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Research paper

Applications of ship digital twins in maritime transport: A systematic review

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ABSTRACT

Ship digital twins are increasingly recognised as enabling technologies for intelligent and sustainable maritime transport; however, their large-scale deployment remains constrained by significant technical, operational, and organisational challenges. To address the fragmented nature of existing research, this study proposes a two-layer analytical framework that integrates quantitative bibliometric mapping with qualitative critical synthesis. First, a PRISMA-guided scientometric analysis of 739 publications was conducted using CiteSpace to reveal the intellectual structure, thematic evolution, and emerging trajectories of ship digital twin research. The results indicate a clear transition from early modelling-oriented studies towards increasingly integrated, intelligent, and application-driven maritime cyber–physical systems. The analysis identified three key dimensions for characterising the current state of ship digital twin research: modelling methodologies, system hierarchy, and model validation and maturity. Second, 214 empirical studies were further selected for in-depth qualitative analysis focusing specifically on ship-based digital twins. These studies were systematically examined across three analytical dimensions: modelling methodologies, system hierarchy, and validation maturity. The review reveals that current ship digital twin research is evolving from isolated component-level simulations towards fleet-scale, interoperable, and adaptive cyber–physical ecosystems. In addition, six representative application domains were critically analysed, while explicitly distinguishing one-way digital shadows from bidirectional digital twins. Based on this two-layer analysis, six key deployment challenges are identified, including interoperability limitations, cybersecurity exposure, ethical and human-centred concerns, real-time operational constraints, legacy system barriers, and limited model generalisability. In response, four strategic research directions are proposed to support the development of scalable, trustworthy, and resilient maritime digital twin ecosystems. This study contributes a structured analytical framework and critical synthesis of ship digital twin research, providing both theoretical insights and practical guidance for advancing next-generation maritime digitalisation.

1. Introduction

Driven by the continuous expansion of global trade and rapid advances in emerging technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI), the maritime industry is undergoing an accelerated process of digital transformation (Ferrarini et al., 2025). Conventional shipping operations, which rely heavily on manual processes and fragmented information systems, often suffer from delayed information exchange and inefficient decision-making, thereby constraining operational efficiency and industry development. In response, digitalisation has enabled the adoption of intelligent ship management systems, real-time data integration, and AI-based route optimisation, contributing to reduced operational costs, enhanced efficiency, and improved supply chain transparency (Riyadh, 2024). Reflecting the growing strategic importance of maritime digitalisation, the 49th session of the International Maritime Organisation (IMO) Facilitation Committee in 2025 proposed a roadmap for the IMO maritime digitalisation strategy, representing a significant milestone in the transition towards an intelligent and data-driven shipping industry.

Ship digital twins are increasingly recognised as a key enabling

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technology in the digital transformation of the maritime industry. A ship digital twin refers to a virtual representation of a physical ship that is continuously constructed, synchronised, and updated through digital technologies and real-time data integration. As illustrated in Fig. 1, operational data collected from onboard sensors is transmitted through communication networks to a centralised platform, where asset-level and component-level models are integrated with multi-source data and physics-based simulations to establish a dynamic digital replica of the ship. Subsequently, the analytics module processes and interprets the data to generate actionable insights that support intelligent decision-making. The resulting optimisation and control strategies can then be fed back to the physical ship, enabling real-time monitoring, prediction, and operational management.

This study provides a systematic review of the development landscape and developmental trends of ship digital twins. Relevant literature was retrieved from the Web of Science (WoS) and Scopus databases (Pranckutė, 2021), and screened in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Sarkis-Onofre et al., 2021). To address the fragmented nature of existing research, this study proposes a two-layer analytical framework that combines quantitative bibliometric mapping with qualitative critical analysis.

In the first analytical layer, CiteSpace software (Chen, 2006) was employed to conduct a bibliometric analysis based on keyword co-occurrence networks, enabling the identification of core research themes, clustering characteristics, and the intellectual structure of the field. Through timeline visualisation, the analysis reveals the distribution of research hotspots and traces the evolution of key concepts and technological trends from early theoretical exploration to practical implementation. This quantitative layer provides a data-driven foundation for understanding the current state of ship digital twin research and identifying emerging development trends.

In the second analytical layer, empirical studies were critically synthesised through a three-dimensional evaluation framework encompassing modelling methodologies, system hierarchy, and model validation maturity. This qualitative analysis extends beyond conventional bibliometric reviews by examining the technical depth, implementation characteristics, and practical maturity of existing ship digital twin applications. In addition, six representative application scenarios were systematically analysed, with a clear distinction established between one-way digital shadows and bidirectional digital twins.

To date, research on ship digital twins has largely focused on isolated technical implementations or case-specific applications. Consequently, the field still lacks a systematic synthesis of research hotspots and topic evolution, provides a limited understanding of the multi-dimensional challenges associated with real-world deployment, and offers insufficient forward-looking guidance for future development.

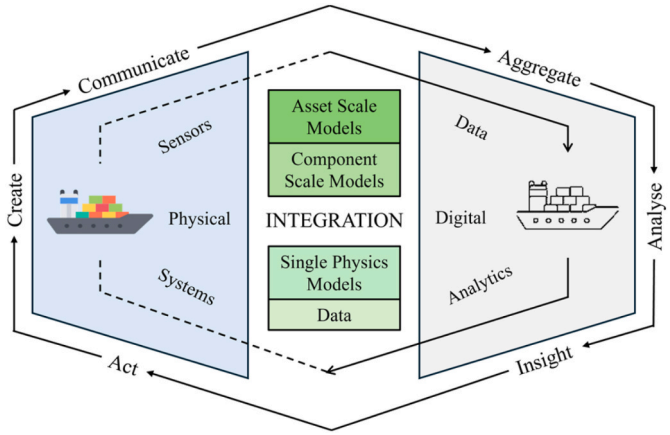


Fig. 1. Illustration of a ship digital twin framework.

The main contributions of this paper are summarised as follows:

(1) A multi-layer analytical framework for ship digital twin research.

This study proposes a two-layer analytical framework that combines PRISMA-guided scientometric mapping with in-depth qualitative synthesis, thereby moving beyond conventional bibliometric reviews. Through CiteSpace-based analysis of 739 publications and critical examination of 214 empirical studies, the review systematically captures both the intellectual evolution and the implementation maturity of ship digital twins. In particular, a three-dimensional analytical framework is established to evaluate empirical studies from the perspectives of modelling methodologies, system hierarchy, and validation maturity.

(2) Conceptual clarification and structured synthesis of ship digital twin systems.

This study provides a structured synthesis of ship digital twin applications across six representative operational domains while explicitly distinguishing one-way digital shadows from bidirectional digital twins. By clarifying the relationships among modelling paradigms, system integration levels, and operational validation stages, the review reveals the ongoing transition of ship digital twins from isolated simulation-oriented applications towards interoperable and adaptive maritime cyber–physical ecosystems.

(3) Identification of strategic deployment barriers and future transition pathways.

The review identifies key constraints limiting large-scale deployment of ship digital twins, including interoperability limitations, cybersecurity exposure, human-centred and ethical concerns, legacy system barriers, real-time operational constraints, and limited model generalisability. Based on these findings, four strategic research directions are proposed to support the development of scalable, trustworthy, and resilient maritime digital twin ecosystems for next-generation intelligent shipping systems.

The remainder of this paper is organised as follows. Section 2 presents the research methodology, including the PRISMA screening procedure and CiteSpace-based bibliometric analysis. Section 3 reports the keyword clustering results and the temporal evolution of ship digital twin research. Section 4 provides a critical three-dimensional analysis of empirical studies, focusing on modelling methodologies, system hierarchy, and model validation maturity. Section 5 examines six representative application scenarios of ship digital twins. Section 6 discusses the key challenges associated with current technological implementation, while Section 7 proposes four future research directions. Finally, Section 8 summarises the whole paper.

2. Methodology

2.1. The proposed framework

This study adopts a two-stage systematic review framework to examine how ship digital twin research has evolved and how existing digital twin systems have been implemented and validated in maritime applications. The framework combines scientometric analysis with qualitative synthesis, allowing both large-scale mapping of the research landscape and detailed evaluation of empirical studies. The overall methodological process is presented in Fig. 2 and consists of three stages: data collection, literature screening, and analytical synthesis.

(1) Data collection. Relevant literature was retrieved using predefined search terms related to digital twins and maritime systems. To ensure broad coverage and improve dataset reliability,

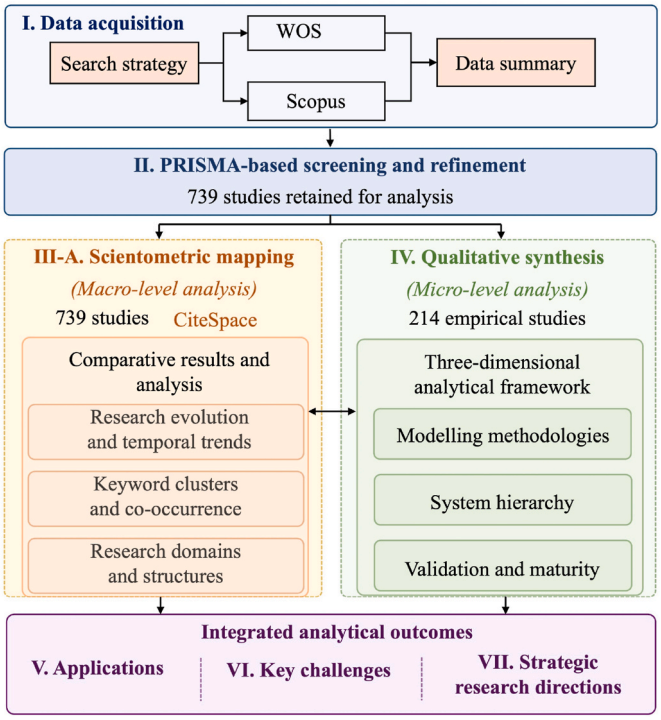


Fig. 2. The overall framework of this paper.

two major academic databases, Web of Science (WoS) and Scopus, were selected as the primary data sources.

(2) Literature screening. The collected studies were screened following the PRISMA 2020 guidelines. The screening procedure included duplicate removal, title and abstract screening, and full-text assessment to ensure a transparent and consistent study selection process.

(3) Analytical synthesis. The retained literature was analysed through a two-stage strategy. First, 739 studies were examined using CiteSpace to identify major research themes, keyword clusters, and the temporal evolution of ship digital twin research. While this scientometric analysis provides an overall view of the field, it is insufficient for assessing implementation maturity and engineering characteristics. Therefore, a second-stage qualitative refinement was conducted. From the 739 studies, 214 empirical studies were further selected after excluding review papers and non-empirical studies. These studies were analysed from three perspectives: modelling methodologies, system hierarchy, and validation maturity. The resulting analysis forms the basis for the subsequent discussion of application scenarios, deployment challenges, and future research directions.

2.2. Literature collection

A systematic search was conducted on June 26, 2025, using the WoS and Scopus databases. The search strategy targeted publications related to digital twin technologies in maritime applications, using the following queries:

In WoS, the Topic field (TS) was searched with: "digital twin*" and ("ship*" or "vessel*"), yielding 512 documents. In Scopus, the Title-Abstract-Keywords field (TITLE-ABS-KEY) was queried with "digital twin" and (ship* OR vessel*), resulting in 788 records. A total of 1300 records were initially retrieved.

2.3. Review protocol: PRISMA 2020 checklist

This review process followed the PRISMA 2020 guidelines throughout literature screening and study selection. The detailed screening procedure is illustrated in Fig. 3.

(1) Identification: A total of 1300 records were initially retrieved from WoS and Scopus.

(2) Deduplication: After removing 347 duplicate records, 953 unique studies remained.

(3) Screening: Titles and abstracts of the 953 studies were screened against the predefined research scope. Studies related to ship digital twins and associated maritime applications were retained for full-text review.

(4) Eligibility assessment: Full-text versions of the 953 studies were assessed according to predefined inclusion and exclusion criteria. Studies unrelated to ship digital twins, together with publication types such as books and book chapters, were excluded during this stage.

(5) Final inclusion: A total of 739 studies were retained for scientometric and systematic review analysis.

(6) Qualitative refinement: To further examine implementation maturity and engineering characteristics, 214 empirical studies were selected from the 739 retained studies for detailed qualitative synthesis after excluding review and non-empirical studies.

3. Results and analysis

Using PRISMA-screened literature, this study applies CiteSpace to generate keyword co-occurrence clustering maps and temporal evolution maps for both the full development cycle (2004-2025) and the most recent five years (2020-2025) in the field of ship digital twins.

3.1. Keyword theme clustering from 2004 to 2025

As shown in Fig. 4, the keyword clustering results reveal eight prominent clusters, which can be broadly categorised into three thematic groups: foundational technologies, intelligent technologies, and practical applications.

(1) Modelling and simulation technologies: Cluster #0 "digital twin" forms the core conceptual framework, supported by #1 "3D reconstruction" as a key enabling technology.

3D reconstruction technology refers to the transformation of physical ship entities into high-fidelity digital models using technologies such as laser scanning and point cloud processing. For example, Wang et al. (2024) proposed a Generative Adversarial Network (GAN) based deep learning neural network that combines shape priors to reconstruct ships

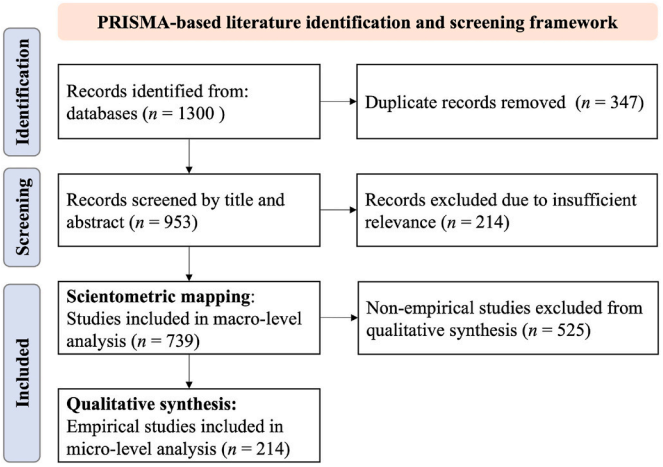


Fig. 3. PRISMA flow chart: literature selection phase.

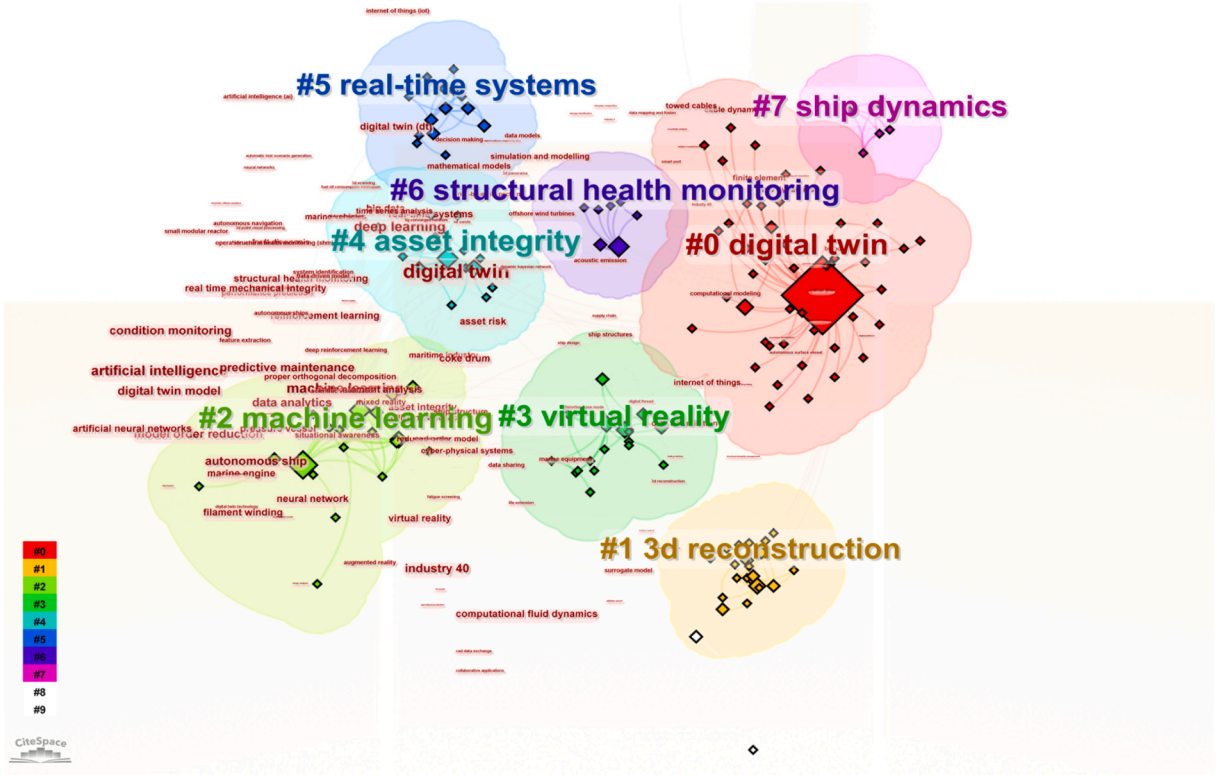


Fig. 4. Keyword theme clustering diagram for ship digital twins (2004-2025).

from single-view images or videos. Liu et al. (2025) introduced a Neural Radiance Fields (NeRF)-GAN network to generate 3D ship models from single-view Unmanned Aerial Vehicle (UAV) images.

(2) Intelligent technologies: In digital twin systems, machine learning (#2), virtual reality (#3), and real-time systems (#5) form the core pillars of intelligent technology, driving the transition from theoretical frameworks to practical applications.

Machine learning enables dynamic modelling, anomaly prediction, and autonomous optimisation in digital twins by uncovering hidden patterns in multi-source data. For instance, Berg et al. (2025) combined deep reinforcement learning with nonlinear model predictive control to synchronise digital and physical ship models. Similarly, Nielsen et al. (2022) integrated a digital twin with first-principles models and Recurrent Neural Networks (RNN) to improve the accuracy of manoeuvring and shallow-water channel predictions in ports.

Virtual reality (#3) enables the creation of immersive interfaces that facilitate intuitive human-machine interaction. By converting digital twin models into interactive 3D virtual environments, VR technology enhances user engagement, collaboration, and operational efficiency. For example, in shipbuilding applications, researchers have integrated VR with gantry welding robots to simulate and optimise welding processes, improving both accuracy and coordination in complex tasks (Zhang et al., 2023a).

Real-time systems (#5) support state synchronisation between digital twins and physical entities through low-latency data exchange. Miyanawala et al. (2024) addressed the challenge of predicting unsteady hydrodynamics in jack-up platforms under irregular waves by developing a deep learning model based on Long Short-Term Memory (LSTM) networks. This approach offers a computationally efficient alternative to traditional simulation methods. Jin et al. (2024) introduced a digital twin framework for steel lazy-wave risers that integrated finite element models with sensor data, enabling accurate estimation of dynamic and structural behaviour while significantly reducing the need for extensive sensor deployment in real-time monitoring.

In addition, researchers have developed an integrated digital twin system for ships that employs real-time data and virtual-physical mapping to support continuous vessel state tracking, real-time prediction, and self-learning updates. Sea trials have been conducted to validate the system's high accuracy, marking a significant step forward in the evolution of intelligent shipping technologies (Xia et al., 2024).

(3) Engineering and operational applications: Digital twins provide a supportive platform for practical engineering and operational tasks by creating a virtual replica and enabling real-time data interaction, encompassing #4 asset integrity, #6 structural health monitoring and #7 ship dynamics.

#4 Asset integrity relies on ship digital twins to achieve full lifecycle tracking of key assets such as hulls and onboard equipment. For instance, Neves et al. (2023) proposed a digital twin methodology for floating, production, storage and offloading (FPSO) hull structures that performs automated finite element model updating based on corrosion models to predict structural failure probability throughout the asset service life. Other researchers examined the development of digital twins for subsea production systems, highlighting key challenges and proposing practical solutions for their implementation in asset integrity management (Rodrigues et al., 2023).

Structural health monitoring (#6) leverages the high-precision simulation capabilities of ship digital twins to deeply integrate finite element models of hull structures with real-world sensor data. For example, Wei et al. (2024) introduced a digital twin methodology for real-time monitoring of ship structure deformation fields based on the inverse Finite Element Method (iFEM). Similarly, Kim et al. (2025) developed a digital twin approach for hull structural integrity monitoring that uses limited sensor data and a base mode selection algorithm to estimate comprehensive hull structural responses.

Ship dynamics technology (#7) combines hydrodynamics and multibody dynamics modelling to simulate vessel behaviour in complex

marine environments. This approach enables the development of dynamic simulation models that capture interactions between ship structures and environmental forces. For instance, Ghorbani et al. (2022) used numerical simulations to investigate the fuel-saving potential of wind-assisted Wing Propulsion Technology (WPT). Their study showed that optimising the main propulsion system to work alongside WPT-generated thrust can significantly improve energy efficiency. Similarly, Westin and Irani (2025)developed a finite element model-based digital twin to address changes in towing cable tension caused by wave-induced ship motions. By integrating real-time sensor data, the system enabled dynamic tension estimation and improved the safety monitoring and control of ship power systems.

3.2. Time evolution of keywords from 2004 to 2025

The timeline visualisation presented in Fig. 5, covering the period from 2004 to 2025, identifies three distinct phases in the development of ship digital twin research. The period between 2004 and 2017 was excluded from detailed trend analysis, as it produced only two publications, providing an insufficient basis for identifying meaningful research patterns or developmental trends.

(1) Early integration (2017-2020): Beginning in 2017, digital twin technology began to gain traction as a foundational framework in maritime applications, supported by emerging technologies such as AI and Industry 4.0. These developments laid the groundwork for virtual–physical mapping. During this phase, researchers started integrating AI with ship digital twins. For example, Liu et al. (2020a) developed a sailing performance prediction model by combining ship digital twins with a grey-box modelling algorithm, incorporating meteorological data to enhance energy efficiency assessment for ocean-going vessels. Similarly, Li et al. (2020) proposed a quality prediction model for shipbuilding fleets, leveraging real-time IoT data mapping and AI analysis to enable intelligent quality control during ship construction.
(2) Technological advancement (2020-2023): After 2020, the field entered a phase of technological maturation, marked by deeper integration of machine learning and deep learning into digital twin systems. Researchers have improved the accuracy and practicality of ship motion prediction by combining machine learning with physical models, providing key technical support for ship digital twins (Schirmann et al., 2022). Others have developed hybrid prediction models by merging first-principle models with RNN, significantly improving the forecasting of ship speed and turning rates during port manoeuvres and in shallow waters (Nielsen et al., 2022). These advancements illustrate the growing synergy between physical and machine learning models, strengthening digital twins' ability to support real-time decision-making.
(3) Frontier exploration (2024-2025): From 2023 onwards, ship digital twin research has entered a frontier exploration stage, characterised by the integration of advanced modelling and intelligent techniques. For instance, Li et al. (2025) proposed a multi-view diffusion model that combines 3D reconstruction with deep learning for ship target modelling. Meanwhile, Karyofyllas et al. (2025) introduced a hierarchical Bayesian modelling framework to quantify parameter uncertainties in finite element models, facilitating real-time structural condition monitoring. This phase reflects a shift towards high-resolution modelling, uncertainty quantification, and intelligent automation in digital twin systems.

3.3. Keyword theme clustering from 2020 to 2025

A co-occurrence keyword map was conducted for the period 2020-2025 using CiteSpace (Fig. 6). When compared to the earlier clustering results from 2004 to 2025 (Fig. 4), a notable evolution in research focus is evident.

The core focus of digital twin technology in the maritime domain has gradually transitioned from foundational topics such as “3D reconstruction” toward more application-oriented areas like “Condition Monitoring”. This shift reflects the evolution of digital twin technology from its initial modelling phase to a more advanced operational phase, where real-time sensing, IoT integration, and data-driven analysis are leveraged for continuous monitoring and dynamic decision-making. For instance, VanDerHorn et al. (2022) developed a digital twin approach for vessel-specific fatigue damage monitoring and prognosis, combining publicly available operational and metocean data with computational models to track fatigue accumulation and forecast remaining fatigue life. Acanfora et al. (2024a) conducted numerical simulations to explore how main engine degradation under harsh sea conditions impacts navigational safety. Using a twin-screw ro-pax vessel as a case study, they developed a digital twin model that integrated the dynamics of the hull, propeller, and engine, highlighting the synergistic role of condition monitoring and digital twins in enhancing ship safety in ensuring ship safety.

In parallel, a notable shift in keyword emphasis from “asset integrity” to “predictive maintenance” reflects a broad transition in research focus, from passive assessment of asset conditions to proactive prediction and data-informed maintenance strategies. Choi et al. (2023), for instance, applied system dynamics modelling to enable predictive maintenance in naval vessels by integrating simulated fault conditions, maintenance schedules, and crew workload. Munkeby (2022) developed a data-driven model to predict daily fuel oil consumption for marine

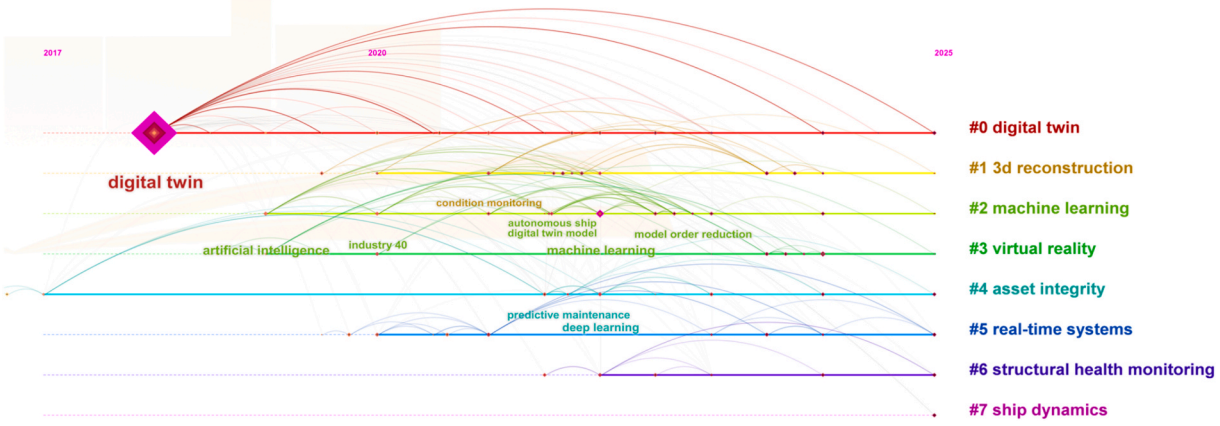


Fig. 5. Ship digital twins keyword timeline analysis (2004-2025).

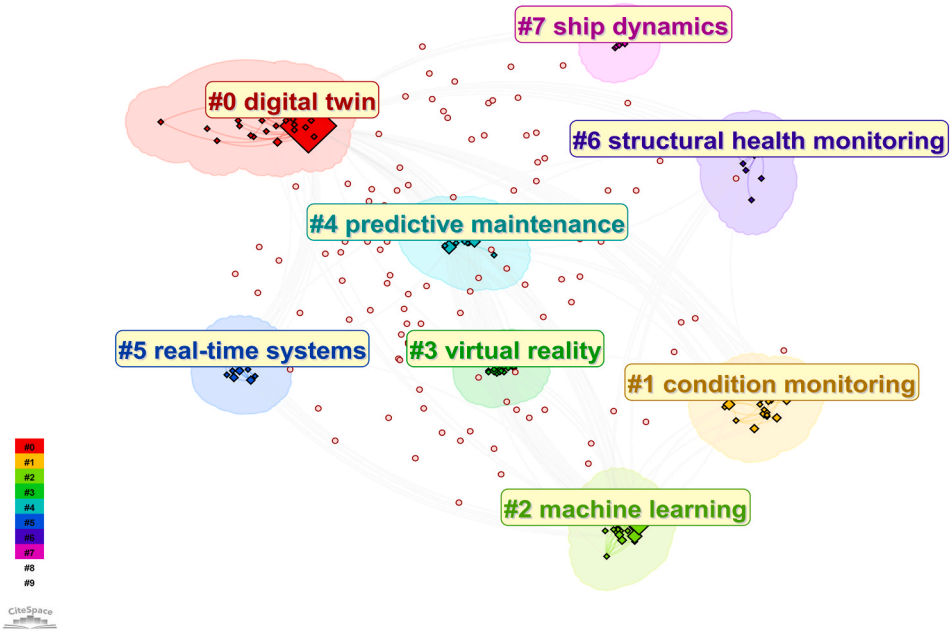


Fig. 6. Keyword theme clustering diagram for ship digital twins (2020-2025).

vessels, and noted the growing adoption of condition monitoring and digital twin systems in the maritime industry.

These developments suggest a clear trajectory in the field: from theoretical frameworks and component-level functions to integrated, intelligent systems capable of supporting real-time diagnostics and operational optimisation.

3.4. *Time evolution of keywords from 2020 to 2025*

The temporal evolution of key terms, visualised in Fig. 7, further confirms the growing prominence of predictive maintenance (#4) and condition monitoring (#1) as core technologies in recent digital twin research. These areas represent a convergence of industrial intelligence and maritime engineering, where data-driven techniques are increasingly integrated with decision-making processes. Samaei and Ghahfarrokhi (2023) highlighted how the adoption of AI algorithms had transformed traditional ship management by enabling predictive maintenance, anomaly detection, and multi-source data fusion. The incorporation of digital twins into these workflows introduces new capabilities for ship health monitoring, allowing for high-fidelity simulations, real-time diagnostics, and forward-looking maintenance strategies.

This evolution marks a pivotal shift in the field from static monitoring and predefined scheduling to dynamic, AI-assisted management, underscoring the critical role of digital twins in shaping the future of intelligent maritime operations.

The bibliometric evidence reveals two parallel transitions in ship digital twin research. From a technological perspective, the field has progressed from static virtual representation and predominantly physics-based modelling towards data-assisted, hybrid, and increasingly intelligent modelling capable of supporting real-time interaction and prediction. From an application perspective, the research focus has shifted from asset representation and passive condition assessment towards predictive maintenance, operational optimisation, and decision support. These trends provide the evidence base for the subsequent in-depth analysis of the 214 empirical studies. Sections 4 and 5 therefore move beyond thematic occurrence and temporal evolution to examine how these technological developments have been implemented in practice, what capabilities have been demonstrated, how they have been validated, and which technical limitations continue to constrain their wider deployment.

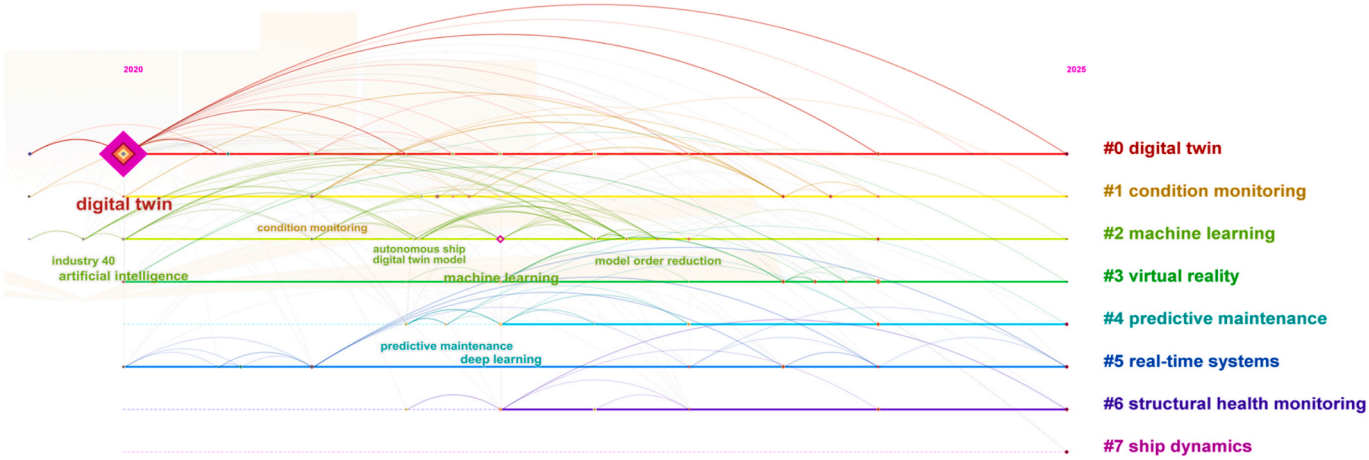


Fig. 7. Timeline analysis of keywords related to ship digital twins (2020-2025).

4. Core themes and analytical findings

Following the PRISMA-guided screening and refinement process, this review employed a two-stage analytical framework to investigate the development and technological maturity of ship digital twins.

In the first stage, 739 studies were retained for bibliometric and scientometric analysis using CiteSpace. This quantitative analysis was conducted to identify major research themes, thematic evolution patterns, interdisciplinary connections, and emerging research trends within the ship digital twin domain. The scientometric results provide a macro-level overview of how ship digital twin research has evolved across different technological and application areas. However, bibliometric mapping alone is insufficient to critically evaluate implementation maturity, modelling trade-offs, and engineering feasibility. Therefore, a second-stage refinement was further conducted. From the initial corpus, 214 empirical studies were selected for in-depth qualitative synthesis based on three criteria: (i) methodological rigour, (ii) implementation specificity, and (iii) direct engineering relevance. Only studies explicitly involving ship systems, including ship components, whole-vessel systems, fleet operations, or ship–shore integration, were retained. Conceptual papers, reviews, and non-empirical discussions were excluded from this stage.

Building upon this refined empirical dataset, the analytical findings are organised around three interrelated dimensions that collectively define the technological architecture and deployment maturity of ship digital twins:

(1) Modelling methodologies, examining how ship digital twins are constructed computationally and analytically;
(2) System hierarchy, investigating the system-level scope and integration architecture of digital twin implementations;
(3) Validation and maturity, evaluating the operational credibility and deployment readiness of existing digital twin systems.

These three dimensions establish a structured analytical framework that moves beyond descriptive literature review towards a critical assessment of the current state, technical bottlenecks, and future development trajectory of ship digital twins.

4.1. Modelling methodologies

The reviewed literature demonstrates that ship digital twin modelling architectures have progressively evolved towards three dominant paradigms: physics-driven models, data-driven models, and physics-informed hybrid models. These paradigms fundamentally reflect different trade-offs among physical fidelity, computational efficiency, data dependency, interpretability, and real-time adaptability.

As summarised in Table 1, the evolution of modelling methodologies reveals a broader transition in ship digital twin research: from traditional high-fidelity numerical simulation towards adaptive cyber–physical intelligence systems capable of real-time interaction with operational environments.

Physics-driven models remain dominant in hydrodynamic simulation, manoeuvring prediction, and energy system analysis due to their strong physical interpretability and high-fidelity representation capability. These approaches formulate ship behaviour through governing equations derived from continuum mechanics (Lu et al., 2022), rigid-body dynamics (Kinaci, 2023), and thermodynamic conservation laws (Yfantis et al., 2023). Representative applications include CFD-based simulations of propeller–rudder interactions, vessel manoeuvring dynamics, and ship energy flow optimisation (Dere and Deniz, 2020). However, the review indicates that their practical deployment remains constrained by computational latency, parameter sensitivity, and limited scalability under real-time operational conditions.

Conversely, data-driven models increasingly leverage ship operational data streams, onboard sensors, and IoT infrastructures to directly learn system behaviour without explicitly enforcing governing physics. Deep learning, probabilistic graphical models, and machine learning techniques demonstrate strong flexibility and computational efficiency in fault diagnosis, condition monitoring, and motion prediction tasks (Taghavi and Perera, 2024; Lin et al., 2025; Patil and Theotokatos, 2023; Miao et al., 2024; Yao et al., 2025). Nevertheless, their weak interpretability and poor extrapolation capability under unseen operational conditions remain major concerns for safety-critical maritime applications.

To bridge the gap between physical fidelity and computational adaptability, recent research increasingly focuses on physics-informed hybrid frameworks (Xia et al., 2024; Qu et al., 2025). These approaches integrate prior physical knowledge into data-driven learning architectures through embedded governing equations, regularisation constraints, or hybrid surrogate modelling strategies. The review suggests that hybrid models currently represent the most promising pathway towards real-time adaptive ship digital twins. However,

Table 1
Overview of modelling methodologies for ship digital twins.

Modelling paradigm	Core principle	Representative methods	References	Key strengths	Major limitations	Typical digital twin applications
Physics-driven models	Construct DTs based on governing physical laws and first-principles formulations	CFD, rigid-body dynamics, thermodynamic and energy balance models	Menon et al. (2024); Lu et al. (2022); Kinaci (2023); Zhang et al. (2023a); Li and Cai (2025); Wang et al. (2023); Hu et al. (2023); Yfantis et al. (2023); Dere and Deniz (2020)	Strong physical interpretability; high fidelity; physically consistent predictions	Computationally intensive; sensitive to parameter uncertainty; limited real-time capability	Hydrodynamic simulation, manoeuvring prediction, energy management
Data-driven models	Learn latent system behaviours directly from operational data	Statistical models, machine learning, deep learning, Bayesian networks	Lin et al. (2025); Taghavi and Perera (2022); Chen et al. (2022); Taghavi and Perera (2024); Patil and Theotokatos (2023); Miao et al. (2024); Yao et al. (2025); Coraddu et al. (2019); Sanguino et al. (2024); Fera and Spandonidis (2024)	Fast inference; adaptive learning capability; scalable for large data streams	Poor interpretability; weak extrapolation ability; physically inconsistent predictions under unseen conditions	Fault diagnosis, condition monitoring, motion prediction
Physics-informed hybrid models	Integrate physical knowledge into data-driven learning frameworks	PINNs, physics-guided ML, hybrid surrogate models	Xia et al. (2024); Li et al. (2024c); Qu et al. (2025); von Brandis et al. (2025); Nielsen et al. (2022); Vasilikis et al. (2023)	Balance between physical consistency and computational efficiency; improved robustness	Optimisation instability; difficulty balancing physics constraints and data fidelity; limited industrial standardisation	Real-time digital twin synchronisation, adaptive control, predictive maintenance

optimisation instability, loss balancing difficulties, and limited industrial standardisation continue to hinder their large-scale deployment.

Overall, the comparative analysis reveals that no single modelling paradigm fully satisfies the operational requirements of ship DTs. Instead, the field is gradually converging towards hybrid cyber–physical modelling strategies that seek to balance physical consistency, computational efficiency, and real-time responsiveness.

4.2. System hierarchy

Beyond modelling methodologies, the reviewed literature demonstrates that ship digital twin development is increasingly characterised by hierarchical system integration. Rather than functioning as isolated simulation models, modern ship digital twins are progressively evolving into multi-layer cyber–physical ecosystems spanning from individual onboard components to fleet-wide operational coordination.

As illustrated in Table 2, ship digital twin architectures can be categorised into four hierarchical levels: sub-component systems, subsystem integration, whole-ship digital twins, and fleet/ship–shore coordination systems.

At the sub-component and subsystem levels, digital twins primarily focus on monitoring, diagnostics, and operational optimisation of individual equipment and integrated ship systems. Typical applications include propulsion health monitoring, converter dynamics analysis, HVAC optimisation, and predictive maintenance of shipboard systems (Zhang et al., 2023b; Tavagnutti et al., 2025; Dini et al., 2024; Barone et al., 2025; Acanfora et al., 2024b; Jeon and Theotokatos, 2024). These lower-level DTs generally demonstrate relatively high implementation maturity because their operational scope is comparatively constrained and physically measurable.

At the whole-ship level, digital twin architectures increasingly integrate navigation, manoeuvring, energy systems, and operational states into unified vessel-scale representations (Zhang et al., 2022; Hasan et al., 2023; Xia et al., 2024). These integrated digital twins support lifecycle management, autonomous navigation, and mission-level operational optimisation. However, the review identifies substantial challenges associated with computational scalability, environmental uncertainty, and multi-system synchronisation.

The most advanced stage of digital twin evolution extends towards fleet-level and ship–shore integrated ecosystems. These architectures incorporate remote communication, cloud-based coordination, and fleet-wide operational optimisation (Chen et al., 2022; Schirmann et al., 2018). Nevertheless, the review reveals that cybersecurity risks, communication latency, interoperability limitations, and standardisation deficiencies remain major barriers to scalable deployment in real maritime environments.

The hierarchical analysis reveals a clear maturity gradient in current ship digital twin development. Component- and subsystem-level digital twins have reached comparatively higher levels of maturity because their physical boundaries, data interfaces, and operational objectives are relatively well defined, allowing their monitoring, diagnostic, and optimisation functions to be validated under controlled or operational conditions. As the scope expands towards whole-ship and fleet/ship–shore digital twins, however, implementation maturity decreases as the problem shifts from modelling individual assets to coordinating heterogeneous and dynamically coupled systems. At these higher levels, the dominant challenges are increasingly associated with cross-system synchronisation, computational scalability, communication latency, interoperability, cybersecurity, and standardisation rather than the accuracy of individual models alone. This maturity gradient indicates that the next stage of ship digital twin development will depend not only on improving individual modelling techniques, but also on establishing scalable and secure architectures capable of integrating heterogeneous onboard and shore-based systems in real time.

4.3. Model validation and maturity

While significant progress has been achieved in modelling and system integration, the operational maturity of ship DTs remains highly heterogeneous across the literature. Existing studies vary substantially in validation depth, deployment realism, and engineering credibility.

To systematically assess implementation maturity, the reviewed empirical studies were classified into four validation categories: conceptual frameworks, numerical validation, semi-physical validation, and full-scale empirical deployment. As summarised in Table 3, these categories reflect increasing levels of operational realism and deployment readiness.

The maturity assessment of the 214 empirical studies reveals a pronounced imbalance in validation depth. Of these studies, 78 (36.45%) were validated primarily through numerical experiments, while 36 (16.82%) employed semi-physical or laboratory-based validation. In contrast, only 33 studies (15.42%) reported full-scale empirical validation under operational maritime conditions. This distribution indicates that, although ship digital twin research has progressed substantially in model development and controlled validation, the transition from proof-of-concept studies to operationally validated systems remains limited.

Numerical validation continues to provide an important foundation for algorithm development and controlled assessment, while semi-physical and hardware-in-the-loop platforms offer an intermediate step towards greater system realism. However, these validation environments cannot fully reproduce the heterogeneous operating conditions, environmental disturbances, communication constraints, and

Table 2
Hierarchical architecture of ship digital twins.

Hierarchy level	Typical system objects	Functional objective	Representative digital twin capabilities	Representative references	Key technical challenges
Sub-component level	Engines, converters, HVAC systems, sensors, cranes	Real-time monitoring and local state estimation	Fault diagnosis, thermal management, equipment-level optimisation	Xu et al. (2025); Xu et al. (2026); Wang et al. (2023); Liu et al. (2024a); Shang et al. (2024); Li and Cai (2025); Liu et al. (2024b)	Sensor reliability, data heterogeneity, interface compatibility
Subsystem level	Power systems, propulsion systems, auxiliary systems	Integrated subsystem coordination and operational optimisation	Energy management, propulsion control, predictive maintenance	Zhang et al. (2023b); Cronin et al. (2025); Xiang et al. (2024); Tavagnutti et al. (2025); Dini et al. (2024); Barone et al. (2025); Acanfora et al. (2024b); Jeon and Theotokatos (2024); Huang et al. (2025); Khawale et al. (2024); Li et al. (2024b)	Multi-physics coupling, real-time synchronisation
Whole-ship level	Integrated vessel systems and onboard operational states	Vessel-wide lifecycle management and autonomous operation	Navigation optimisation, manoeuvring prediction, mission planning	Zhang et al. (2022); Méxas et al. (2022); Hasan et al. (2023); Xia et al. (2024); Xiao et al. (2022)	Computational scalability, dynamic environmental uncertainty
Fleet and ship–shore level	Multi-vessel networks and remote communication systems	Cross-platform coordination and fleet-level decision support	Fleet scheduling, remote maintenance, fatigue and risk assessment	Chen et al. (2022); Schirmann et al. (2018)	Cybersecurity, communication latency, interoperability standardisation

Table 3
Validation maturity framework for ship digital twins.

Validation level	Percentage	Validation environment	Validation characteristics	Representative references	Technical strengths	Major limitations	Deployment readiness
Conceptual framework	31.31%	Theoretical and architectural design studies	Defines digital twin architecture, interfaces, and system objectives without operational verification.	Bickford et al. (2020); Wu et al. (2021); Zavareh et al. (2021)	High conceptual flexibility; establishes foundational digital twin architecture.	Lack of empirical verification and operational evidence.	Low
Numerical validation	36.45%	Simulation-based environments	Validates digital twin outputs against numerical or synthetic datasets.	Liu and Ren (2022); Wei et al. (2024a, 2024b)	High controllability; suitable for early-stage model development.	Sensitive to modelling assumptions and simulation fidelity.	Medium-low
Semi-physical validation	16.82%	Hardware-in-the-loop (HIL) and laboratory platforms	Combines physical components with virtual models for integration testing.	Li (2022); Li et al. (2024a)	Improved realism and system integration assessment.	Limited scalability and portability across platforms.	Medium
Full-scale empirical validation	15.42%	Real operational maritime environments	End-to-end validation under realistic onboard conditions.	Fan et al. (2025); Hu et al. (2025)	Highest operational credibility and engineering relevance.	Expensive deployment; limited generalisability across vessels and scenarios.	High

Note: The majority of existing ship DT studies remain focused on numerical and semi-physical validation, whereas large-scale operational deployment remains limited. Current bottlenecks are increasingly associated with system-level challenges, including interoperability, cybersecurity, dynamic cyber–physical synchronisation, and the lack of unified industrial standards.

long-term degradation processes encountered in real maritime operations. Full-scale studies provide stronger evidence of operational feasibility (Fan et al., 2025; Hu et al., 2025), but the reviewed cases remain relatively scarce and are often specific to particular vessels, components, or operating scenarios, limiting the generalisability of the reported outcomes.

The validation evidence suggests that the principal bottleneck in ship digital twin development is gradually shifting from model-level feasibility towards system-level operational credibility. Future progress therefore requires broader full-scale validation across vessel types and operating conditions, together with systematic evaluation of interoperability, cyber–physical synchronisation, cybersecurity, and long-term reliability. Such evidence is essential for determining whether performance demonstrated in numerical and semi-physical environments can be sustained in real-world maritime deployment.

5. Applications

Ship digital twins have been investigated across an expanding range of maritime applications, reflecting a broader transition from virtual representation and state monitoring towards prediction, optimisation, and decision support. Based on the reviewed literature, six major application areas are identified: ship design and optimisation, condition monitoring, predictive maintenance, energy efficiency management, navigation safety, and intelligent shipyard operations.

Table 4 provides a comparative synthesis of representative studies across these six application areas, linking the engineering problems addressed and technical approaches adopted to their demonstrated capabilities, validation settings, digital twin (DT)/Digital Shadow (DS) characteristics, and remaining limitations. For comparative purposes, implementations are distinguished as DTs or DSs according to the direction of information exchange between the physical and virtual systems. DSs primarily involve one-way information flow from the physical asset to its virtual representation, supporting monitoring, simulation, or prediction without a complete feedback loop. DTs involve bidirectional information exchange, whereby operational data update the virtual representation and the resulting predictions, recommendations, or control information can subsequently inform physical-system operation. This distinction provides an additional perspective for assessing application maturity. The following subsections build upon the comparative evidence in Table 4 to examine the technical progress and remaining research gaps within each application domain.

5.1. Ship design and optimisation

Ship design requires the reconciliation of multiple and often competing objectives related to hydrodynamic performance, structural integrity, energy efficiency, system configuration, and lifecycle operation. Conventional design processes rely heavily on iterative numerical simulations and assumptions made during the design stage, while knowledge generated during subsequent vessel operation is not always incorporated into model refinement. DTs provide a potential mechanism for connecting design models with physical and operational information, allowing virtual representations to evolve throughout the ship lifecycle.

As summarised in Table 4, existing studies have addressed this problem through design optimisation, multi-physics modelling, and lifecycle-oriented virtual–physical integration. Casanova Mombiela (2021) applied optimisation algorithms for ship power plants during initial design steps, demonstrating how digital modelling can support the systematic evaluation of alternative configurations. However, because this approach primarily relies on design-stage and historical information without continuous feedback from the physical vessel, it is more appropriately characterised as a DT. Xiao et al. (2022) proposed a cross-dimensional design approach that combines historical experience with real-time operational information to develop evolving digital twin models throughout the ship's lifecycle.

The reviewed evidence therefore indicates a progression from static design optimisation towards lifecycle-informed and dynamically updated ship representations. Nevertheless, existing implementations remain concentrated on particular design stages or engineering domains, and continuous information exchange across design, construction, operation, and maintenance remains insufficiently demonstrated. The principal research challenge is consequently to establish interoperable lifecycle DT architectures that can integrate heterogeneous engineering models and operational feedback while maintaining model consistency across lifecycle stages.

Beyond peer-reviewed studies, industrial initiatives indicate growing practical interest in this direction. For example, HD Hyundai has collaborated with Siemens and NVIDIA to develop a virtualised shipyard environment in which vessels can be digitally simulated, evaluated, and optimised prior to physical production (Digest, 2026). Such developments demonstrate the potential industrial scale of DT-supported design and production, although industrial implementation should be distinguished from peer-reviewed empirical validation when assessing technical maturity.

Table 4
Applications of ship digital twins.

Applications	Representative study	Main technical approach	Demonstrated capability/outcome	Validation/evidence setting	DT or DS	Key limitation/gap
Ship design and optimisation	Casanova Mombiela (2021)	Design-stage optimisation of ship power-plant configuration	Supports systematic evaluation and optimisation of alternative power-system configurations.	Offshore Supply Vessel case study using operational load-profile data and design-stage simulation.	DT concept[a]	Continuous physical–digital operational feedback was not demonstrated.
	Xiao et al. (2022)	Vertical–horizontal lifecycle architecture integrating historical and real-time data	Provides a framework for lifecycle DT model construction, evolution, and cross-stage information integration.	Conceptual architecture and lifecycle operation-mechanism analysis; no empirical case validation.	DT (conceptual architecture)	Cross-stage model integration and lifecycle interoperability require further validation.
Condition monitoring	VanDerHorn et al. (2022)	Ship-specific structural DT integrating operational and environmental information	Monitors accumulated fatigue damage and predicts future fatigue damage to support maintenance and operational decision-making.	Ship-specific operational and environmental data	DT	Validation is based on a vessel-specific containership case study using position and wave-condition data.
	Acanfora et al. (2024a)	Numerical DT simulation of hull–propeller–engine interactions with component degradation in irregular seas.	Distinguishes degradation-induced changes from wave-induced variations to support condition monitoring.	Simulation-based Ro-Pax case study under irregular head-sea conditions.	DT simulation model/DT concept	Simulation-based evidence only; real-time physical–digital coupling and onboard validation were not demonstrated.
Predictive maintenance	Choi et al. (2023)	System-dynamics-based modelling integrating faults, maintenance schedules, and crew workload	Reveals non-intuitive interactions and potential problems in naval ship operation and maintenance.	ROK Naval ship operation-and-maintenance system simulation.	DT (simulation-based)	Evidence is application-specific; broader operational and cross-vessel validation remains limited.
	Soliman et al. (2024)	Bibliometric analysis of DT-enabled predictive maintenance	Identifies research development and emerging trends in maritime predictive maintenance.	Bibliometric analysis of 1074 publications (2016–2023)	N/A (review study)	Does not provide direct technical or operational validation.
Energy efficiency management	Munkeby (2022)	Physics-based and data-driven fuel-consumption modelling	Predicts vessel fuel consumption from operational information.	Vessel operational data	DT-related data-driven model/DT concept	Model focuses on fuel-consumption prediction rather than demonstrating continuous physical–digital interaction or closed-loop operation.
	Jing et al. (2025)	Sensor-driven real-time data acquisition integrated with a GA-LSTM energy-efficiency model and 3D digital-twin visualisation	Enables real-time ship-status and energy-efficiency monitoring, dynamic navigation-scene visualisation, and simulation-based energy-efficiency assessment.	Intelligent research/training vessel ("New Hongzhuan"); onboard sensor data acquisition and system-level real-time monitoring and visualisation.	DS	Prediction, optimisation, and closed-loop control remain underdeveloped; physical actuation based on digital-model outputs was not demonstrated.
	Elias Yfantis et al. (2023)	Integrated ship energy-flow modelling	Estimates power demand, fuel consumption, and emissions and supports evaluation of decarbonisation options.	Specific-vessel case study using real navigational data, with comparison against available raw data.	DT concept/ model-based DT	Core model validation was still under development; continuous real-time physical–digital coupling was not demonstrated.
Navigation safety	Lee et al. (2022)	Real-time wave reconstruction and prediction integrated with coupled seakeeping–maneuvering simulation.	Predicts near-future wave fields, ship responses, operational risk, and performance to support navigation guidance.	Numerical and experimental validation of real-time wave and ship-response prediction.	DS[b]	Navigation guidance is generated, but automatic closed-loop actuation of the physical vessel is not demonstrated.
	Qu et al. (2025)	Hybrid DT model integrating a 3-DOF physics-based USV model with dynamically updated DSW-UKF parameter estimation	Improves short-term USV navigation-attitude prediction accuracy and robustness under environmental disturbances and sensor-data loss.	Real-vessel experiments under wind and wave disturbances, including 10-s-ahead prediction and sensor-data-loss tests.	DT	Validation is limited to a 3-DOF single-USV setting; extension to 6-DOF dynamics and more complex environmental disturbances remains necessary.
Intelligent shipyard operations	Iwańkowicz and Rutkowski (2023)	Conceptual shipbuilding DTS integrating production planning, monitoring, resource management, process analysis, and dimensional quality management	Provides an integrated framework for digitalising and coordinating ship design and production processes.	DT-system concept demonstrated using a simplified ship-construction example, with particular emphasis on dimensional quality management.	DT concept	Scalability and transferability across shipyard environments remain uncertain.
	Liland (2023)	Data-driven labour-hour prediction using regression, clustering, and machine-learning models for shipyard resource management.	Automates labour-hour estimation for new vessel projects, supporting more accurate resource allocation and cost management.	Case study at a Norwegian shipyard using historical vessel/project data; predictive performance evaluated on unseen data.	DT concept	Limited to a single Norwegian shipyard and historical project data; integration with operational systems and continuous physical–digital data exchange was not demonstrated.

Note: DT indicates digital twin, and DS is digital shadow.
[a] Design-stage DT concept rather than a fully operational bidirectional Digital Twin.
[b] Authors describe the system as a digital twin, but classification in this review follows the stricter information-flow criterion.

5.2. Condition monitoring

Condition monitoring is a comparatively mature application of ship DTs because safe and reliable vessel operation depends on continuously assessing the condition of machinery, propulsion systems, and structural components under changing operational and environmental conditions. Conventional monitoring approaches commonly rely on individual sensor measurements, predefined thresholds, or periodic inspections and may therefore provide limited information about the evolving physical state of an asset. DT-based approaches seek to overcome this limitation by integrating operational observations with virtual models that are continuously or periodically updated to represent asset-specific conditions.

The studies compared in Table 4 demonstrate a progression from simulation-based degradation assessment towards ship-specific and dynamically updated health representations. Acanfora et al. (2024a) modelled different degradation levels of key engine components to investigate their effects on vessel operation, illustrating how virtual models can support systematic assessment of machinery degradation. VanDerHorn et al. (2022) incorporated ship-specific operational and environmental information into an evolving structural representation for tracking and predicting fatigue damage. The technical development therefore extends beyond conventional condition monitoring towards state updating and forward-looking degradation assessment.

However, the available validation remains predominantly component- or vessel-specific, and evidence of transferability across different vessel classes, operating profiles, and environmental conditions remains limited. Furthermore, some implementations primarily transfer information from the physical asset to the virtual representation without closing the feedback loop to operational decision-making, and therefore function more closely as DSs. Further progress requires transferable health models, uncertainty-aware state estimation, robust multi-source sensor integration, and broader full-scale validation before DT-based condition monitoring can reliably support vessel- and fleet-level decision-making.

5.3. Predictive maintenance

Predictive maintenance extends condition monitoring from estimating current system health towards anticipating future degradation and supporting maintenance intervention before failure occurs. This capability is particularly important in maritime operations, where unexpected equipment failures can lead to costly downtime, operational disruption, and safety consequences. DTs provide a framework for integrating equipment condition, operational history, simulated degradation behaviour, and maintenance information to support forward-looking maintenance decisions.

Existing studies have explored the use of DTs to simulate fault conditions, estimate maintenance requirements, and support proactive resource allocation. Choi et al. (2023), for example, incorporated simulated fault conditions, maintenance schedules, and crew workload into a DT-supported naval-vessel maintenance framework, demonstrating how digital representations can support proactive rather than purely reactive maintenance planning. At the broader literature level, Soliman et al. (2024) identified increasing research attention to DT-enabled predictive maintenance in the maritime sector. As a bibliometric study, however, this work provides evidence of the development of the research field rather than direct technical validation of predictive-maintenance performance.

The literature indicates that predictive-maintenance research is moving from condition awareness towards prediction-oriented maintenance decision support. However, long-term operational validation remains limited, particularly for failure prediction and remaining-useful-life estimation under heterogeneous loading, environmental, and maintenance conditions. The critical research gap therefore lies not only in improving prediction performance but also in demonstrating that predictive capability can be maintained over extended operational periods and transferred across vessels and equipment types. Future studies should place greater emphasis on longitudinal operational validation, uncertainty quantification in degradation prediction, and tighter integration between predicted asset condition and practical maintenance decisions.

5.4. Energy efficiency management

Energy efficiency management is inherently dynamic because vessel energy consumption is affected by speed, loading condition, machinery performance, hull condition, weather, and sea state. Conventional strategies based on static performance maps or operational experience may therefore struggle to account for continuously changing operating conditions. DTs address this problem by combining vessel-specific models with operational and environmental data to estimate energy flows, predict fuel consumption, evaluate performance, and support adaptive operational optimisation.

As shown in Table 4, existing approaches range from energy-flow modelling to data-driven fuel prediction and real-time performance monitoring. Elias Yfantis et al. (2023) developed an integrated ship energy-flow representation to support component-level energy analysis and operational decision-making. Munkeby (2022) combined physics-based and data-driven models to predict ship fuel consumption, while Jing et al. (2025) developed a real-time energy-efficiency monitoring system for evaluating vessel performance under varying sailing conditions. Collectively, these studies demonstrate a transition from retrospective energy-performance assessment towards continuously updated prediction and operational evaluation.

Nevertheless, the comparative evidence also reveals a gap between predictive capability and fully interactive DT operation. Many existing implementations can monitor or predict energy performance using operational data but do not establish a complete feedback loop between prediction, optimisation, and physical vessel operation. In addition, validation is often vessel- or operating-condition-specific, leaving uncertainty regarding generalisability across hull conditions, propulsion configurations, loading states, routes, and environmental conditions. The next stage of development therefore requires stronger cross-vessel validation, explicit treatment of environmental and model uncertainty, and closer integration between energy prediction and real-time operational optimisation.

Industrial deployment provides emerging evidence of this transition. For example, the Syroco platform deployed on the M/T Alcyone integrates vessel and environmental information to estimate operational behaviour and support navigation optimisation, incorporating propulsion performance, hull hydrodynamics, and wind-assisted propulsion within an integrated framework (Ribbens, 2025). Such cases indicate increasing industrial adoption, although independently reported quantitative validation remains important for establishing the generalisability of their operational and environmental benefits.

5.5. Navigation safety

Navigation safety represents a particularly demanding DT application because vessel dynamics, environmental disturbances, surrounding traffic, and navigational constraints evolve continuously and interact with one another. Conventional warning systems primarily identify hazards based on current or historical observations, whereas autonomous and decision-supported navigation increasingly requires anticipation of future vessel and environmental states. DTs can provide a virtual environment in which multi-source information is integrated with dynamic vessel and environmental models to support state estimation, risk assessment, trajectory prediction, and prospective navigation decisions.

Existing studies have addressed both vessel-state prediction and vessel–environment interaction. Qu et al. (2025) proposed a digital

twin-based method for predicting the navigation posture of unmanned surface vehicles using unscented Kalman filters, improving autonomous navigation reliability. Lee et al. (2022) introduced DTs to simulate sea waves and hydrodynamic performance, enabling real-time prediction of risks and optimal routes. These studies demonstrate a progression from real-time state monitoring towards predictive representations of vessel–environment interactions and anticipatory navigation support.

However, current validation remains limited relative to the complexity of real-world navigation. Existing studies often address specific vessel platforms or individual sources of uncertainty, whereas operational navigation requires simultaneous consideration of vessel dynamics, environmental disturbances, surrounding traffic, sensing uncertainty, and communication constraints. Moreover, prediction and simulation alone do not constitute fully interactive DT operation unless the resulting information is systematically incorporated into subsequent physical decision or control processes. Future research should therefore prioritise multi-vessel and multi-environment validation, uncertainty-aware prediction, and closed-loop integration with onboard or shore-based navigation decision-support systems.

Reported industrial developments also indicate movement towards operational application. For example, Totoheo Global has introduced a DT platform integrating vessel-specific operational information with fuel consumption, weather conditions, vessel draft, speed, and port information to support continuously updated voyage planning (SMI, 2025). These developments demonstrate emerging practical interest, although their evidence level should be distinguished from peer-reviewed full-scale validation.

5.6. Intelligent shipyard operations

Shipbuilding involves highly interdependent design, production, logistics, workforce, and resource-allocation processes. Coordination across workshops and construction stages is therefore challenging, particularly when production states and resource requirements change dynamically. DTs provide a means of constructing synchronised virtual representations of shipyard processes through which production sequences, resource utilisation, and operational scenarios can be monitored, simulated, and optimised before or during physical execution.

The reviewed studies indicate a gradual transition from the digitalisation of individual production tasks towards integrated representations of shipyard operations. Liland (2023) demonstrated the use of digital twin technology in improving operational management at Norwegian shipyards. Iwańkowicz and Rutkowski (2023) proposed a digital twin system for the entire ship design and production process, defining key areas for digitising actual processes and categorising planning, monitoring, and process analysis activities. These developments suggest that DTs are increasingly being considered not only as simulation tools for individual production activities but also as integration platforms for coordinating broader shipbuilding processes.

Despite this progress, the principal challenge lies in integrating heterogeneous production data and models across workshops, equipment, processes, and organisational systems. Evidence of fully integrated and continuously synchronised shipyard DTs remains limited, while interoperability, data consistency, computational scalability, and real-time coordination become increasingly difficult as system scope expands. Further research should therefore focus on standardised information models, interoperable production interfaces, cross-process synchronisation, and quantitative validation of productivity, safety, and operational benefits at shipyard scale.

Large-scale industrial initiatives illustrate the potential direction of development. Shanghai Waigaoqiao Shipbuilding's “Digital Twin Shipyard 1.0” platform integrates production layouts, three-dimensional workshop models, and operational dashboards to support functions including block-lifting simulation, dock-scheduling optimisation, workshop coordination, and safety monitoring (SWS, 2025). Such initiatives demonstrate the increasing scale of industrial DT implementation, although systematic and independently reported evidence remains necessary to establish broader transferability and performance benefits.

5.7. Cross-application synthesis

The comparative evidence in Table 4 reveals an uneven maturity landscape across the six application domains. Condition monitoring, equipment-level health assessment, and energy-performance monitoring have progressed comparatively further because they generally operate within relatively well-defined system boundaries and can exploit directly measurable physical and operational data. By contrast, lifecycle-wide design integration, closed-loop navigation support, and shipyard-scale coordination require substantially greater integration across heterogeneous models, data sources, physical systems, and organisational processes. This pattern is consistent with the system-hierarchy analysis in Section 4, where increasing integration scope is associated with greater challenges in synchronisation, interoperability, computational scalability, and operational validation.

A second cross-application pattern concerns the transition from DSs to fully interactive DTs. As illustrated by the representative evidence in Table 4, many existing applications remain centred on one-way monitoring, simulation, or prediction even when they are discussed within the broader DT literature. The field has therefore achieved substantial progress in virtual representation, state estimation, and predictive capability, but the transition towards reliable bidirectional interaction and closed-loop decision support remains incomplete. This distinction is particularly evident in energy management, condition monitoring, and navigation applications, where technically useful predictive capabilities do not necessarily imply direct integration with physical-system control or operational decision processes.

The validation evidence further indicates that demonstrated capabilities are frequently established for individual components, specific vessels, controlled environments, or application-specific datasets. Consequently, strong performance within a particular implementation does not necessarily establish transferability across vessel classes, environmental conditions, or operational contexts. This limitation becomes increasingly important as DT applications progress from component-level monitoring towards whole-vessel, ship–shore, and lifecycle-wide integration.

Overall, the application-level evidence suggests that the principal challenge in ship DT research is shifting from demonstrating isolated modelling and prediction functions towards establishing generalisability, interoperability, uncertainty robustness, cyber–physical synchronisation, and full-scale operational credibility. Addressing these challenges will be essential for transforming successful application-specific demonstrations into scalable and trustworthy DT ecosystems capable of supporting lifecycle-wide and fleet-level maritime operations. These evidence-derived limitations also provide the basis for the research directions discussed in the subsequent section.

6. Key challenges in the development and deployment of ship digital twins

Drawing on the insights derived from keyword clustering, co-occurrence networks, and temporal evolution analysis, this section synthesises the principal challenges that currently constrain the effective development, deployment, and scaling of ship DTs. These challenges are not isolated technical issues but are deeply interrelated, reflecting systemic barriers across technological, organisational, regulatory, and human dimensions.

6.1. Technical integration and the lack of standardisation

Ship digital twins constitute highly complex cyber-physical systems that integrate heterogeneous components, including onboard sensor

networks, real-time data acquisition systems, high-fidelity simulation models, IoT platforms, and AI algorithms. In practice, these components are often developed independently by different vendors using proprietary architectures, closed communication protocols, and incompatible data formats. A fundamental challenge arises from the coexistence of heterogeneous modelling paradigms within the ship digital twin domain. Physics-driven, data-driven, and physics-informed hybrid approaches each rely on distinct mathematical representations, modelling assumptions, and computational architectures, thereby making seamless integration across different digital twin frameworks inherently complex. Such fragmentation poses substantial barriers to interoperability, cross-platform integration, and lifecycle continuity of digital twin systems.

More critically, the absence of unified technical standards across the maritime sector severely constrains system reusability and scalability. Even well-validated twins cannot be reliably transferred across vessels or operational contexts without standardised data schemas and interface definitions. Without common data schemas, interface definitions, and model representation standards, digital twins tend to remain bespoke solutions tailored to individual vessels or operators. This not only inflates development and maintenance costs but also limits the diffusion of digital twin technologies across fleets and supply chains, undermining their potential for system-wide optimisation and resilience enhancement.

6.2. Cybersecurity risks and regulatory gaps

Ship digital twins rely on continuous, bidirectional data exchange between physical assets and their virtual counterparts, exposing them to cyber vulnerabilities throughout the entire data lifecycle. Unlike one-way DSs that primarily support monitoring and visualisation, true digital twins establish a bidirectional cyber–physical interaction loop in which optimisation strategies, control commands, or operational adjustments are continuously fed back to the physical vessel. While this closed-loop architecture is fundamental for advanced applications such as predictive maintenance, autonomous decision-making, and navigation safety, it simultaneously and substantially expands the cyber exposure surface of maritime systems. Onboard systems routinely handle sensitive information, including navigational trajectories, propulsion states, cargo conditions, and, in some cases, crew-related data. These data streams present attractive attack surfaces for malicious actors.

Compromised digital twins do not merely affect information integrity but may directly influence real-world ship operations through automated or semi-automated control loops. Manipulation of virtual models or decision-support outputs could therefore trigger hazardous operational outcomes, such as collision risks, grounding incidents, or propulsion failures. Despite the growing recognition of maritime cybersecurity risks, existing regulatory frameworks remain fragmented and largely reactive, offering limited guidance specific to digital twin architectures. This regulatory lag creates uncertainty regarding accountability, liability, and minimum security requirements for digital twins-enabled vessels.

6.3. Ethical concerns and limitations in human-centred design

Beyond technical performance, the deployment of ship digital twins raises important ethical and socio-technical considerations. Data-driven models embedded within digital twin systems are fundamentally influenced by the quality, representativeness, and inherent biases of the datasets used for training and calibration. This issue is particularly pronounced in black-box learning frameworks, where limited interpretability makes biased or erroneous predictions difficult to identify, trace, or correct. Consequently, incomplete or unbalanced datasets may lead to systematically distorted outputs, potentially affecting voyage routing, scheduling strategies, fuel optimisation, and emergency response decisions.

At the operational level, tensions may emerge when algorithmically generated recommendations conflict with crew experience, contextual judgement, or practical constraints that are insufficiently represented within the model. Such human–machine conflicts are especially critical in safety-sensitive scenarios, including navigation, collision avoidance, and shipyard coordination, where effective cooperation between operators and intelligent systems remains essential. In the absence of clearly defined accountability structures, such conflicts raise ethical questions regarding responsibility for decision outcomes, particularly in safety-critical situations. Limited transparency and explainability of complex AI-driven components further exacerbate trust deficits between human operators and automated systems, constraining effective human-machine collaboration.

6.4. Balancing prediction accuracy and real-time responsiveness

Achieving an effective balance between predictive accuracy and real-time responsiveness remains a central technical challenge in ship digital twin development, particularly under dynamic, uncertain maritime conditions. In practice, sensor data streams are frequently affected by noise, latency, missing values, and communication interruptions caused by harsh environmental conditions, equipment limitations, or unstable connectivity. These issues directly compromise the reliability of digital twin-enabled risk assessment and operational decision support.

The underlying trade-off is well recognised. Physics-based models provide strong physical consistency and interpretability but often suffer from prohibitive computational costs that limit real-time applicability. In contrast, data-driven approaches enable rapid inference and scalable deployment but may exhibit unstable behaviour or degraded robustness under rapidly changing operational conditions.

At the algorithmic level, many existing digital twin frameworks still struggle to effectively integrate heterogeneous multi-source and multi-scale data. Current approaches frequently prioritise isolated sensor streams while insufficiently incorporating broader contextual information, including traffic interactions, environmental dynamics, and operational intent. As a consequence, prediction systems may exhibit delayed responses, unstable outputs, or reduced reliability precisely in scenarios where timely and robust decision-making is most critical, such as collision avoidance, route adjustment, and emergency manoeuvring.

6.5. Digital transformation barriers in legacy maritime systems

A significant proportion of the global maritime fleet continues to rely on ageing hardware and legacy information infrastructures that were not originally designed for continuous data exchange, advanced analytics, or cyber–physical integration. Common limitations include outdated sensing equipment, incompatible communication protocols, closed-system architectures, fragmented data ownership, and restricted interoperability between onboard and shore-based systems. These structural constraints significantly increase both the technical complexity and economic cost associated with digital twin deployment.

The persistence of legacy infrastructure also explains why many existing validation studies remain confined to numerical simulations or semi-physical environments. Full-scale implementation and validation on operational vessels often require extensive retrofitting, system integration, and communication upgrades, making deployment financially and operationally challenging.

More broadly, establishing an end-to-end digital twin pipeline encompassing data acquisition, model construction, simulation, validation, and operational feedback remains particularly difficult within legacy maritime environments. Consequently, digital twin adoption continues to vary considerably across vessel classes, operators, and geographic regions, slowing the sector's broader digital transformation and reinforcing existing technological disparities within the maritime industry.

6.6. Limited generalisability in dynamic and unfamiliar environments

Ship digital twins are expected to operate across highly dynamic and continuously evolving operational environments characterised by changing sea states, traffic densities, cargo conditions, voyage profiles, and environmental uncertainties. However, many existing digital twin implementations remain heavily dependent on data-driven models trained primarily on historical operational datasets. Although such approaches often perform effectively within familiar operating conditions, their adaptability to rare events, abnormal situations, and previously unseen environments remains limited.

To address these limitations, increasing attention has been directed towards integrating physics-based simulation capabilities into digital twin architectures. Hybrid frameworks that combine physics-based simulations with learning-based models offer a promising pathway for improving robustness and extrapolation capability beyond observed data distributions. As highlighted in previous studies (Menges and Rasheed, 2024; Rasheed et al., 2020), simulation-driven components support "what-if" analyses, enable the generation of synthetic data for rare or safety-critical scenarios, and improve predictive reliability under data-sparse conditions.

By complementing purely data-driven learning with physically grounded system representations, physics-informed digital twin frameworks enhance generalisability, robustness, and transferability across different vessel types, operational profiles, routes, and geographic regions. Such capabilities are increasingly recognised as essential for ensuring the long-term operational reliability of ship digital twins in complex and unfamiliar maritime environments.

7. Strategic research directions for next-generation ship digital twins

The preceding analysis demonstrates that the future development of ship digital twins depends not merely on incremental improvements in modelling accuracy, but on the establishment of scalable, trustworthy, and interoperable maritime cyber–physical ecosystems. Current limitations increasingly arise from system-level fragmentation, insufficient operational robustness, cybersecurity exposure, and limited deployment scalability. Addressing these challenges requires coordinated advances across data infrastructure, modelling paradigms, operational architectures, and industrial integration strategies. Against this background, four strategic research directions are identified for the next generation of ship digital twins.

7.1. Towards interoperable and secure maritime digital twin ecosystems

Achieving scalable deployment of ship digital twins will depend fundamentally on interoperable maritime data infrastructures. Existing digital twin implementations remain highly fragmented due to heterogeneous data formats, proprietary software ecosystems, incompatible communication protocols, and inconsistent model representations across vessels, ports, and operational platforms. Consequently, future research should move beyond isolated digital twin applications towards unified cyber–physical ecosystems that support seamless interaction throughout the vessel lifecycle, spanning design, construction, operation, maintenance, and decommissioning.

In this context, interoperability must extend beyond simple data exchange to include semantic and functional consistency across sensing systems, simulation environments, and decision-support modules. Standardised ontologies, unified model representation frameworks, and open communication architectures will therefore become increasingly important for ensuring scalability and cross-platform compatibility. Closer collaboration among classification societies, regulatory agencies, technology providers, and maritime stakeholders will also be necessary to establish common industrial standards and governance mechanisms.

At the same time, the increasing integration of digital twins into operational and safety-critical decision-making substantially expands cybersecurity exposure. As digital twins evolve from passive monitoring systems towards bidirectional cyber–physical control architectures, cybersecurity can no longer be treated as an auxiliary technical layer. Instead, future digital twin frameworks will require security-by-design principles that integrate anomaly detection, intrusion monitoring, encrypted communication, and privacy-preserving analytics throughout the operational lifecycle. In parallel, regulatory and certification frameworks must evolve to clarify accountability, liability, and assurance requirements for digital twin-enabled maritime operations.

7.2. Hybrid intelligence and human-centred digital twin systems

Future ship digital twins are expected to increasingly converge towards hybrid intelligence frameworks that combine physics-based modelling with data-driven learning. This transition reflects the growing recognition that neither purely physics-driven nor purely data-driven approaches alone can fully satisfy the operational requirements of maritime digital twin systems. Hybrid architectures provide a pathway to balance predictive capability, physical consistency, interpretability, and robustness under uncertain or data-sparse conditions.

Beyond algorithmic integration, future digital twin development must also become increasingly human-centred. Current digital twin research remains heavily focused on technical optimisation, while comparatively limited attention has been devoted to operator interaction, cognitive workload, and decision transparency. In practice, however, effective maritime operation depends on close cooperation between human expertise and intelligent systems, particularly in safety-critical contexts such as navigation, collision avoidance, and emergency response.

Consequently, future digital twin systems should prioritise explainability, transparent decision logic, and actionable operational feedback rather than fully autonomous optimisation alone. Clarifying the boundaries between algorithmic recommendations and human judgement will be essential for improving trust, accountability, and operational acceptance. Expanding digital twin representations to incorporate organisational workflows, operational intent, crew behaviour, and regulatory constraints may further enhance the realism and practical relevance of maritime digital twin systems.

7.3. Real-time adaptive and resilient digital twin architectures

Ensuring reliable real-time performance under dynamic maritime conditions remains a central challenge for ship digital twins. Future development will therefore require a transition from static and centrally processed digital twin frameworks towards adaptive, distributed, and resilient operational architectures.

From a system perspective, edge and fog computing paradigms are likely to play an increasingly important role by enabling localised data processing, reducing communication latency, and improving operational resilience under unstable connectivity conditions. At the algorithmic level, advances in multimodal data fusion, adaptive weighting mechanisms, and context-aware learning will be necessary to improve the integration of heterogeneous operational data streams, including environmental conditions, vessel interactions, traffic dynamics, and onboard sensing information.

In parallel, future digital twins must become increasingly adaptive to evolving operational environments. Online learning, continual learning, and self-updating model architectures offer promising pathways for improving robustness under changing sea states, operational profiles, and abnormal scenarios. The integration of structured maritime knowledge, historical incident repositories, and simulation-enhanced learning environments may further strengthen early warning capability and operational reliability in safety-critical situations.

7.4. Scalable deployment across legacy and heterogeneous fleets

A major obstacle to industry-wide digital twin adoption remains the continued prevalence of legacy vessels equipped with ageing hardware, fragmented information infrastructures, and limited digital connectivity. As a result, scalable deployment strategies will be critical for ensuring that digital twin technologies can be implemented beyond newly designed smart vessels.

Future research should therefore prioritise modular and incremental deployment approaches that minimise disruption to existing ship operations. Lightweight digital twin architectures, plug-and-play communication interfaces, and standardised integration gateways may provide practical pathways for connecting legacy onboard systems with next-generation digital twin platforms without requiring extensive hardware replacement.

At the same time, improving model generalisability across heterogeneous operational conditions will remain essential. Many existing digital twin systems are trained primarily on narrow historical datasets and consequently exhibit limited transferability to unfamiliar environments, vessel classes, or operational scenarios. Future digital twin development will therefore increasingly depend on adaptive and transferable modelling strategies capable of operating across varying sea conditions, traffic densities, cargo configurations, and geographic regions.

Hybrid simulation-driven learning frameworks may play a particularly important role in this transition. By combining operational data with physics-based simulation and synthetic scenario generation, such approaches can improve robustness under rare, extreme, or safety-critical conditions that remain underrepresented in historical datasets. Ultimately, achieving scalable deployment across diverse maritime contexts will be essential for establishing ship digital twins as resilient and operationally dependable infrastructures for next-generation maritime systems.

Therefore, these strategic directions indicate that the evolution of ship digital twins is no longer driven solely by advances in sensing technologies or predictive algorithms. Rather, the field is progressively transitioning towards integrated maritime cyber–physical ecosystems characterised by interoperability, adaptive intelligence, human-centred operation, and lifecycle-scale coordination. Achieving this transition will be essential for enabling ship DTs to evolve from isolated experimental applications into scalable, trustworthy, and operationally resilient infrastructures for the future maritime industry.

8. Conclusions

This study presents a systematic review of ship digital twin research following the PRISMA 2020 framework, based on literature retrieved from the WoS and Scopus databases. CiteSpace-based bibliometric and scientometric analysis of 739 studies reveals a clear evolution of the field from modelling- and simulation-oriented research towards increasingly data-assisted, predictive, and application-oriented digital twin systems. The development of enabling technologies, particularly AI, machine learning, hybrid modelling, advanced sensing, and real-time data interaction, has progressively expanded the role of ship digital twins from virtual representation and condition assessment towards prediction, optimisation, and operational decision support.

To further examine this technological progression in greater depth, 214 empirical studies were analysed across three analytical dimensions: modelling methodologies, system hierarchy, and validation maturity. Three principal modelling paradigms, physics-driven, data-driven, and physics-informed hybrid approaches, were identified, each presenting different trade-offs among physical fidelity, computational efficiency, interpretability, data dependency, and adaptability. The reviewed evidence indicates growing interest in hybrid approaches that combine physical knowledge with data-driven learning to address some of the limitations of purely physics- or data-driven models. At the system level, digital twin implementations are also expanding from component- and subsystem-level applications towards whole-ship and fleet/ship–shore integration. However, increasing system scale introduces additional challenges related to model synchronisation, interoperability, computational scalability, communication, cybersecurity, and standardisation.

The analysis of validation maturity shows that technological development has progressed more rapidly than operational validation. Among the 214 empirical studies, 36.45% relied primarily on numerical validation and 16.82% employed semi-physical or laboratory-based validation, whereas only 15.42% reported full-scale empirical validation under operational maritime conditions. These results indicate that, although considerable progress has been achieved in model development and controlled validation, the transition from research prototypes to operationally validated digital twin systems remains limited. Moreover, full-scale evidence is frequently vessel-, component-, or scenario-specific, leaving further questions regarding the transferability and generalisability of reported performance across heterogeneous maritime operating conditions.

Across the six major application domains identified in this review, ship design and optimisation, condition monitoring, predictive maintenance, energy efficiency management, navigation safety, and intelligent shipyard operations, the reviewed studies demonstrate a growing range of technical capabilities. These include lifecycle-informed design modelling and optimisation, ship-specific condition and degradation assessment, predictive maintenance support, fuel-consumption and energy-performance prediction, anticipatory navigation support, and integrated planning and monitoring for shipyard operations. Collectively, these developments indicate a gradual progression from descriptive and monitoring-oriented functions towards predictive and decision-support capabilities. However, the comparative evidence also reveals uneven maturity across application domains. Many reported capabilities remain application-specific and dependent on customised models, datasets, or experimental settings, while evidence of their integration into broader operational processes remains comparatively limited.

An important finding emerging from the application-level analysis concerns the distinction between DSs and fully interactive digital twins. A substantial part of the existing literature demonstrates useful monitoring, simulation, diagnostic, or predictive functions through predominantly one-way physical-to-digital information flows, while reliable bidirectional interaction and closed-loop operational implementation are less widely demonstrated. Increasing predictive capability should therefore not necessarily be interpreted as equivalent to increasing digital twin maturity. Rather, the evidence suggests that further development requires stronger integration between modelling and prediction, physical–digital interaction, operational decision-making, and real-world validation.

Synthesising the evidence from the bibliometric, modelling, system-hierarchy, validation, and application analyses, six recurring challenges emerge: technical integration and standardisation, cybersecurity and regulatory gaps, human-centred and ethical considerations, the trade-off between predictive accuracy and real-time responsiveness, integration with legacy maritime systems, and limited generalisability under dynamic and unfamiliar operating conditions. These challenges are interconnected and indicate that the barriers to further ship digital twin development increasingly extend beyond the performance of individual models to the reliability, interoperability, governance, adaptability, and scalability of the wider cyber–physical system. In particular, the persistence of legacy infrastructure and heterogeneous onboard and shore-based systems continues to complicate full-scale implementation and validation. At the same time, reliance on historical operational data raises continuing concerns regarding model performance under rare, abnormal, and previously unseen conditions.

These challenges provide the evidence base for four strategic research directions for next-generation ship digital twins: (1) interoperable and secure maritime digital twin ecosystems; (2) hybrid

intelligence and human-centred digital twin systems; (3) real-time adaptive and resilient digital twin architectures; and (4) scalable deployment across legacy and heterogeneous fleets. Rather than representing independent research themes, these directions respond directly to recurring technical and deployment limitations identified across the reviewed literature. Future progress will therefore depend not only on improvements in individual predictive algorithms, but also on interoperable data and model infrastructures, secure physical–digital interaction, explainable and human-centred intelligence, adaptive modelling under changing operational conditions, and practical integration strategies for existing fleets. These priorities are consistent with the four strategic directions developed from the preceding challenge analysis in Section 7.

Overall, the findings indicate that ship digital twin research is progressing from isolated modelling and monitoring applications towards increasingly integrated, predictive, and decision-oriented systems. However, the transition from application-specific prototypes to mature and broadly deployable operational digital twin systems remains incomplete. The next stage of development is therefore likely to depend less on isolated improvements in modelling accuracy and more on the ability to integrate, validate, and scale digital twin capabilities across heterogeneous real-world maritime environments. By combining bibliometric and scientometric analysis with a systematic examination of modelling approaches, system hierarchy, validation maturity, application-level technical developments, and recurring deployment challenges, this review provides an evidence-based synthesis of how ship digital twin research has evolved, what technical capabilities have been demonstrated, where current implementations remain constrained, and which research priorities are most important for further development.

This review has several limitations. First, the literature search was limited to the WoS and Scopus databases; therefore, relevant studies indexed in other databases may not have been included. Second, although a PRISMA-based screening procedure was adopted, the classification of application scenarios and research categories necessarily involves some interpretative judgement. In particular, distinctions between digital shadows, hybrid digital systems, and bidirectional digital twins are not always consistently defined in the existing literature. Third, the assessment of validation maturity is based on the validation evidence reported in the reviewed publications and may not fully capture subsequent or unpublished industrial deployment. Finally, given the rapid development of maritime digitalisation technologies, recent industrial implementations may not yet be fully represented in the peer-reviewed academic literature. These limitations should be considered when interpreting the findings and proposed research directions.

CRediT authorship contribution statement

Huanhuan Li: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jincheng Gong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation. **Alan J. Murphy:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis. **Zaili Yang:** Writing – review & editing, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis.

Declaration of competing interest

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

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