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ORIGINAL ARTICLE

Technological forecasting of port digitalization using patent analysis

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Abstract

The rapid growth of cargo volumes has highlighted the increasing importance of marine terminals. To enhance efficiency and productivity, the port technology sector has been actively adopting digital technologies. However, despite the growing need for continuous innovation, there is a lack of studies analyzing quantitative data on digital technologies in ports. To address this gap, through a port patent analysis, this study aims to identify promising technological areas, as well as promising new technologies that require further research and development. Using the Latent Dirichlet Allocation (LDA) algorithm for topic modeling, we identify four key technological areas in port digitalization: (1) Intelligent vessel condition monitoring, (2) Shipping wireless communication network, (3) Port operations optimization, and (4) Container inspection and monitoring. Moreover, we apply Generative Topographic Mapping (GTM) to visualize the technological landscape. This revealed technological vacuums in intelligent vessel condition monitoring and port operations optimization. By providing a quantitative analysis of port digital technologies, based on 989 relevant patents extracted from 35,410 records, this study offers insights into technological trends and uncovers areas for future innovation. The findings are expected to guide innovation in port-related technologies, contributing to more efficient port operations and advancements in the maritime sector.

Keywords Port digitalization · Patent analysis · Text mining · Topic modeling · Generative topographic mapping · Technological forecasting

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1 Introduction

With the rapid growth of global trade, maritime transportation is being emphasized even more. The volume of global maritime trade reached approximately 12 billion tons in 2022, and is expected to grow more than 2% annually between 2024 and 2028 (UNCTAD 2024). This increase in cargo volumes places pressure on port operations. The growing use of ultra-large container vessels—some exceeding 24,000 TEU—demands advanced equipment and digital systems to maintain efficiency. As demand for maritime transport continues to rise, port digitalization has become essential to reduce congestion and improve operational performance (Triska et al. 2024).

The International Maritime Organization (IMO) recognizes the importance of digitalization in the maritime industry, including ports (Fruth and Teuteberg 2017). To enhance efficiency, IMO has mandated the use of Maritime Single Window (MSW) for electronically exchanging information about ships entering foreign ports. This initiative includes mandatory support for electronic customs procedures, aiming to simplify and streamline maritime transport administration. In preparation for this, the IMO Facilitation Convention has begun developing a Reference Data Model in recent years, to harmonize key standards for ship clearance. The model will ensure consistent data exchange across countries and ports, promoting digitalization and automation in maritime operations, ultimately facilitating global trade (IMO 2024; Cauwer et al. 2021).

When inspecting the digitalization of ports in the past, ports were considered as passive systems, and human intervention was essential in all matters. The development of electronic data interchange systems in the 1960s and 1970s paved the way for the first digital transformation in the maritime industry (Heilig et al. 2017). After that, various technological transformation attempts towards digitalization were made. However, ports have traditionally been conservative in adopting new technologies, facing several barriers such as high implementation costs, lack of standardization and interoperability across IT systems, organizational resistance to change, and insufficient digital strategies and capabilities (Raza et al. 2023; Heilig et al. 2017). Moreover, the complexity of the maritime ecosystem, involving multiple independent stakeholders, and the absence of unified industry standards, continues to hinder digital transformation efforts (Raza et al. 2023). Such conservatism stems from the high risk of operational disruption, as even minor system failures can trigger cascading effects across the supply chain, making operators reluctant to adopt untested technologies. For this reason, the digitalization of ports has accelerated slowly.

With technological advances following the Fourth Industrial Revolution, the digitalization of ports began to be promoted around the world (Heilig et al. 2017). Hamburg Port has introduced the Smart Port project, an Internet of Things (IoT)-based cloud communication platform focused on operational and energy efficiency. The project results in a 75% reduction in operating costs and a 15% decrease in port congestion (Pham 2023). Singapore is developing the Tuas Megaport project, aiming to complete the world's largest automated port by 2040. By implementing the digitalPORT@SG™ system, a port digitalization platform and an automated guided vehicle (AGV) system, Singapore aims to enhance port operational efficiency (Lee et al. 2025). Los Angeles Port is drawing attention by establishing an energy management system that introduces solar power and electric trucks for eco-friendly operations (Wang et al. 2023). As ports become increasingly digitalized and automated, the connection between ports and ships is becoming more critical. In particular, the development of the *Internet of Ships* (IoS) facilitates the real-time sharing of sensor-collected data between ships and ports (Aslam et al. 2020). By utilizing automatic identification system (AIS) data to monitor ship information in real time, ports can minimize ship waiting times and optimize loading and unloading processes, thus improving operational efficiency (Chen et al. 2023).

While ports are undergoing digitalization globally, there is a pressing need for strategic research from a technological standpoint, particularly considering that this realm is still in its nascent stage. Hence, we aim to extract strategic insights for port digitalization by analyzing patent data that represents technological advancements. We analyze port digitalization technologies using U.S. patents through *topic modeling*. Specifically, the Latent Dirichlet Allocation (LDA) model is applied to identify promising technologies, while Generative Topographic Mapping (GTM) is used to detect underdeveloped technological domains within port digitalization. This integrated LDA–GTM framework represents a novel contribution to maritime research. Although LDA has been widely applied in patent analyses across other fields, its combination with GTM for spatial visualization of technology landscapes has not been previously utilized in port digitalization studies. The combined approach is particularly valuable for capturing the complexity of the maritime ecosystem, enabling both thematic identification of emerging technologies and visual mapping of research gaps—an essential step given the diversity of the technologies involved in port digitalization.

The remainder of this paper consists of the following. Section 2 presents existing studies on forecasting future smart port technologies. Section 3 describes the research framework and the techniques used in the proposed framework. Section 4 describes the experimental setup and the results of the experiments. Section 5 provides the conclusions and implications of the study.

2 Literature review

2.1 Forecasting port digitalization technologies

2.1.1 Conceptual and strategic perspectives on Port digitalization

The increasing dependence of global trade on shipping highlights the importance of ports (Brooks and Faust 2018). With the advent of new technologies, there is growing interest in the digitalization of ports, and various studies have examined the conceptual and strategic aspects of this transition. Meyer et al. (2019) and Heikkilä et al. (2022) suggest that collaboration, automation, and sustainability are core ingredients in port digitalization. Bhalodi (2019) predicts that port digitalization would aid in determining port charges, bunker prices, vessel speed and fuel consumption, as well as in identifying operational excellence, migrating activities, and new business opportunities. Chen et al. (2019) propose governance policies for green and smart port construction, while Del et al. (2022) identify business models that support environmental, economic, and social goals through ship–port digital integration, in alignment with the United Nations (UN) 2030 Agenda for Sustainable Development Goals (SDGs). Li et al. (2023) develop a smart port performance indicator to evaluate the future development of smart ports.

2.1.2 Key technologies for port digitalization

Beyond these conceptual and strategic perspectives, a growing body of research focuses on identifying and forecasting the key technologies that will drive port digitalization. IoT-based connectivity is frequently cited as a foundational element, with Yang et al. (2018) emphasizing that IoT-enabled infrastructure will play a crucial role in future port development. Priya et al. (2024) show that real-time container monitoring improves vessel scheduling efficiency. Building on this, data analytics and AI technologies have emerged as central enablers of operational improvement. Rajabi et al. (2018) identified big data processing—particularly the analysis of AIS information—as essential for enhancing port efficiency, while Inkinen et al. (2021) underscored artificial intelligence, data analysis, automation, IoT, and social media analytics as core technologies, noting that cybersecurity will be particularly important in the near term. Yang and Hsieh (2024) further showed that the digital solutions dimension holds the highest importance in smart port development, reinforcing the role of data-driven and optimization-oriented technologies. Research has also examined secure information-exchange mechanisms, with Kuo and Chen (2022) predicting that blockchain-based platforms would support real-time, secure data exchange among port stakeholders. Overall, these studies collectively point to IoT connectivity, AI-driven analytics, and secure information-sharing technologies as the primary technological pillars guiding the digital transformation of ports.

2.2 Patent analysis

A patent is a document issued by an authorized governmental agency, or designated authority, granting exclusive rights to an inventor, or assignee, to exclude others from producing or using a specific new device, apparatus, or process for a specified number of years (Griliches 1998; Hanel 2006). Since patents are officially examined and publicly disclosed documents, this makes them suitable sources of data for technological analysis. Moreover, patents contain a large amount of technical information and are classified according to standardized systems such as the International Patent Classification (IPC), facilitating the analysis of the technology (Ernst 2003).

In the past, patent information was used for research on technological innovation or monitoring rival companies, or measuring technological portfolios. Nowadays, with global competition intensifying, and technology rapidly evolving, it has become essential for companies to monitor these changes (Lee and Su 2016). Furthermore, research aimed at identifying and understanding trends in industries and technologies, as well as the competitiveness of companies or countries, is actively being conducted using patent information (Fujii and Managi 2018; Kim et al. 2019; Evangelista et al. 2020). In the United States wellness care industry, patent data from the United States

Patent and Trademark Office (USPTO) are collected to predict the potential of technologies. Research has also been conducted on the future directions of technological development, by analyzing patent indicators, and performing technology mapping (Kim and Bae 2017). Additionally, Shubbak (2019) comprehensively presented the definition of solar technology systems and analyzed technical, organizational, and geographical technological trends using patent indicators from PATSTAT (Worldwide Patent Statistical Database) to review global trends in solar power generation. Pantano and Pizzi (2020) focused on chatbots, a new form of online customer support, to gain insight into the technological advancements of AI. Based on 20 years of chatbot patent data, their study utilized topic modeling techniques to identify the distribution of research topics and analyze trends in technological advancements.

Previously, patent analysis mostly depended on expert opinions or qualitative methods. However, with recent advancements in text data analysis techniques, such as *topic modeling* and patent mapping, *machine learning* approaches are increasingly being used for patent analysis. In particular, topic modeling and patent mapping approaches have been widely applied to structure large-scale patent data and to explore latent technological themes and vacant technologies in technology-intensive industries (Yoon et al. 2002; Son et al. 2012). As such, these data-driven approaches provide a suitable foundation for forecasting the evolution of port digitalization technologies.

Wu et al. (2016) created the patent map based on self-organizing map (SOM), and they were able to identify vacant technologies among film solar cell technologies. However, using PCA and SOM to identify vacant technologies has several limitations. PCA performs only linear transformations when reducing high-dimensional data, which cannot adequately capture the complex nonlinear relationships inherent in patent data. Moreover, the principal components derived from PCA are often difficult to interpret intuitively, and the boundaries of vacant areas are not clearly distinguishable. Although SOM can learn nonlinear patterns, it lacks a probabilistic framework, making it impossible to quantify uncertainty, and its outcomes may vary significantly depending on the initial weight settings. Consequently, both PCA and SOM require considerable effort for interpretation and often lead to subjective or inconsistent identification of technological gaps (Son et al. 2012). Therefore, a study has been proposed to discover GTM based vacant technology that overcomes these limitations.

Recently, studies have been conducted using GTM to identify vacant technologies. Teng et al. (2021) identified vacant technology based on GTM to explore technological opportunities in the field of proton exchange membrane fuel cells. Jeong et al. (2019) used GTM to identify QLED technology as an emerging research and development (R&D) field by utilizing intellectual property data, including patents, designs, and trademarks. Feng et al. (2021) applied GTM to patents in the mining machinery industry, identifying 13 vacant technologies to develop new business models. Wu et al. (2018) used Universal terrestrial radio access (UTRA) technology as a case study to identify vacant technology based on existing standard documents, uncovering potential standard essential patents. Wang et al. (2024) proposed an automated technology opportunity discovery approach based on patent analysis. A GTM-based patent map was built, and semantic similarity was used to assess novelty and identify opportunities.

3 Methodology

This work consists of a three-step process, shown in Fig. 1. First, patent data related to port digitalization are collected and pre-processed. Pre-processing of the unstructured patent texts includes removing punctuation marks, numbers and irrelevant terms, standardizing letter cases, and unifying words into their base forms, while retaining only terms relevant to port digitalization and the subsequent topic modeling analysis. After that, LDA is utilized to extract key topics of promising technologies for port digitalization and to grasp technological trends. Promising technologies refer to those that have reached the stage of practical application and commercialization and are gradually being adopted within the industry. These technologies have significant potential for further development through ongoing R&D and investment, with expectations for both technological stability and market acceptance. Finally, GTM is applied to identify gaps in the technological landscape, with relatively limited patent activity but potential for future development as emerging or underexplored technologies, and to forecast the future direction of port digitalization technologies. Detailed descriptions of the LDA and GTM methodologies are provided in Appendix A.

4 Results

4.1 Data description

Patent data were extracted from Korea industrial property information service (KIPRIS). Patents related to port digitalization that were filed and registered in the United States from 2004 to January 2024 were collected. U.S. patents were selected because that country operates a comprehensive and internationally recognized patent system that attracts filings from global innovators. Previous studies have also commonly included United States Patent and Trademark Office (USPTO) data as a core source,

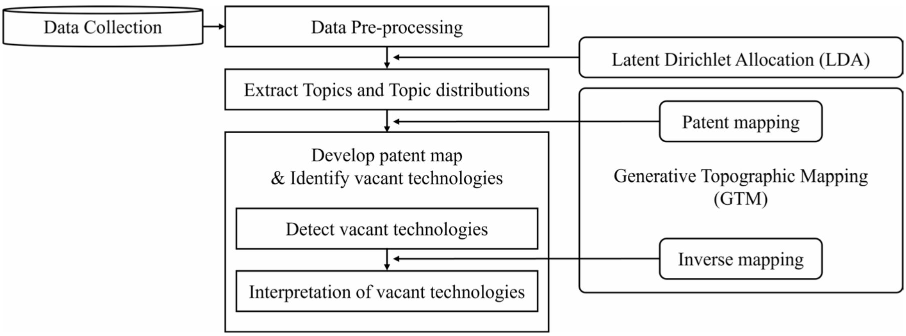


Fig. 1 Research framework

while the use of other national patent offices varies across research works. Although this focus may limit generalizability, it remains suitable for capturing global trends in port digitalization technologies. In addition, the period of analysis was determined by considering the point at which previous studies (Heilig et al. 2017; Triska et al. 2024; Gao et al. 2024) indicated that the digitalization era in port and maritime technologies has begun in earnest.

A total of 35,410 patent data were collected, 989 of those specifically related to port digitalization, identified through data preprocessing, which removed irrelevant patents. As shown in Fig. 2, the trend in patent applications for port digitalization has been steadily increasing, with a significant surge beginning 2018. This trend highlights the growing importance of digitalization, driven by rapid technological advancements brought about by the Fourth Industrial Revolution, which is accelerating the development of digital technologies in the maritime logistics industry (Min 2022).

In addition, Fig. 3 presents the top 15 IPC subclasses among the 989 patents. The distribution shows a strong concentration in data-processing-related technologies, such as G06Q (administrative, commercial, financial, managerial, supervisory, or forecasting data processing) and G06F (electric digital data processing), which align with the optimization and planning attributes of port digitalization.

Furthermore, the presence of subclasses such as H04W (wireless communication networks), H04L (digital information transmission), and H04B (transmission) indicates a substantial technological base in communication systems. Subclasses related to monitoring and inspection, including G08B (signalling systems), G01S (radio navigation), and G06K (data recognition), are also well represented.

The IPC distribution confirms that the dataset covers diverse technological domains relevant to port digitalization, including computing, communication, and monitoring.

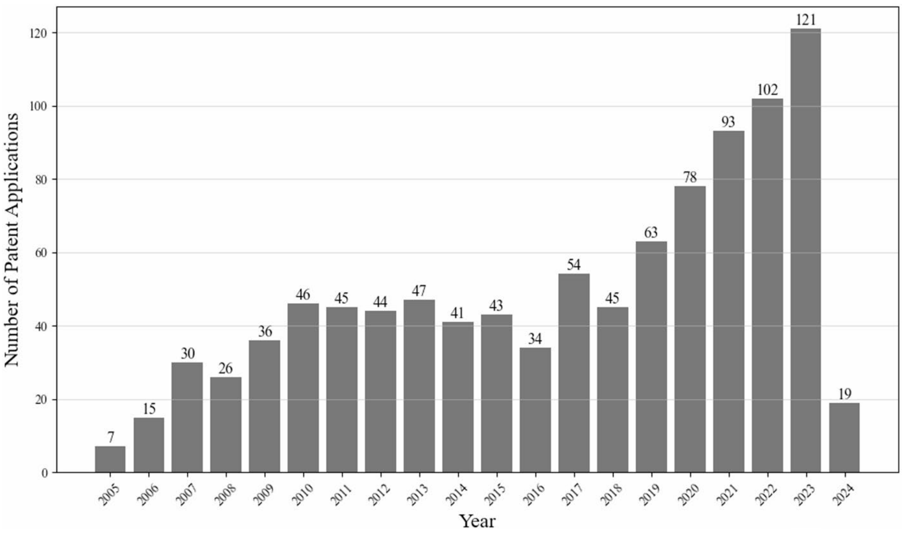


Fig. 2 Trend of patent applications in port digitalization technologies

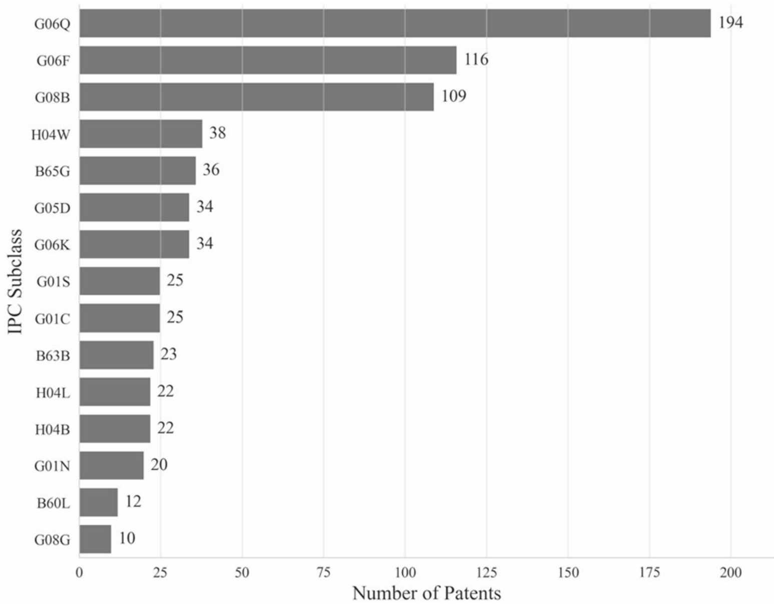


Fig. 3 Distribution of top 15 IPC subclasses

4.2 LDA-based topic modeling for port digitalization technologies

This study employs LDA-based topic modeling, using the Gibbs Sampling method to estimate the parameters of the LDA model (Grün and Hornik 2011). The optimal number of topics (K) was determined using the perplexity metric (Blei et al. 2003), which measures how well a topic model represents the underlying dataset.

Generally, lower perplexity values indicate that the topic model better fits the actual data and is more effective in learning from it. However, a low perplexity value does not always imply a good model, as overfitting can occur. In this study, the perplexity curve in Fig. 4 shows that the value reaches its minimum and stabilizes at K = 4, indicating that additional topics do not improve model fit. Since perplexity does not guarantee interpretability, K = 4 was chosen as the optimal number of topics based on both quantitative evaluation and interpretability. Consequently, a total of 4 topics were generated through 1000 iterations of sampling, as shown in Table 1.

4.3 GTM-based patent map for port digitalization technologies

The GTM-based patent map is visualized in Fig. 5. Figure 5a illustrates the posterior mean projection, showing the relative distance between patents' original locations and their positions in the latent space but may not clearly identify patent vacuums. Figure 5b illustrates the posterior mode projection, where each data point is mapped to the latent grid, showing patent vacuums more clearly. Each 'o' in Fig. 5b represents the keyword distribution of a specific latent point, emphasizing patent vacuums and

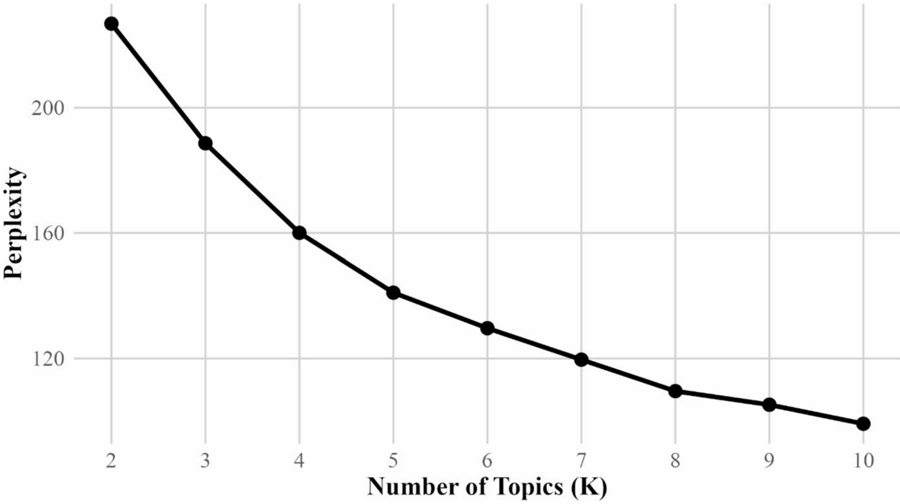


Fig. 4 Perplexity of the different number of topics (K) for the LDA model

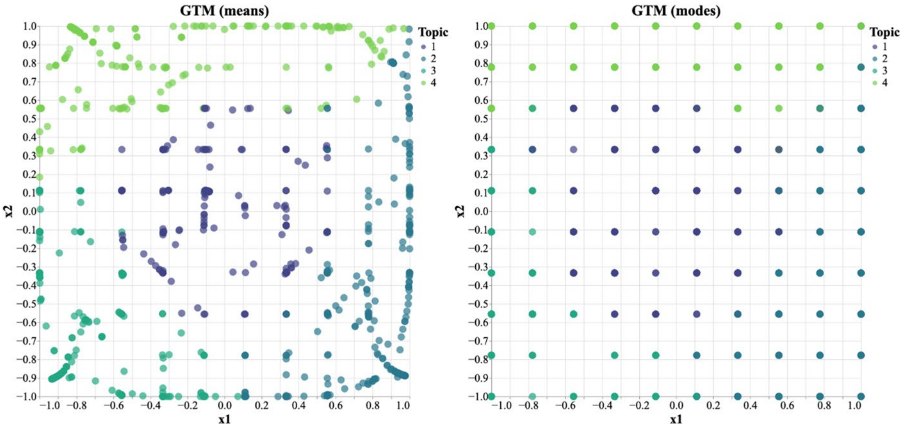
Table 1 The result of topic modeling

No	Keywork	Topic
Topic 1	vessel, image, sensor, temperature, monitor, capture, camera, automatic identification system, autonomous vehicles, navigation, unman, detector	Intelligent vessel condition monitoring technologies
Topic 2	communication, wireless, track, tag, remote, monitor, radio frequency identification, sensor, transceiver, global positioning system, antenna, identification	Shipping wireless communication network technologies
Topic 3	shipment, schedule, route, logistic, cost, monitor, warehouse, plan, forecast, optimization, fuel, predict	Port operations optimization technologies
Topic 4	container, cargo, sensor, lock, door, crane, inspection, radiation, seal, monitor, identification, security	Container inspection and monitoring technologies

making the posterior mode projection more suitable for identifying them. The GTM hyperparameter settings used to generate this patent map are provided in Appendix B.

The GTM-based patent map based on mode projection is composed of a grid, and each patent is located in each grid cell, so empty grid cells can be identified as a vacuum. Figure 6a shows the patent vacuums identified in the GTM-based patent map with 'X', and each patent vacuum is labeled with a number on Fig. 6b. Through posterior-mode projection, a total of 2 patent vacuums were found out of 100 potential points. Because the GTM-based patent map is constructed using the 4 topics generated by LDA, the resulting latent space exhibits relatively continuous transitions across topic regions, which reduces the likelihood of identifying a larger number of vacuums.

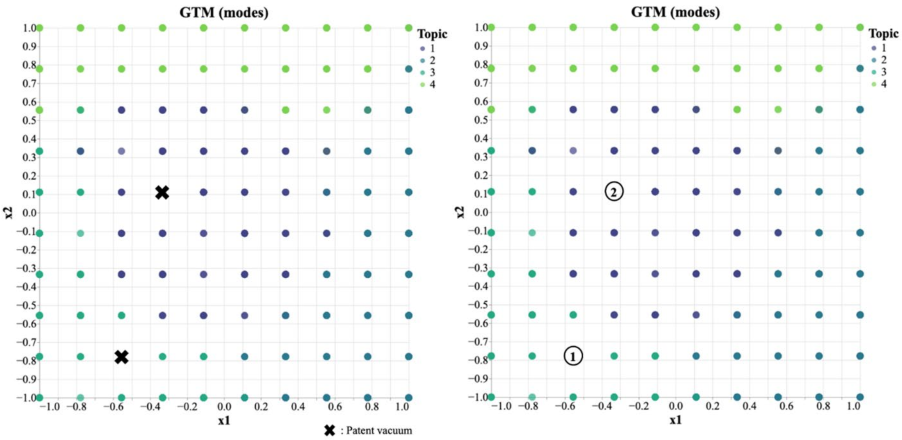
Patent vacuums can be interpreted in terms of their associated technological themes derived from the LDA topic modeling results. Each vacant area in the GTM-based patent map can be assigned to a specific topic. Table 2 shows the final results of the patent vacuum interpretation, presenting the mapping results for each patent



(a) The posterior – mean projection

(b) The posterior – mode projection

Fig. 5 GTM-based patent map



(a) The posterior – X patent visulization

(b) The posterior – number patent visulization

Fig. 6 Visualization of patent vacuums

Table 2 Extraction of vacant technologies

Patent vacuum no	Topic
1	Topic 3
2	Topic 1

vacuum. These results verify whether patents containing these specific topics exist within the data. Interpreted patent vacuums are worth investigating intensively for the development of new technologies. The detailed interpretation procedure is provided in the Appendix C.

4.4 Technological forecasting of port digitalization

4.4.1 Promising technologies

Global logistics and shipping industries play an important role in improving the sustainability of port operations, focusing on digital transformation and technological innovation. In particular, the digitalization of ports aims to enhance efficiency, safety, and operational transparency, as insufficient visibility into port operations can delay decision-making, hinder coordination among stakeholders, and reduce overall operational effectiveness. In this study, we analyze the impact of major promising technologies that lead shipping and logistics industries in four aspects: intelligent vessel condition monitoring, shipping wireless communication networks, port operations optimization, and container inspection and monitoring technologies.

Intelligent vessel condition monitoring technologies—i.e., systems that monitor the condition of key ship components using sensor data– have been highlighted in prior studies in the context of IoT-based sensing (Lazakis et al. 2016; Aslam et al. 2020), digital twins (Errandonea et al. 2020), and their integration with port digitalization (Muñuzuri et al. 2020). Within the set of patents classified as relevant to intelligent vessel condition monitoring, IPC subclass G06F—electric digital data processing—emerges as the most prominent group. This subclass encompasses data-processing methods used for condition monitoring and maintenance applications, including technologies that integrate vibration and thermal data from onboard equipment, as well as performance data collected through onboard IoT sensors to support condition diagnosis and predictive maintenance. It also includes maritime-specific data-processing techniques, such as receiving AIS information containing vessel identifiers and positions, querying servers connected to maritime networks, smart-radar data mining and target-tracking systems, and energy-management systems that control power supply to vessel propulsion units.

Shipping wireless communications network technologies provide seamless connectivity that enables real-time data exchange among maritime stakeholders (Slamnik-Kriještorac et al. 2023). The patents identified in this category relate predominantly to the fundamental communication capabilities required to support high-bandwidth, low-latency operations and large-scale automation, while some address more advanced concepts such as 5G-based wireless communication systems for connectivity between ships and ports, as well as maritime informatics frameworks that are expected to underpin future smart ports. Within the set of patents related to shipping wireless communications networks, IPC subclass H04W—wireless communication networks—emerges as the most prominent and promising technology group. The patent data highlight several maritime-specific applications within this subclass, including satellite relay systems for vessels and barges, implemented in container-sized rack structures for mobility and rapid deployment; unmanned surface vehicles equipped with high-frequency antenna arrays for signal interception, recording, and intelligence gathering; power-efficient data-communication modules that monitor and transmit environmental or operational information; and wireless communication chains that establish directional links between multiple mobile ships and fixed antennas to maintain stable maritime communication channels.

Port operations optimization technologies enhance the efficiency of cargohandling and port operations, optimizing loading and unloading processes, berth allocation, cargo management, and administrative workflows, thereby improving overall logistics performance. Enabled by AI, big data analytics, IoT, and digital twin technologies, these solutions support real-time data-driven decision-making and automation, leading to flexible scheduling of berth and yard operations, optimized resource allocation, and reduced operational costs (Ichimura et al. 2022; Rodrigues and Agra 2022; Woo et al. 2024; Lee and Cho 2025). Within the set of patents analyzed in this study, related technologies are primarily classified under IPC codes G08G and G06F. G08G covers traffic-control systems for land, water, and air transportation, corresponding to vessel arrival time prediction, port traffic management, berth scheduling, and route optimization; the patent data include methods that model operational incompatibilities arising from conflicting constraints in traffic planning and optimization, such as mismatches between berth availability, yard capacity, and loading or unloading sequences. G06F encompasses digital data-processing technologies supporting machine learning methods for predicting vessel arrival times and simulation models based on digital twins; relevant patents include multi-purpose optimization systems that incorporate factors such as tidal conditions and energy consumption for berth optimization, as well as robotic transport mechanisms equipped with multi-legged structures and embedded computing units that execute optimization components. These technologies reduce idle time and congestion, improve operational efficiency, and enhance the competitiveness of maritime logistics.

Container inspection and monitoring technologies enhance the safety, reliability, and efficiency of logistics operations by enabling real-time tracking and condition assessment of containers throughout transport. Leveraging deep learning and IoT sensing, modern systems automatically detect structural damage, seal breaches, unauthorized cargo, and environmental anomalies such as temperature or humidity deviations (Akcay et al. 2018; Muñuzuri et al. 2020; Bahrami et al. 2022). These capabilities reduce cargo damage, prevent logistics errors, and increase inspection throughput. Furthermore, the emergence of next-generation networks such as 6G is expected to further reinforce these functions by providing ultra-low latency, full-dimensional wireless coverage, and massive IoT connectivity, enabling more reliable sensing and seamless data exchange for next-generation smart logistics environments (Nguyen et al. 2021). Related IPC technologies include G08B for anomaly detection and alerting, G01S for precise container tracking, and G06K for data and identification recognition. The patent data reveal various container-specific innovations within these categories, including systems for monitoring internal air temperatures, RF-tag–based tracking solutions suitable for metal-walled containers, multi-level scanning methods using movable racks, and stacked-container inspection systems designed for high-density storage environments.

The four technology groups—intelligent vessel condition monitoring, wireless communication networks, port operations optimization, and container inspection and monitoring—represent core technological directions that support the ongoing digitalization of ports. These technologies enhance operational efficiency, improve the reliability of maritime logistics systems, and enable data-driven, real-time decision-making. More importantly, they shift port operations beyond traditional, physically oriented connections toward digitally integrated interactions between vessels, ports, and logistics stakeholders. As digital transformation accelerates, these technologies are expected to play an increasingly significant role in shaping the future of shipping and port operations.

4.4.2 Vacant technologies

4.4.2.1 Intelligent vessel condition monitoring technologies In the context of smart port transformation, intelligent vessel condition monitoring has emerged as a critical enabler for comprehensive port digitalization (Cheliotis et al. 2020; Heij et al. 2011). Despite demonstrated technical feasibility in stand-alone applications, its systematic integration into holistic port digital ecosystems remains limited. This limitation has prompted initiatives to enhance cross-country interoperability of digital maritime services that jointly consider both vessels and ports. For example, a recent Korean government R&D program is developing an S-100–based onboard navigation system to ensure compatibility among the different digital maritime services operated independently by different countries. The program also delivers a reference implementation aligned with IALA G1161 to standardize the technical components of a maritime connectivity platform, enabling vessels to access Korean port information and digital services even when operating within foreign territorial waters.

Next-generation smart ports require real-time, predictive insights across all functional domains to optimize resource allocation, automate decision-making, and ensure operational continuity. However, without real-time vessel condition data, predictive port operations cannot fully optimize berth scheduling, cargo-handling resource deployment, or supply chain coordination. Moreover, the absence of standardized protocols for integrating vessel condition data impedes the development of comprehensive and high-fidelity port digital twins. Without incorporating vessel condition parameters as input variables, existing digital twins remain functionally limited representations that cannot fully capture dynamic interactions between vessels and port operations, thereby reducing their effectiveness for strategic planning and real-time optimization (Lazakis et al. 2018). This shortcoming extends to the broader port IoT ecosystem, where vessel-borne sensors should interoperate seamlessly with port infrastructure sensors to create unified, real-time operational intelligence platforms.

Therefore, intelligent vessel condition monitoring technology must evolve from isolated maritime applications to foundational pillars of comprehensive port digitalization strategies. Through this transformation, ports can achieve the fully integrated, predictive, and autonomous operational capabilities that define next-generation smart port ecosystems.

4.4.2.2 Port operations optimization technologies Port operations optimization technologies encompass comprehensive solutions designed to enable efficient maritime operations through advanced digital integration. While these technologies demonstrate significant potential for transforming port operations, substantial gaps remain in their practical implementation and systemic integration within the maritime ecosystem.

Loading and unloading optimization and berth planning are central to improving port efficiency, but they continue to face challenges in achieving full digital synchronization between vessels and port operations. Effective port digitalization requires seamless, real-time exchange of vessel data, enabling ports to access up-to-date vessel status, cargo information, and cargo stowage information onboard. Such real-time visibility extends beyond conventional AIS-based positioning and estimated time of arrival (ETA), allowing port systems to anticipate actual arrival and readiness states, dynamically adjust berth and yard plans, and allocate cargohandling resources more effectively (Brunila et al. 2021). In the absence of this level of synchronization, optimized loading and unloading protocols remain difficult to implement, resulting in operational bottlenecks, inefficient resource utilization, and cascading inefficiencies.

Although Port Community Systems (PCS) can facilitate integrated workflows covering vessel arrival, cargo handling, and customs clearance (Aiello et al. 2020), limitations in data quality and system interoperability still prevent large-scale deployment. While terminal optimization and digitalization already rely on a wide range of sensors and systems, including those deployed at gates, yard cranes, ship-to-shore cranes, and internal transport vehicles, effective end-to-end coordination additionally requires reliable integration of vessel-side data. Overcoming these challenges requires strengthening vessel IoT sensor capabilities and maritime communication infrastructure to enable reliable data exchange, establishing internationally standardized data protocols validated in diverse operational contexts, and building unified digital platforms that can process and analyze vessel–port data streams in real time. Equally important is embedding blockchain-based trust mechanisms and advanced cybersecurity measures to safeguard data integrity (International Maritime Organization (IMO) 2025b). However, the low throughput and high latency inherent in current blockchain architectures limit their ability to process large-scale transactions, making practical implementation in port environments difficult (Ahmad et al. 2021). In addition to these technical constraints, blockchain deployment also requires cross-organizational consensus, unified governance structures, and substantial computational resources, further complicating large-scale adoption. Sustained collaboration among vessel operators, port authorities, and technology providers is therefore essential to ensure scalability and long-term viability.

Cargo management extends beyond the stowage of goods on vessels, to encompass their coordination with land-based transport. At ports, vessel and truck cargo flows occur simultaneously, and delays often arise when information integration and stakeholder coordination are insufficient. In practice, terminals use buffer zones to absorb uncertainty in truck arrivals, but this does not address the underlying causes. Although simulation-based studies using mathematical models have shown that optimizing truck arrivals and internal routing can improve overall logistics flows (Baldouski et al. 2025), real-world implementation remains constrained by uncertainties in truck arrival times, a lack of real-time data sharing, and limited stakeholder cooperation. Addressing these constraints calls for advanced prediction models that integrate diverse data sources—including machine learning and deep learning–based

ETA forecasts, real-time location tracking, and traffic and congestion analytics—combined with secure, reliable data transmission technologies. Field validation in operational port environments, together with structured stakeholder engagement, will be essential for the successful deployment and scaling of such integrated platforms.

Customs and documentation processes are being digitalized and converted to electronic formats in accordance with global regulations such as MSW. Nevertheless, differences in national legislation, policy priorities, and security protocols continue to slow standardization and effective integration. Even with the IMO's mandatory MSW requirements, paper-based procedures remain common in many ports (International Maritime Organization (IMO) 2025a). Advancing digital transformation in this domain requires the adoption of electronic documentation systems and standardized data exchange protocols that meet international norms while retaining flexibility to accommodate national legal frameworks (International Maritime Organization (IMO) 2025c). Incorporating encryption-based security and tamper-proof audit trails will be critical for ensuring data reliability and transparency. Furthermore, coordinated global initiatives, including large-scale pilot projects and cross-border interoperability frameworks, can accelerate adoption and enhance the efficiency and resilience of global logistics networks.

5 Conclusion

Technological advances and the increasing policy interest in port digitalization have led many countries to consider it an essential component of their maritime strategies. Nevertheless, the adoption of digital technologies in ports remains slower than in other sectors, and many ports are still moving toward integrated digital operations. Therefore, it is important to analyze the current technological status, identify promising technologies and existing gaps, and define strategic directions for future development. This study has presented a technology-based roadmap for port digitalization derived from a systematic patent analysis.

This study follows a three-step analytical procedure. First, patent data related to port digitalization were collected and pre-processed through validity checks and lemmatization. The LDA algorithm was then used to extract major technological themes and identify overall trends, resulting in four key areas: intelligent vessel condition monitoring, shipping wireless communication networks, port operations optimization, and container inspection and monitoring. Finally, GTM was applied to visualize the technological landscape and identify technological gaps in port digitalization. The analysis revealed gaps in intelligent vessel condition monitoring and port operations optimization, indicating that these areas require further development.

The gaps identified through our analysis point to two major areas where substantial development is required. First, intelligent vessel condition monitoring has demonstrated technical feasibility in maritime applications but remains insufficiently integrated into port-wide digital ecosystems. The lack of standardized protocols, interoperable data platforms, and real-time connectivity between vessel-borne sensors and port infrastructure limits its contribution to predictive operations, digital-twin modeling, and automated decision-making. Second, port operations optimization technologies face similar barriers. Despite their potential to improve berth planning, cargo-handling efficiency, and landside coordination, their implementation is restricted by inadequate real-time data exchange, limited vessel–port synchronization, fragmented documentation systems, and challenges in deploying secure and scalable digital platforms. These constraints indicate clear technological opportunities in both domains, where advancing sensing capabilities, data standardization, reliable information-sharing mechanisms, and integrated operational platforms will be essential for achieving the next stage of port digitalization.

The contribution of this study is threefold. First, it identifies two underdeveloped yet strategically significant technological domains—intelligent vessel condition monitoring and port operations optimization—through systematic patent analytics, providing a robust quantitative basis for setting R&D priorities in port digitalization. Second, by integrating topic modeling with technological mapping analysis, it introduces a structured methodological framework rarely applied in maritime technology research. Third, the findings, aligned with IMO-driven initiatives and global digitalization trends, offer actionable insights for policymakers, technology developers, and industry practitioners to accelerate the transition toward predictive, autonomous, and fully integrated smart port ecosystems.

Future research could validate and strengthen the robustness of the findings by incorporating complementary datasets, such as scientific publications or patent records from other major patent offices (e.g., EPO, JPO). In addition, this study has several limitations. The analysis is based solely on U.S. patent data, which may not fully capture regional technological developments or variations in innovation intensity. Topic interpretation in LDA involves a degree of subjectivity, and the GTM approach, while useful for visualization, does not assess the economic or operational feasibility of each technology. Addressing these limitations through multi-source data integration, expert evaluation, and methodological advancement would contribute to more balanced and comprehensive insights in future research.

Appendix A: methodological details

This appendix describes the methodological details of LDA and GTM, which are employed in the analytical framework shown in Fig. 1. To estimate the parameters of the LDA model, the Gibbs sampling method is used (Grün and Hornik 2011). As the number of topics is not specified a priori, the optimal number of topics, k, is determined based on the complexity algorithm of the language model. Using the document-word matrix constructed from the patent corpus, LDA infers the latent structure of documents and generates k topics using a Dirichlet distribution for the words in the documents (Blei et al. 2003). Model perplexity is used to evaluate how well the model fits the probability distribution of the observed words in the document corpus and to assess the generalization ability of the topic model (Du and Liu 2021). Deriving the optimal k value not only yields better topic detection results but also reduces time and spatial costs (Huang et al. 2017). Figure 7 is a schematic diagram of the LDA algorithm process. The goal is to infer the latent variables from the observed words. The parameter α pertains to the Dirichlet distribution. The topic assignment for a word in document d is obtained through and derived from the entire set of topics (Blei 2012). The outer square box in the diagram represents the document, while the inner square box represents the repetitive selection of topics and words within the document. The notations for LDA are shown in Table 3.

GTM is a probabilistic density model for visualizing high-dimensional data in a low-dimensional latent space as illustrated in Figure 8 (Bishop et al. 1998). Each latent point x is transformed into the data space through a nonlinear mapping function parameterized by a weight matrix $\mathbf{W}$ and a noise term represented by the precision parameter β , with model parameters estimated using the Expectation–Maximization (EM) algorithm. The likelihood of observing t given a latent point x is modeled using a Gaussian distribution, as shown in Eq. 1. This likelihood increases when t is close to the transformed position $y(x, \mathbf{W})$, indicating a better representation of the patent by that latent point. The notations for the GTM are presented in Table 4.

$$p\,(t \mid x, \mathbf{W}, \beta\,) = \left(\frac{\beta}{2\pi}\right)^{-\frac{D}{2}} \exp\left\{-\frac{\beta}{2}\sum_{d=1}^{D}\left(t_d - y_d\,(x, \mathbf{W})\right)^2\right\} \tag{1}$$

To construct a discrete latent grid, GTM incorporates the concept used in the SOM concept, in which an unsupervised neural network projects high-dimensional data onto a low-dimensional grid while preserving topological order. Following this principle, the latent space is discretized into a regular grid, allowing each patent to be associated with predefined nodes. Figure 9 illustrates a 4 by 4 grid structure in both the latent and data spaces and shows how patents are mapped onto these nodes. Once the latent grid is defined, the EM algorithm estimates the model parameters and assigns each patent to the latent node with the highest posterior probability (Bishop et al. 1998). These assignments produce the two-dimensional GTM map used in the subsequent analysis to identify technology clusters and patent vacuums.

Table 3 Notations of LDA

α	Dirichlet parameter
D	Number of documents
d	Number of documents of each topic
$\theta_{\,d}$	Proportion of topic in document d
$Z_{d,n}$	Topic assignment for n^{th} word in document d
$W_{d,n}$	n^{th} observed word in Dirichlet parameter
K	Number of topics
$\varphi_{\,k}$	Frequency of words for k^{th} topic
β	Topic hyper-parameters

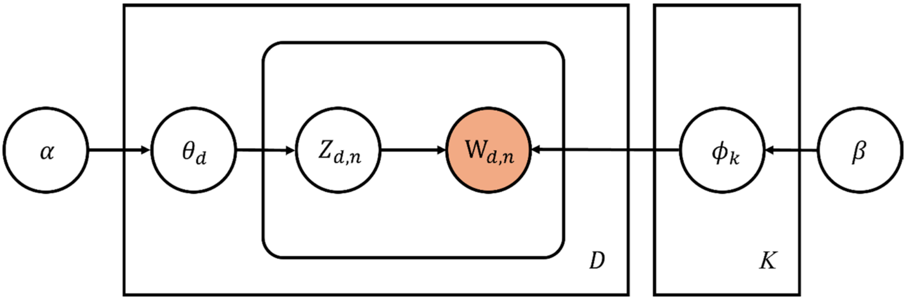


Fig. 7 Process of LDA

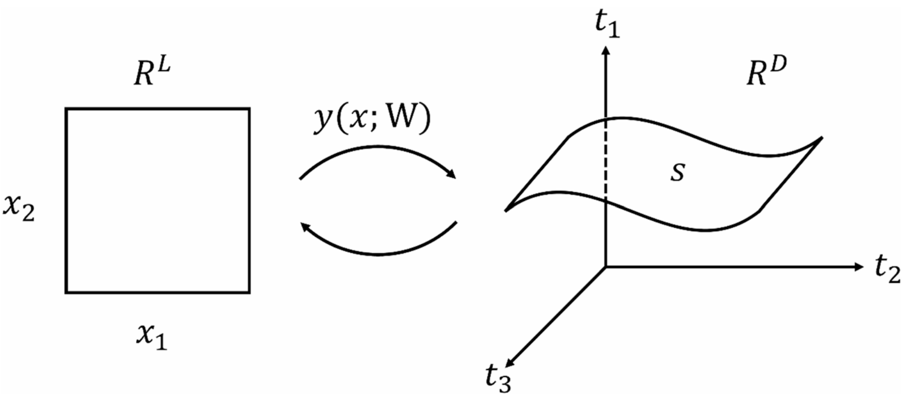


Fig. 8 Basic concept of GTM

Table 4 Notations of GTM

t	The observed data vector in the high-dimensional data space
x	The latent data vector in the reduced latent space
$\mathbf{W}$	The weight matrix used to transform the latent space into the data space
D	The dimension of the data space
t_d	The d-th component of the observed data vector t
$y_d(x, \mathbf{W})$	The d-th component of the transformed latent data vector $y(x, \mathbf{W})$
β	The precision parameter (inverse of the variance) of the Gaussian distribution
K	The number of grid pointers
x_k	A grid point in the latent space
R^L	2-dimension latent space with axes x_1, x_2
$y(x; W)$	Latent space to data space mapping function
R^D	3-dimension data space with axes $t_1,\ t_2,\ t_3$
s	Non-linear manifold in data space
$\Phi\ (x)$	M fixed basis functions of latent variables

Appendix B: hyperparameter settings

This appendix describes the hyperparameter settings used for the GTM based patent mapping. The GTM-based patent map is developed from topic distributions obtained through LDA. The parameters for GTM include the number of latent points, basis functions, width parameters, weight normalization coefficients, and the number of iterations (Fig. 9).

In this study, the latent space was represented as a grid consisting of 100 points in a 10×10 configuration. This resolution balances the need for manifold smoothness with computational tractability, as too few latent points may lead to a loss of smoothness, whereas an excessively large number increases computational cost (Bishop et al. 1998; Son et al. 2012). The Radial Basis Function (RBF) centers were arranged in a 4×4 layout, yielding 16 centers distributed uniformly in the latent space, consistent with the recommendation that radially symmetric Gaussian basis functions placed on a uniform grid promote stable mapping behavior (Son et al. 2012). The RBF width was set to 0.3, reflecting its role in controlling the effective distance between basis functions and selected to maintain appropriate overlap among them, which is essential for smooth manifold formation (Bishop et al. 1998). Finally, the number of EM iterations was fixed at 500, which ensured stable convergence while avoiding unnecessary computational burden, in line with prior work emphasizing that GTM parameters should be tuned individually for each problem (Bishop et al. 1998; Son et al. 2012).

Appendix C: topic-based interpretation of vacant areas

This appendix describes the method for interpreting vacant areas in the GTM-based patent map. Patent vacuums can be converted into the probability that each dimension is assigned to a specific topic to reflect the characteristics of each vacuum. As shown in Figure 10, these probability values reflect the probability distribution derived from

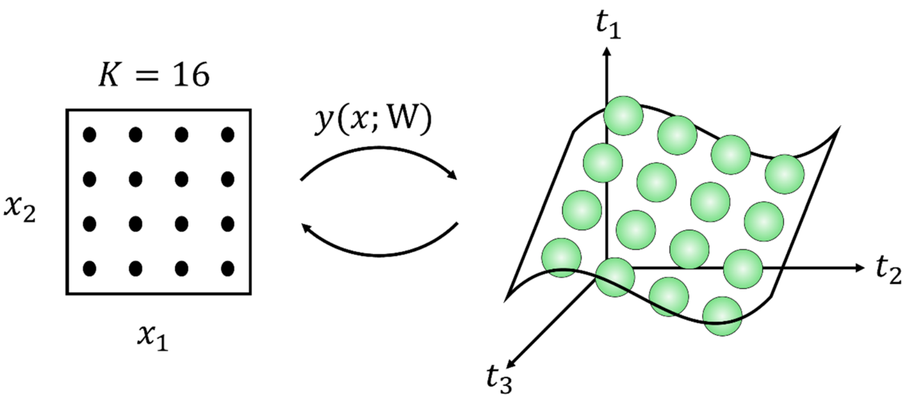
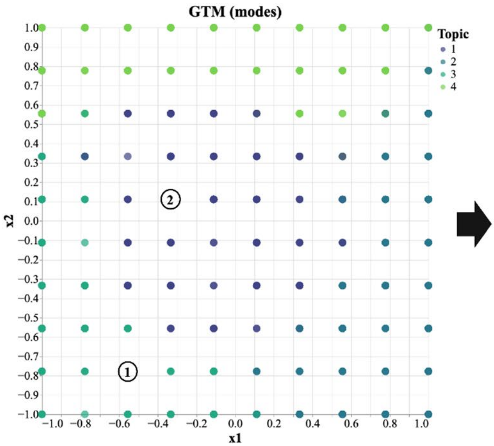


Fig. 9 Mapping regular grids into the data space



	Topic 1	Topic 2	Topic 3	Topic 4
①	0.13120515	0.0460767	0.81449017	0.00823417
②	0.98030363	-0.0024161	0.04976652	-0.0276551

Fig. 10 The result of inverse mapping

Table 5 Transforming into binary values

	Topic 1	Topic 2	Topic 3	Topic 4
①	0	0	1	0
②	1	0	0	0

the LDA topic modeling results. For example, if the probability that Dimension 3 is assigned to Topic 1 is high, it indicates a high relevance to Topic 1.

For the interpretation and identification of vacant areas, the results of the mapping are converted into binary values according to a threshold. Therefore, the probability of assignment to a specific topic obtained through the mapping is filled with 0 or 1 based on the threshold, as shown in Table 5. Taking into account the characteristics of the probability of assignment to a specific topic, the threshold was set to 0.5. For the first identified patent vacuum, Topic 3 has a value of 1, and for the second identified patent vacuum, Topic 1 has a value of 1. This means that each patent vacuum identified in the GTM-based patent map can be interpreted as associated with specific topics.

Table 2 shows the final results of the patent vacuum interpretation, presenting the mapping results of each patent vacuum. These results verify whether patents containing these specific topics exist within the data. Interpreted patent vacuums are worth investigating intensively for the development of new technologies.

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Data Availability The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Competing Interests The authors declare that they have no competing interests.

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