



Article

Digital Twins in the Marine Industry

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Abstract: The ocean holds abundant resources, but the utilization of those resources for the marine economy presents a complex and dynamic industrial situation. Exploring sustainable development in this industry is of practical value, as it involves the rational use of marine resources while protecting the environment. This study provides an innovative review of the current application status of Digital Twins Technology (DTT) in various sectors of the marine industry, including the ship-building industry (SBI), Offshore Oil and Gas Industry, marine fishery, and marine energy industry. The findings reveal that DTT offers robust support for full life cycle management (LCM) in SBI, including digital design, intelligent processing, operation, and error management. Furthermore, this work delves into the challenges and prospects of DTT application in the marine industry, aiming to provide reference and direction for intelligent systems in the industry and guide the rational development and utilization of marine resources in the future.

Keywords: marine industry; Digital Twins; life cycle management; marine economy; sustainable development



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1. Introduction

The 21st century has witnessed an unprecedented economic boom, with sustained development in global economies. Among these, the marine economy has experienced remarkable growth, providing humanity with diverse resources such as food, minerals, shipping, and water [1,2]. However, this growth has also led to new challenges in the marine economic sector, including issues such as over-fishing. The expansion of urbanization and industrialization has further intensified pollution and limited the carrying capacity of marine waters, posing a threat to the self-regulation abilities of the marine ecological environment. Consequently, a series of social problems and regional conflicts over marine resources has emerged [3]. Therefore, there is an urgent practical need to strengthen the protection mechanism of the marine ecological environment while exploring and utilizing marine resources. In response to this, countries such as China, Japan, and Italy have formulated relevant strategies to enhance their marine power and develop their marine economy. Indeed, the rational and responsible development and utilization of marine resources can support the infrastructure of the marine economy, maintain the marine ecological environment, and promote sustainable development.

The utilization of advanced technologies such as the Internet of Things (IoT), deep learning, cloud computing, and artificial intelligence (AI) is increasingly expanding beyond traditional sectors and making its way into the marine industry. For instance, Ashraf (2021) [4] highlighted that IoT sensors positively impact the intelligent advancement of services in smart cities, including transportation, energy, infrastructure, health, agriculture, and entertainment. This facilitates the autonomous development of future smart cities. Among these technologies, Digital Twins Technology (DTT), which serves as digital mapping systems for critical and interconnected entities, has been widely adopted in various

domains such as product design, manufacturing, medical analysis, construction, and engineering [5,6]. The DTT enables the transfer of real-world physical information to virtual models, allowing for simulations, analysis, data accumulation, mining, and e-application. Consequently, the digital model contributes to enhancing the performance of the physical system [7]. In the marine industry, DTT plays a significant role in providing feedback from the operation and maintenance of marine industrial products and production lines, informing design decisions. As such, the application of DTT serves as a practical reference for the intelligent and digital transformation of the marine industry.

Under the trend of rapid development in the marine economy, the current situation, challenges, and prospects of the application of DTT in the marine industry have been discussed to achieve the purpose and motivation of rational exploitation of marine resources and environmental protection. This comprehensive review provides a novel perspective on the current state of DTT and its applications in various fields, including the ship-building industry (SBI), full life cycle management (LCM), Offshore Oil and Gas Industry (OOGI), marine fishery, and marine emerging energy industry. The challenges and prospects of implementing DTT in the marine industry are thoroughly discussed to serve as a valuable reference for fostering intelligent development and sustainable exploitation of marine resources by utilizing DTT.

The subsequent paragraph delineates the overarching structure of this review. Section 1 outlines the current development situation of the marine industry and the motivation for using DTT to it, as well as the novelty and organization of this review. Section 2 introduces the theoretical foundations of DTT and reviews the present state of DTT deployment in various industries. Section 3 examines the current application state of DTT in the marine industry, including ship-building and full life cycle monitoring, offshore oil industry, marine fisheries, and marine new energy business. Section 4 summarizes the research challenges of DTT in the marine industry by reviewing its current status and presents the research outlook of DTT in the marine industry. Section 5 elucidates the findings of this review, along with a summary of subsequent outlook-related content.

2. Overview of Digital Twins Theory

The concept of Digital Twins, which was initially formulated by the National Aeronautics and Space Administration following Grieves' proposal during a product PLM training exercise at the University of Michigan in 2003, involves the comprehensive utilization of physical models, sensor updates, and historical operational data to integrate multi-disciplinary, multi-physical, multi-scale, and multi-probabilistic simulation processes, thereby creating a virtual representation of the physical world. This technology has the potential to map out the entire life cycle process of specific physical equipment. For instance, Sahal et al. (2022) [8] utilized blockchain in conjunction with Digital Twins to develop a decentralized system for tracking epidemics and triggering alarms. Moreover, Sahal et al. (2021) [9] demonstrated the capabilities of Digital Twins in error identification and diagnosis by automatically detecting unstable operational data in manufacturing systems. Initially, DTT was employed primarily for predicting aircraft service life.

As depicted in Figure 1, the number of publications related to Digital Twins remained relatively stable from 2012 to 2017 but exhibited an exponential growth trend after 2017. This phenomenon has led scholars from various fields to focus on exploring the applications of DTT in diverse domains.

Over time, the scope of application of DTT has been expanded to encompass the entire life cycle, including the detection of mission requirements, prediction, and fault diagnosis in subsequent research efforts. The system architecture for the specific application of DTT is shown in Figure 2.

Figure 2 showcases various examples of how DTT is applied in the context of intelligent ships. As physical entities that exist objectively in space, intelligent ships can carry out specific tasks by leveraging data from the service system. This data encompasses the "human-ship-environment" interactions and is sensed, mapped, and transmitted syn-

chronously to the digital space. Subsequently, in the data processing step, the physical and digital world data are combined through cross-space fusion and undergo denoising, feature extraction, feature fusion, data conversion, and data reorganization. The resulting data are then applied to ship design, structural analysis, navigation, and management. The development of intelligent ships has progressed through stages of automation, digitalization, networking, and intelligence, culminating in the era of machine intelligence that enables the realization of these advanced vessels. Intelligent ships can perceive and access heterogeneous, multi-source, real-time data through the Digital Twins system and undergo fusion analysis. Ultimately, the interconnection and integration of the “people-ship-environment” elements are achieved.

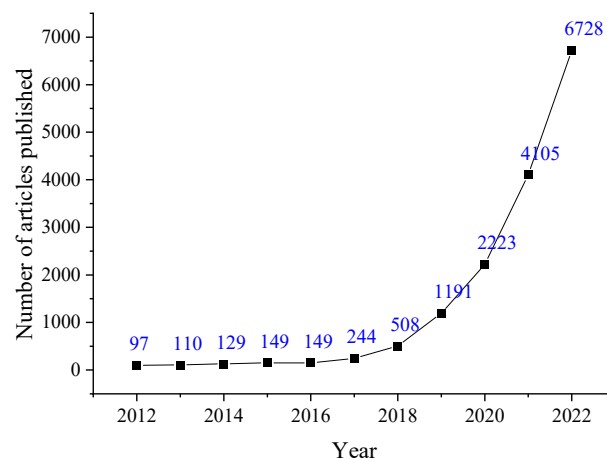


Figure 1. Graphical representation of the DTT -related literature publication trend from 2010 to 2022.

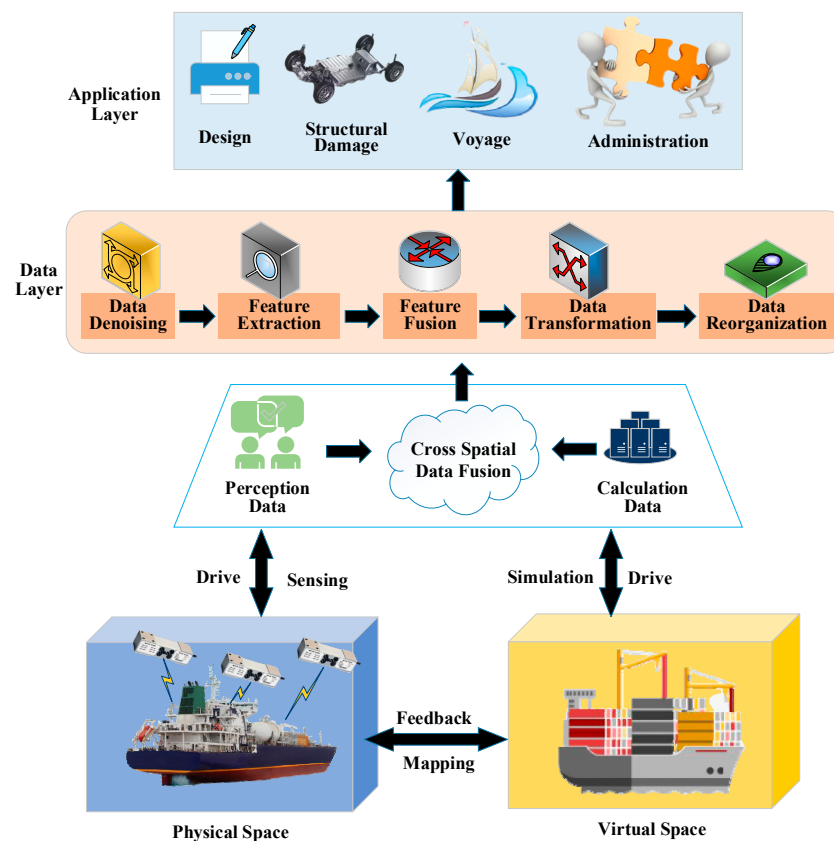


Figure 2. System architecture for specific application of DTT.

DTT has been studied and applied in various domains by different scholars. Sahal et al. (2021) [10] proposed a ledger-based collaborative Digital Twins framework that prioritizes real-time operational data analysis and distributed consensus algorithms, combining blockchain, predictive analytics techniques, and DTT. This framework has shown superior performance in intelligent logistics and predictive railroad maintenance. Kamel Boulos et al. (2021) [11] introduced application examples of DTT in personalized medicine, public health, and smart health cities. They discussed key technologies and challenges involved in such applications, including ethical issues arising from DTT-modeled humans. Wanasinghe et al. (2020) [12] reviewed the literature on distributed transmission in the context of the O&G industry. They found that DTT was applied mainly in asset integrity monitoring, project planning, and LCM in the O&G industry. Cybersecurity, sub-standardization, and uncertainty were identified as key challenges for the O&G industry in deploying distributed transmission. El Marai et al. (2020) [13] investigated and discussed the use of road Digital Twins System (DTS). They introduced recognition and tracking modules to identify objects and track video frames in which these objects appeared. The results showed that the road DTS created was effective and was a key component in intelligent mobility systems for autonomous vehicles. Wang et al. (2021) [14] explored the spatial structure and safety performance of Unmanned Aerial Vehicle (UAV) systems based on spatial Digital Twins. They fused DTT and Convolutional Neural Network (CNN) with the autonomous network of a UAV to construct the Digital Twins of the UAV data transmission system. Their findings showed that the constructed UAV-oriented DTS could significantly improve the safety performance of UAV airspace flight, providing an experimental reference for the later application of UAVs. Anshari et al. (2022) [15] conducted an evaluation of Digital Twins as a personalized intelligent financial advisor to support fintech services and management. The findings revealed that the robot financial advisory service, which was enabled by DTT, transcended temporary financial assistance and evolved into a user-centric, comprehensive, and dynamic financial advisory service. Chen et al. (2022) [16] proposed a novel approach by integrating blockchain and deep learning to build a Digital Twins model for managing the coronavirus disease 2019 (COVID-19) pandemic. The model, which was based on blockchain and Bi-directional Long Short-Term Memory, demonstrated exceptional network security performance and significantly improved information interaction efficiency and accuracy. This study provides empirical evidence for the growing trend of information security and epidemic prevention and control in smart cities. Mortlock et al. (2021) [17] defined the concept of cognitive DTS as the next stage of development for Digital Twins. They proposed a novel method to implement cognitive DTS during the design stage of manufacturing products, utilizing graph learning techniques. The results showed that cognitive DTS empowered enterprises to creatively, effectively, and efficiently leverage tacit knowledge extracted from existing manufacturing systems. This led to improved autonomy in decision-making and control, ultimately enhancing the overall performance of the enterprise on a large scale. Kaarlela et al. (2022) [18] presented a cutting-edge distance education support platform for robotics, which was supported by Industry 5.0, that enabled remote usage and learning of robots. The platform facilitated seamless two-way data transfer between physical and digital counterparts, leveraging DTT. The study demonstrated that the proposed system enabled remote operation, remote programming, real-time monitoring of controlled robots, and social interaction between robots and users. Table 1 summarizes the diverse application fields of DTT. Sahal et al. (2022) [19] highlighted the potential of DTT in improving personalized healthcare in various areas, including COVID-19 infection prevention and treatment, COVID-19 survivor care, COVID-19 medication development, osteoporosis prevention, cancer survivor care, and nutrition.

The findings of the aforementioned scholars indicate that DTT has been extensively utilized in various fields, including O&G transportation, communication, UAV, and industrial manufacturing, making it applicable throughout the entire production life cycle.

Moreover, DTT exhibits distinctive characteristics when implemented in different domains. Firstly, it entails real-time mapping, necessitating a high level of synchronization and fidelity between the physical and virtual spaces in the Digital Twins [20]. Secondly, it involves interaction and convergence, as a Digital Twin System (DTS) integrates the entire process, elements, and business, allowing for interconnected data in the physical space and facilitating real-time and historical data interactions [21]. Thirdly, it demonstrates self-evolution, whereby the DTS can update data in real-time and continuously adjust the virtual model by comparing it with the physical space data, thus enhancing physical systems [22].

Table 1. Summary of the application fields of DTT.

Scholars	Technology/Algorithm	Application Fields	Role/Achievements
Sahal et al. (2021) [10]	DTT and blockchain	Logistics	Real-time logistics forecasting and railroad pre-maintenance.
Kamel Boulos et al. (2021) [11]	Digital twinning	Urban public health	Ability to promote the development process of the new era of medicine and smart city public health
Wanasinghe et al. (2020) [12]	DTT	O&G transportation	Monitoring, planning, and LCM of O&G transportation.
El Marai et al. (2020) [13]	DTT	Communication	Road DTT became the key component of the intelligent movement of autonomous vehicles.
Wang et al. (2021) [14]	DTT and CNN	UAV	The safety performance of UAV airspace flight based on DTS was obviously superior to the existing system.
Anshari et al. (2022) [15]	DTT	Finance	It can be used as a personalized intelligent financial advisory system to support fintech services and management.
Chen et al. (2022) [16]	Blockchain, DTT, and deep learning	Intelligent medical treatment	Provide strong support for information security and epidemic prevention and control of medical systems in smart cities.
Mortlock et al. (2021) [17]	DTT	Manufacturing industry	Realizes more independent decision-making and control of the production line.
Kaarlela et al. (2022) [18]	DTT	Education	Allows for remote operation, remote programming, and real-time monitoring of controlled robots to enable social interaction between users.
Sahal et al. (2022) [19]	DTT	Medical care	Personalized care, personalized osteoporosis prevention, personalized cancer survivor follow-up care, and personalized nutrition.

3. Application Status of Digital Twins in the Marine Industry

The marine economy is a multi-faceted realm that encompasses the exploitation, utilization, and conservation of marine resources and spaces, giving rise to various ocean-related industries such as marine fisheries (including marine fishing and mariculture), saltwater production and salinization, OOGI, marine transportation (including ports and shipping), coastal mining, and shipping, as well as other material production-related sectors such as coastal tourism and seabed storage [23]. In addition, it encompasses seawater desalination, comprehensive utilization of seawater, marine energy development, marine drug utilization, marine space utilization, deep-sea mining, marine engineering, comprehensive marine science and technology education services, marine information services, and environmental protection [24]. Thus, the marine industry serves as the cornerstone and driving force of the marine economy, comprising a collection of economic activities with similar attributes, and serving as a prerequisite for the existence and growth of the marine

economy. In recent times, DTT has found applications in the marine industry, including ship manufacturing, LCM, OOGI, and marine resource development (Figure 3), facilitating intelligent industry development while safeguarding the marine environment [25–27].

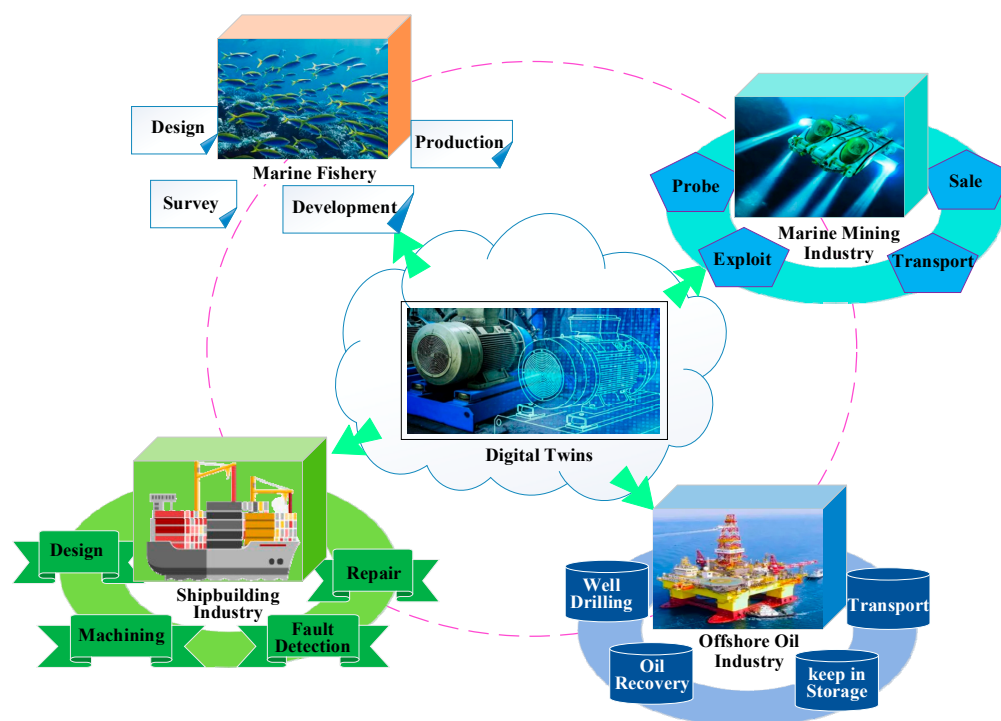


Figure 3. Schematic diagram of DTT applied to the marine industry.

This review examines the current state of DTT applications in various sectors, including the SBI, LCM, the OOGI, marine fishery, and the emerging marine energy industry. A comprehensive evaluation of these applications can highlight the significance of DTT in promoting the sustainable and rational exploitation and development of marine resources.

3.1. Application Status of DTT in SBI and Full LCM

In the SBI, the assembly, design, processing, and manufacturing stages are crucial for ensuring safe and efficient navigation at sea. Similarly, accurate early warnings and prompt equipment maintenance are essential for improving the efficient utilization of ship equipment and optimizing the overall LCM [28,29]. In recent times, DTT has rendered significant strides in its application to the entire LCM process of equipment in the SBI. This advancement is expected to provide robust support for digital design, intelligent processing, smart operation, fault prediction, and equipment maintenance in the marine industry.

3.1.1. Application Status of DTT in the Product Design Stage of SBI

The initial step in ship production is the design phase, which has become increasingly complex with the advent of advanced ship equipment and platforms. Traditional design methods often struggle to adapt to these new requirements. However, the integration of DTT in intelligent ship design has proven to be effective in addressing various challenges, such as lengthy design cycles and high costs associated with the final application [30]. Several researchers have explored the application of DTT in ship design. Arrichiello and Gualeni et al. (2020) [31] argue that DTT offers a comprehensive view of the cruise system and holds potential for applications in the SBI. Xiao et al. (2022) [32] proposed a vertical–horizontal design approach that combines historical experience (vertical) with real-time data (horizontal) to model and optimize Digital Twins at each stage of the life cycle of a ship. Based on this approach, they developed a framework for Digital Twins

in the entire LCM of ships, elucidating the operational mechanism from the four stages of design, construction, operation and maintenance, and scrapping and recycling. Their findings provide valuable insights for the future transformation and upgrading of the SBI. Fonseca and Gaspar (2021) [33] applied DTT in ship design by introducing it into relevant dimensions of product data modeling to standardize ship data. The Digital Twins environment proved capable of meeting the requirements of data modeling and ship design, and the experience and lessons learned from ship design were extracted to form an open standardization of Digital Twins data to aid digital drawing in ship design. Wang et al. (2022) [34] focused on the characteristic scenario and key parameter design of ship engines and freight container operation. They established a ship-design-oriented DTS based on Maya and Unity 3D platforms and integrated a Bayesian Neural Network into the virtual model layer and data support layer of the DTS to handle the fusion of multi-source ship operation data. The collected data could then be extracted and aggregated, with the working temperature selected as the key parameter for ship design. Verification experiments showed that the DTS demonstrated acceptable performance under different conditions, with the optimal Mean Percentage Deviation (MPD) between prediction and test values of DTS at 3.18% and the best MPD at 5.22%.

In summary, the analysis conducted by the aforementioned scholars indicates that there is limited research on the utilization of DTT in ship design, with most studies focusing on process planning, refinement, and verification. The application of function and performance models is still in the exploratory stage. Furthermore, DTT does not fully encompass all aspects of the design process, such as structural layout, main dimensions, and performance parameter simulation. There are minimal digital enhancements in identifying equipment, pipe system, and structural collisions, and there have been no attempts to address unreasonable or incorrect designs, particularly for relatively independent systems such as power units and rudder propeller systems. However, by leveraging the visual advantages of Digital Twins, there is potential to develop a platform that enables designers to intuitively reflect on design status and problem-solving, which can serve as a direction for the future application of DTT in ship design.

3.1.2. Application Status of DTT in Ship-Building Manufacturing

The conventional vessel manufacturing system relies on a manufacturing execution system to collect real-time production data and monitor production parameters such as progress, quality, and workload. However, handling exceptions or errors often requires manual supervision and reconfiguration, resulting in reduced efficiency, especially in cases in which high processing accuracy is required, such as in steam turbine units. Even a minor defect during processing can lead to scrapping of the entire part, which imposes stringent requirements on the entire processing and assembly process [35,36]. In contrast, when DTT is applied to ship-building manufacturing, it enables the mapping of physical space data to virtual space in real-time, facilitating effective management of workshop or factory production resources. This results in improved production efficiency, product quality, and reduced production costs [37]. Numerous scholars have explored the application of DTT in ship-building. For example, Wu et al. (2021) [38] reviewed DTT in intelligent manufacturing and proposed an innovative system framework for intelligent ship manufacturing enabled by DTT. The framework that comprised multiple layers, including physical, model, data, system, and application layers, and the operational mechanism were explained. They also analyzed the design, twin modeling structure, application process, and implementation of the pipeline processing production line in the ship-building intelligent manufacturing system to provide a reference for the SBI [38]. Pan et al. (2021) [39] investigated the production logistics system of industrial parks and analyzed the operation mode, dynamic perception, and synchronization management and control between different stages in a dynamic environment. They proposed a decision information architecture driven by DTT, which included a real-time dynamic synchronization control mechanism to synchronize the production logistics

system throughout the transportation phase. The feasibility and effectiveness of the proposed method under dynamic interference were verified through a case analysis. Pang et al. (2021) [40] developed a novel framework that combined Digital Twins and Digital Threads for enhanced data management, promoting innovation, and improving production processes and performance while ensuring continuity and traceability of information. The framework integrated behavioral simulation and physical control components. The results showed that the components relied on the connection between Digital Twins and threads to facilitate information flow and exchange, thus promoting innovation. This research found that the developed framework optimized the operation process and information traceability in the physical world, particularly in the context of industrial shipyard 4.0.

Chen et al. (2022) [41] developed a machine tool model utilizing DTT to investigate the energy consumption of computer numerical control (CNC) machine tools during milling. The Genetic Algorithm (GA) and the Simulated Annealing Algorithm (SAA) were combined to optimize the cutting tool path, resulting in a highly optimized solution. The findings revealed that the optimized milling parameters minimized the expected milling power, and the GA-improved SAA significantly reduced blank cuttings through projection machining and spiral machining. Moreover, the optimization algorithm enhanced processing efficiency and reduced energy consumption. Lv et al. (2022) [42] proposed an equipment fault recognition and elimination model based on Active Learning–Deep Neural Networks (AL-DNNs) and Domain-Adaptive Neural Networks (DANNs), which were aided by the Digital Twins model for intelligent manufacturing and management of the workshop. The results demonstrated that the precision of AL-DNNs surpassed 99.248%, and the DANN exhibited the ability to identify and diagnose faults under varying working conditions. The performance of the deep learning algorithms was improved by 20.256%, resulting in more stable outcomes. Therefore, the integration of DTT empowered the equipment fault diagnosis and status prediction with scientific and effective reference data for the intelligent manufacturing field. Liu et al. (2023) [43] proposed a blockchain-based point-to-point data exchange mechanism for industrial Digital Twins to address bandwidth competition and access delay challenges of enterprise DTS to manufacturing cloud centers. The findings indicated that blockchain-enabled DTS facilitated effective and secure data exchange, reduced dependence on enterprise cloud, and enhanced workshop flexibility. The research work verified the effectiveness of the Digital Twins method in intelligent manufacturing. Yan et al. (2022) [44] presented an improved Digital-Twins-driven production line model that enabled simultaneous control of the physical entity and digital entity. The model accelerated the design flow of the production line through virtual–real linkage. An example of a smartphone assembly line was provided to demonstrate the effectiveness of the improved model in diversifying production line design schemes and improving production efficiency. Zhao et al. (2022) [45] focused on the assembly process of a specific type of mobile phone assembly and combined the production process with the heuristic balance method to classify workstations and reallocate working hours. An optimized hybrid workshop design model was established and verified by using the semi-physical simulation technology of Digital Twins. The proposed scheme successfully balanced and optimized the production line, improving efficiency and reducing costs. The conclusion offered a technical solution for designing and optimizing large-scale mobile phone assembly workshops, enabling multi-batch production and dynamic flow adjustments based on customer orders.

The findings and analyses of the aforementioned scholars indicate that current research on DTT is focused primarily on implementing Digital Twins in local production lines for numerically-controlled cutting and pipe system processing. However, with further advancements and applications, DTT has the potential to establish a visual control system that incorporates real-time video monitoring and sensor feedback. This system would enable timely tracking and monitoring of the entire production flow, quality, and

capacity [46]. Furthermore, in the SBI, Digital Twins can be utilized to visualize the structure, equipment layout, assembly flow, and specification requirements through 3D simulations, images, and other visualization methods on handheld terminal display equipment. This would support on-site technicians in carrying out their tasks effectively. Figure 4 illustrates the proposed DTS architecture in the context of an automated ship production line.

According to Figure 4, the automated ship production line is a sophisticated electromechanical integration system that encompasses various technologies. It is characterized by a comprehensive and systematic paradigm. A DTS for an automatic production line typically consists of three components: a virtual and real interaction layer, a twin-data layer, and an application and service layer. These layers are interconnected to enable information exchange. The physical entity layer, which includes CNC machining centers, industrial robots, production and quality detection equipment, transmission devices, programmable logic controllers, staff, and other components, serves as the collection of all physical entities in the automated production line for product manufacturing. This layer also includes industrial computers, sensor data acquisition cards, radio frequency identification readers, and other functional components [47]. These physical elements work in close coordination and co-operation to carry out product processing, assembly, and transportation based on instructions from the controller. On-device sensors collect relevant manufacturing data to monitor and analyze equipment status. The virtual model layer is a digital representation of the physical entity layer in the information space, visualizing equipment data related to geometry, physics, rules, and behavior through complex digital modeling by using data collected from various sources. In comparison, the twin data layer stores and analyzes data from the physical entity layer, virtual model layer, application services layer, and fused data in product manufacturing. During vessel manufacturing, the twin data layer is continuously updated and mined in real-time to provide comprehensive and accurate information for the DTS. The application service layer interacts directly with users. Thanks to the DTS, the automated production line is mapped in real-time to the information space. The virtual model can monitor the manufacturing process, and the massive twin data can simultaneously realize fault warnings, optimization decision-making, and other services during manufacturing. Ultimately, users are presented with an accurate and intuitive representation of ship design and manufacturing, along with solutions for intelligent health monitoring in ship manufacturing and processing [48–50].

Moreover, the application of DTT can be employed to model the ship manufacturing and automation production line. This modeling process encompasses various aspects including entity modeling, virtual modeling of Digital Twins, and association modeling through mapping. Entity modeling pertains to the representation of elements involved in production activities, such as production line equipment, products in process, and staff. During this stage, the production environment significantly influences the product manufacturing process. In light of these factors, this section utilizes a formal modeling language to encode the key elements in the manufacturing process of the production line. The model is defined according to Equation (1).

$$PS = PE \triangleleft PP \triangleleft PW \quad (1)$$

In Equation (1), *PS* refers to the physical space of the key elements of the production line manufacturing process; *PE* is the collection of the production line equipment in physical space; *PP* represents the collection of the products under production in the physical space; *PW* signifies the collection of the staff in physical space; \triangleleft denotes the natural connection (interaction) between *PE*, *PP*, and *PW*. These three sets are all dynamic, and the set elements and their states are constantly updated with the dynamic operation of the manufacturing process of the production line.

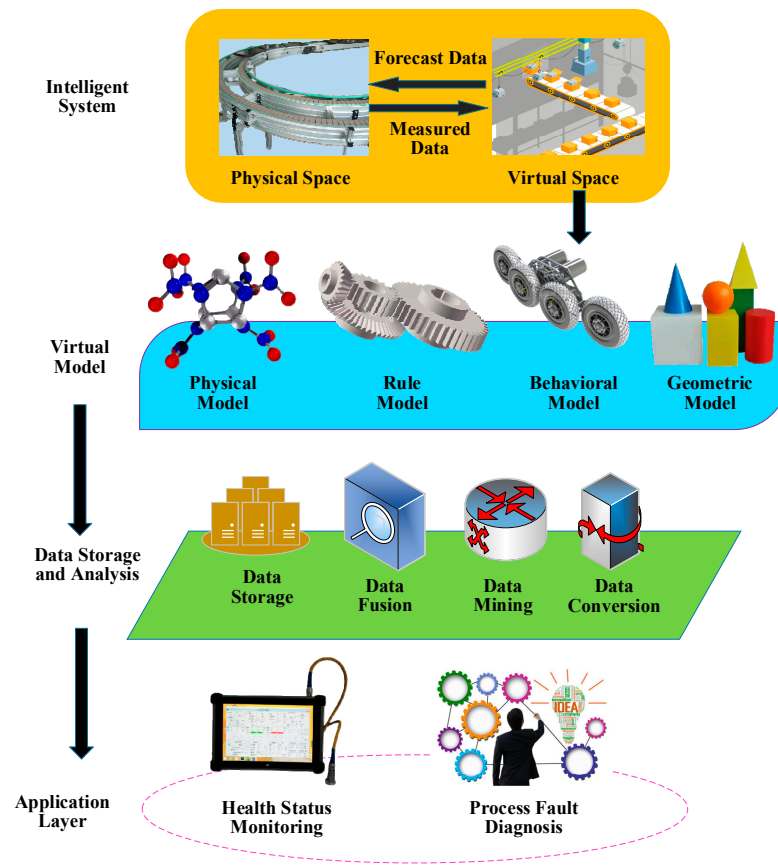


Figure 4. Manufacturing system architecture of a DTT-based automatic ship production line.

Digital Twins models necessitate a high level of modularity, scalability, and dynamic adaptability and can be effectively constructed in the information space through parametric modeling techniques. Specialized software tools, such as Tecnomatrix, Demo3D, and Visual Components, facilitate the creation of virtual models that define the geometric characteristics and topological relationships of the automated production line. Moreover, the model encompasses comprehensive dynamic engineering information and detailed descriptions of individual physical objects. The parameterized multi-dimensional attributes of the model enable real-time mapping of the automated production line. Further definitions within the Digital Twins model are presented in Equation (2).

$$CS = DE \triangleleft DP \triangleleft DW \quad (2)$$

In Equation (2), CS refers to the information space of the key elements of the production line manufacturing process; DE stands for the collection of the Digital Twins models of the production line equipment in information space; DP denotes the collection of the Digital Twins models of the products under production in the information space; DW denotes the collection of the Digital Twins models of the staff in information space; \triangleleft represents the natural connection (interaction) between DE , DP , and DW . These three sets are dynamic. The set elements and their states in information space are updated synchronously with the dynamic operations of the manufacturing process in physical space.

Finally, the virtual \rightleftharpoons real mapping relationship is modeled. On the basis of implementing physical space entity model PS and information space twin model CS , the virtual \rightleftharpoons real mapping relationship is further established, and formal modeling language is used to model their virtual \rightleftharpoons real mapping relationship. The precise delineation of the model is as follows:

$$PS \overset{1:1}{\rightleftharpoons} CS \quad (3)$$

In Equation (3), $\overset{1:1}{\rightleftarrows}$ refers to the two-way real mapping between the physical space entity model and the information space twin model. The symbol \triangleleft represents the natural connection (interaction) between different models. The synchronization of physical equipment (*PE*) and twin equipment (*DE*), physical product (*PP*) and twin product (*DP*), and physical personnel (*PW*) and twin personnel (*DW*) is imperative based on the mapping relationship. Consequently, the intelligent health monitoring of processing equipment and the representation of product surface quality information are synchronized in the information space. This virtual and synchronous representation facilitates dynamic adjustments to the operation of the automatic production line in the physical space, ultimately achieving the modeling objective.

3.1.3. Application Status of Digital Twins in Ship Operation

The operation of ships is fraught with challenges due to the unpredictable marine environment, the complex technologies required to manage the operating system of the ship, and the need for efficient staff coordination. In particular, large vessels require coordination among multiple systems for navigation and maneuvering, as the overall system scheduling lacks a unified digital control. Introducing DTT in ship operation and navigation systems has the potential to greatly enhance safety and reliability by enabling real-time monitoring of the overall status of the ship and the prediction of faults based on historical data [51]. The academic community has made significant contributions to the application of DTT in the realm of ship equipment products. For instance, Lee et al. (2020) [52] proposed a real-time DTS for offshore ship operations. The proposed DTS could predict risks related to seakeeping and maneuverability by analyzing wave and hydrodynamic performance data for real-time route optimization. The system utilized a complex algorithm for wave reconstruction by using measured wave radar images, successfully predicting the future evolution of the three-dimensional wave field in front of the ship. This research was of great significance in predicting risks and the performance of ships in various marine environments. Similarly, Assani et al. (2022) [53] posited that the Digital Twins of that ship, which are digital records or software clones of ship behavior, could be leveraged for simulations that would have been very difficult or expensive to carry out in real life. Their findings revealed that DTT could reduce costs, provide early warnings, optimize the performance of individual ship systems or the overall ship operation, and assist in ship management. Furthermore, Van der Horn et al. (2022) [54] introduced a Digital Twins model for monitoring and predicting fatigue and damage in active ships, based on the comparison between actual ship-specific operation and the operation that was expected during the design phase of the ship. The Digital Twins were updated by using sensor-obtained data, and the proposed method was compared with fatigue estimates that were obtained from design references regarding wave conditions. The researchers noted that the Digital Twins model could accurately predict the remaining service life of the ship, providing valuable insights for ship inspection, maintenance planning, and operational decision-making.

In addition to the above literature, there have been several studies examining the use of DTT in complex equipment operations. Ren et al. (2022) [55] integrated Machine Learning modules into Digital Twins to design a comprehensive equipment-centric DTS that explores the collective application of sub-models and Machine Learning. They also proposed the feasibility of their management method with an example from predictive maintenance of diesel locomotives, showcasing the potential of combining DTT with Machine Learning. Zhang et al. (2022) [56] presented a Rapid Construction Method of Equipment Model (RCMEM) for discrete manufacturing in workshop-oriented DTS. The designed RCMEM aims to assist complex manufacturing and business scenarios, improving the efficiency and quality of device-level Digital Twins model construction, and forming an efficient equipment-centric digital modeling approach. The results demonstrated the reuse of Data Transfer Object (DTO) functions in Digital Twins models, promising high scalability, reusability, and quality. Furthermore, a Rapid Mounting and Communication Configuration Mechanism (RMCCM)

was introduced to achieve fast DTO network communication, enhancing interoperability in multi-source data environments. The experimental findings reflected the effectiveness of the proposed model in complex business environments. Barni et al. (2020) [57] utilized DTT to model and analyze operating system failures in industrial woodworking workshops. Their findings revealed that the high variability in cycle time prevented the joinery from reaching its production goal. However, Digital Twins combined with an optimization strategy could compensate for the performance loss caused by variable cycle time. Cheng et al. (2022) [58] presented a semi-physical simulation method driven by DTT to evaluate industrial software. The reliability and robustness of the proposed DTS were verified through the semi-physical simulation of a stepping motor production line, significantly reducing the test and verification time of industrial software. Their findings provided inspiration for fault prediction and prevention research. Kousi et al. (2021) [59] discussed a design and re-design method for a flexible assembly system based on DTT and examined the advantages of the approach through a case study in the automobile industry. Alves de Araujo Junior et al. (2021) [60] developed a water-cooled Digital Twins model with auxiliary equipment by using an automatic extraction algorithm of fuzzy logical rules. The proposed model determined the optimal number of fans based on operator decisions. The results demonstrated that the Digital Twins model could adapt to varying conditions, maintain steady-state operation, and handle start and stop slope and instability, showcasing its robustness.

Recent studies have highlighted the significant advantages of applying DTT to monitor the operational status of ships and optimize transportation efficiency, maintenance schedules, and personnel management. Ships operating in the ocean for extended periods exhibit multiple characteristics that can be harnessed for optimization. Scholars have observed and verified that DTT can enhance the safety performance of the ships and improve the return on investment for ship owners. Currently, the application of DTT in the operational stage of ships involves primarily real-time monitoring of equipment operation, working conditions, and virtual restoration through on-site image acquisition and equipment data acquisition. The DTS displays comprehensive information on the overall status of the offshore platform, production activities, personnel conditions, and surrounding environment by using videos, images, data, and tables. This allows offshore platform and remote headquarters management personnel to grasp relevant information and effectively manage production activities in different locations, thereby enhancing efficiency and involvement through strengthened team management, improved technology, and diversified methods [61–63]. Furthermore, the processed and packaged data are sent to the shipyard for secondary development and utilization, providing valuable insights for ship design and construction optimization, along with suggestions and strategies. The feedback loop between the Digital Twins model and actual operation data facilitates continuous fine-tuning and improvement of the model, ensuring its accuracy and effectiveness in optimizing ship operations.

3.1.4. Application Status of DTT in Ship Inspection and Maintenance

In the realm of ship operations, fault detection and maintenance play a pivotal role in ensuring smooth and efficient functioning. Regular routine maintenance is essential for ships to operate at their optimal level. The emergence of DTT has revolutionized fault simulation and prediction, enabling real-time monitoring of the health status of a ship, identification of key maintenance points, and proactive fault prediction and repair. In the unfortunate event of a ship failure, the crew can analyze the impact of the failure on the virtual twin model and devise a proposed maintenance plan by leveraging relevant data from reliable sources [64,65]. Numerous scholars have delved into the application of DTT in ship fault detection and maintenance. Li et al. (2021) [66] pioneered the deployment of a Digital-Twins-driven Virtual Sensor (DTDVS) structure to construct a secure trailing suction hopper dredger. Four distinct Machine Learning algorithms were utilized to independently predict torsional vibration in mechanical failure, and their performance was assessed by calculating the potential intrinsic relationship between construction data. The findings

revealed that different Machine Learning algorithms exhibited varying levels of prediction accuracy, with the Deep Belief Network (DBN) model surpassing other comparison models. Consequently, DBN was chosen as an integral part of the virtual sensor to forecast and analyze the state of the trailing suction dredger. The experimental results indicated that DTT offered a more stable and environmentally friendly approach to construction safety control in trailing suction dredgers. On one hand, DTDVS facilitated enhanced monitoring of construction state through physical sensors, increasing sensor sensitivity while reducing sensing costs. On the other hand, building behavior was diagnosed by analyzing the residuals between physical and virtual sensors, enabling accurate prediction of fault conditions. This research has significantly improved time utilization in trailing suction dredgers and provided a vital guarantee for construction safety.

In addition, the utilization of DTT in fault detection and maintenance has been explored in various domains of complex products and equipment. For instance, Xiong et al. (2021) [67] investigated a predictive maintenance framework for an aero-engine by using the Implicit Digital Twins model. The validity and consistency of the model were verified through virtual and real data assets, and a data-driven Long Short-Term Memory model was integrated with deep learning techniques. The effectiveness of the fusion method was demonstrated through an example of an aero-engine, achieving high prediction accuracy with 80% training data. Specifically, the root mean square error of aero-engine prediction was 13.12, surpassing other experimental approaches. Furthermore, Guo et al. (2021) [68] enhanced the Random Forest (RF) algorithm by employing hierarchical clustering of decision trees to filter high-accuracy and low-deviation ones and then utilized the improved RF for fault diagnosis in physical production lines with the aid of DTT. The feasibility of the RF algorithm improved by DTT was verified in the rear axle assembly line of a car factory, achieving an accuracy of 97.8% at the end of the experiment. In another study, Jiang et al. (2022) [69] described a Digital Twins channel approach that utilized online map data to check the clearance of underpasses in highway widening projects, providing an economic and efficient method for clearance verification. The result analysis suggested that DTT could be fully leveraged in future research for assisting with road widening and other applications related to overpasses, bridges, tunnels, and traffic safety infrastructure. Additionally, Xu et al. (2020) [70] developed an Internet of Vehicles (IoV)-oriented deep reinforcement learning method for offloading the authorization service of Digital Twins for IoV in Edge Computing. Comparative analysis demonstrated that the Service Offloading approach was effective and adaptable to different environments. Moreover, Lv et al. (2022) [71] established a traffic accident prevention and prediction system based on DTT and AI. The proposed method integrated target tracking algorithms with Digital Twins as a video analysis system for road traffic accidents of motor vehicles. The research findings indicated that the proposed system could effectively improve traffic processing efficiency, ensure accuracy and fairness, and provide valuable data support for the application of DTT in intelligent transportation.

Hence, the utilization of DTT in ship maintenance focuses primarily on fault prediction and health management. Ships operating in harsh environments that are characterized by high humidity, salinity, and strong corrosion are susceptible to defects, mis-operations, and external factors that can lead to failures, posing risks to the crew's safety and property. To mitigate such risks, it is imperative to develop a scientific and rational maintenance plan, establish a parts replacement cycle, and proactively address issues before faults occur. Additionally, real-time monitoring can enable swift emergency response upon any ship failure, including system shutdown, emergency firefighting, and timely release of life-saving equipment, to minimize losses and prevent further damages. The ship maintenance process should also entail a thorough analysis of fault causes based on available data, remediation of defects, and reinforcement of relevant systems [72–74]. As depicted in Figure 5, DTT is applied throughout the entire lifecycle of the maritime industry.

Figure 5 illustrates how DTT can contribute to various phases of the life cycle of a ship, including the design phase, production phase, operating phase, and maintenance

optimization phase. In the ship design phase, DTT can significantly shorten the product design cycle, especially for large ship equipment or platforms with lengthy design cycles and high costs. By mapping design data from the physical space to virtual space and continuously adjusting ship parameters, DTT enables efficient ship product design. During the manufacturing and processing stage of ships, DTT can be employed in the parts processing line to generate a virtual production line. This line can provide instructions and guide the physical production processes, such as storage, cutting, grinding, labeling, engraving, grouping, and welding of smart ship products. This application of production lines facilitates automated and streamlined manufacturing processes. In the operational phase of a ship, DTT enables real-time monitoring of all systems, instant status updates, and historical data for navigation assistance and defect prediction. The information collected from the operation of the ship can be fed into the Digital Twins model for construction and design, providing valuable real-world operational data for both domains. This data can be utilized to generate optimization recommendations for future ship design and fault reduction, thereby enhancing the performance and safety of the ship. Furthermore, DTT can establish a visual remote monitoring model for optimizing ship equipment maintenance. By analyzing real-time parameters from equipment sensors or control systems, this model can review the status of the equipment, issue timely warnings if necessary, and recommend appropriate maintenance procedures. This holistic approach of integrating and interpreting physical knowledge and data measurements for detection tasks, instead of relying solely on sensor data, renders DTT a comprehensive and effective method for maintenance optimization. Moreover, DTT can simulate typical failure modes and mechanisms, aiding in the analysis of underlying causes and the prediction of degradation progress. This capability enhances the understanding of ship equipment performance and helps in proactive maintenance planning. In summary, DTT offers a powerful solution for various phases of the life cycle of a ship, ranging from design and manufacturing to operation and maintenance. Its ability to integrate physical knowledge and data measurements, provide real-time monitoring, generate optimization recommendations, and simulate failure modes renders it a valuable tool for ship design, production, and operation optimization in the maritime industry.

3.2. Application Status of DTT in the OOGI

Recent years have seen substantial growth in the application of DTT in the OOGI, which encompasses the exploration, exploitation, transportation, and processing of oil and natural gas in the sea-shore and seabed. DTT has played a crucial role in the digital transformation of the OOGI [75], as evidenced by the study conducted by Wanasinghe et al. (2020) [12]. The authors applied DTT to develop a system framework for the OOGI. The research results demonstrated that the proposed Digital Twins framework had a positive impact on the productivity, operation efficiency, and safety of the OOGI. Furthermore, it helped reduce variability in capital and operating costs, health and environmental risks, and the projected life cycle of oil and gas assets. To accurately predict the Remaining Useful Life (RUL) of components in oil and gas plants, Desai et al. (2021) [76] developed a Digital Twins model in combination with a deep learning model to represent industrial friction systems. They achieved a training accuracy of over 99% and a test accuracy of at least 95% by using parameters such as friction, temperature, and load as key sensor inputs. This model-free learning approach was used to predict the RUL of ball-bearing-type contacts, and the proposed model could be integrated into tribology machine components to trigger automatic maintenance without considering the wear coefficient. In another study, Benzon et al. (2022) [77] proposed an operational Digital Twins framework based on UAV inspection images for large-scale OOGI. The DTS was used primarily as a virtual characterization of the structure, with the old information being updated by physical changes during the entire life cycle of the structure. The method was evaluated on the transition part of wind turbines in the OOGI, and the results demonstrated that the detected paint defects/damages could be digitized and mapped to the reconstructed 3D structure.

The developed framework could also be regularly updated with inspection images to capture geometric deviations and paint defects/damages during manufacturing. This proposed framework has potential applications in various fields such as the O&G industry, aerospace, and ocean transportation. DTT has also been applied to estimate the probability of failure of offshore wind turbine substructures, as shown by the study conducted by Augustyn et al. (2021) [78]. In their framework, DTT was used to quantify and update the uncertainties and load modeling parameters of the structural dynamical conditions during fatigue accumulation. The accumulated fatigue damage probability was then updated to measure the structural reliability. The authors sampled two representative numerical cases of offshore wind turbines and observed that the updated wave load significantly influenced the reliability of the joint in the splash zone. The uncertainty associated with the virtual sensor used for updating the wave load increased, leading to a reduction in the reliability of the structure. In addition, Haghseenas et al. (2023) [79] developed a Digital Twins platform based on Unity 3D visualization and OPC-UA data communication for detecting potential failures of wind turbine components in the OOGI. The detected failure data were visualized in Augmented Reality to enhance the user experience. The results showed that the proposed model was intuitive and easy to use and had great potential in application scenarios such as offshore wind farms.

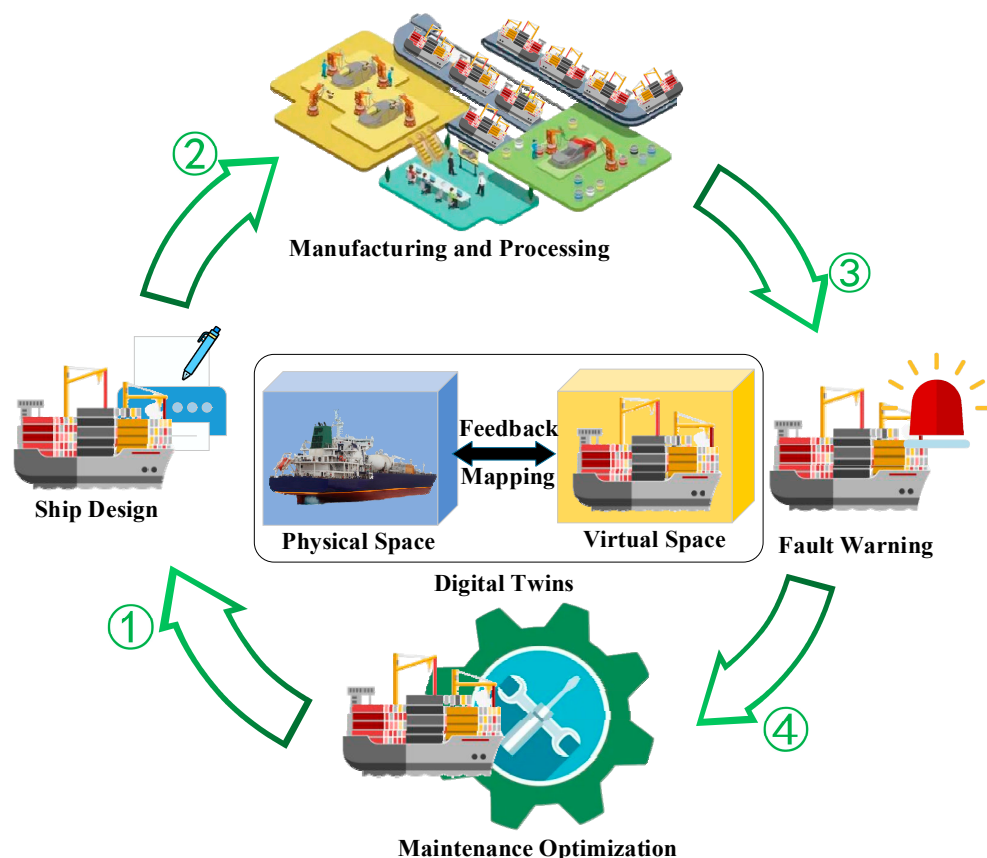


Figure 5. The application of DTT in the whole life cycle of the SBI (1–4 represents the full lifecycle of DDT application in the shipbuilding industry, where 1 represents ship design, 2 represents manufacturing and processing, 3 represents fault warning, and 4 represents maintenance optimization).

According to the existing literature, the digital transformation of the OOGI is continuously evolving, necessitating the urgent need for new and innovative ideas to develop the OOGI and optimize the benefits of the entire industry value chain. Notably, DTT has emerged as a promising solution to seamlessly integrate various digital technologies, such as data sharing, security, and application cloud, thereby enabling intelligent oilfield construction, engineering intelligent manufacturing and factory design, and Internet-trade

platforms. However, it is crucial to thoroughly consider network security and other brand systems while building Digital Twins models for the OOGI. The application of DTT in the offshore oil industry is shown in Figure 6.

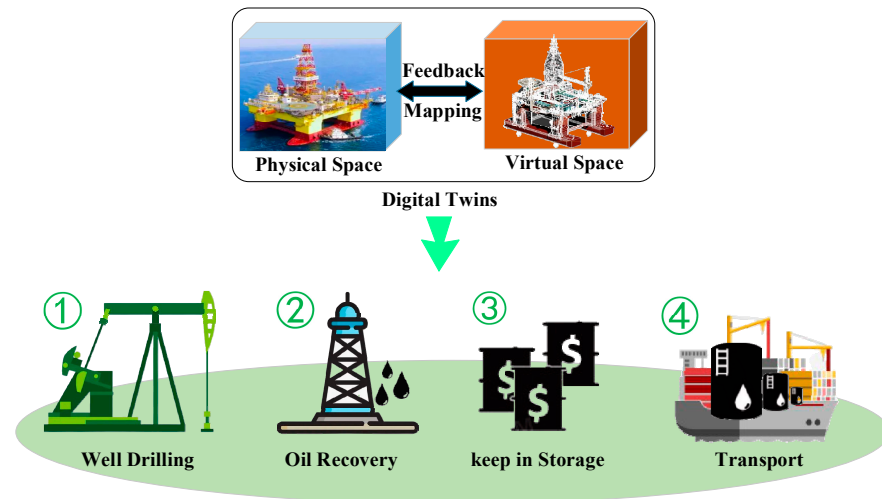


Figure 6. Schematic diagram of the full lifecycle application of DTT in the offshore oil industry (1–4 represents the full lifecycle of DDT application in the offshore oil industry, where 1 represents well drilling, 2 represents oil recovery, 3 represents keep in storage, and 4 represents transport).

Further modeling is necessary to investigate the application of DTT to drilling processes in the offshore oil industry. DTT is involved in scheduling and modeling the petroleum production line during drilling. The petroleum production line will require the processing of n components $\{P_1, P_2, \dots, P_n\}$ on m machine tools $\{M_1, M_2, \dots, M_n\}$, where each component P requires multiple operations $\{op_{i,1}, op_{i,2}, \dots, op_{i,n}\}$. Each machine part can be processed only at a certain time and undergoes only one operation, which will be completed without any pauses. Any machine can start working at time zero, and all component operations can begin at time zero. During the scheduling process, the operations of each component will be arranged to be processed on suitable machines to minimize the total processing time W_t of the petroleum production line during drilling, as shown in Equation (4).

$$\text{Min}W_t = \min(\max(W_t)), 0 < t < m \quad (4)$$

Moreover, a mathematical model for dynamic scheduling is established to verify the feasibility of the dynamic scheduling of the oil production line during drilling. The machine tool constraint model for the production line, SM , is shown in Equation (5).

$$SM = (MG, MS, ML) \quad (5)$$

In Equation (5), MG represents the processes that the machine tool can perform; MS indicates whether the machine tool has any malfunctions; and ML indicates whether the machine tool is currently available. Equation (6) indicates the intelligent manufacturing production planning model for parts in the oil production line.

$$SP = (SH, SD) \quad (6)$$

In Equation (6), SH refers to whether the processing task is an expedited order, and SD suggests whether this process has been processed.

3.3. Application Status of Digital Twins in Marine Fisheries

Marine fishery resources encompass a wide array of economically valuable aquatic animals and plants, including fish, crustaceans, and shellfish, that hold significant sustainable

development value within fishery waters due to their reliance on the marine ecological environment [80,81]. While marine fishery resources are renewable, their over-harvesting and exploitation pose challenges of recession and exhaustion. In this context, DTT has emerged as a crucial tool for predicting fishing quantity in marine fisheries [82]. Several studies have made notable contributions to this area. For instance, Lv et al. (2022) [83] proposed a distributed-hybrid Fish Swarm Optimization Algorithm (FSOA) based on underwater environment mobility, artificial fish swarm theory, and DTT. This study demonstrated improved communication and information sharing among sensor nodes, enhancing the global search ability of FSOA and ensuring uniform distribution density of nodes and events. Furthermore, intelligent ships empowered by DTT have been effective in predicting ship operation statuses. Lambertini et al. (2022) [84] designed a prototype Unmanned Underwater Vehicle named Blucy, which serves as a geographic reference for marine Digital Twins and accurately surveys underwater targets by using non-invasive techniques to address the sustainable development and environmental protection needs of fishery ecosystems. Lan et al. (2022) [85] analyzed the demand for digital transformation infrastructure by using five-tier Digital Twins and deployed multi-mode sensors on fish farms through precise aquaculture methods. The authors also generated multiple datasets to pre-train data-driven prediction models that enhance the decision-making ability of fish farmers, leading to improved monitoring and control of automatic aquaculture machines and maximizing farm output. These research findings have significant implications for the effective management and monitoring of aquaculture farms and the enhancement of traditional fish farm management efficiency.

According to pertinent research, marine fishery resources are considered a public asset. However, determining property rights for these non-exclusive public resources is complex. Over-harvesting and over-exploitation of marine fishery resources are becoming inevitable due to fierce competition among fishery practitioners, resulting in a serious depletion of these resources. As a consequence, when marine fishery resources and the marine ecological environment fail to meet human fishery production quotas, the effectiveness of mediation will significantly decrease. This may result in the unsustainable development of fishery resources and potential damage to the marine ecological environment system [86,87]. Fortunately, introducing DTT offers the possibility of conducting adequate simulations and analyses of the fishing situation in a virtual space, allowing for responsible fishing practices that do not compromise environmental protection. The application of DTT in marine fisheries is presented in Figure 7.

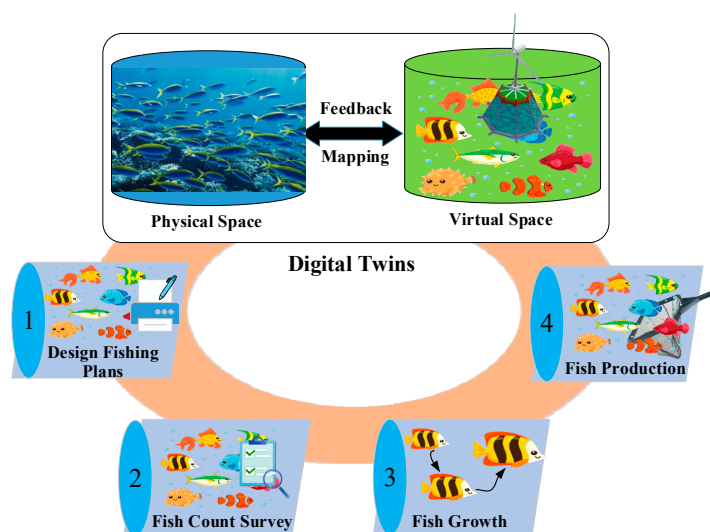


Figure 7. Schematic diagram of the full lifecycle application of DTT in marine fisheries (1–4 represents the full lifecycle of DDT application in marine fisheries, where 1 represents design fishing plans, 2 represents fish count survey, 3 represents fish growth, and 4 represents fish production).

A model for detecting the motion of fishing nets in the ocean is developed to explore the use of DTT in the fishing industry. A series of concentrated mass points are employed to construct the fishnet model via Digital Twins. Each net mesh has its mass concentrated at both ends of the net, connected by springs with stiffness and damping but no mass. The motion equations for the entire model are described in Equation (7), considering the mass, stiffness, and damping of the net.

$$M(p, a) + C(p, v) + K(p) = F(p, v, t) \quad (7)$$

In Equation (7), $M(p, a)$ stands for the inertial moment matrix; $C(p, v)$ denotes the damping moment matrix; $K(p)$ represents the stiffness moment matrix; and $F(p, v, t)$ signifies the external force vector, i.e., the hydrodynamic force from ocean currents. The variables p , v , a , and t denote the position, velocity, acceleration, and time of the fishnet, respectively. The hydrodynamic force on a moving object from waves and currents can be calculated by using the Morrison equation. The hydrodynamic force per unit length of a cylindrical object is represented by Equation (8).

$$F_w = C_m \frac{\pi D^2}{4} \dot{u} - C_a \rho \frac{\pi D^2}{4} a + \frac{1}{2} \rho C_d D |u - v| (u - v) \quad (8)$$

In Equation (8), C_m , C_a , and C_d represent the inertia, additional mass, and drag force coefficient, respectively, where $C_m = 1 + C_a$. D and ρ refer to the outer diameter of the cylinder and the density of seawater, respectively. \dot{u} and u are the acceleration and velocity of the fluid water particle, respectively.

3.4. Application Status of DTT in the Marine Emerging Energy Industry

Thanks to the increasing utilization of DTT, the emerging marine high-tech industry is making significant strides toward comprehensive development. The integration of science and technology is accelerating the transformation and upgrading of the traditional marine industry, which is contributing to the growth of the marine economy [88]. Experts have been actively exploring the application of DTT in the emerging marine energy industry. For instance, Liu et al. (2021) [89] proposed a maritime transport Digital Twins system by adding relay nodes to the data transmission path, creating a relay co-operative IoT network. Simulation experiments demonstrated that this proposed system could accumulate energy to enhance data transmission power, resulting in improved communication performance and security rates. In fact, the proposed Digital Twins system exhibited superior security performance compared to existing data transmission systems, providing a promising experimental foundation for intelligent and safe maritime transport in the future. Agostinelli et al. (2022) [90] proposed energy-saving programs and strategies in alignment with current infrastructure digitization policies. The authors advocated for the integrated production of renewable energy systems to achieve sustainable mobility and optimize maintenance processes and energy efficiency in port areas to transforming them into zero energy development zones. Analyzing the energy system revealed the potential for energy self-sufficiency of the infrastructure. Furthermore, the fusion of Building Information Modeling and Geographic Information Systems could maximize the positive impacts of energy efficiency measures. Li and He (2021) [91] argued that the popularization of marine renewable energy could contribute to marine environmental protection while also promoting technological diversification of energy supply systems and accelerating energy structure adjustments. Thus, it holds significant importance for the sustainable development of the marine economy. However, with the increasing complexity of renewable energy systems, effective asset management and operational reliability of power equipment have become pressing concerns. The establishment of remote, online, and reliable monitoring and inspection technology is urgently needed. Their research suggested that DTT could serve as a reliable approach for assessing the status of power equipment throughout its life cycle. Solman et al. (2022) [92] studied the role of DTT as a boundary object and twin modeling as

a boundary work, involving multiple aspects such as offshore wind energy development and decision-making. The findings revealed the evolution mode of DTT and the function of boundary work of Digital Twins in promoting sustainable energy systems during the transition. The demand for increased transparency in the technological decision-making process for wind energy projects and their integration into the landscape was evident.

In general, the literature review indicates that DTT, as a novel technical tool, is well suited for virtual simulation, condition monitoring, power optimization, and fault diagnosis in the marine high-tech industry. Primarily, this industry encompasses renewable energy generation, transmission, conversion equipment, and storage (Figure 8). The review provides an organized and summarized overview of the diverse applications of DTT to elucidate its current and future trends in renewable energy.

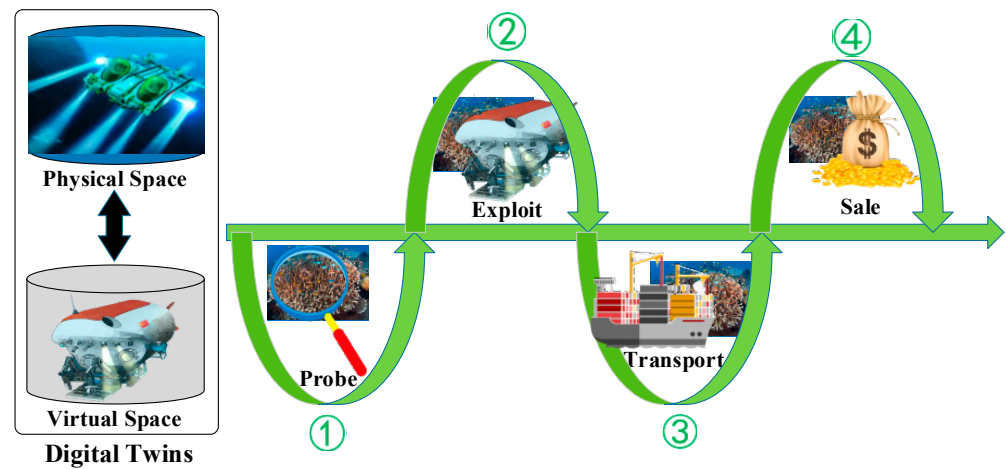


Figure 8. Schematic diagram of the full lifecycle application of DTT in the marine emerging energy industry (1–4 represents the full lifecycle of DDT application in the marine emerging energy industry, where 1 represents probe, 2 represents exploit, 3 represents transport, and 4 represents sale).

The detection path of DTT applied to emerging marine resources is also modeled. When emerging resources in virtual marine space are explored by using a deformable tracked robot, the pose state of the robot is influenced by the differential balance mechanism, active deformation mechanism, and robot position. The attitude of the deformable tracked robot (detection robot) can be represented by the symbol M , as shown in Equation (9).

$$M = P + T + L \quad (9)$$

In Equation (9), P represents the positional information of the detection robot in virtual marine space, with the axis center point as the reference point; T denotes the differential balance attitude of the detection robot; L refers to the attitude information of the deformation mechanism of the detection robot. By expanding the above expressions and establishing a mapping function between control variables and descriptive variables, the relationship can be expressed as Equation (10).

$$M(Grid_x, Grid_y, Grid_z, \theta, \beta_l, \beta_r, \mu_l, h_l, \mu_r, h_r) = f(x, y, z, a, \alpha, c_l, c_r) \quad (10)$$

In Equation (10), $(x, y, z, a, \alpha, c_l, c_r)$ represent the control variables, i.e., the known variables that can be obtained through motion control or sensors. Among them, (x, y, z) is the position information of the robot, as determined by the robot positioning subsystem; a refers to the moving distance of the sliding table controlled by setting the stepper motor parameters; α signifies the rotation angle of the differential balance bar that an absolute value encoder can measure; and (c_l, c_r) refer to the rotation cycles of the left and right deformation motors, respectively.

$(Grid_x, Grid_y, Grid_z, \theta, \beta_l, \beta_r, \mu_l, h_l, \mu_r, h_r)$ represent the mathematical descriptive variables that cannot be directly obtained through sensors. They are the most intuitive evaluation parameters of the attitude of the robot, and the eight variables uniquely determine the posture of the detection robot in three-dimensional space. $(Grid_x, Grid_y, Grid_z)$ denote the hexagonal grid coordinates of the location of the robot. θ refers to the pitch angle of the main vehicle body; (β_l, β_r) refer to the deflection angle of the left and right walking parts relative to the pivot axis. (μ_l, μ_r) denote the rotation angle of the active rod in the left and right four-link track mechanism. Finally, (h_l, h_r) signify the height of the walking part of the detection robot from the ground.

4. Research Challenges and Prospects of DTT in the Marine Industry

4.1. Research Challenges of DTT in the Marine Industry

As a comprehensive and ongoing effort, the management of the entire life cycle of the marine industry through the utilization of DTT poses long-term challenges. The review of practical examples becomes crucial to address these challenges. For instance, Wang et al. (2022) [93] employed DTT as a predictive maintenance model for electromechanical equipment. They gathered physical and spatial signals from sensors to model electromechanical devices and subsequently developed a robust fault diagnosis method. Through experiments, the accuracy of the model was validated, surpassing other methods. It enabled the prediction of remaining equipment life and facilitated maintenance decision-making. Similarly, Mourtzis et al. (2021) [94] proposed a conceptualized design and preliminary development of a ship platform to optimize equipment design by using data from the marine industry environment. The framework encompassed data acquisition, processing, and simulation for ship operation. The applicability of the proposed framework was validated in a laboratory-based machine shop by using real industrial data, confirming its effectiveness and stability. Furthermore, Wei et al. (2023) [95] proposed a Digital Twins framework and applied it to real-time decarbonization regulatory compliance prediction in ship routes. In this framework, the Digital Twins method can utilize real-time environment and operational data to improve the estimation of the probability of specific vessels complying with regulations during navigation, and is universal in handling various decarbonization regulations. In addition, Song et al. (2022) [96] investigated the application characteristics of DTT in battle damage tests and marine industrial equipment evaluation. They developed a DTS for this purpose, and their findings offered theoretical references and methodological guidance for utilizing DTT in marine battlefield damage assessment. This research holds significant implications for the advancement of Digital Twins in battlefield and battlefield damage assessments.

Given the wealth of existing research on the application of DTT, this section delves into the potential challenges that may arise when implementing Digital Twins in the context of digital design, intelligent processing, intelligent operation, fault warning, and maintenance throughout the entire LCM of the marine industry. To illustrate, the ship building process is subdivided into four distinct stages:

First, a proficient design methodology plays a crucial role in ship-building, encompassing a continuous cycle of demonstration, analysis, verification, and re-design, ultimately leading to the acceptance of the final design scheme [97]. This intricate process involves multiple disciplines, complex procedures, advanced technological requirements, substantial computational resources, and an extensive time frame. Nonetheless, it constitutes the most data-intensive phase in the ship-building process. The key challenge in utilizing DTT for ship design lies in accurately and efficiently representing physical entities through virtual models.

Second, ship-building encompasses a diverse range of tasks, intricate processes, lengthy production cycles, substantial capital and labor investments, and extensive workloads, as is typical in discrete manufacturing [98]. In order to successfully complete ship construction, a shipyard must possess comprehensive infrastructure, specialized equipment, an ample workforce of technical and management personnel, reliable suppliers,

favorable port facilities, and sufficient financial resources, among other essential conditions. Tyagi and Sreenath (2021) [99] highlighted the challenges faced by Cyber-Physical Systems in the SBI. They proposed that addressing the complexities of large and intricate systems, including ship systems, requires more advanced and robust technologies such as the IoT and DTT to ensure their security. Furthermore, the current reliance on traditional shipyard manufacturing technologies, methods, and practices serves as a bottleneck that hampers the development of the SBI.

Third, the operation of ships is influenced by numerous factors, stemming from both internal and external sources. Of particular significance is the dynamic water environment, which constantly impacts the economic, safety, and reliability aspects of ship operations. However, the effective utilization of DTT is also contingent upon the level of digitalization of the ship and the availability of shore-based communication systems, which impose limitations on its application.

Fourth, ship maintenance considerably affects the service life of the ship, as well as its safety and economic performance. The implementation of scientifically informed, or at the very least, well-reasoned maintenance practices, can extend the operational time of the ship, enhance its safety, reduce maintenance costs, and improve overall work efficiency. Ship maintenance comprises routine and suspension maintenance activities, which are complicated by the inherent complexities and uncertainties of the system of the ship, as well as the dynamic water environment. These challenges pose significant obstacles to the effective application of DTT in ship maintenance.

4.2. Research Prospect of DTT in the Marine Industry

The field of DTT is experiencing rapid advancements, driven by the emergence of new-generation information technology, including fifth-generation mobile communication, cloud computing, big data analytics, AI, wireless sensor networks, and the IoT, along with increasing computing capabilities. Additionally, the strong support and promotion of DTT at the state policy and enterprise strategic levels have laid the groundwork for its development. This review indicates that DTT is poised for significant growth and holds promising prospects. Specifically, based on an evaluation of the current application status and challenges of DTT in the marine industry, the following aspects warrant further consideration.

To begin with, DTT offers a means to share and model the marine industry in a uniform and secure manner. Unlike traditional modeling techniques, which are often slow and limited in their ability to accurately represent the physical world, DTT employs virtual twin modeling to restore real-world scenes. Rapid 3D modeling technology can significantly aid in creating virtual twin scenes and visualizing real-time data from the physical world, thus identifying and highlighting issues in an efficient and effective manner [100,101]. In a recent study by Ning and Jiang (2022) [102], a multi-layer defense-in-depth approach was proposed to detect and deter stealth attacks. Effective mitigation techniques were deployed to minimize the adverse effects of such attacks. The method was tested on a laboratory-scale cyber-physical system platform that utilized an industrial communication network and physical sensors. The results demonstrated the effectiveness and safety of the developed approach. The use of industrial 3D modeling-based data visualization and intelligent monitoring systems has created an innovative environment for the marine industry, enabling intelligent visualization of marine industry data through advanced infrastructure and service systems. Emphasis is placed on visual modeling of the marine industry, and the marine-industry-oriented intelligent data visualization and monitoring system can facilitate rapid, accurate, and effective chemical product debugging and information processing. According to Cao et al. (2022) [103], the intelligent monitoring system for the marine industry provides real-time data visualization support for the development of industrial plants. The application of DTT has the potential to greatly enhance the production efficiency of industrial manufacturing, ultimately laying the foundation for intelligent data visualization and effective data aggregation within the marine industry.

Furthermore, DTT offers the potential for effective integration of physical and digital models, enabling the marine industry to achieve digital intelligence in virtual environments such as the Metaverse. The fusion of information from virtual and physical models involves data acquisition, transmission, mining, and collaborative control, among other methods. However, there is a need to improve the robustness and applicability of fusion algorithms, as DTTs handle various forms of structured, semi-structured, or unstructured data. Despite ongoing efforts to standardize information, dealing with heterogeneous data types remains a challenge. The use of different standards for data representation in inter-machine communication with a large number of data types leads to lower reliability of information exchange [104,105]. This is particularly relevant in the marine industry, in which marine equipment operates in harsh environments with constant load changes, necessitating higher requirements for data interaction and integration. In the maritime sector, DTT can expedite the development of digital representations of the marine industry. For instance, Yang et al. (2022) [106] summarized the current application status of pumps and fans in fluid machinery from the perspectives of DTT and Metaverse. Research found that DTT and Metaverse technology played a crucial role in the development of new pump products and technologies, and were widely used in numerical simulation and fault detection of various pumps and other fields of fluid machinery. Lv et al. (2022) [107] also discussed the use of DTT in conjunction with virtual reality techniques to map physical objects in the real world onto virtual environments. Specifically, the marine industry can rapidly actualize its digital models in virtual spaces such as the Metaverse by integrating DTT with virtual reality and game engines.

In conclusion, the integration of DTT and AI technology serves to enhance the development and utilization of marine energy and deep-sea resources. As the marine economy continues to evolve, it is imperative to effectively leverage existing coal and natural gas resources while actively exploring and utilizing renewable energy sources such as salt, wind, and ocean tides and currents. DTT and AI technology should be incorporated into the process of harnessing renewable resources to promote the emergence of marine energy. This approach will contribute to the coordinated, healthy, and sustainable development of the marine industry [108]. Furthermore, it is crucial to strive for the industrialization of the marine economy with the guidance of science and technology. This will enable the transformation of the marine economic structure to be more technology-intensive and intelligent, thus driving the rapid development of various marine industries, including emerging marine high-tech sectors. Ultimately, the seamless integration of DTT and AI technology will provide a clear direction for the transformation and upgrading of the marine industry.

5. Conclusions

DTT is gaining momentum in various industries, although it is still in its early stages and requires further research and refinement. This review focuses on the utilization of DTT in the marine industry to achieve the dual objectives of rational exploitation of marine resources and environmental protection. An innovative overview of current Digital Twins applications in marine industries, such as ship-building, total life cycle monitoring, offshore oil, marine fisheries, and emerging marine energy, is presented. The use of DTT provides robust support for digital design, intelligent processing, smart operation, and fault warning and maintenance, facilitating total life cycle management in the marine sector. Nevertheless, challenges and prospects of Digital Twins applications in the offshore industry are discussed, particularly in the areas of digital design, intelligent processing, smart operation, early warning, and fault maintenance throughout the full life cycle of offshore operations. Through standardized and collaborative modeling, the marine sector has the potential to be transformed into a digitally intelligent domain with the utilization of DTT in the future. This transformation could be further enhanced by integrating physical and digital models in virtual environments such as the Metaverse. Finally, the integration of Digital Twins and AI technology can synergistically contribute to the advancement

of research and the application of marine energy and deep-sea technologies. Given the cross-fertilization of technologies such as big data, IoT, and AI, DTT is expected to have significant prospects in the complete life cycle management, intelligent operation, and maintenance of the marine sector.

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