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EVOLUTION OF REMOTE-CONTROL TECHNOLOGIES FOR MARITIME AUTONOMY

A Patent-Based Analysis

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1 Introduction

Remote-control technologies in shipping have evolved, moving from theoretical frameworks to practical implementations. The industry has witnessed a surge in innovation, particularly in propulsion systems, power management and vessel control algorithms (Ivanova et al., 2021). Yet, despite this momentum, there is a lack of comprehensive understanding of how these technologies interconnect and which areas are likely to see accelerated development in the coming decade.

While existing literature has examined individual technological components like navigation interfaces (Burmeister et al., 2020) and remote perception methods (Clunie et al., 2021), less attention has been paid to mapping the entire technology ecosystem. Maritime remote control consists of numerous interlocking systems spanning navigation, perception, communication and safety functions – all of which must work in harmony to enable effective shore-based operations.

Patents offer a window into technological evolution, capturing formalised "*deeds to intellectual property*" that give innovation pathways (Campbell, 1983). As the World Intellectual Property Organisation (WIPO) notes, roughly 70–90% of technological information in patent documents is not published elsewhere (Asche, 2017), making patent analysis an important approach for understanding emerging technologies.

Despite the growing body of literature on individual maritime technologies (e.g. Burmeister et al., 2020; Clunie et al., 2021), there remains a significant gap in understanding how these technologies interconnect as an integrated ecosystem and which specific areas will drive future innovation.

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Additionally, while patent analysis has been extensively applied in other sectors (de Oliveira et al., 2024; Cho et al., 2021; Qiu and Wang, 2022), its application to maritime remote-control technologies is limited and does not allow mapping of technology relationships or forecasting of development trajectories. Furthermore, recent advances in patent-based technology mapping have shown promise for understanding maritime autonomous systems broadly (Belabyad et al., 2025b), yet comprehensive analysis specifically focused on remote-control technologies remains absent.

This chapter addresses three core questions: (*1) What are the key technology clusters in maritime remote-control systems? (2) How do these technologies interconnect and influence each other within the innovation ecosystem?* and *(3) What is their relative maturity and potential future trajectory?* By answering these questions, this chapter contributes to the body of knowledge. First, a systematic categorisation of maritime remote-control technologies is provided using BERTopic modelling. Second, the network analysis quantifies technological relationships through centrality metrics, identifying critical bridging technologies that facilitate cross-domain integration. Third, technology maturity is assessed and forecasted using Bass diffusion modelling, providing clear trajectories for the technology landscape for various stakeholders, including shipowners, shipbuilding companies, maritime education and training centres, seafarers and maritime professionals and academics.

The chapter is structured as follows: Section 2 reviews current trends in maritime autonomy and relevant literature on technology diffusion and patent analysis. Section 3 provides the methodological framework. Section 4 presents the findings on technology clusters, their interconnections and development trajectories. Finally, Section 5 discusses the implications, concluding with limitations and future research directions.

2 Literature Review

2.1 Current Trends in Maritime Autonomy and Remote-Control Systems

The maritime industry is heading towards enhanced remote-control capabilities and increased vessel autonomy, transforming traditional approaches to ship management and navigation. Early studies by Rødseth and Nordahl (2017) and Porathe et al. (2018) discussed the emergence of advanced remote operation technologies within a multi-tiered ecosystem including interconnected sensing, telecommunication and decision-support frameworks. Recent industry standardisation efforts by Det Norske Veritas (DNV) (DNV-CG-0264) and assessments by the European Maritime Safety Agency (EMSA, 2024) conceptualise maritime remote control along a continuum including varying degrees of off-ship control and monitoring functionalities.

Ivanova et al. (2021) documented a surge in innovations, particularly in propulsion, power management and ship control algorithms. Their review indicated that communication technologies, which are important for remote operations, saw patent filings double between 2018 and 2019, driven by the demand for connectivity in distributed systems. At the same time, the integration of artificial intelligence (AI) and the internet of things (IoT) aligns with the "Industry 4.0" paradigm, enabling real-time data exchange and decision-making (Razmjooei et al., 2023).

A key example of these advancements is the remote navigation interfaces, which have developed significantly, going from simple command transmission systems to complex control platforms that support sophisticated decision-making in maritime settings (Burmeister et al., 2020). This parallels the rise of advanced remote perception methods, which combine sensor data from radar, LiDAR, optical and infrared technologies to establish comprehensive situational awareness frameworks for operators at a distance (Clunie et al., 2021). As a result, operators at shore-based facilities can now achieve environmental awareness that matches or surpasses that of traditional onboard navigation.

Moreover, maritime remote-control communication infrastructures are now enabling high-bandwidth, low-latency data transmission essential for real-time vessel monitoring and intervention from shore-based facilities (Höyhtyä et al., 2017). This progression has facilitated the development of remote operations centres (ROCs), which function as centralised hubs for monitoring vessel performance and environmental conditions across distributed maritime assets (Porathe et al., 2014; Ramos et al., 2019).

Furthermore, remote decision support systems using AI and machine learning algorithms have enabled more sophisticated functions such as remote collision avoidance, route optimisation and anomaly detection (Zhang et al., 2023). These computational frameworks provide predictive capabilities that go beyond simple reactivity to environmental conditions, allowing anticipatory decision-making in complex operational scenarios even when vessel control is distributed between onboard systems and shore-based operators.

These remote-control systems demonstrate significant operational differentiation across navigation functions, engineering systems, safety protocols and commercial operations, reflecting the multi-domain nature of maritime activities that must be addressed in remote operation contexts (Ringbom, 2019).

2.2 Technology Diffusion: A Theoretical Background

Understanding how innovations get adopted is key to predicting where remote-control technologies are heading next. Technology diffusion is a concept that explains the process through which new tools and innovations catch on with users. It shows a path from first adopters to widespread use (Stokey, 2020). This back-and-forth between innovation and adoption is not new; just like radar completely changed maritime shipping decades ago, today's autonomous systems are following similar paths to becoming integrated in the maritime sector (Clott and Hartman, 2022; Yusup, 2024).

Different theoretical models help us understand how technology diffusion works. The Bass model, which is a fundamental one in this area, suggests that technology adoption follows an S-curve – starting slow, then escalating quickly and eventually saturating (Bass, 1969). Research shows that the speed of adoption is significantly influenced by network effects and economic conditions, highlighting how innovation and diffusion strategies depend on each other (Wang et al., 2007; Yu, 2011). For instance, deploying autonomous vessels depends on having the right ecosystem in place, including regulations, technological infrastructure and a culture that's open to innovation (Clott and Hartman, 2022).

More recent work in diffusion research points out how important social networks are in adoption behaviours (Rao and Kishore, 2010). In maritime autonomy specifically, the interconnected nature of shipping, with collaborations, knowledge sharing and joint projects, plays a key role in driving broader acceptance. Organisations rarely operate in isolation; they rely on collective expertise and shared practices to navigate technological shifts. External factors such as policies and financial incentives also shape this diffusion process, either accelerating or slowing the adoption of new technologies (Yang et al., 2023; Wang et al., 2024).

2.3 Technology Mapping and Forecasting Using Patent Analysis

Patents are basically formalised "deeds to intellectual property" that capture evolutionary technological trajectories, offering standardised documentation of innovation pathways shaped by scientific frameworks, market pressures and the interactions between technologies (Campbell, 1983; Nelson and Winter, 1982). Their value for analysis comes from the exclusive information they contain, with roughly 70–90% of technological information in patent documents not published anywhere else, making them a unique resource for forecasting technology trends (WIPO, n.d.; Asche, 2017).

The International Patent Classification (IPC) system provides a hierarchical taxonomy with eight sections and around 80,000 subdivisions, offering precise positioning and mapping of technological trajectories (Gomez and Moens, 2014). This standardisation enables analytical approaches that go beyond traditional bibliometric analyses. Current methodologies demonstrate how advanced text mining techniques, combined with network analysis, can visualise technological relationships and emerging patterns (Aristodemou and Tietze, 2018).

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

While patent analysis is being widely applied for technological mapping and forecasting across numerous sectors, its application in maritime research, particularly in 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 after 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 four subgroups (26 patents) in specialised applications, demonstrating the hierarchical nature of technological development in this field. 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. More recently, Belabyad et al. (2025b) demonstrated the effectiveness of integrated patent analytics for maritime autonomous systems, identifying 20 technological domains and highlighting the critical role of sensor integration technologies, while illustrating technology maturity patterns across different maritime domains.

3 Methodology

Figure 1.1 provides the overall analytical framework that integrates bibliometric analysis (step 1), BERTopic modelling (step 2), network analysis (step 3) and technology forecasting (step 4) to analyse the technology landscape. It progresses from descriptive analytics to predictive modelling.

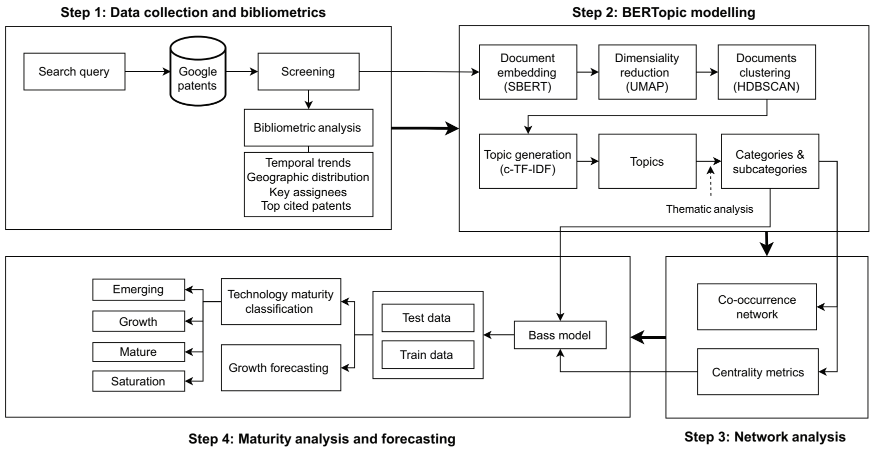

FIGURE 1.1 Research framework

3.1 Step 1: Data Collection and Bibliometric Analysis

Patent data is collected using Google Patents via BigQuery, focusing on remote-control technologies in maritime autonomy. For clarity, within this chapter, these technologies are defined based on previous work by DNV (DNV-CG-0264) and EMSA (2024) as

> Systems that enable vessel functions to be operated, monitored and controlled from a distance, without requiring personnel to be physically present at the location of operation, facilitating On-board control and/or Off-ship control.

These systems serve the following core functions:

- Navigation functions (e.g. route planning, collision avoidance, manoeuvring)
- Engineering functions (e.g. propulsion, power management, machinery control)
- Safety functions (e.g. fire detection, watertight integrity, emergency communications)
- Operations functions (e.g. cargo operations, commercial activities)

Based on this definition, a comprehensive search query is developed:

> *((“remote control” OR “remote operation” OR “remote supervision” OR “remote monitoring” OR telecontrol OR “off-ship control” OR*

"remote operations center" OR "remote operations centre" OR ROC OR "remote workstation")

AND

("maritime" OR "marine" OR "nautical" OR "naval" OR ship OR vessel* OR boat* OR "watercraft" OR "water craft" OR "sea-going" OR seagoing OR "ocean-going" OR "oceangoing" OR "waterway" OR "offshore" OR "coastal")*

AND

("propulsion" OR "navigation" OR "steering" OR "maneuvering" OR "collision avoidance" OR "object detection" OR "situational awareness" OR "monitoring system" OR "control system" OR automat OR autonomy* OR "decision support" OR "supervised autonomy" OR "connectivity" OR "communication link" OR "data link" OR "connectivity link" OR "fallback state")*

AND

(IPC:(B63B OR B63H OR B63J OR B63K OR G05D1 OR G08C OR H04B7 OR G06Q50/30))

NOT

("toy" OR "model" OR "hobby" OR "fish" OR "fishing" OR "recreational" OR "sport").

Please note that in the query, words are included in the search when the 'AND' operator is used, alternatives are considered with 'OR', and words are excluded using the 'NOT' operator. The wildcard symbol (*) expands the search to include words that begin with the same letters.

The first official traces of autonomous shipping date back to 2015 when the United Kingdom, International Association of Institutes of Navigation (IAIN) and the Institute of Marine Engineering, Science and Technology (IMarEST) submitted a document entitled "IMO Regulatory Framework and its Application to Maritime Autonomous Systems" to the IMO Maritime Safety Committee (Stępień, 2024). The 2010–2024 timeframe is selected to cover the pre-regulatory innovation works up to the most recent available yearly data.

Patents were collected using filing dates rather than publication dates, as filing dates more accurately reflect when inventions were created and legally protected. They also help avoid the lag introduced by publication delays, which usually take around 18 months on average.

The initial search resulted in 3,341 patents, which were refined to 1,875 after removing duplicates and irrelevant patents. Duplicates were identified and removed manually by comparing patent titles and publication numbers to ensure no patent was counted multiple times. Moreover, irrelevant patents were excluded based on predetermined criteria: patents focusing primarily on offshore oil and gas technologies without maritime vessel applications, aquaculture and fish-farming technologies that lacked remote-control elements for vessel operations, and recreational or toy vessel technologies that did not address commercial maritime applications.

A bibliometric analysis was conducted, focusing on four critical elements: time distribution, assignees, regional distribution and most frequently cited patents.

3.2 Step 2: Topic-Modelling Using BERTopic

The topic-modelling technique BERTopic was chosen for this analysis due to several key advantages over traditional methods like LDA or non-negative matrix factorization (NMF): (1) it leverages contextual BERT embeddings that capture semantic relationships more accurately than LDA's bag-of-words approach, (2) it automatically determines the optimal number of topics without requiring manual parameter tuning, (3) it can identify outlier documents that don't fit into main topics, which LDA cannot handle effectively and (4) it generates more coherent and interpretable topic clusters through its combination of uniform manifold approximation and projection (UMAP) dimensionality reduction and hierarchical density-based spatial clustering of applications with noise (HDBSCAN) clustering (Egger and Yu, 2022).

BERTopic integrates bidirectional encoder representations from transformers (BERT) embeddings with class-based term frequency–inverse document frequency (TF-IDF) to generate more coherent topic clusters. The algorithm operates by first embedding textual data using sentence-BERT (SBERT), reducing dimensionality via UMAP and subsequently clustering similar documents through HDBSCAN (Grootendorst, 2022). BERTopic can automatically determine the optimal number of topics without manual preset parameters and identify outlier documents that do not fit neatly into main topics.

BERTopic operates through three stages (see step 2 in Figure 1.1). First, document embeddings are generated using SBERT, transforming each document d_i into an n-dimensional vector $\vec{v_l} \in \mathbb{R}^n$ where semantic similarity between documents is preserved as cosine similarity in the embedding space:

Equation 1

$$\text{sim}\;\; d_i, d_j \;\; = \frac{\vec{v_i}, \vec{v_j}}{\left|\vec{v_i}\right|\left|\vec{v_j}\right|} q$$

Second, dimensionality reduction via UMAP transforms these high-dimensional embeddings into a lower-dimensional manifold $\mathbb{R}^m$ where $m \ll n($typically $m = 5)$ preserving both local and global structure through:

Equation 2

$$\min \sum_{i,j} p_{i,j} \log\left(\frac{p_{ij}}{q_{ij}}\right)$$

where $p_{i,j}$ are high-dimensional similarities and q_{ij} low-dimensional similarities.

Finally, HDBSCAN performs density-based clustering by identifying regions of high density separated by regions of low density, generating clusters without requiring a pre-specified number of topics.

Each cluster c_k is then characterised using class-based TF-IDF:

Equation 3

$$c - TF - IDF_{t,c} = \frac{f_{t,c} / w_c}{\sum_i f_{t,c} / w_c}$$

where $f_{t,c}$ is the frequency of term t in class c, and w_c is the number of words in class c.

For our implementation, we combined patent titles and abstracts since these contain the highest density of relevant technical information, and such a technique is usually used in previous patent-based analysis studies (Qiu and Wang, 2022; Ghaffari et al., 2024). One advantage of using BERTopic is that there is no need for preprocessing as with traditional topic-modelling approaches. The contextual embeddings capture semantic relationships between words regardless of their form, and even stopwords can carry meaningful information in context. We only performed minimal cleaning to handle special characters and formatting inconsistencies in the patent text. When applying BERTopic to our dataset, we experimented with different UMAP and HDBSCAN parameters to balance topic granularity and coherence.

3.3 Network Analysis

Based on the topic modelling results, a co-occurrence network is constructed to visualise and analyse relationships between technology subcategories. In the network representation, each node corresponds to a technology subcategory identified through topic modelling in step 2. Node size is proportional to patent count, and edge weights represent the co-occurrence frequency of technology pairs within the same patents, highlighting convergence between the technologies.

Applying citation network analysis (CNA) (McLaren and Bruner, 2022), node importance and network structure are quantified by calculating three key centrality metrics: degree centrality (measuring how many direct connections a technology has, which indicates its breadth of integration across the ecosystem), betweenness centrality (measuring how often a technology serves as a bridge between other technologies, showing which technologies are essential for connecting different technology clusters), and eigenvector centrality (measuring connections to other highly connected technologies, which help identify technologies that are embedded within the most influential parts of the network and therefore likely to drive future development) (Wasserman and Faust, 1994; Li et al., 2020).

3.4 Maturity Analysis and Forecasting

In technology evolution modelling, the literature uses a foundational assumption that technology adoption typically follows an S-curve pattern, where diffusion begins slowly during the innovation phase, accelerates during widespread adoption, and then plateaus as the market saturates (Foster, 1986; Christensen, 1992), forming a sigmoidal curve. This pattern has been observed and validated across numerous technology domains (Andersen, 1999; Chen et al., 2012; Miwornunyuie et al., 2024).

Among various S-curve growth models available for technology forecasting, the Bass diffusion model, introduced by Bass (1969), was selected. This model was considered an effective approach for forecasting technology diffusion patterns in different sectors (Meade and Islam, 2006; Daim and Suntharasaj, 2009; Wang and Sun, 2021). It's suitable for patent analysis as it assumes that technology adoption is governed by innovators (coefficient p: early adopters who decide independently to adopt the innovation, uninfluenced by others) and imitators (coefficient q: those influenced by previous adopters; social influence), who both characterise technology diffusion.

Mathematically, the core of the Bass model is expressed by the differential equation:

Equation 4

$$\frac{dN(t)}{dt} = \left(p + q\frac{N(t)}{m}\right)(m - N(t))$$

where $N(t)$ 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 m is the total market potential, representing the upper limit of adoption.

In its implementation, network centrality metrics calculated in step 3 were used to parameterise the Bass model. Following the theoretical works of Muller and Peres (2019) and Burt (1999), betweenness centrality was used to parameterise the innovation coefficient (p), while eigenvector centrality was used to parameterise the imitation coefficient (q):

- High betweenness centrality suggests that a technology (or firm) introduces novel connections and serves as a conduit for knowledge flow, much like innovators in the Bass model who adopt independently of earlier adopters.
- Technologies with high eigenvector centrality are embedded within a dense network of influential adopters, meaning their adoption is likely influenced by previous adopters, similar to the imitation effect (q) in the Bass model.

A train-test-forecast methodology was employed to validate the proposed approach. The model was first fitted to data from 2010 to 2019 using non-linear least squares optimisation. Validation was conducted on test data from 2020 to 2024 by calculating out-of-sample prediction accuracy using the mean absolute percentage error (MAPE). For future projections, forecasts were extended to 2033 (a 10-year horizon) and 95% confidence intervals were generated using Monte Carlo simulation with 1,000 iterations.

Technologies are then mapped using both the q and p to construct a two-dimensional diffusion characteristic matrix, positioning each technology based on its primary adoption mechanism: high p (innovation-driven), high q (imitation-driven) or a combination of both.

Finally, to assess technology maturity, progress percentage is calculated as the ratio of current cumulative patents to the estimated market potential (current patent cumulative count divided by m). Based on this metric, technologies were classified into four maturity stages (following Andersen's (1999) seminal study on S-curves):

- Emerging ($P < 25\%$): Technologies in early adoption
- Growth ($25\% < P < 60\%$): Technologies in the acceleration phase
- Maturity ($60\% < P < 80\%$): Technologies approaching saturation
- Saturation ($P > 80\%$): Technologies with limited growth potential

4 Results and Analysis

4.1 Bibliometric Analysis

As shown in Figure 1.2, the number of patent filings started increasing gradually from 2010, reaching its peak in 2022 at 253 patents, after which it declined rapidly up to 2024. This can potentially be attributed to changing R&D priorities in the sector following global economic uncertainties. In

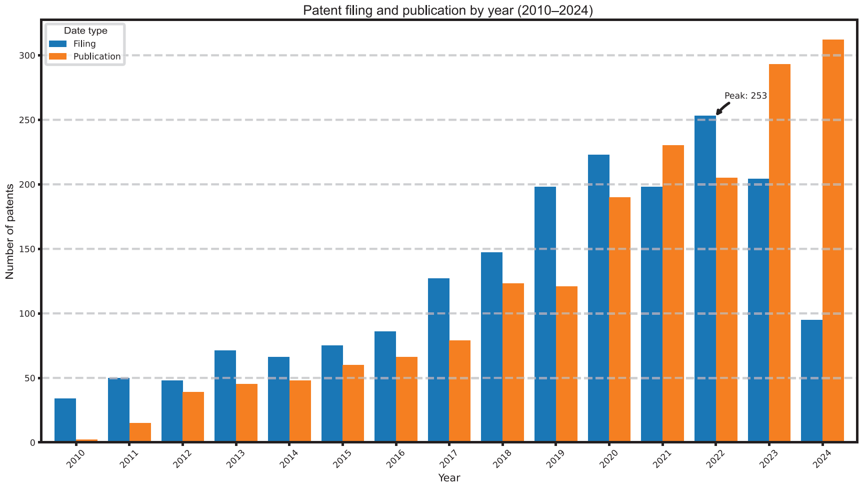

FIGURE 1.2 Distribution of patents by years (filing versus publication years)

contrast, patent publications experienced continued growth from 2010 to 2024, except for 2023, when they decreased slightly. This pattern reflects the typical 18-month lag between filing and publication in the patent system. Up to 2021, the number of patents filed was higher than those published, except for 2021. From 2023 onwards, the number of patents published is significantly higher than the number filed, highlighting the processing of the backlog of applications from the peak innovation years.

In terms of assignees (Figure 1.3), Furuno Electric (a Japanese electronics company) is leading with 74 patents, followed by Brunswick Corporation (an American international marine manufacturer) with 49 patents, and Yamaha Motor (another Japanese manufacturer) with 39 patents. Looking at the assignees figure, we observe that this ecosystem is diverse, comprising marine and navigation technology organisations (e.g. Furuno Electric, Brunswick), automotive and motor manufacturer (e.g. Yamaha Motor, Honda Motor), shipbuilders (e.g. Daewoo), shipping organisations (e.g. Nippon Yusen), technology and IT solutions (e.g. Fujitsu Limited), and universities and research institutions (e.g. Wuhan University of Technology, Dalina Maritime University). Interestingly, six universities are competing within the top 15 assignees, indicating the significant role of academic research in this area.

Concerning the regional distribution of patents (Figure 1.4), 51% of patents are registered in China, followed by 17.5% in Korea and 10.9% in the United States. These three countries comprise almost 80% of all patents. A fraction of patents is registered with the World Intellectual Property Organisation (WIPO) and the European Patent Office (EPO), which manage patent applications in the international and European context respectively.

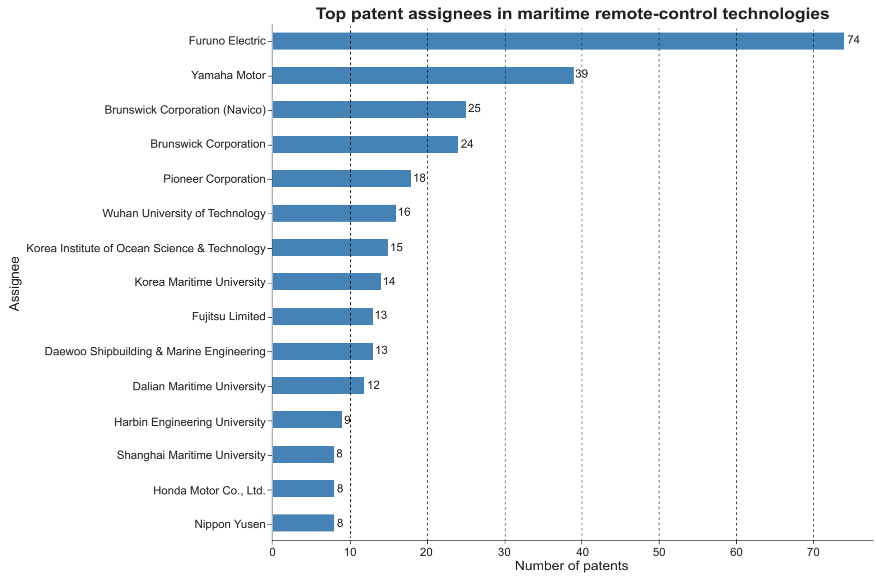

FIGURE 1.3 Top assignees in maritime remote-control-related technologies

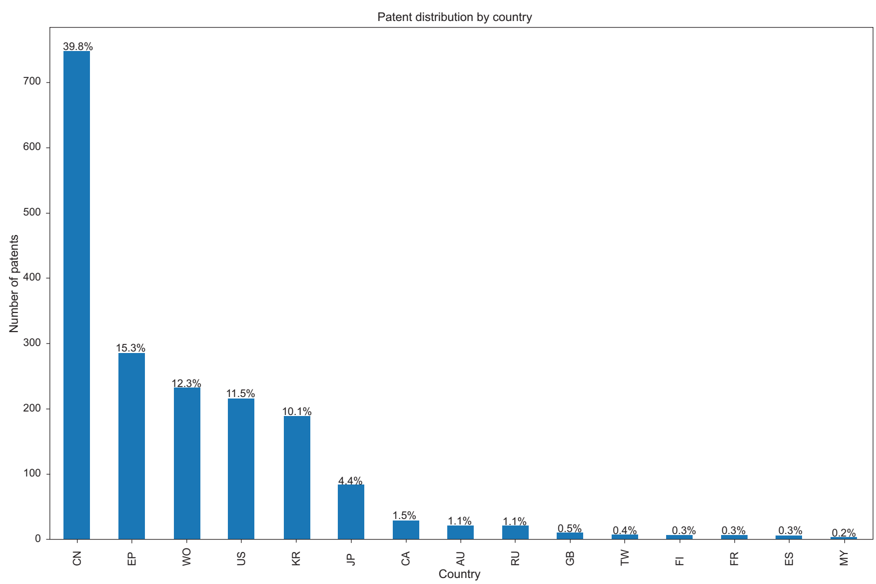

FIGURE 1.4 Patent distribution by country

Table 1.1 presents the most cited patents in the dataset. It shows that foundational control systems, collision avoidance and autonomous navigation technologies are influential in the innovation network.

TABLE 1.1 Top cited patents

Patent number	*Patent title*	*Overview*	*Cited*
US-6273771-B1	"Control system for a marine vessel"	A marine vessel control system that uses a communication bus to manage multiple devices.	19 times
KR-101937439-B1	"Alternative route generation and rudder angle control support system for collision avoidance of autonomous ship and other ships"	A system that generates alternative navigation routes and controls the rudder for collision avoidance.	12 times
KR-101941896-B1	"System for controlling auto sailing of vessel"	An autonomous navigation control system that stabilises a vessel in emergencies	11 times

4.2 Topic Modelling Using BERTopic

Using BERTpoic, 30 topics were generated and further categorised into eight main categories. The sunburst diagram (Figure 1.5) shows these categories and sub-categories with their sizes according to the number of patents.

BERTopic generated keyword distributions for each identified topic, grouping semantically similar patents into coherent clusters. These keyword clusters were then qualitatively and thematically analysed to infer the underlying technological domains. For example, clusters containing terms such as "camera", "vision", "image", "video", "visual" and "recognition" were classified under the "camera & visual systems" subcategory within the broader "perception & detection" category.

"Remote Control Systems" is the largest category, with subcategories including "Remote Navigation Interfaces" (which dominated this space), followed by "Command & Control Infrastructure", "Wireless Control Systems", "Remote Propulsion Control" and "Teleoperation Networks". A representative patent in this category is US-12214854-B2, "Vessel azimuth control apparatus and azimuth control method", which enables precise remote control of vessel direction through an intuitive interface that compensates for environmental factors. This dominance suggests that foundational control infrastructure remains the primary innovation focus, indicating continued investment in making remote operations more reliable and intuitive.

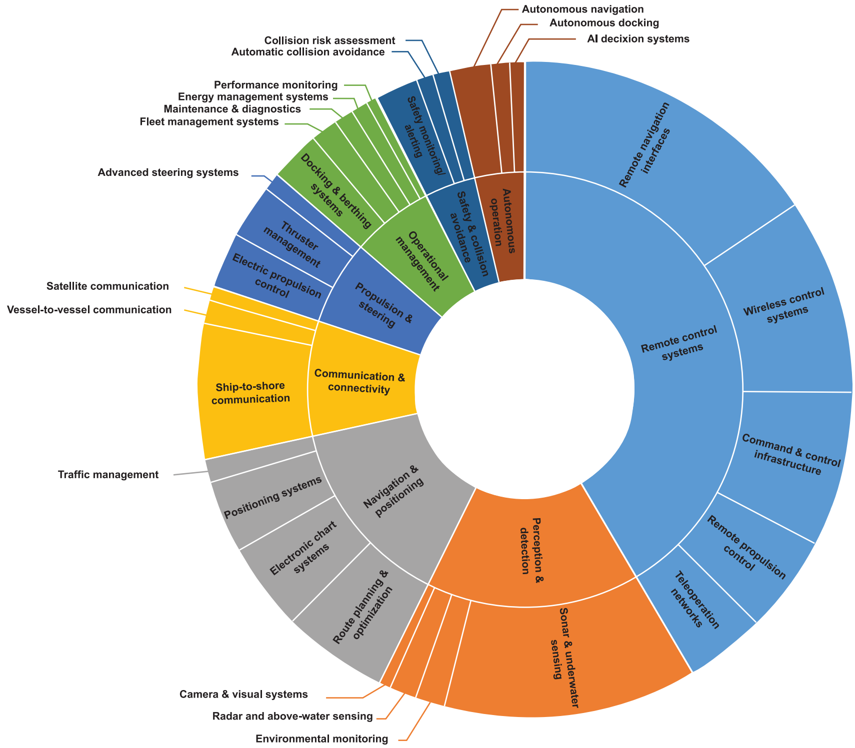

FIGURE 1.5 Technologies categories and subcategories

"Perception & Detection Technologies" formed another major cluster, with "Sonar & Underwater Sensing", followed by "Camera & Visual Systems", "Radar & Above-Water Sensing", "Multi-Sensor Integration" and "Environmental Monitoring". These technologies essentially form the "eyes and ears" of remote and autonomous maritime systems. US-2025036144-A1, "Underwater vehicles for vessel characterisation", exemplifies this category with its innovative approach to using autonomous underwater vehicles to gather data about vessel hulls and underwater structures. This cluster indicates that achieving comprehensive situational awareness remains a fundamental requirement for significant technological development in remote-control technologies.

"Navigation & Positioning Technologies" includes "Route Planning & Optimisation", "Electronic Chart Systems", "Positioning Systems" and "Dynamic Navigation and Traffic Nanagement". These are technologies that establish where vessels are and where they should go. EP-4506663-A1, "Systems and methods for generating routes for watercraft", demonstrates advanced algorithms that optimise vessel routes based on multiple factors, including weather, traffic, fuel efficiency and safety parameters. The centrality of route optimisation within this category suggests that this area serves as a critical foundation for effective maritime operations.

"Safety & Collision Avoidance Systems" are composed of "Safety Monitoring & Alerting", "Collision Detection Systems", "Collision Risk Assessment", "Automatic Collision Avoidance" and "Emergency Response Systems". The relatively smaller patent counts in this category may be surprising given safety's importance in the sector, but many safety functions are likely integrated within other systems. KR-102617981-B1, "Collision avoidance system for autonomous ships", represents breakthrough technology that can autonomously identify collision risks and execute avoidance manoeuvres without human intervention. The relatively smaller patent counts in this category are notable given safety's importance, suggesting that safety functions may be integrated within other systems rather than developed as standalone technologies.

"Communication & Connectivity Technologies" included "Ship-To-Shore Communications", "Vessel-to-Vessel Communications", "Satellite Communications", "Maritime Broadband" and "Communication Security & Resilience". WO-2018149901-A1, "Route planning of a vessel", illustrates how connectivity technologies enable real-time route adjustments based on information shared between shore stations and vessels, highlighting the critical nature of reliable communication links. This suggests the enabling role of connectivity in maritime remote operations, facilitating real-time information exchange and coordination.

"Propulsion & Steering Technologies" covered "Electric Propulsion Control", "Advanced Steering Systems", "Thruster Management" and "Propulsion Efficiency Systems". EP-3978352-B1, "Marine propulsion control system and method with collision avoidance override", shows the integration of safety protocols with propulsion systems, allowing automated override of propulsion commands when collision risks are detected. This cluster focuses on electric propulsion control and efficiency systems, suggesting a shift towards more environmentally sustainable and precisely controllable propulsion technologies.

"Operational Management Systems" encompassed "Energy Management Systems", "Docking & Berthing Systems", "Fleet Management Systems", "Performance Monitoring" and "Maintenance & Diagnostic Systems". These handle specialised aspects of maritime operations. EP-3898405-C0, "System for docking a submarine vessel to a docking port", presents sophisticated technology that enables precise automated alignment and connection procedures for underwater vessels, demonstrating the complexity of operational management systems. This suggests that shore-based operational models are becoming increasingly sophisticated and specialised.

Finally, "**Autonomous Operation Technologies**" included "Autonomous Navigation", "AI Decision Systems", "Autonomous Perception", "autonomous docking" and "Human-Autonomous Interaction". WO-2021242413-A3, "Adaptable control for autonomous maritime vehicles", showcases an advanced framework that balances autonomous decision-making with human supervision, allowing the dynamic shifting of control authority based on situational complexity and risk assessment. The emphasis on balancing autonomous capabilities with human supervision indicates that hybrid human-machine operations represent the current focus of autonomous maritime development.

4.3 Network Analysis

The network analysis examines how different technology clusters connect and influence each other. Looking at the co-occurrence network visualisation (Figure 1.6), there is a dense cluster centring around "Safety & Collision Avoidance Systems" in the top portion of the network, showing tight integration between sensing technologies and safety systems. A second major cluster forms around "Navigation & Positioning Technologies", connected to autonomous operation capabilities. "Remote-Control Systems" and "Communication & Connectivity" technologies form a third significant grouping, with multiple connections to other clusters.

In terms of centrality (as shown in Table 1.2), "Route Planning & Optimisation" has the highest degree centrality (0.162), meaning it has the most direct connections to other technologies. This reflects its key role in connecting various requirements (navigational and operational). Its high betweenness centrality (0.090) further confirms that it serves as a bridge between different technologies.

"Safety Monitoring & Alerting" shows the highest eigenvector centrality (0.389), suggesting a strong connection to other influential technologies. This indicates that safety systems must integrate with numerous other vessel systems to operate effectively. Similarly, "Collision Detection Systems" and "Collision Risk Assessment" (both with an eigenvector centrality of 0.266) form part of this critical safety cluster.

"Command & Control Infrastructure" exhibits high betweenness centrality (0.254) despite having fewer connections, indicating its role in bridging different technologies. "Remote Navigation Interfaces" has the highest patent count (285) but relatively low centrality metrics, suggesting it is a specialised area that has seen substantial development but with limited integration across the innovation landscape.

Furthermore, several technologies show zero connections in the network, including "Emergency Response Systems", "Automatic Collision Avoidance"

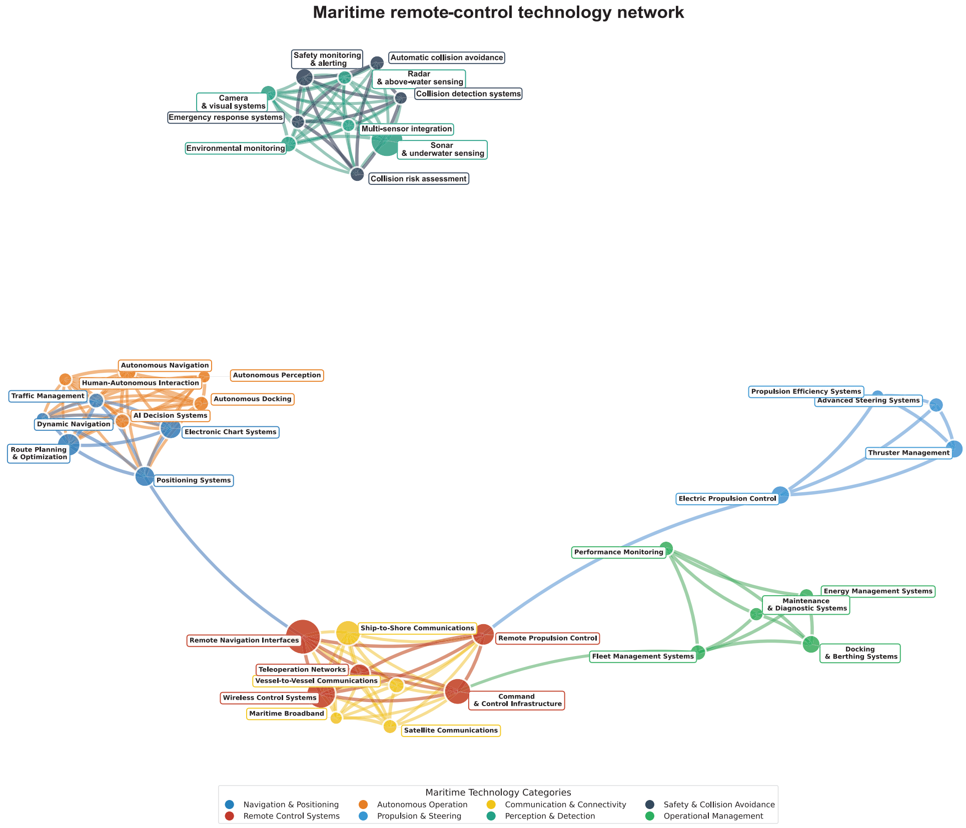

FIGURE 1.6 Network visualisation: co-occurrence relationships between maritime remote-control technology subcategories (node size = patent count, edge thickness = co-occurrence frequency, colours = technology categories)

TABLE 1.2 Key technologies based on centrality metrics

Technology subcategory	*Category*	*Patent count*	*Degree centrality*	*Betweenness centrality*	*Eigenvector centrality*
Route Planning & Optimisation	Navigation & Positioning	96	0.162	0.090	0.380
Safety Monitoring & Alerting	Safety & Collision Avoidance	41	0.135	0.058	0.389
Command & Control Infrastructure	Remote-Control Systems	142	0.054	0.254	0.260
Wireless Control Systems	Remote-Control Systems	178	0.054	0.000	0.105
Electric Propulsion Control	Propulsion & Steering	51	0.108	0.032	0.161
Sonar & Underwater Sensing	Perception & Detection	232	0.054	0.029	0.105
Remote Navigation Interfaces	Remote-Control Systems	285	0.027	0.000	0.078
Autonomous Navigation	Autonomous Operation	37	0.081	0.004	0.196
Ship-to-Shore Communications	Communication & Connectivity	124	0.027	0.000	0.027
Autonomous Docking	Autonomous Operation	17	0.135	0.075	0.329

and "Human-Autonomous Interaction" and therefore are not presented in the table shown. This suggests these areas are either emerging innovations or are being developed in isolation from the main innovation streams.

Overall, we have a network organised around several key technology hubs. Navigation and safety technologies form the most connected clusters, while newer autonomous technologies show less integration. We can infer that the industry, in this area, is transitioning as established remote-control technologies are well-developed but not fully integrated with emerging autonomous capabilities.

4.4 Maturity Analysis and Forecasting

The maturity analysis directly addresses our third and final research question regarding the relative maturity and future trajectory of maritime remote-control technologies, as outlined in Section 1. The Bass diffusion modelling results provide clear evidence that this technological domain remains in active development rather than approaching standardisation.

Given the large number of technology subcategories identified in this analysis, this Section focuses primarily on the main categories for forecast visualisation while incorporating subcategories for maturity assessment.

The citation-based Bass model was fitted to training data (2010–2019) and then tested against actual patent data for the period 2020–2024. This validation approach resulted in MAPE values ranging from 2.98 to 13.11, confirming the model's predictive accuracy. The model was compared with linear and exponential forecasting approaches, and the citation-based Bass model consistently outperformed these alternatives.

The S-curve forecasts are shown in Figure 1.7.

- **"Remote-Control Systems"** (five subcategories, 42.4% of potential, growth stage): This largest category shows strong continued growth potential, with forecasts suggesting cumulative patent counts could reach 1,640 by 2033 from the current 765 patents. The steep slope of the forecast curve indicates accelerating innovation in this area.
- **"Navigation & Positioning"** (four subcategories, 18.6% of potential, growth stage): Currently at 265 patents, this category shows substantial room for growth, with projections reaching approximately 520 patents by 2033. The moderately steep S-curve suggests steady rather than explosive growth.
- **"Perception & Detection"** (four subcategories, 26.3% of potential, growth stage): With 296 current patents, this category shows considerable growth potential, projected to reach approximately 710 patents by 2033.
- **"Autonomous Operation"** (three subcategories, 21.6% of potential, growth stage): Despite relatively few current patents (74), this category shows steep projected growth, potentially reaching 185 patents by 2033. The steepness of the forecast curve suggests this emerging area may see accelerated development.
- **"Communication & Connectivity"** (three subcategories, 18.7% of potential, growth stage): Currently at 159 patents, projections suggest growth to approximately 365 patents by 2033. The moderate slope suggests steady development.
- **"Propulsion & Steering"** (three subcategories, 36.3% of potential, growth stage): With 118 current patents, this category shows moderate growth potential to approximately 245 patents by 2033. The flatter slope suggests these mature technologies may see more incremental innovation.
- **"Safety & Collision Avoidance"** (three subcategories, 23.9% of potential, growth stage): With 81 patents currently, this category could reach approximately 215 patents by 2033. The steepening forecast curve suggests increasing attention to safety as autonomous systems develop.
- **"Operational Management"** (four subcategories, 6.6% of potential, emerging stage): This is the only category in the emerging stage with just 113 patents and substantial growth potential to approximately 300 patents by 2033. The J-shaped forecast curve suggests this area may be approaching an acceleration point.

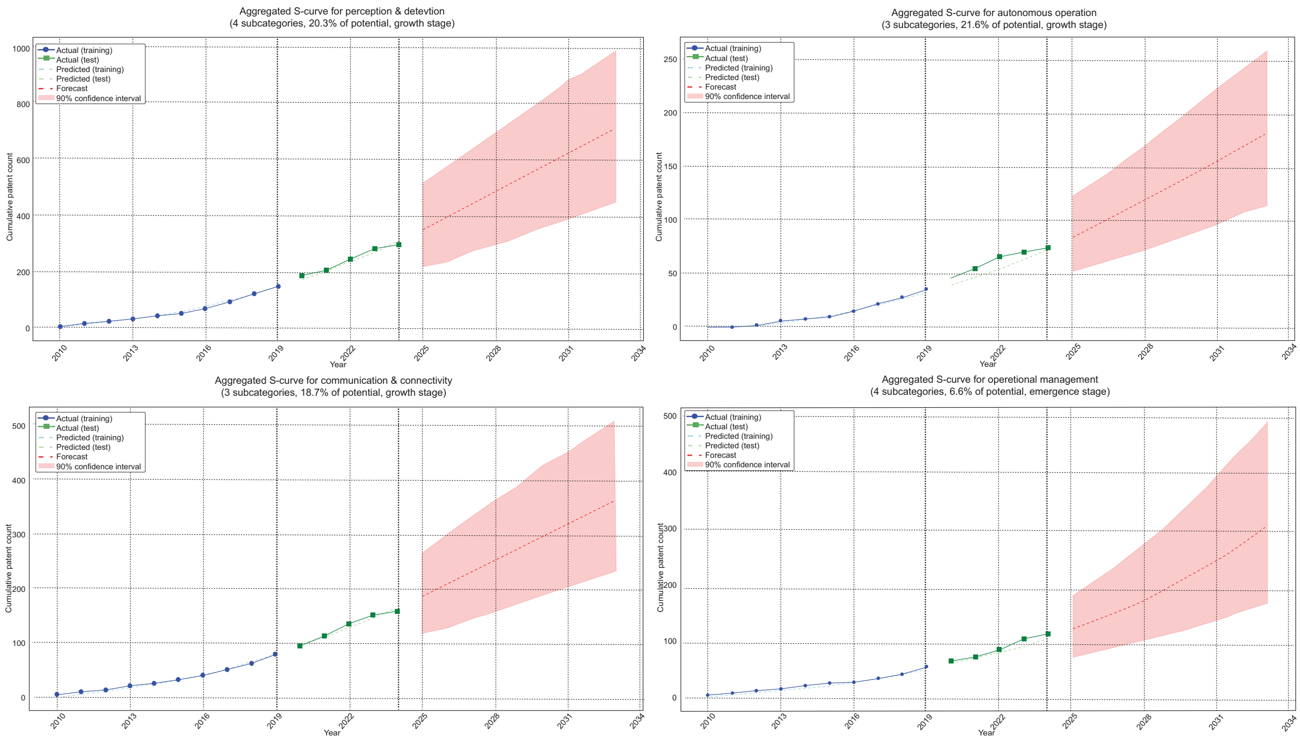

FIGURE 1.7 S-curve fitting and forecast

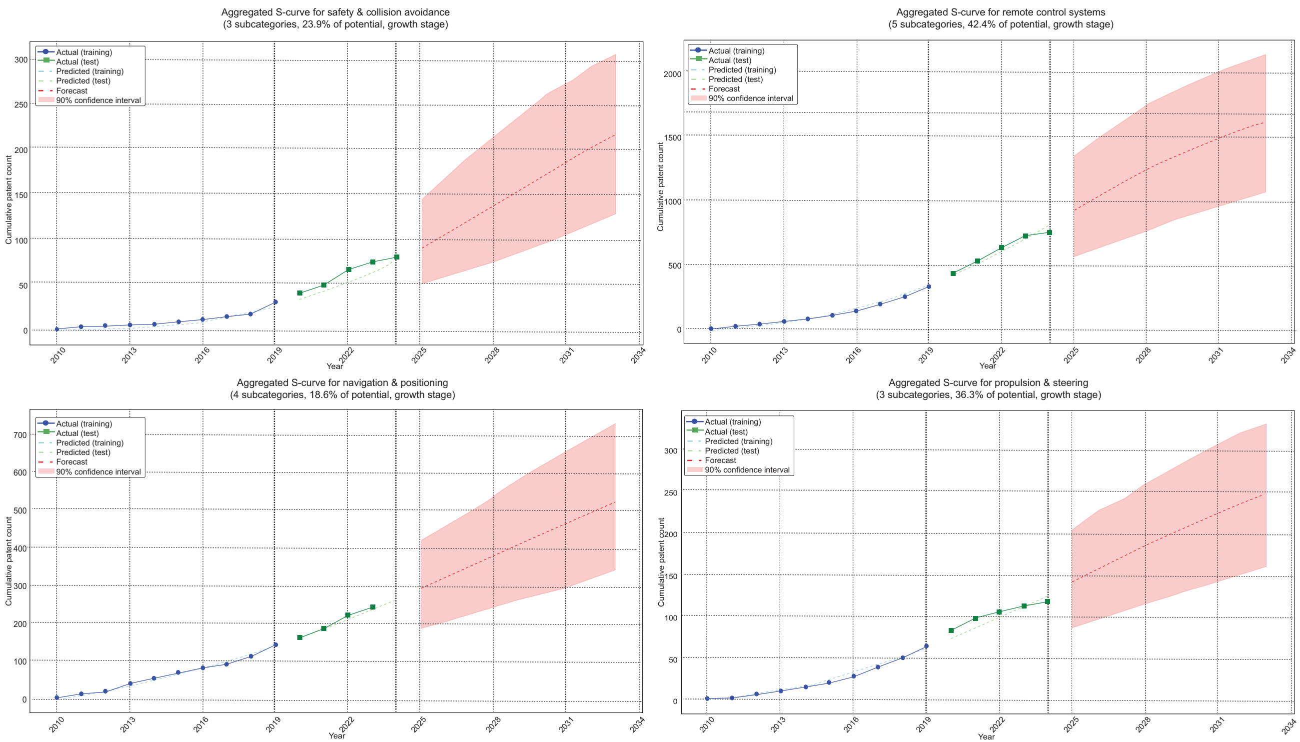

FIGURE 1.7 (Continued)

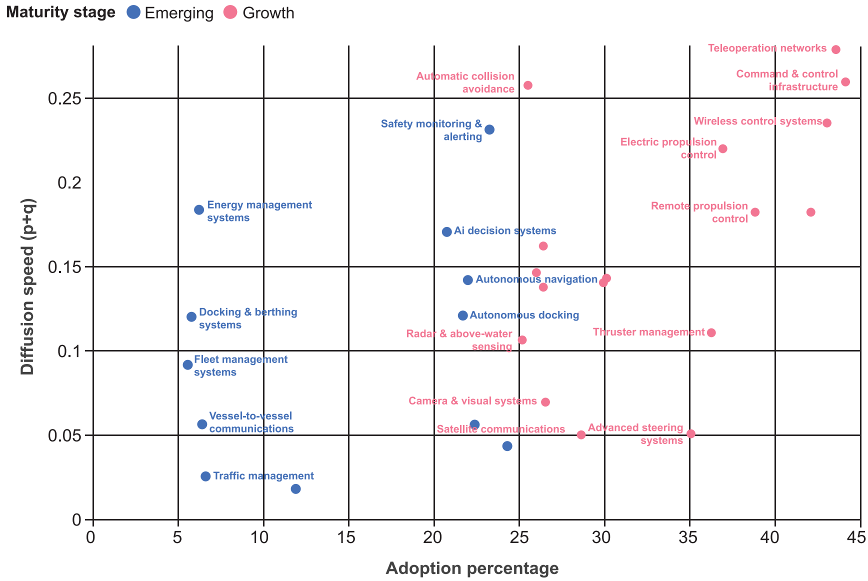

FIGURE 1.8 Diffusion speed ($p + q$) versus current adoption (some technology labels may be omitted due to space constraints)

Moreover, Figure 1.8 (Diffusion speed $(p + q)^1$ versus current adoption) shows four technology clusters based on market penetration and diffusion dynamics. Overall, of all technologies (subcategories), 65.5% are in the growth stage while 34.5% are in the merging stage.

The upper-right quadrant (high diffusion/high adoption) includes technologies like “Teleoperation Networks”, “Command & Control Infrastructure” and “Wireless Control Sysltems”. These technologies have reached widespread adoption (40–60% of market potential) while maintaining high diffusion speeds (0.24–0.28), suggesting they are established but still actively evolving.

On the other hand, the lower-left quadrant contains technologies like “Traffic Management”, “Positioning Systems” and “Vessel-to-Vessel Communications” with both low adoption rates (<10%) and slow diffusion speeds (<0.06). These represent either highly specialised niches or very early-stage innovations that haven’t yet gained significant traction.

Finally, Figure 1.9 (Innovation versus imitation parameters) offers complementary insights by revealing the dominant adoption mechanisms. Technologies positioned higher on the *y*-axis (*q* coefficient), like “Teleoperation Networks” and “Wireless Control Systems” ($q > 0.22$), spread primarily through imitation effects where companies adopt technologies based on competitive pressures and established successes. These technologies benefit from network effects and industry standardisation.

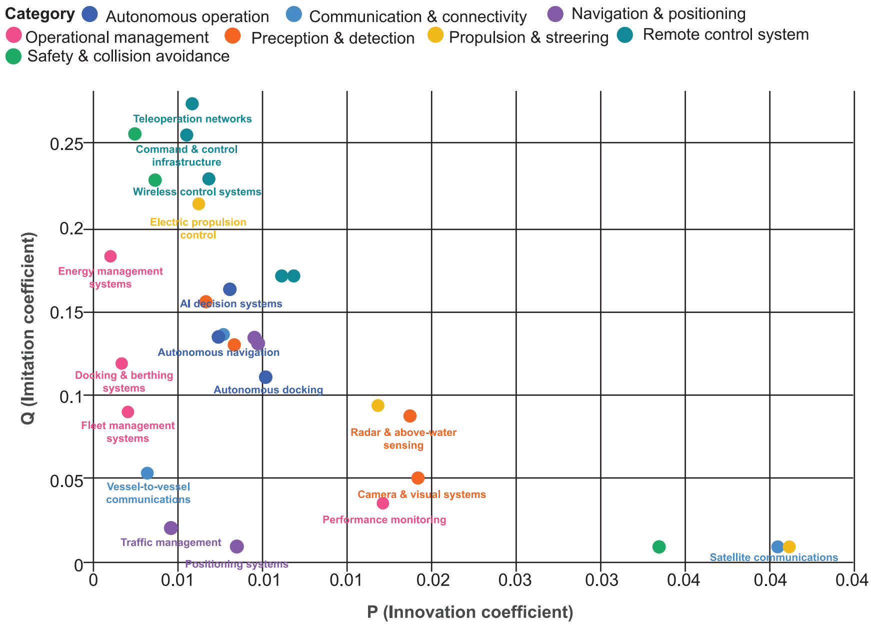

FIGURE 1.9 Innovation versus imitation parameters (some technology labels may be omitted due to space constraints)

Technologies with higher innovation coefficients (p) like "Advanced Steering Systems" and "Satellite Communications" ($p > 0.04$), but low imitation effects spread through breakthrough innovation rather than mimetic adoption. Their development is driven by pioneer companies rather than industry-wide imitation.

Most technologies cluster in the middle-left region with moderate imitation coefficients (0.10–0.20) and low innovation coefficients (<0.02), suggesting balanced development patterns with greater emphasis on incremental improvements than radical innovation (breakthroughs).

Looking at maturity stages across both visualisations, several patterns can be observed:

- **"Remote-Control Systems"** category shows the most mature technologies, with three subcategories in the widespread adoption phase.
- **"Navigation & Positioning"** technologies show moderate adoption (30–40%) with varied diffusion mechanisms.
- **"Autonomous Operation"** technologies remain largely in early adoption phases despite moderate diffusion speeds.
- **"Safety & Collision Avoidance"** technologies show some differences, with some reaching widespread adoption (**"Safety Monitoring"**) while others remain in early phases (**"Collision Risk Assessment"**).

The complete absence of technologies in the market maturity and saturation phases confirms that maritime remote-control technology as a field has not reached maturity. Even the most established technologies still have high growth potential while the numerous technologies in early adoption phases suggest considerable innovation activity remains ahead.

5 Discussion and Conclusion

5.1 Discussion

This study mapped and forecasted the technological landscape of maritime remote-control systems using patent data and advanced modelling techniques. Patent filings surged from 2010, peaking in 2022 before a recent decline, while publications continue to rise, reflecting sustained momentum. Leading contributors include traditional maritime firms, tech innovators and academic institutions, with China dominating geographically, followed by Korea and the United States.

The topic modelling indicated "Remote-Control Systems" as the dominant category, with "Remote Navigation Interfaces" leading the charge. These systems are necessary for shore-based vessel control. "Perception & Detection" technologies, essential for situational awareness, rely on multi-sensor integration, while "Navigation & Positioning" systems, specifically "Route Planning & Optimisation", anchor operational precision. "Safety & Collision Avoidance" technologies show varied integration and "Communication & Connectivity" are the basis of all remote functions. "Emerging Operational Management" systems signal a shift to shore-based roles, while "Autonomous Operation" technologies remain at early stages, suggesting a future of hybrid human-machine operations. Network analysis highlights the centrality of "Route Planning & Optimisation" and the influence of "Safety Monitoring & Alerting" yet technologies such as "Emergency Response Systems" remain isolated.

The maturity analysis conclusively demonstrates that maritime remote-control technology remains in early developmental stages, with 65.5% of technologies in the growth phase and 34.5% in the emerging phase. None have reached maturity or saturation, confirming the sector remains in active evolution rather than standardisation. The Bass diffusion modelling indicates different adoption mechanisms across technologies: "Remote-Control Systems" show predominantly imitation-driven diffusion (high q values), while "Autonomous Operation" technologies demonstrate more innovation-driven patterns (higher p values).

5.2 Implications

This chapter provides several key implications.

The network analysis shows **"Route Planning & Optimisation"** has the highest degree centrality and significant betweenness centrality, positioning it as a critical bridge technology. This suggests route planning systems serve as integration hubs that connect various maritime technologies. Developers should prioritise open APIs and standardised data exchange formats for route planning systems to facilitate integration with collision avoidance, propulsion control and sensor systems.

"Safety Monitoring & Alerting" shows the highest eigenvector centrality (0.389), indicating its connections to other influential technologies. This central position suggests safety systems require extensive integration with numerous vessel systems to function effectively. When implementing remote-control technologies, organisations should ensure safety systems can access data from navigation, propulsion and perception systems. For instance, a safety alert about potential collision risks should automatically integrate data from radar systems, vessel positioning and environmental conditions to provide operators with complete situational awareness.

The network analysis identified several technologies with zero connections, including **"Emergency Response Systems"**, **"Automatic Collision Avoidance"** and **"Human-Autonomous Interaction"**. This isolation suggests these critical technologies are developing independently of the main innovation ecosystem. Industry stakeholders should create focused integration initiatives to connect these isolated technologies with the broader network. For emergency response systems, this might involve developing standardised emergency protocols that can be triggered by multiple systems and coordinated through the command infrastructure.

It's particularly concerning that **"Human-Autonomous Interaction"** appears disconnected from other technologies, as this interface will be crucial during the transition to more autonomous operations. The isolation of "Human-Autonomous Interaction" technologies presents significant risks for maritime safety and operational effectiveness. This disconnection suggests that these systems are being developed independently from other critical technologies such as navigation, safety monitoring and communication systems. Such isolation could lead to poor integration when these systems are deployed together, potentially resulting in loss of situational awareness as operators struggle to understand autonomous system decisions. This could also lead to inappropriate trust calibration where operators either over-rely on or under-trust autonomous capabilities and ineffective intervention capabilities when human oversight is required. The lack of integration may also indicate that current development is not adequately considering the broader technological ecosystem in which these interfaces must operate. Design guidelines should mandate that autonomous systems maintain clear communication channels with human operators, providing transparency about system status, decision-making processes and requesting intervention when appropriate.

Beyond technological infrastructure, this patent analysis has important workforce implications. The emergence of hybrid remote-autonomous systems indicated by the network analysis suggests maritime education must move past traditional seamanship. As Belabyad et al. (2025a) emphasise, successful implementation of these technologies requires workforce transformation, with operators needing hybrid competencies that combine traditional knowledge with digital proficiency. Training institutions should develop programmes specifically addressing the cognitive demands of transitioning between observation and intervention roles. Certification frameworks will need restructuring to recognise these new competencies that blend maritime expertise with digital literacy. As a result, industry partnerships between technology developers, operators and educators will be essential to align skill development with technological trajectories identified in this forecast, which shows all clusters remain in growth phases without approaching saturation.

5.3 Limitations and Future Research

The reliance on patent data may overlook unpatented innovations, skewing the technological landscape. Maturity assessments based on patent counts do not fully reflect operational considerations, as some technologies may be widely used despite fewer filings. Network connections show relationships but not their practical strength; an "isolated" "Emergency Response System" might still be effective as a standalone. These gaps call for field studies on operator experiences and deeper subcategory analysis to validate this chapter's findings.

Furthermore, future research should specifically investigate why human-autonomous interaction appears as an isolated technology cluster despite its critical importance for safe maritime operations. Research priorities should include examining the barriers preventing its integration with other maritime technologies, developing frameworks for seamless human-machine collaboration in maritime contexts, and establishing design principles that ensure these systems can effectively interface with navigation, safety and communication technologies.

5.4 Conclusion

This patent analysis of maritime remote-control technologies showcases a dynamic and rapidly evolving field. Through the analysis of 1,875 patents using BERTopic modelling, network analysis and Bass diffusion forecasting, eight core technology clusters were identified, with "Route Planning & Optimisation" serving as a critical bridge technology and "Safety Monitoring & Alerting" as highly influential within the innovation ecosystem.

The forecasting results indicate that all identified technologies remain in growth or emerging phases, with none nearing saturation, projecting significant expansion through 2033. This finding, combined with the network analysis highlighting isolated yet critical technologies such as "Human-Autonomous Interaction", emphasises the need for stakeholders to prioritise technological interoperability and integration strategies.

For industry practitioners, these insights provide a roadmap for strategic technology investments and partnership decisions. For researchers, the identified gaps in technology integration present opportunities for future investigation, particularly in bridging isolated but critical capabilities such as emergency response systems and human-machine interaction interfaces. As the maritime industry continues its digital transformation, understanding these technological trajectories becomes essential for shaping the future of shore-based maritime operations.

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Note

1 "$p + q$" represents the total diffusion speed of a technology, combining both innovation (p) and imitation (q) effects. Technologies with higher $p + q$ values will spread more rapidly through the market regardless of whether adoption is primarily driven by external factors (p) or internal factors (q).

References

Andersen, B. (1999). The hunt for S -shaped growth paths in technological innovation: A patent study. *Journal of Evolutionary Economics*, *9*(4), 487–526.

Aristodemou, L., & Tietze, F. (2018). The state-of-the-art on Intellectual Property Analytics (IPA): A literature review on artificial intelligence, machine learning and deep learning methods for analysing intellectual property (IP) data. *World Patent Information*, *55*, 37–51. https://www.sciencedirect.com/science/article/pii/S0172219018300103

Asche, G. (2017). '80% of technical information found only in patents' – Is there proof of this [1]? *World Patent Information*, *48*, 16–28.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, *15*, 215–227.

Belabyad, M., Kontovas, C., Pyne, R., & Chang, C. H. (2025a). Skills and competencies for operating maritime autonomous surface ships (MASS): A systematic review and bibliometric analysis. *Maritime Policy & Management*, 1–26.

Belabyad, M., Pyne, R., Paraskevadakis, D., Chang, C.-H., & Kontovas, C. (2025b). Technology evolution in maritime autonomous systems: A patent-based analysis. *Ocean & Coastal Management*, *267*, 107744.

Burmeister, H.-C., Constapel, M., Ugé, C., & Jahn, C. (2020). From sensors to MASS: Digital representation of the perceived environment enabling ship navigation. *IOP Conference Series Materials Science and Engineering*, *929*(1), 012028–012028.

Burt, R. S. (1999). The social capital of opinion leaders. *The ANNALS of the American Academy of Political and Social Science*, *566*(1), 37–54.

Campbell, R. S. (1983). Patent trends as a technological forecasting tool. *World Patent Information*, *5*(3), 137–143.

Chen, C.-J., Huang, Y.-F., & Lin, B.-W. (2012). How firms innovate through R&D internationalization? An S-curve hypothesis. *Research Policy*, *41*(9), 1544–1554.

Cho, R. L.-T., Liu, J. S., & Ho, M. H.-C. (2021). The development of autonomous driving technology: Perspectives from patent citation analysis. *Transport Reviews*, *415*, 1–27.

Christensen, C. M. (1992). Exploring the limits of the technology s-curve. Part I: Component technologies. *Production and Operations Management*, *1*(4), 358–366.

Clott, C., & Hartman, B. C. (2022). Do maritime innovation centers produce results?. *WMU Journal of Maritime Affairs*, *Springer Science+Business Media*, *21*(3), 283–326.

Clunie, T., DeFilippo, M., Sacarny, M., & Robinette, P. (2021). Development of a perception system for an autonomous surface vehicle using monocular camera, LIDAR, and marine RADAR. *2021 IEEE International Conference on Robotics and Automation (ICRA),* 14112–14119.

Daim, T., & Suntharasaj, P. (2009). Technology diffusion: Forecasting with bibliometric analysis and Bass model. *Foresight*, *11*(3), 45–55.

de Oliveira, M. N., Mosquéra, L. R., Helena, P., Luiz, A., Bispo, G. D., Vergara, G. F., Saiki, G. M., Neumann, C., & Gonçalves, V. P. (2024). Tracking biofuel innovation: A graph-based analysis of sustainable aviation fuel patents. *Energies*, *1715*, 3683. https://www.mdpi.com/1996-1073/17/15/3683

DNV. (2024). Class guidelines: Autonomous and remotely operated vessels – DNV-CG-0264. https://standards.dnv.com/explorer/document/61F34A49A17F4929A6BE38765C68A19B (Accessed 27 January 2025).

Egger, R., & Yu, J. (2022). A topic modeling comparison between LDA, NMF, Top2Vec, and BERTopic to demystify Twitter posts. *Frontiers in Sociology*, *7*. https://www.frontiersin.org/articles/10.3389/fsoc.2022.886498/full

EMSA. (2024). *CMOROC final report – identification of competences for MASS operators in remote operations centres*. EMSA. https://www.emsa.europa.eu/publications/reports/download/7675/5089/23.html

Foster, R. N. (1986). Innovation: the attacker's advantage. Summit Books.

Ghaffari, M., Aliahmadi, A., Khalkhali, A., Zakery, A., Daim, T. U., & Zamani, M. (2024). Exploring the technological leaders using tire industry patents: A topic modeling approach. *Technology in Society*, Pergamon, *78*, 102664. https://www.sciencedirect.com/science/article/pii/S0160791X24002124

Gomez, J. C., & Moens, M.-F. (2014). A survey of automated hierarchical classification of patents. In G. Paltoglou, F. Loizides and P. Hansen, eds., Professional search in the modern world. Springer. https://doi.org/10.1007/978-3-319-12511-4_11

Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. arXiv preprint arXiv:2203.05794.

Hoyhtya, M., Huusko, J., Kiviranta, M., Solberg, K., & Rokka, J. (2017). Connectivity for autonomous ships: Architecture, use cases, and research challenges. *2017 International Conference on Information and Communication Technology Convergence (ICTC),* 345–350.

Ivanova, A., Butsanets, A., Breskich, V., & Zhilkina, T. (2021). Autonomous shipping means: The main areas of patenting research and development results. *Transportation Research Procedia*, *54*, 793–801.

Karetnikov, V., Ol'Khovik, E., Ivanova, A., & Butsanets, A. (2020). Technology level and development trends of autonomous shipping means. *International Scientific Conference Energy Management of Municipal Facilities and Sustainable Energy Technologies EMMFT*, *2019*, 421–432.

Li, X., Fan, M., Zhou, Y., Fu, J., Yuan, F., & Huang, L. (2020). Monitoring and forecasting the development trends of nanogenerator technology using citation analysis and text mining. *Nano Energy*, *71*, 104636.

Lin, Y., Wang, X., Yang, J., & Wang, S. (2024). Core technology topic identification and evolution analysis based on patent text mining – A case study of unmanned ship. *Applied Sciences*, *14*(11), 4661–4661.

Liu, W., Yao, J., & Bi, K. (2024). Identifying emerging technologies to foresee the future of intelligent ships: A machine learning approach to patent data. *International Journal of Technology Policy and Management*, *24*(4), 417–442.

McLaren, C. D., Bruner, M. W. (2022). Citation network analysis. *International Review of Sport and Exercise Psychology*, *15*(1), 179–198.

Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation – A 25-year review. *International Journal of Forecasting*, *22*(3), 519–545. https://www.sciencedirect.com/science/article/pii/S0169207006000197

Miwornunyuie, N., Mao, G., Benani, N., Ampah, J. D., & Hunter, J. (2024). Investigating the research and development status and trends of constructed wetlands: A bibliometric and patent analysis. *Journal of Water Process Engineering*, *63*, 105430–105430.

Muller, E., & Peres, R. (2019). The effect of social networks structure on innovation performance: A review and directions for research. *International Journal of Research in Marketing*, *36*(1), 3–19. https://www.sciencedirect.com/science/article/pii/S0167811618300284#s0005

Nelson, R. R., & Winter, S. G. (1982). An evolutionary theory of economic change. Harvard University Press.

Porathe, T., Hoem, Å., Rødseth, Ø., Fjørtoft, K., & Johnsen, S. O. (2018). At least as safe as manned shipping? Autonomous shipping, safety and 'human error'. *Safety and Reliability – Safe Societies in a Changing World*, 417–425.

Porathe, T., Prison, J., & Man, Y. (2014). Situation awareness in remote control centres for unmanned ships. *Proceedings of Human Factors in Ship Design & Operation*, 26–27 (p. 93).

Qiu, Z., & Wang, Z. (2022). Technology forecasting based on semantic and citation analysis of patents: A case of robotics domain. *IEEE Transactions on Engineering Management*, *Institute of Electrical and Electronics Engineers*, *69*(4), 1216–1236.

Ramos, M. A., Utne, I. B., & Mosleh, A. (2019). Collision avoidance on maritime autonomous surface ships: Operators' tasks and human failure events. *Safety Science*, *116*, 33–44.

Rao, K. U., & Kishore, V. V. N. (2010). A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews*, *14*(3), 1070–1078.

Razmjooei, D., Alimohammadlou, M., Ranaei Kordshouli, H.-A., & Askarifar, K. (2023). Industry 4.0 research in the maritime industry: A bibliometric analysis. *WMU Journal of Maritime Affairs*, *22*.

Ringbom, H. (2019). Regulating autonomous ships – Concepts, challenges and precedents. *Ocean Development & International Law*, *50*(2–3), 141–169.

Rødseth, Ø., & Nordahl, H. (2017). Definitions for autonomous merchant ships. 10.13140/RG.2.2.22209.17760.

Stępień, B. (2024). Navigating new waters: IMO's efforts to regulate autonomous shipping. *Chinese Journal of International Law*, *23*(3). https://academic.oup.com/chinesejil/article/23/3/599/7758205

Stokey, N. L. (2020). Technology diffusion. *Review of Economic Dynamics*, *42*, 15–36.
Sun, M., Tong, T., Jiang, M., & Zhu, J. X. (2024). Innovation trends and evolutionary paths of green fuel technologies in maritime field: A global patent review. *International Journal of Hydrogen Energy*, *71*, 528–540.
Wang, F., Yan, F., & Hou, Y. (2007). The influence of network externality on technology diffusion. *2007 International Conference on Wireless Communications, Networking and Mobile Computing*, *IEEE*, 5783–5786.
Wang, H., & Sun, B. (2021). Diffusion mechanism of leading technology in the new energy industry based on the bass model. *Frontiers in Energy Research*, 9.
Wang, J., Hu, R., & Xu, H. (2024). Coupled simultaneous evolution of policy, enterprise innovation awareness, and technology diffusion in multiplex networks. *Mathematics*, *12*(13), 2078.
Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications. Cambridge University Press.
WIPO (n.d.) Module 6 – Patent Information [online]. https://www.wipo.int/export/sites/www/sme/en/documents/pdf/ip_panorama_6_learning_points.pdf.
Yang, X., Liu, C., & Lan, J. (2023). Sustainable technology diffusion manufacturing outwards FDI firms: Evidence from China using numerical simulation methods. *Sustainability*, *15*(4), 3108–3108.
Yu, Z. H. (2011). Diffusion channel of generic technology in equipment manufacturing industry. *Advanced Materials Research*, *328–330*, 708–716. https://doi.org/10.4028/www.scientific.net/amr.328-330.708
Yusup, M. F. B. (2024). The role of business incubators in encouraging maritime technology start-up innovation. *Maritime Park: Journal of Maritime Technology and Society*, *3*(3), 158–162.
Zhang, Y., Zhang, D., & Jiang, H. (2023). A review of artificial intelligence-based optimization applications in traditional active maritime collision avoidance. *Sustainability*, *15*(18), 13384–13384.