.101**	**61.068**	**9.893**	0.996	−0.61	73.843	13.895
3	Underwater Vehicle Systems	0.999	0.867	8.226	3.456	**0.997**	**0.985**	**2.634**	**1.233**	0.995	−0.49	25.84	11.435
4	Structural Systems	**0.989**	**0.862**	**2.952**	**2.326**	0.994	0.318	7.303	6.761	0.992	−1.265	13.307	13.234
5	Marine Environment Monitoring	0.977	−0.833	10.507	17.46	**0.984**	**0.253**	**10.069**	**16.387**	0.984	−1.323	13.707	22.249
6	Multi-sensor Object Detection	**0.999**	**0.95**	**10.232**	**2.662**	0.995	0.813	20.621	7.292	0.995	0.942	11.438	3.498
7	Hull & Water Sensing	0.998	0.18	23.383	7.49	**0.998**	**0.97**	**3.911**	**1.151**	0.998	−1.191	33.332	10.89
8	Intelligent Navigation	0.999	0.871	25.798	5.463	0.993	0.92	22.065	4.935	**0.996**	**0.971**	**13.281**	**3.625**
9	Environmental Measurement	**0.997**	**0.963**	**4.055**	**2.542**	0.984	0.956	4.556	2.937	0.988	−2.608	41.169	23.501
10	AIS Data Processing	**0.996**	**0.948**	**11.318**	**2.986**	0.997	0.014	51.107	12.322	0.995	−1.659	83.936	19.89
11	Platform & Drive Systems	0.994	−0.055	18.864	9.863	0.984	−8.049	54.231	26.856	**0.988**	**0.296**	**15.13**	**8.472**
12	Sensor Integration	0.998	−2.293	74.033	14.006	0.998	−6.45	101.511	19.005	**0.998**	**0.369**	**29.534**	**5.731**
13	Motion Control & Dynamics	**0.999**	**0.934**	**11.923**	**2.197**	0.994	0.417	33.209	9.204	0.989	−1.142	63.655	16.436
14	Maritime Activity Management	**0.995**	**0.985**	**1.198**	**1.391**	0.996	0.765	5.096	4.574	0.996	−1.039	15.025	13.702
15	Surface Operations	0.999	0.521	54.465	9.916	**0.995**	**0.789**	**35.565**	**5.327**	0.999	0.299	64.827	9.933
16	Acoustic Positioning	0.995	0.473	7.237	4.374	**0.996**	**0.481**	**5.906**	**4.9**	0.992	−1.097	11.869	10.01
17	Propulsion Control Systems	**0.998**	**0.751**	**24.215**	**5.019**	1	0.716	25.571	4.609	0.999	0.72	25.399	6.286
18	Route Planning & Display	0.996	0.901	18.963	4.659	**0.993**	**0.937**	**15.758**	**3.193**	0.991	0.566	41.33	8.641
19	Sonar & Search Systems	**0.994**	**0.978**	**1.845**	**2.298**	0.956	0.304	9.847	12.175	0.952	0.8	5.274	5.707

5. Discussion

5.1. General discussion

This study maps the technological landscape of autonomous shipping through an integrated analytical framework combining bibliometric analysis, topic modelling, network analysis, and technology lifecycle forecasting. This methodological approach identified patterns that traditional single-method analyses might miss, particularly in understanding the interconnected nature of technological development.

The bibliometric analysis showed an exponential growth in patent activity from 2010 to 2023, with a CAGR of 19.8 %. This means that there is an increasing global commitment to autonomous shipping technologies. The dominance of China indicates that the Asia-Pacific region is a primary innovation hub. The presence of academic institutions (e.g., Wuhan University of Technology, Dalian Maritime University) alongside industry players (e.g., Yamaha Motor Co., Ltd., Navico Holding) suggests collaboration between academia and industry.

The topic modelling identified 20 technological topics organised into seven primary clusters: Autonomous Control & Navigation, Perception & Awareness, Safety & Navigation, Data & Communications, Environmental Monitoring, Infrastructure & Platforms, and Maritime Operations. The network analysis of these topics reveals a hierarchical knowledge flow pattern. Technologies like Remote Control Operations show high outward citation flows but few inward citations, indicating they generate foundational knowledge. In contrast, Maritime Activity Management receives more citations than it generates, suggesting it builds upon other technologies. At the centre of this network, Sensor Integration emerged as the most influential technology, serving as a bridge between basic control systems and advanced capabilities like Collision Avoidance. This finding has significant implications for R&D strategy, suggesting that resources should be directed toward integration challenges and cross-domain optimisation rather than isolated technology development.

The technology mapping study's identification of Sensor Integration as the central enabling technology aligns well with DNV's newly released Autonomous and Remotely Operated Ships (AROS) notations framework (DNV, 2025). While the study emphasises Sensor Integration's role in bridging basic control systems with advanced capabilities, DNV's AROS framework takes this further by establishing specific functional requirements for different autonomy modes - from remote control to full autonomy. The forecasting models' identification of 2025–2030 as the critical investment window coincides with IMO's timeline for the Maritime Autonomous Surface Ships (MASS) Code implementation; experience-building phase from 2025 and mandatory by 2032 (DNV, 2024).

The maturity analysis showed autonomous shipping is in active development rather than early experimentation, with most technologies (65 %) in growth phase. This aligns with Jovanović et al.'s (2024) observation that research into autonomous shipping is also in its growth phase, drawing a parallel between scientific research and patenting. The mature and saturated technologies (Platform & Drive Systems, Maritime Activity Management, Hull Sensing) focus on optimisation of existing capabilities, while growth-phase technologies show distinct evolutionary patterns. Early-growth technologies like Remote Control Operations and Communication Modules are undergoing fundamental reimagining, as evidenced by their high patent activity despite low maturity. Meanwhile, mid-growth technologies such as Collision Avoidance and AIS Processing demonstrate strong interconnections in this study's network analysis, indicating that advancement requires synchronised development across multiple domains. This pattern challenges traditional maritime innovation models where technologies develop independently.

As for the forecasting models, different advantages and limitations emerged for each growth model. The Bass model proved optimal for safety and perception technologies (including Collision Avoidance and

Table 5
Forecasting results based on best model for each technology.

Topic ID	Topic Name	Best Model	Current Progress (P)	Growth Rate (G)	Annual Patents	Maturity Stage	Classification Reason	Inflection Year	Current Number of patents (2023)	2026 Forecast	2030 Forecast
0	Remote Control Operations	Gompertz	16.37	20.13	39.85	Growth	Base classification: Progress 16.4 % < 25 %; High growth override: Growth rate 20.1 % > 20 %	2030	**258.57**	**394.25**	**596.22**
1	Collision Avoidance	Bass	44.05	27.79	64.8	Growth	Base classification: 25 % ≤ Progress 44.1 % < 60 %	2025	**330.39**	**533.8**	**717.61**
2	Communication Modules	Gompertz	17.99	21.97	84.7	Growth	Base classification: Progress 18.0 % < 25 %; High growth override: Growth rate 22.0 % > 20 %	2029	**516.44**	**803.52**	**1219.83**
3	Underwater Vehicle Systems	Gompertz	54.17	13.26	20.93	Growth	Base classification: 25 % ≤ Progress 54.2 % < 60 %	2020	**209.51**	**264.21**	**315.97**
4	Structural Systems	Bass	69.81	8.57	5.3	Maturity	Base classification: 60 % ≤ Progress 69.8 % < 80 %	2015	**80.19**	**93**	**103.98**
5	Marine Environment Monitoring	Gompertz	32.84	14.63	5.51	Growth	Base classification: 25 % ≤ Progress 32.8 % < 60 %	2015	**47.83**	**64.51**	**85.18**
6	Multi-sensor Object Detection	Bass	38.37	23.08	49.07	Growth	Base classification: 25 % ≤ Progress 38.4 % < 60 %	2025	**285.86**	**445.45**	**621.32**
7	Hull & Water Sensing	Gompertz	65.16	10.26	22.55	Maturity	Base classification: 60 % ≤ Progress 65.2 % < 80 %	2019	**289.09**	**344**	**390.73**
8	Intelligent Navigation	Logistics	63.18	30.02	65.71	Growth	Base classification: 60 % ≤ Progress 63.2 % < 80 %; High growth override: Growth rate 30.0 % > 20 %	2022	**354.53**	**493.26**	**550.08**
9	Environmental Measurement	Bass	34.08	20.38	22.36	Growth	Base classification: 25 % ≤ Progress 34.1 % < 60 %	2026	**143.13**	**217**	**307.92**
10	AIS Data Processing	Bass	30.96	13.93	42.5	Growth	Base classification: 25 % ≤ Progress 31.0 % < 60 %	2028	**374.65**	**511.21**	**700.07**
11	Platform & Drive Systems	Logistics	80.92	14.71	18.41	Saturation	Base classification: Progress 80.9 % ≥ 80 %	2020	**196.88**	**228.56**	**240.54**
12	Sensor Integration	Logistics	76.05	14	46.13	Maturity	Base classification: 60 % ≤ Progress 76.1 % < 80 %	2020	**480.83**	**572.28**	**617.32**
13	Motion Control & Dynamics	Bass	31.83	16.39	50.09	Growth	Base classification: 25 % ≤ Progress 31.8 % < 60 %	2027	**383.51**	**547.48**	**768.83**
14	Maritime Activity Management	Bass	86.82	12.38	8.71	Saturation	Base classification: Progress 86.8 % ≥ 80 %	2021	**91.48**	**114.18**	**134.56**
15	Surface Operations	Gompertz	20.85	28.54	95.87	Growth	Base classification: Progress 20.9 % < 25 %; High growth override: Growth rate 28.5 % > 20 %	2027	**487.95**	**811.17**	**1248.41**
16	Acoustic Positioning	Gompertz	50.32	11.79	11.03	Growth	Base classification: 25 % ≤ Progress 50.3 % < 60 %	2021	**119.26**	**149.33**	**180.52**
17	Propulsion Control Systems	Bass	33.64	18.58	56.81	Growth	Base classification: 25 % ≤ Progress 33.6 % < 60 %	2026	**391.9**	**579.01**	**819.66**
18	Route Planning & Display	Gompertz	18.92	17.37	57.87	Emerging	Base classification: Progress 18.9 % < 25 %	2030	**423.97**	**615.46**	**891.51**
19	Sonar & Search Systems	Bass	33.53	19.4	12.41	Growth	Base classification: 25 % ≤ Progress 33.5 % < 60 %	2026	**83.83**	**124.02**	**174.59**

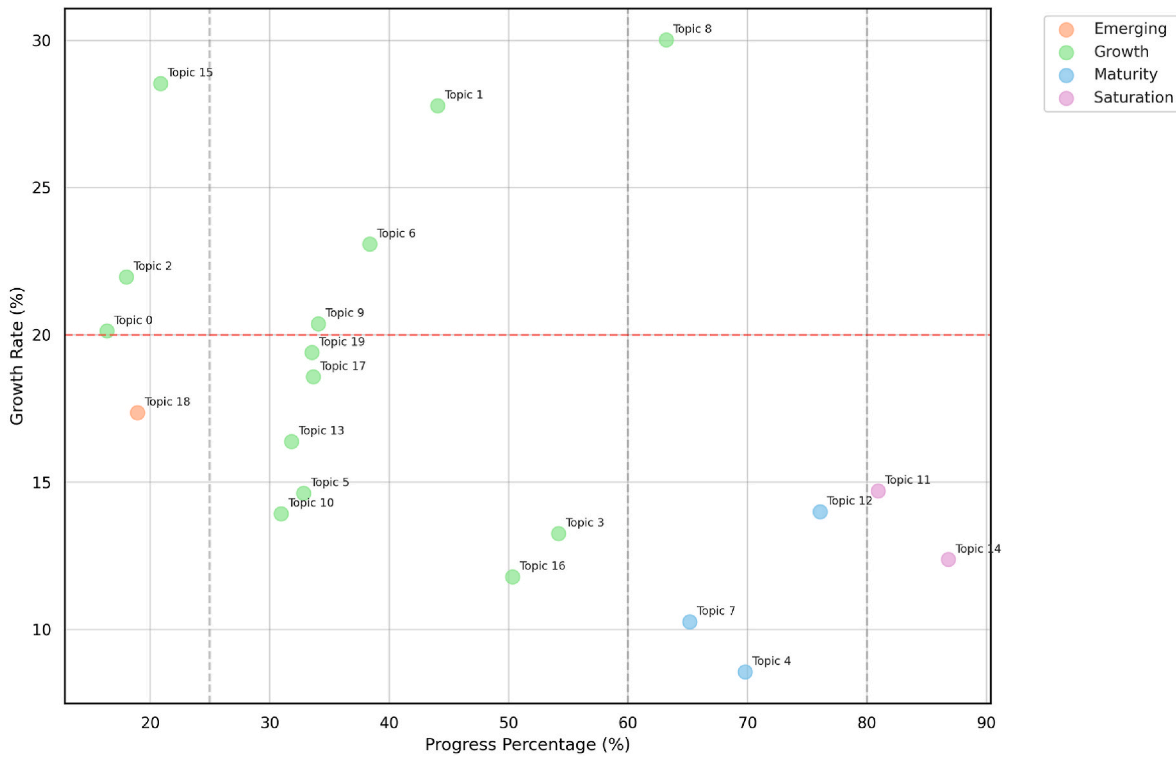

Fig. 11. Technology Maturity Map plotting Growth Rate versus Progress Percentage for all 20 technological domains.

Multi-sensor Detection), indicating their development is driven by industry-wide adoption mechanisms and regulatory requirements. Its primary advantage lies in effectively capturing both external innovation drivers and internal adoption dynamics, making it suitable for technologies influenced by regulatory requirements. The primary limitation observed was its reduced accuracy for technologies requiring substantial infrastructure development, as evidenced by poor performance when applied to Communication Modules.

In contrast, the Gompertz model better predicted technologies with complex technical prerequisites, such as Remote Control Operations and Communication Modules, suggesting their growth faces initial barriers but accelerates once these are overcome. Its key advantage is the asymmetric growth curve that accommodates slow initial development followed by accelerated growth once technical barriers are overcome. However, the model showed limitations when applied to technologies driven primarily by industry adoption rather than technical constraints. Furthermore, the Logistics model showed best fit for technologies requiring established infrastructure or ones serving as integration points within the technological ecosystem, particularly Intelligent Navigation, reflecting more gradual, resource-dependent development. Its strength lies in capturing symmetrical growth patterns for technologies building upon established foundations. The primary limitation was its reduced effectiveness for technologies experiencing non-uniform development trajectories or those heavily influenced by external factors. These findings confirm that technology forecasting in autonomous shipping benefits from model selection aligned with the fundamental development characteristics of each technological domain, rather than applying a single modelling approach across all technologies.

The forecasting analysis showed a critical investment timing and technology prioritisation period for autonomous shipping development spanning over 2025–2030, as it is a decisive window where most growth-phase technologies reach their inflection points, indicating optimal timing for strategic investment. Within this window, three distinct investment priorities emerge. First, technologies enabling cognitive capabilities demand immediate attention - Route Planning & Display shows exceptional growth potential (from 424 to 891 patents by 2030) despite being in emerging stage, indicating a fundamental shift toward intelligent decision-making systems. Second, safety and perception technologies (particularly Collision Avoidance and Multi-sensor Detection) present prime investment opportunities, with projected growth exceeding 117 % through 2030 and strong network centrality indicating their critical role in system integration. In contrast, hardware-focused technologies like Platform & Drive Systems (80.92 % progress) and Maritime Activity Management (86.82 % progress) show signs of saturation with declining innovation activity, suggesting limited returns on further investment.

Looking forward, it is anticipated that safety and perception technologies will remain focal points for development, particularly as regulatory frameworks evolve to accommodate autonomous operations. The integration of AI-driven decision-making, edge computing, and real-time sensor fusion will likely define the next phase of innovation. Additionally, the sustained innovation in environmental monitoring technologies underscores the industry's parallel focus on ecological sustainability, aligning with global maritime decarbonisation efforts.

5.2. *Implications*

This progression carries profound implications for industry stakeholders. First, it suggests that future innovation will increasingly focus on software and algorithms rather than hardware. Second, it indicates that success in autonomous shipping will depend more on system integration capabilities than excellence in individual components. Third, Industry stakeholders should recognise the centrality of sensor integration and navigation intelligence in achieving operational autonomy, prioritising investment in these domains. Lastly, it signals that the industry is approaching a critical maturity phase where practical, commercial deployment of autonomous vessels becomes feasible. Regulatory bodies must anticipate the rapid technological shifts in autonomous shipping, ensuring that safety protocols, liability frameworks, and operational standards evolve in tandem with emerging capabilities. Moreover, research institutions play a critical role in bridging foundational research with commercial applications, particularly in

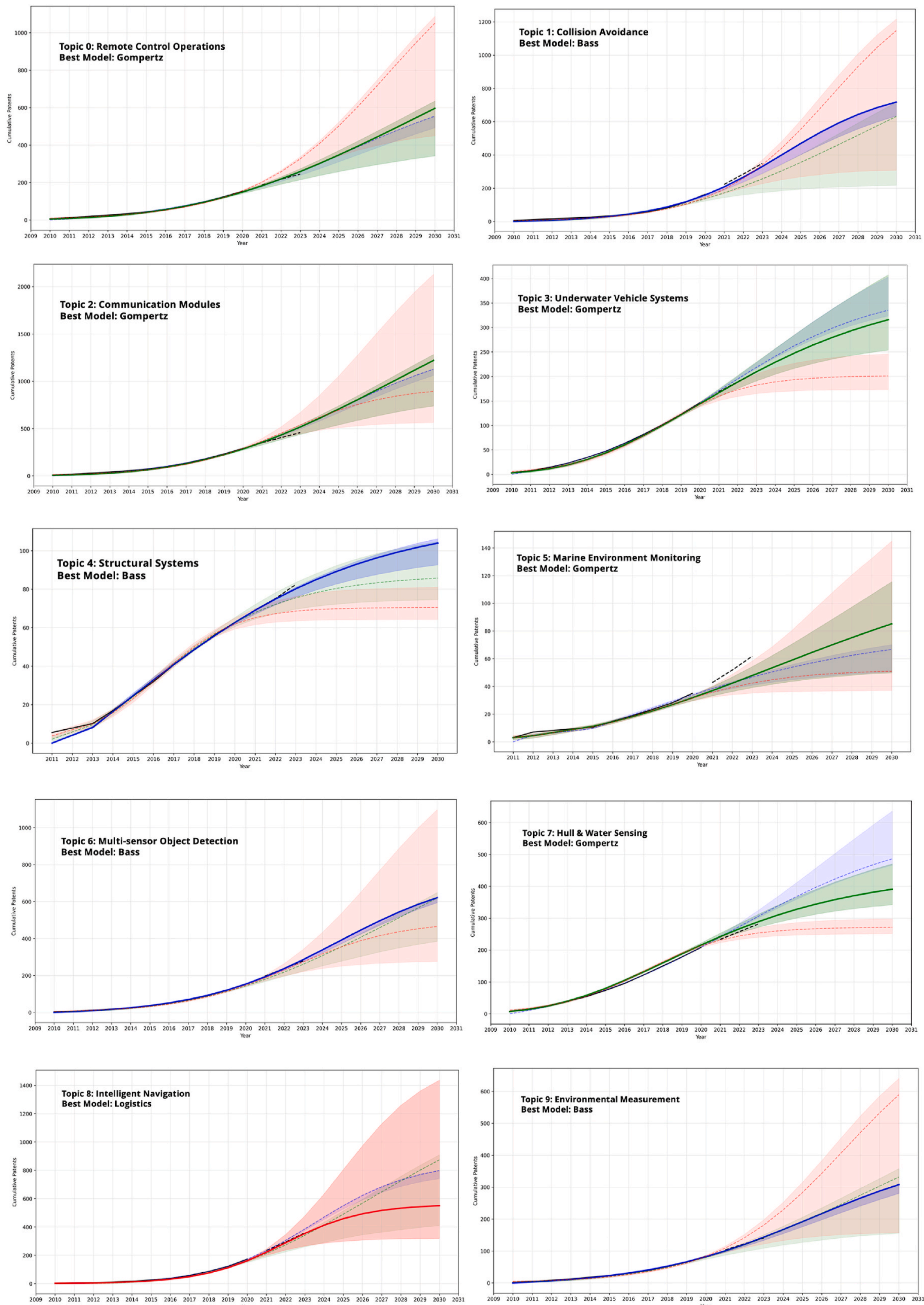

Fig. 12. S-curve fittings and forecasting with confidence intervals for the 20 topics - Blue: Bass model; Green: Gompertz model; Red: Logistics model; Black: Actual observations (dashed: test data; continuous: train data); Best model highlighted and in bold. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

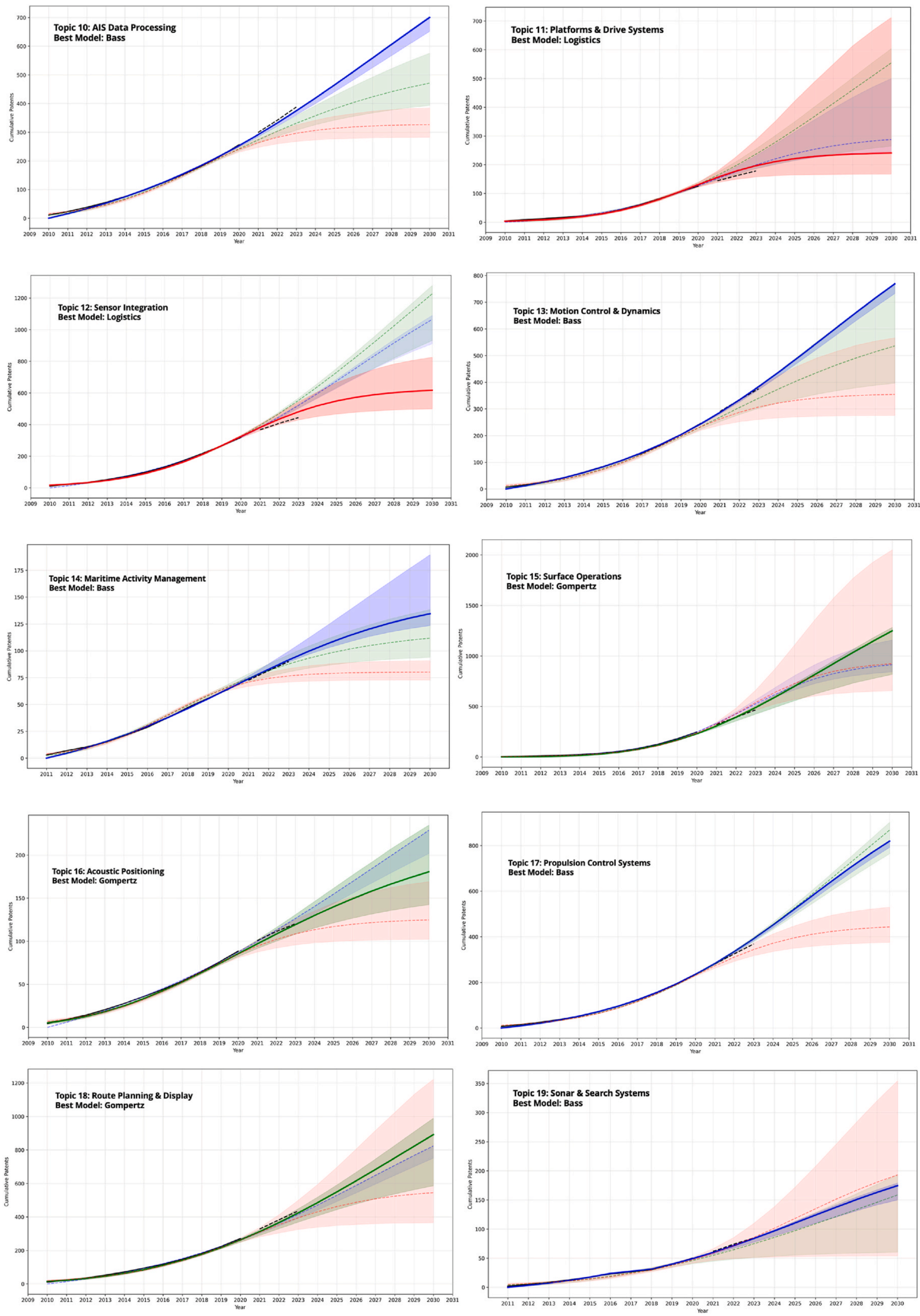

Fig. 12. (*continued*).

enhancing the robustness of multi-sensor fusion, predictive navigation, and cybersecurity for autonomous maritime operations. Beyond technological considerations, the evolution toward cognitive capabilities and system integration also has important implications for maritime workforce development. Belabyad et al. (2025) emphasise that successful autonomous shipping implementation requires workforce transformation, with maritime professionals needing hybrid competencies combining traditional knowledge with digital proficiency and higher-order thinking skills.

Looking ahead, this analysis suggests that the period between 2025 and 2030 will be transformative. During this window, many growth-phase technologies will reach their peak development period, creating a crucial opportunity for industry players to establish leadership positions. However, this won't be achieved through isolated technological advancement as success will need capability in integration and cognitive capabilities.

5.3. Limitations and future research

This patent-based analysis proposed in this study, while providing systematic insights into technological evolution, presents some methodological considerations. First, patents represent only a subset of technological innovation, with some companies protecting key developments through trade secrets rather than patent filings. Second, this analysis treats all patents with equal weight, not accounting for varying impact levels or implementation success rates that would better represent actual technological significance. Third, the LDA methodology itself has some limitations for mapping technological landscapes. As a "bag-of-words" approach, LDA cannot capture contextual relationships between terms, potentially missing technological connections that depend on semantic context. Lastly, patent publication lag (period from filing to publication) effects inherently influence the visibility of recent innovations, particularly relevant for 2023–2024 data, while strategic patent filing behaviours may disproportionately represent certain technological domains.

Furthermore, the forecasting models, though showing high statistical accuracy, are inherently influenced by historical patent filing patterns and may not fully account for disruptive innovations or regulatory-driven technological shifts. Additionally, while this approach maps technological evolution, it does not directly measure market adoption or implementation success, which ultimately determine real-world impact.

Future research directions should address several critical analytical dimensions. First, incorporating text mining of patent claims could provide deeper insights into technological functionality and integration requirements, particularly important for understanding system-level innovations. Second, the development of hybrid forecasting models that combine patent metrics with market indicators could better predict technological commercialisation trajectories. Third, research should explore cross-domain technology transfer, particularly examining how advances in broader autonomous systems influence maritime automation. Additionally, future studies should investigate the alignment between technological capabilities identified through patent analysis and actual operational requirements, perhaps through case studies of autonomous vessel deployments.

Future research could address these limitations through enhanced approaches. Incorporating transformer-based topic modelling techniques such as BERTopic could overcome LDA's contextual limitations by leveraging semantic understanding of patent text. BERTopic's ability to capture contextual similarities between patents could better identify technologies combining multiple domains. Future studies should also explore the integration of market signals and citation impact metrics with patent data to better capture commercial relevance. Additionally, research should investigate cross-domain technology transfer patterns, particularly examining how advances in automotive or aerial autonomous systems influence maritime automation development. Comparative studies between patent-derived technology capabilities and actual operational implementations through case studies of deployed autonomous vessels would provide valuable validation of analytical findings and better inform development roadmaps.

CRediT authorship contribution statement

Mehdi Belabyad: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Robyn Pyne:** Supervision, Methodology, Conceptualization. **Dimitrios Paraskevadakis:** Writing – review & editing, Supervision, Methodology. **Chia-Hsun Chang:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Christos Kontovas:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used different AI-assisted technologies to improve readability and language of the work. After using these tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ocecoaman.2025.107744.

Data availability

Data will be made available on request.

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