

Review

Human Digital Healthcare Engineering for Enhancing the Health and Well-Being of Seafarers and Offshore Workers: A Comprehensive Review

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Abstract: With over 50,000 merchant vessels and nearly two million seafarers operating globally, more than 12,000 maritime incidents in the past decade underscore the urgent need for proactive safety measures to ensure the structural integrity of aging ships and safeguard the well-being of seafarers, who face harsh ocean environments in remote locations. The Digital Healthcare Engineering (DHE) framework offers a proactive solution to these challenges, comprising five interconnected modules: (1) real-time monitoring and measurement of health parameters, (2) transmission of collected data to land-based analytics centers, (3) data analytics and simulations leveraging digital twins, (4) AI-driven diagnostics and recommendations for remedial actions, and (5) predictive health analysis for optimal maintenance planning. This paper reviews the core technologies required to implement the DHE framework in real-world settings, with a specific focus on the well-being of seafarers and offshore workers, referred to as Human DHE (HDHE). Key technical challenges are identified, and practical solutions to address these challenges are proposed for each individual module. This paper also outlines future research directions to advance the development of an HDHE system, aiming to enhance the safety, health, and overall well-being of seafarers operating in demanding maritime environments.

Keywords: Digital Healthcare Engineering (DHE); Human Digital Healthcare Engineering (HDHE); seafarer well-being; digital twins; human digital twins



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1. Introduction

As reported by the International Chamber of Shipping, over 50,000 merchant vessels and nearly two million seafarers are currently operating worldwide. Shipping is recognized as one of the most globalized industries and, at the same time, one of the most hazardous. According to the European Maritime Safety Agency, 12,502 maritime incidents involving various types of vessels occurred between 2014 and 2022, resulting in numerous crew casualties, as shown in Figure 1. Maritime accidents have profound consequences for human lives, property, and the environment [1]. Notably, the “human element”, often referred to as “human error” or the “human factor”, is widely recognized as the leading cause of marine casualties. The complexity of the global maritime environment means that even minor human errors can escalate into major accidents.

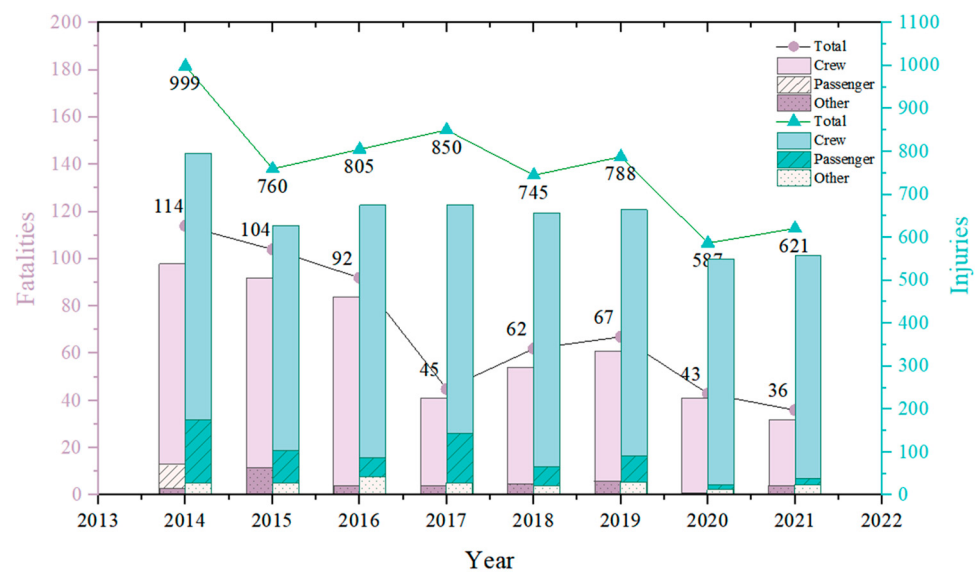


Figure 1. Number of fatalities and injuries on board during 2014–2021 (from EMSA).

Despite advancements in ship design, stability, equipment, and crew training, human errors continue to account for 60% to 90% of maritime accidents. The shipping process involves numerous human-driven operations and decisions, significantly increasing the risks inherent in the industry [2–5]. In more detail, maritime operations widely vary across vessel types, with some working environments being particularly susceptible to human error. For example, fishing vessels typically operate during irregular hours and under physically demanding conditions, leading to fatigue and a heightened likelihood of errors. In contrast, cargo ships often benefit from more standardized schedules and higher levels of automation, which help mitigate such risks. Overall, the problem of seafarer fatigue is not to be underestimated.

Like other industries, the maritime sector has entered a new era of digital transformation, adopting advanced digital and communication technologies to revolutionize ship design, construction, and operation. This transformation also offers promising solutions for protecting the health and well-being of seafarers and offshore workers. Monitoring the health and well-being of seafarers has become a key strategy for mitigating risks associated with human error [6–9].

One such solution is the concept of Digital Healthcare Engineering (DHE), introduced by Paik [10,11], which aims to address these challenges. The DHE framework has been explored for enhancing the safety and sustainability of aging ships and offshore structures [12] as well as subsea pipelines [13]. The system focuses on real-time health monitoring by collecting on-site data and performing detailed analytics and simulations at land-based centers, leveraging Digital Twin (DT) technology. Communication between ships, offshore installations, and land-based centers is enabled through low Earth orbit (LEO) satellites.

In addition, the Human Digital Twin (HDT)—a derivative of DT technology applied to human bodies—is expected to be integrated into the maritime sector. HDT enables real-time monitoring of crew members' health and well-being, ultimately improving the reliability of human operations [14,15].

However, seafarers and offshore workers face unique challenges compared to land-based workers, as they operate in confined, enclosed environments under harsh marine conditions. These factors significantly increase their work stress and intensity, placing both their physical and mental health under considerable strain. Fatigue and discomfort among seafarers heighten the likelihood of human error. Although extensive research has been conducted on seafarers' health, safety concerns for both crew members and vessel naviga-

tion remain unresolved in the industry. Moreover, existing data indicate that the economic burden resulting from seafarers' poor health and stress-related incidents is considerable. For instance, medical evacuations cost on average USD 100,000 per case, while indirect costs from delays, insurance claims, and crew turnover significantly affect operational efficiency. And a report by the International Maritime Health Association (IMHA) estimated that each mental health-related repatriation costs shipping companies approximately USD 168,000 on average, factoring in transportation, medical care, and re-staffing.

Therefore, this study aims to provide a comprehensive review of current technologies and applications of DHE for seafarers. To explore the application of DHE systems in seafarers' healthcare, this review aims to conduct a state-of-the-art analysis and address the following three fundamental questions:

- Why should DHE systems be introduced to ensure the safety of seafarers?
- What technical support is needed to build a DHE system, and what are the latest advancements in these technologies?
- What are the existing challenges in deploying DHE systems, and what is their potential?

The scope of this review includes journal and conference publications related to seafarers and healthcare monitoring from 2014 to 2024. Dissertation theses were also incorporated to ensure thorough coverage. Articles were sourced from online academic databases, including Web of Science (webofknowledge.com, accessed on 20 January 2025), ScienceDirect (sciencedirect.com, accessed on 20 January 2025), Google Scholar (scholar.google.com, accessed on 20 January 2025), and Scopus (scopus.com, accessed on 20 January 2025). Reference management software Mendeley (mendeley.com, the version is 1. 19. 8) was used to organize the selected papers. In total, 93 relevant articles were identified as the foundation for this investigation. To maintain currency, most papers reviewed were published within the last decade, with only a small number of older papers addressing foundational principles.

The search strategy involved using a combination of keywords such as “seafarer”, “crew”, “mariner”, and “sailor” alongside terms like “human health”, “healthcare”, and “well-being”. Analysis of publication trends indicates that the number of articles related to these keywords and their combinations has been annually increasing. While a significant volume of papers exists in the categories of seafarers (or crew, mariners, sailors) and healthcare (or human health, well-being), the intersection of these two fields (seafarers' healthcare) has fewer publications. Moreover, there is no comprehensive article addressing the technologies underlying a seafarers' healthcare system, as illustrated in Figure 2.

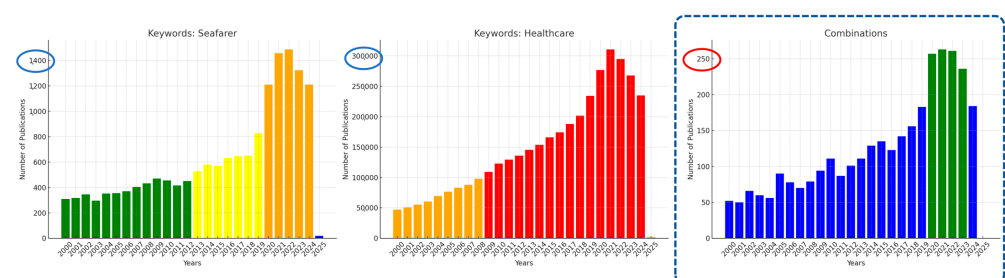


Figure 2. Search trends for different keywords in Scopus over the year.

The structure of this article is outlined in Figure 3.

Section 2 introduces the general DHE framework and proposes the concept of Human Digital Healthcare Engineering (HDHE).

Section 3 reviews recent advancements in key technologies for HDHE systems.

Section 4 outlines the challenges in implementing DHE systems for seafarers' healthcare and explores their implications for health and well-being.

Section 5 concludes with key insights from this review.

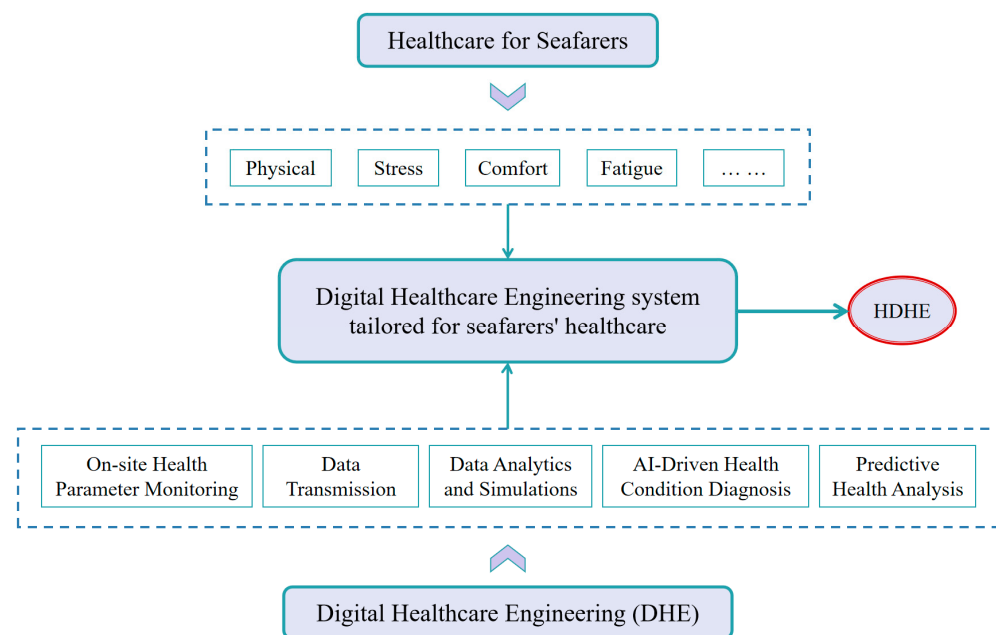


Figure 3. Structure of this review article.

2. Human Digital Healthcare Engineering (HDHE) Framework

This section introduces the concepts and research progress of Digital Twin (DT) and Human Digital Twin (HDT) and proposes the new topic of Human Digital Healthcare Engineering (HDHE) based on the Digital Healthcare Engineering (DHE) framework.

2.1. Research Progress in DTs and HDTs

Digital Twin (DT) was first introduced by Grieves in 2003 [16] and has since gained significant attention in both industry and academia as a method for digitally understanding and transforming the world [17]. The concept was initially applied by NASA during the Apollo program. Figure 4 illustrates the evolution of DT.

The milestones of Digital Twin (DT) developments

- | | |
|--|--|
| <p>2003 A simple concept of DT was proposed by Michael Grieves.</p> <p>2005 Three subtypes of the mirrored spaces model were differentiated.</p> <p>2012 DT was listed as a key technology by NASA and the U.S. Air Force, and NASA applied DT in its aircraft design and health monitoring.</p> <p>2014 A whitepaper of DT was published.</p> | <p>2015 GE developed DT platforms for real-time monitoring.</p> <p>2016 Siemens applied DT in Industry 4.0.</p> <p>2018 A five-dimensional DT model was proposed by Beihang University.</p> <p>2019 Gartner listed DT as one of the top 10 technological trends with strategic values.</p> |
|--|--|

Figure 4. Developmental process of DT.

A DT system consists of five subsystems: physical objects (or physical entities), virtual models (or virtual entities), connections, data, and service systems. The relationships among these subsystems are shown in Figure 5. DTs provide a unique capability for digitally representing physical entities [18,19]. Using sensory data acquisition and advanced big data analysis, DTs are highly effective for monitoring, diagnostics, prognostics, and op-

timization [20,21]. Once connected with digital representations of facilities, environments, and individuals, DTs support decision-making by assessing current conditions, diagnosing past issues, and predicting future trends [22].

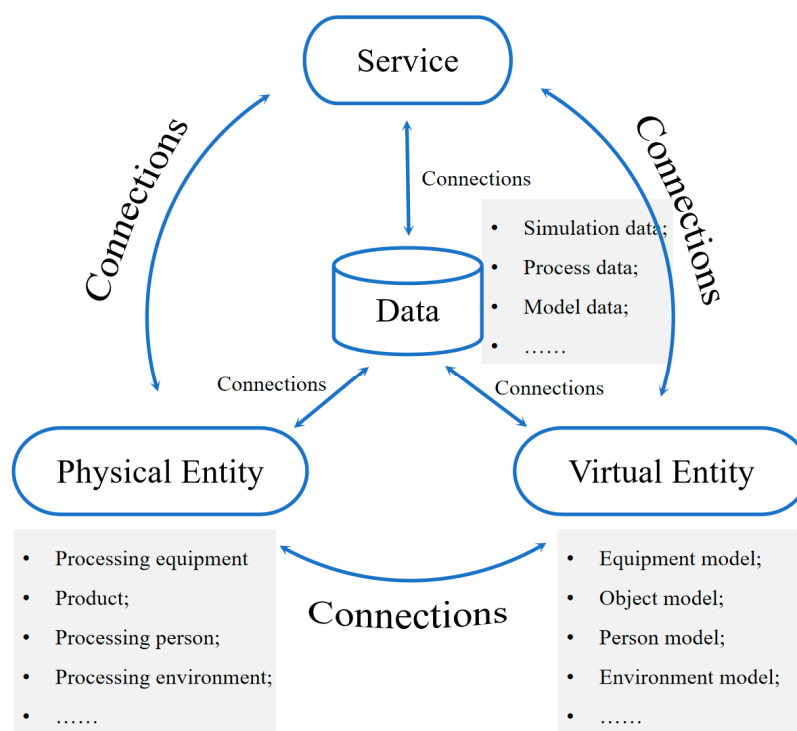


Figure 5. Relationships between five subsystems of DT.

Human Digital Twin (HDT) is referred to when the physical entity in a DT is shifted from inanimate assets to humans. Figure 6 depicts the evolution of HDT. First proposed by Graessler and Poehler [23], HDT initially referred to simulating human attributes and behaviors in cyber–physical production systems. Later, Chakshu et al. categorized HDTs into three types (passive, semi-active, and active) and introduced the concept to healthcare [24]. However, the conceptual model of HDT was not clarified until 2021, when Shengli and Naudet et al. defined it as “a real-time mirroring computerized system of a human agent [25–27], able to simulate or emulate their characteristics and behavior in context”. In 2022, Taylor et al. integrated HDT into Maritime 4.0, specifically focusing on seafarers [28].

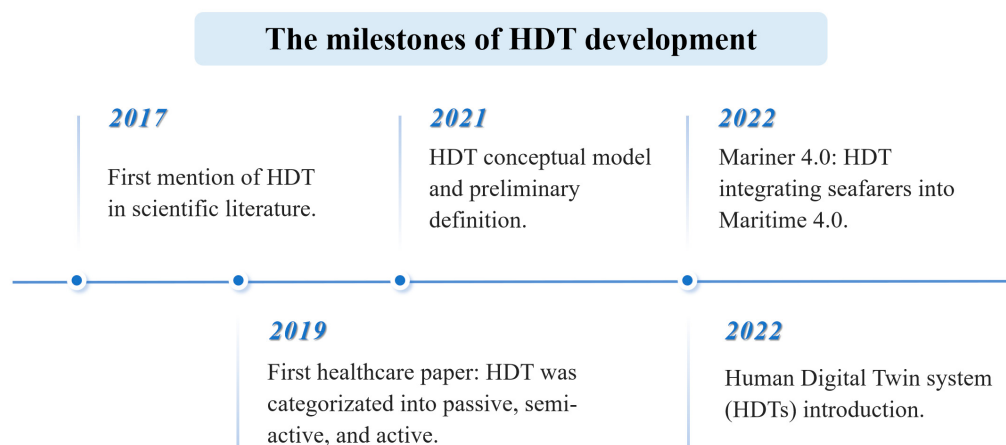


Figure 6. Key moments in the evolution of HDT [23–28].

2.2. Research Progress in DHE

Digital Healthcare Engineering (DHE), introduced by Paik [10,11], aims to deliver continuous healthcare for aging engineered structures such as ships and offshore platforms under hostile ocean environments in remote locations throughout their lifecycle. The DHE system comprises five key modules:

1. Real-time on-site monitoring and digitalization of health parameters.
2. Data transmission to land-based analytics centers via low Earth orbit (LEO) satellites.
3. Advanced data analytics and simulations using digital twins.
4. AI-driven diagnostics and automated treatment recommendations.
5. Predictive health analysis for proactive care planning.

Sindi et al. explored advancements and challenges in industrializing DHE systems to enhance the safety and sustainability of aging ships and offshore structures [12]. Fadzil et al. made a literature review, aiming at the development of DHE systems for aging subsea pipelines [13]. They proposed prototype systems with practical solutions to address these challenges. Figure 7 illustrates a prototype DHE system for aging ships and their seafarers [11].

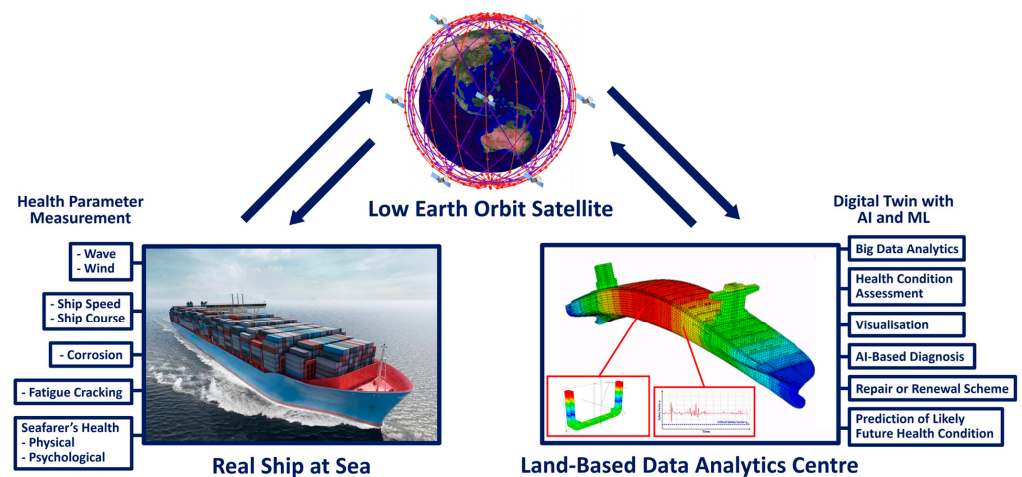


Figure 7. Prototype DHE system designed for the structures of aging ships. Reprinted with permission from Ref. [11]. 2024, Jeom-Kee Paik.

2.3. Concept of HDHE

Human Digital Healthcare Engineering (HDHE) is an integrated system dedicated to ensuring the safety, health, and well-being of seafarers and offshore workers who are working under hostile ocean environments in remote locations. It leverages HDT as a revolutionary tool for healthcare personnel to remotely monitor seafarers' health and conditions. By creating a digital replica of each seafarer's physiology, behavior, and environment, HDHE provides advanced medical services such as predictive diagnostics, real-time monitoring, and personalized medical support.

HDHE offers an efficient, cost-effective way to monitor seafarers' health, enabling proactive measures and informed decision-making. It can track vital signs (e.g., heart rate, blood pressure, respiratory rate), operational conditions (e.g., maneuvering, ship speed, vibration, noise), and environmental factors (e.g., sea state, temperature). Additionally, HDHE monitors mental and emotional states, such as stress, fatigue, and anxiety. These data can identify health risks and guide proactive interventions. Figure 8 illustrates a prototype HDHE system for seafarers' healthcare.

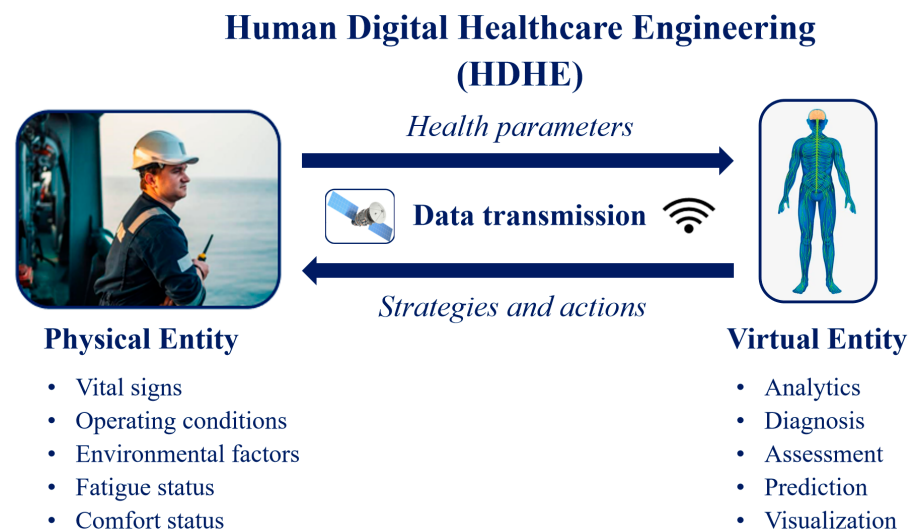


Figure 8. Prototype HDHE system designed for seafarers' healthcare.

While HDHE shares conceptual similarities with frameworks in smart healthcare and remote worker safety, its novelty lies in tailoring these approaches to maritime conditions. Unlike land-based systems, HDHE addresses the unique challenges of seafarers, including long-term isolation, harsh environments, limited medical resources, and cross-jurisdictional constraints. These distinctions necessitate adaptive architectures and maritime-specific data pathways that substantially differ from conventional wearable AI or industrial health-monitoring models.

3. Key Technologies for HDHE Systems

The development of the Human Digital Healthcare Engineering (HDHE) system is critical to effectively manage the health of crew members and enhance their work efficiency and training. Similar to Digital Healthcare Engineering (DHE), the HDHE system involves five main steps: (1) real-time health parameter monitoring, (2) data transmission, (3) data analytics and simulations using Human Digital Twins (HDTs), (4) AI-driven health condition diagnosis, and (5) predictive health analysis. The data flow of the HDHE system is illustrated in Figure 9, which outlines the interaction among three core components: physical objects, virtual models, and service systems. Sensors worn by seafarers collect and transmit health-related data. Virtual models receive and process this information, simulate physiological states, and generate diagnostic decisions. These decisions are then executed by service systems, which provide timely feedback. This closed-loop structure enables continuous, intelligent health management tailored to the maritime environment.

3.1. Real-Time Health Parameter Monitoring

The initial step in establishing the HDHE system is real-time monitoring of seafarers' health status. Real-time monitoring involves on-site and continuous observation of physical parameters in their natural environment, enabling effective data collection and analysis of seafarers' health conditions. Sensing technology is a promising method for monitoring these parameters and is integral to the HDHE system, ensuring timely and reliable data acquisition from the physical space, as illustrated in Figure 9.

In recent years, wearable sensors have become a significant focus for monitoring various health parameters, including heart rate [29,30], body temperature [31], blood pressure [32,33], respiration rate [34], and sweat rate [35]. Equipped with the ability to capture accurate sensory data in real time, these sensors provide valuable insights into the

physical health of crew members. Practical applications of wearable sensing technologies are shown in Figure 10.

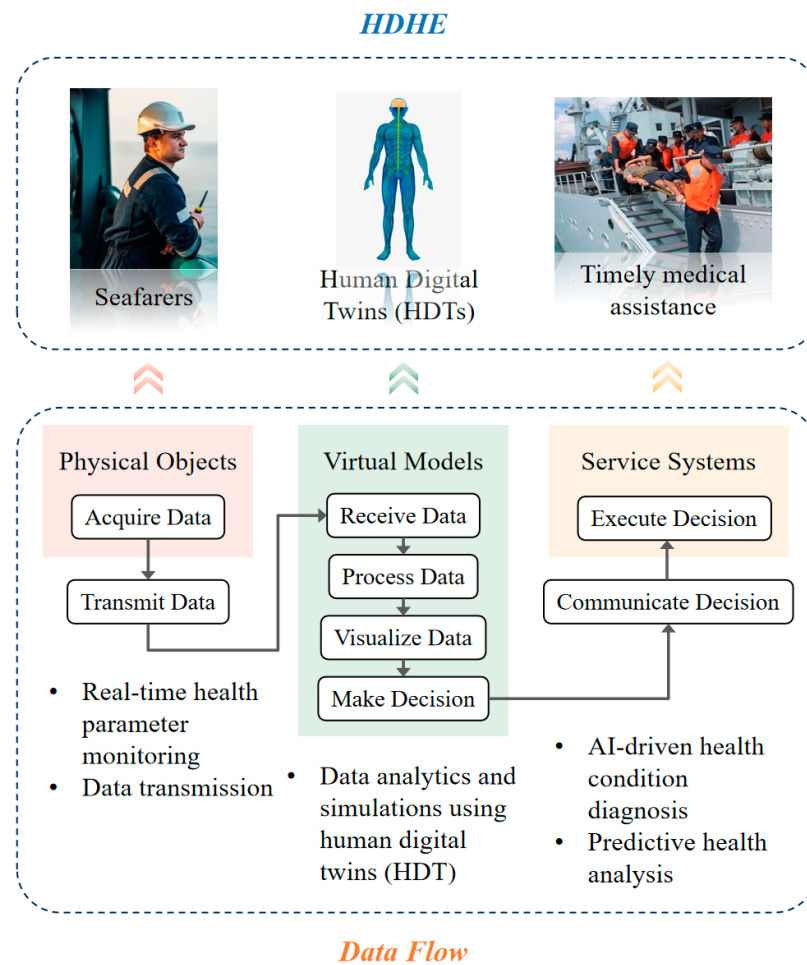


Figure 9. Monitoring process and data flow for the HDHE system.

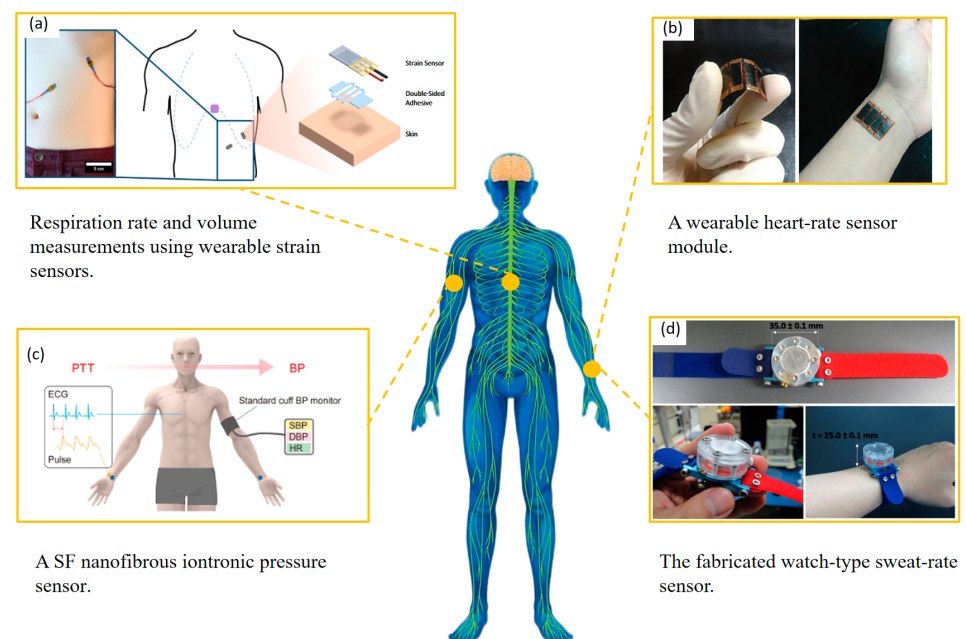


Figure 10. Practical applications of sensing technology for wearable sensors [30,33–35].

The accuracy and reliability of sensor measurements are foundational to the effectiveness of wearable devices, particularly in maritime environments where extreme conditions such as humidity, temperature fluctuations, and mechanical vibrations can compromise sensor performance. For instance, Kun et al. developed a laser-induced graphene temperature sensor with enhanced stability under mechanical stress, a critical feature for seafarers exposed to constant vessel movements [36]. Similarly, Yu et al. proposed stretch-resistant sensors that maintain temperature sensitivity despite physical strain, addressing challenges posed by seafarers' dynamic tasks like heavy lifting or climbing ladders [37].

Wearing comfort is equally vital, as seafarers often wear devices for extended periods during demanding shifts. Flexible materials such as silicone-based polymers or textile-integrated sensors [38–41] minimize skin irritation and accommodate motion, ensuring compliance in confined onboard spaces. However, traditional electronic sensors face limitations in maritime settings, including corrosion from saltwater exposure and electromagnetic interference from ship machinery. Recent advancements in optical fiber sensors (OFSs) [42–45] offer a robust alternative: their non-metallic composition resists corrosion, while immunity to electromagnetic interference ensures reliable data transmission in environments crowded with electronic equipment. Additionally, OFSs' biocompatibility reduces allergic risks, further enhancing their suitability for long-term health monitoring at sea.

Future developments in wearable sensing technologies are expected to focus on the following points:

- Miniaturization: reducing device size to micron or nanometer scales without compromising performance.
- Low energy consumption: minimizing energy use, ideally powered by solar energy or body heat.
- Interconnectivity: enabling integration with other smart technologies.
- Eco-friendliness: using sustainable materials to ensure environmental conservation.

3.2. Data Transmission

Data transmission and communication technologies form the backbone of the HDHE system, facilitating seamless data flow. Over the years, transmission technologies have significantly evolved, enabling faster and more reliable communication over long distances. This section explores data transmission methods applicable to HDHE systems for maritime workers, focusing on onboard and ship-to-shore communication. Figure 11 illustrates a schematic of the network field.

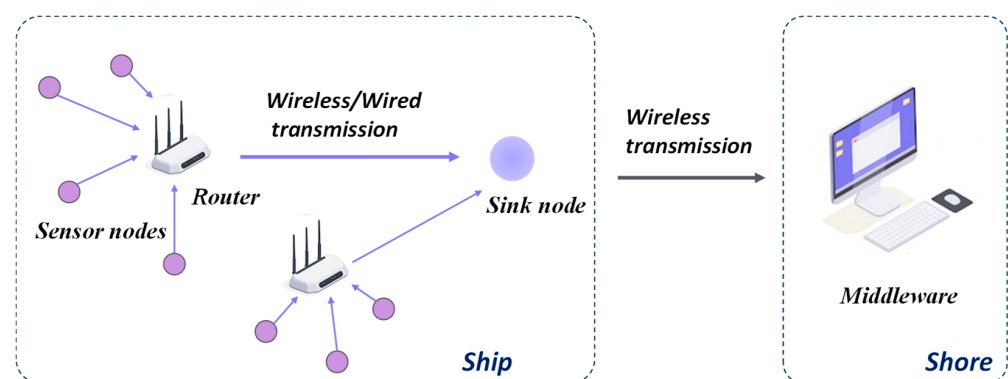


Figure 11. Schematic diagram of the network field.

3.2.1. Onboard Data Transmission

For onboard data transmission, both wired and wireless technologies are viable options. Wired transmission methods, such as twisted-pair cables, coaxial cables, and fiber optics, offer high transmission rates. For instance, the single-channel rate of fiber optics increased from 2.5 Gb/s in 1982 to 400 Gb/s in 2020 [46]. However, wired systems are challenging to install and maintain in ships due to their complex internal structures and exposure to harsh maritime environments.

Wireless transmission technologies provide a practical alternative, with methods such as Zigbee, Bluetooth, Wi-Fi, Ultra-Wideband (UWB), and Near-Field Communication (NFC) offering diverse applications. Each method has distinct benefits and drawbacks, with evaluation results based on criteria such as distance, speed, power consumption, delay, and reliability shown in Figure 12.

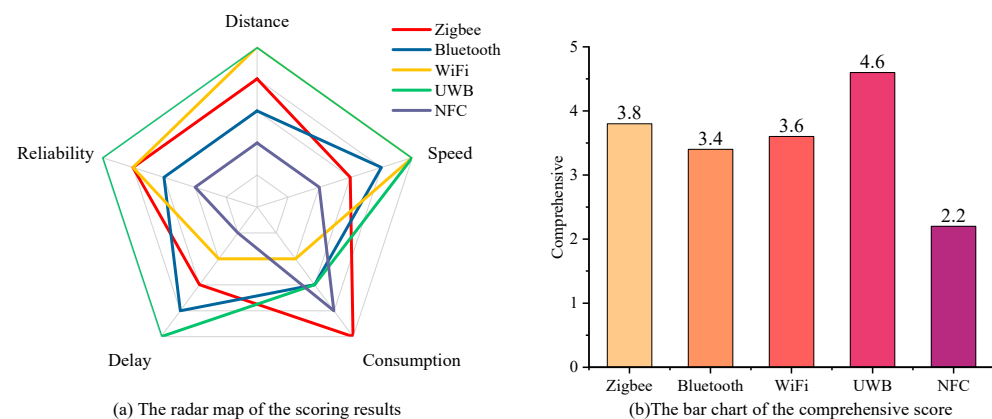


Figure 12. Evaluation results of five wireless transmission technologies.

- Zigbee and Bluetooth are ideal for short-distance, low-power communication, suitable for sensor integration.
- Wi-Fi excels in medium-distance, high-speed data transmission, making it ideal for transferring large datasets.
- UWB is particularly suited for long-distance communication requiring high-speed data transfer, making it a promising choice for HDHE systems.

3.2.2. Ship-to-Shore Data Transmission

Ship-to-shore communication is crucial for relaying HDHE system data to onshore centers. Satellite communication systems, such as the BeiDou Satellite Navigation Sensor System (BDS) [47] and frameworks like the Ship Emission Monitoring Sensor Web (SEMSW) [48], are commonly used for this purpose. Figure 13a,b shows two typical satellite-based communication architectures. The left panel depicts a standard system involving vessels, satellites, and ground stations. The right panel illustrates an applied framework where ships transmit data via satellites to shore-based centers, enabling remote health monitoring and operational coordination. The gradual reduction in satellite communication costs has led to its widespread adoption in maritime industries.

3.3. Data Analytics and Simulations Using Human Digital Twins (HDTs)

Data analytics and simulations enhance the application of the data. It can improve modeling and simulation for the proposed HDT-driven HDHE to outline the virtual world. Advanced applications of data can further analyze, evaluate, and estimate human status.

The core of HDT is to establish virtual human models, which can accurately reflect the physiological, structural, and motion characteristics of the human body. Currently, based on

simulation techniques such as the finite element method (FEM) and computer-aided design (CAD), researchers can simulate the response of the human body in different environments, such as biomechanical response in motion, posture optimization, and load distribution. In an assembly example, a predefined virtual model of the robot is designed with CAD, and the digital human body model is represented by a deformable mesh [49].

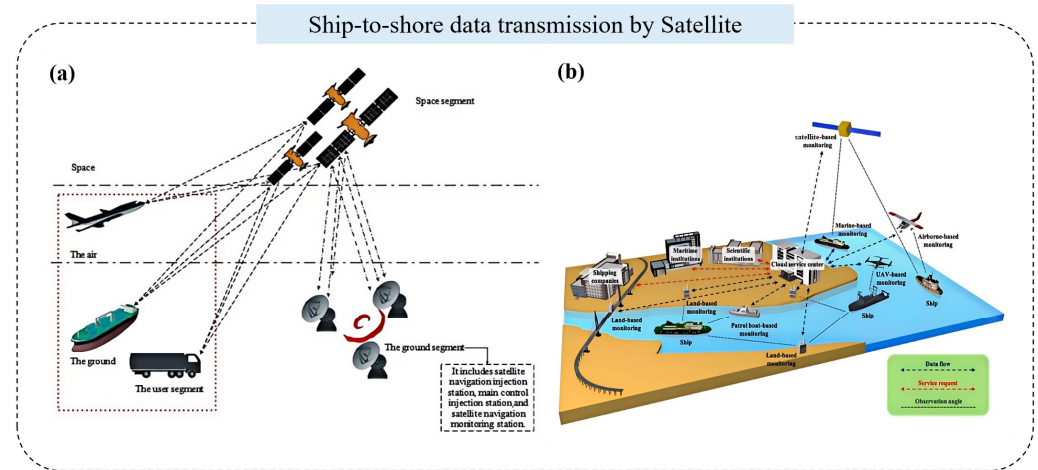


Figure 13. Practical applications for ship-to-shore data transmission.

In order to accurately simulate the human motion process, simulation technology has gradually integrated the latest research results in the fields of biomechanics, computer vision, and artificial intelligence [50]. For example, dynamic modeling and control algorithms based on the musculoskeletal system can predict and simulate the motion behavior of the human body in complex environments, as shown in Figure 14. Through the combination of motion capture technology (such as the Vicon system) and simulation models, more realistic and accurate human motion simulation can be carried out [51].



Figure 14. A human simulation [51].

At the same time, personalized health simulation has attracted more and more attention, especially in individualized treatment and precision medicine. By simulating the impact of different treatment programs on individual physiological states, it helps doctors make more scientific and personalized treatment plans [52–55]. For example, virtual patient models based on HDT can be used to simulate drug treatment effects, surgical procedures, etc., thereby reducing the risk and cost of clinical trials.

In recent years, virtual reality (VR) and augmented reality (AR) technologies have been widely used in the simulation research of HDT [56,57]. They enable users to interact with virtual human models in immersive environments, helping to better understand the

physiological and health conditions of the human body. In the future, data analysis and simulations will continue to develop towards real-time and interactivity.

3.4. AI-Driven Health Condition Diagnosis and Predictive Health Analysis

The operation of HDHE systems generates vast amounts of data, necessitating the use of advanced analytics to derive meaningful insights. Artificial intelligence (AI) plays a pivotal role in processing and analyzing these data. Integrating AI with digital twins (DTs) enhances the analytical capabilities of HDHE systems, enabling intelligent decision-making and predictive healthcare services [19,58]. Machine learning (ML) and deep learning (DL) are the most commonly used AI algorithms to analyze and evaluate human health conditions now.

3.4.1. Machine Learning (ML)

Machine learning (ML) is widely used for analyzing patterns in health-related data, including motion analysis [59], fatigue detection [60], and stress assessment [61]. Algorithms such as linear regression (LR), k-nearest neighborhood (KNN), support vector machine (SVM), decision tree (DTr), random forest (RF), gradient boosting (GB), and naive Bayes (NB) are commonly applied. For example:

- Ferreira et al. established a KNN prototyping scheme for embedded human activity recognition with online learning [62].
- Subramanian et al. developed a real-time emotion-recognition system using GB for healthcare applications [63].
- Moztarzadeh et al. employed ML methods including LR, DTr, RF, and GB to evaluate treatment progress and disease severity using DTs [64].

3.4.2. Deep Learning (DL)

Deep learning (DL), a subset of ML, excels at analyzing high-dimensional data and extracting complex patterns. Models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), deep neural networks (DNNs), and long short-term memory (LSTM) networks are particularly effective.

- Ahmed et al. integrated DL with DTs to detect COVID-19 in X-ray images, achieving 94% accuracy [65].
- Wang et al. proposed a CNN-based framework for cognitive fatigue classification with 88.85% accuracy [66].
- Su et al. proposed an automated human activity recognition network HDL with smartphone motion sensor units, which combines DBLSTM (deep bidirectional long short-term memory) and a CNN. Its accuracy and F1 score are as high as 97.95% and 97.27% [67].

The integration of ML and DL methods often yields superior results. For instance, Irfan et al. enhanced motion recognition accuracy by combining CNN, LSTM, and BiLSTM models [68]. By leveraging these technologies, the HDHE system can deliver robust healthcare solutions, significantly improving seafarers' safety and well-being. Table 1 lists some model cases and provides a comparison of their accuracy.

Table 1. Empirical research on AI-driven human healthcare.

Type	Model	Accuracy	Detection	Ref.
ML	DTr	82.6%	Fatigue	[69]
	KNN	78.4%	Motions	[62]
	SVM	80.3%	Stress	[70]
	NB	85.5%	Stress	[71]
	RF	73%	Stress	[72]
DL	CNN	\	Motions	[73]
	BiLSTM	99.9%	Fatigue	[74]
	CNN	88.85%	Fatigue	[66]
Hybrid	CNN + LSTM + BiLSTM	98.38%	Motions	[68]
	CNN + RNN	85.71%	Stress	[75]
	RF + SVM	98%	Stress	[76]

4. Discussion

4.1. Challenges and Practical Solutions

While the HDHE system holds promise for revolutionizing seafarer healthcare, it also presents several challenges. Some of the key hurdles include the following:

4.1.1. Resource Constraints

Due to limited access to healthcare facilities while at sea, the development of accurate HDHE systems necessitates sophisticated technologies like sensors, wearables, and computers that may not be readily available [77]. Moreover, the adoption of such technology can be hindered by its high cost, posing a barrier to entry for smaller shipping companies [78–80].

It is crucial to promote the use and integration of medical equipment on ships to address these challenges. Overcoming technical obstacles and demonstrating the tangible benefits of HDHE systems to stakeholders are essential steps towards widespread adoption in the maritime industry. Providing education and training programs for seafarers and healthcare professionals is also needed to enhance acceptance and utilization of this system.

In addition, natural disasters and severe weather may disrupt communication and power supply, affecting the stability of HDHE systems. To ensure reliability, future systems should include backup communication methods, satellite links, and automated emergency protocols.

4.1.2. Privacy Concerns

Privacy concerns surrounding the collection of sensitive medical data are another challenge. Compliance with the European Union’s General Data Protection Regulation (GDPR) [81] and the International Maritime Organization’s (IMO) Guidelines on Shipowners’ Responsibilities for Seafarers’ Health [82] ensures alignment with stringent data privacy and crew welfare standards. Emerging ethical AI frameworks, such as UNESCO’s Recommendation on the Ethics of Artificial Intelligence [83], further underscore the need for transparency and accountability in AI-driven health diagnostics to mitigate biases and uphold seafarers’ rights. Seafarers may hesitate to disclose personal medical information due to apprehensions regarding confidentiality, potential data breaches, or misuse of their data [84]. Moreover, navigating the sharing of personal data across diverse jurisdictions can be complex due to varying regulations, leading to legal ambiguities. This increases the difficulty of protecting seafarers’ privacy [85,86].

Practical measures to address these concerns include strict adherence to data protection regulations, employing secure data transmission methods, and implementing robust data storage protocols [87]. Notably, blockchain technology emerges as a promising solu-

tion to mitigate these challenges. By establishing a secure and transparent framework for storing and transferring data, it can minimize the risk of data breaches [88,89]. Furthermore, blockchain facilitates more streamlined sharing of health records across different jurisdictions, thereby resolving legal uncertainties [90].

4.1.3. Additional Stress

In addition, continuous health monitoring may lead individuals to overfocus on their well-being, with potential psychological effects, causing excessive vigilance and worry about small fluctuations or normal changes in health indicators, particularly when the information is intricate or conflicting [81,91,92].

To address these issues, we need to design user-friendly interfaces and establish clear communication channels to facilitate data understanding and interpretation. In the meantime, appropriate adjustment for the frequency of notification and alarm should be carried out to reduce the psychological burden.

4.2. Implications and Economic Benefits

In future practice, the integrated HDHE platform has great potential to improve both crew health and operational efficiency. At present, with the rapid development of various technologies, researchers have begun to develop similar systems. For example, Battineni and Amenta introduced a telemedicine platform designed to enhance onboard medical decision-making by non-medical personnel [85]. Seafarers are able to quickly create medical requests to transmit symptom information to doctors on shore to obtain remote health management guidance.

Stakeholders involved in HDHE systems include seafarers, ship owners, healthcare providers, technology providers, and others. Employee performance, accident frequency, maintenance costs, medical expenses, etc. are indicators for these stakeholders to measure whether benefits can be obtained [29,93,94]. The substantial implications and economic advantages that HDHE systems carry for them are mainly reflected in the following aspects:

- Health monitoring for seafarers: HDHE systems enable real-time remote monitoring of seafarers' health. This aids in early detection of potential health issues, averting their escalation into critical conditions necessitating medical evacuation [95,96].
- Cost reduction for ship owners: HDHE can provide early prevention of health problems, reduce the frequency of accidents caused by human factors, and reduce the downtime of ships. At the same time, it can reduce the need for medical personnel on board and reduce medical costs.
- Improving diagnostic accuracy for healthcare providers: HDHE systems enable the accumulation and analysis of large amounts of seafarers' health data and medical history so that physicians can recommend the appropriate treatment for each individual [97]. This reduces the possibility of misdiagnosis or inappropriate treatment and improves diagnostic accuracy and efficacy.
- Increase revenue for technology providers and training institutions: HDHE systems create new revenue generation opportunities for technology vendors and training institutions. As more companies invest in this system, they will benefit from the need for monitoring equipment, data analysis tools, and specialized project training.

5. Conclusions

Seafarers face unique health challenges due to the nature of their work, which involves extended periods at sea, isolation, and exposure to harsh environmental conditions. HDHE systems being explored now, as a derivative of DHE, which focus on human health, have proven valuable in monitoring and improving the health and well-being of seafarers and

offshore workers. Since its introduction in 2017, the concept of HDT has gained widespread application across industries, particularly in healthcare, and has become a promising tool within the HDHE framework.

This paper provides a comprehensive exploration of the enabling technologies required for implementing HDHE systems in seafarer healthcare. It comprehensively examines each stage of the operational workflow of the HDHE system and reviews in detail three key enabling technologies: data collection systems, data transfer methods, and data analysis techniques. Furthermore, this paper discusses the problems that the HDHE system may face in the development and practical implementation, such as resource shortage and privacy concerns, and puts forward the corresponding solutions. The impact and economic benefits of the system are also explored.

Through our literature review, several key insights have emerged:

- **Unique Health Challenges:** Seafarers and offshore workers face distinctive health risks due to long periods away from medical facilities and exposure to extreme weather, physical labor, and isolation.
- **Role of Digital Twins:** HDT is central to HDHE systems, enabling continuous real-time monitoring of seafarers' health, predictive diagnostics, and personalized medical care. They integrate physical and digital data to allow ongoing health assessments and interventions.
- **Enabling Technologies:** Successful implementation of HDHE systems hinges on advanced technologies, including sensing technology, wearable devices, satellite communication, wireless networks, and AI-driven data analysis.
- **Operational Workflow:** HDHE systems involve several stages, including data collection via sensors and wearables, data transmission to onshore facilities, processing through AI algorithms, and providing real-time feedback for medical interventions.
- **Challenges and Barriers:** Implementation of HDHE systems faces technical complexities, organizational challenges, ethical issues related to privacy and security, and practical limitations like cost and resource constraints.
- **Potential Impact:** HDHE systems have the potential to transform healthcare for seafarers by enabling remote monitoring, accurate diagnostics, timely medical interventions, and personalized healthcare services, thereby improving their overall well-being, productivity, and safety onboard.
- **Rapid Development:** Though HDHE technology is still in its early stages and currently expensive, rapid advancements are underway. Ongoing research and development are expected to make these systems more accessible, affordable, and efficient in the near future.

In summary, HDHE systems offer tremendous potential for enhancing seafarers' healthcare by harnessing advanced technologies and addressing existing challenges. As these systems evolve, they are poised to revolutionize the maritime industry, ensuring the safety, health, and well-being of seafarers worldwide.

Future research could explore adaptive architectures like the Adaptive Organizational Systems Framework (AOSF) [98] to enhance HDHE's responsiveness to dynamic maritime conditions. Integrating reconfigurable digital twins with AI-driven decision-making, as demonstrated in recent healthcare reviews [99,100], may further bridge gaps between primary, secondary, and tertiary care data interfaces. Systematic analyses of AI's role in organizational agility [101] also offer insights into optimizing HDHE workflows for real-time adaptability.

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Abbreviations

The following abbreviations are used in this manuscript:

DHE	Digital Healthcare Engineering
HDHE	Human Digital Healthcare Engineering
EMSA	European Maritime Safety Agency
DT	Digital Twin
HDT	Human Digital Twin
LEO	Low Earth Orbit
UWB	Ultra-Wideband
NFC	Near-Field Communication
BDS	BeiDou Satellite
SEMSW	Ship Emission Monitoring Sensor Web
FEM	Finite Element Method
CAD	Computer-Aided Design
VR	Virtual Reality
AR	Augmented Reality
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
LR	Linear Regression
KNN	K-nearest Neighborhood
SVM	Support Vector Machine
DTr	Decision Tree
RF	Random Forest
GB	Gradient Boosting
NB	Naive Bayes
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
GAN	Generative Adversarial Network
DNN	Deep Neural Network
LSTM	Long Short-Term Memory

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