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Article

A Systematic Literature Review of Vibration-Induced Fatigue Assessment in Ship Structures: Publication Trends, Research Themes, Bibliometric Insights, and Future Research Directions (2002–2026)

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Abstract: One of the main causes for deterioration of marine structures and reduction of their service life is the fatigue by vibration. Fatigue damage accumulates over time due to cyclic loading from ocean wave and machinery excitation, hydroelastic response and operational vibration in service, with implications for structural integrity, operational safety and maintenance efficiency. There has been a dramatic increase in the research on this problem in the last two decades. It now includes conventional fatigue assessment, numerical simulation, structural health monitoring, machine learning and more recently, Digital Twin technology. A broad synthesis of the development of this literature is still missing. This study fills the gap with a systematic literature review (SLR) based on the bibliographic metadata of 75 scientific publications published from 2002 to 2026. This review is reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure transparency and reproducibility of the review process. Instead of full-text findings, the study synthesizes metadata and focuses on the publication characteristics, classification of themes, methodology development, bibliometric patterns, and emerging directions of research. The literature is classified into eight research themes based on the analysis: (1) fatigue assessment methods, (2) wave-induced fatigue, (3) hydroelasticity and hull girder vibration, (4) vibration-induced fatigue of local structural components, (5) numerical simulation and finite element analysis, (6) structural health monitoring, (7) artificial intelligence and machine learning applications, and (8) fatigue prediction based on Digital Twin. The results indicate a transition from deterministic and physics-based fatigue assessment to intelligent, data-driven and real-time monitoring approaches. Recent research has applied machine learning, sensor-based monitoring, and virtual models of ship structures. Few studies combine these into one predictive maintenance framework. Several gaps remain: real-world operational ship data is scarce, physics-based models are rarely integrated with artificial intelligence, no comprehensive Digital Twin framework exists for fatigue prognosis, multisensor data fusion is limited, and validation against long-term onboard monitoring data is rare. These gaps clearly indicate opportunities for future work on intelligent, explainable, and adaptive fatigue prediction systems that can support predictive maintenance and decision making in maritime engineering. The results offer a snapshot of the state of vibration-induced fatigue research to researchers, naval architects, classification societies and industry practitioners and provide a foundation for future work towards Digital Twin-enabled structural health monitoring and remaining useful life prediction in ship structures.

Keywords: Systematic Literature Review; Vibration-Induced Fatigue; Ship Structures; Fatigue Assessment; Structural Health Monitoring; Digital Twin; Machine Learning; Bibliometric Analysis; Predictive Maintenance; Remaining Useful Life (RUL).

1. Introduction

The maritime industry underpins the global economy and more than 80 per cent of cross-border trade is carried by sea. The demand for bigger, faster and more energy-efficient ships has driven advances in ship design and structural optimisation. Modern merchant vessels like ultra-large container vessels, liquefied natural gas (LNG) carriers, bulk carriers and offshore support vessels have light-weight but efficient structural configurations, so that they can maximize cargo capacity and minimize fuel consumption. However, the same improvements also increase the susceptibility of the structures to fatigue damage due to repeated cyclic loading during the vessel's operational life.

Vibration-induced fatigue is one of the most serious engineering problems among the deterioration mechanisms affecting marine structures. Fatigue is not a static failure. It happens over time and is caused by repeated cycles of stress, often well below the ultimate strength of the material. During operation, cyclic loading takes place because of wave action, propulsion systems, excitation of the engine, vibration of the propeller, response of the hull girder, hydroelastic phenomena, slamming, springing, whipping and manoeuvring. Repeated loading creates microcracks which may lead to structural failures if not detected and corrected in time.

Fatigue failures have serious consequences for the maritime safety, operational reliability and maintenance cost. Cracking occurs in weld joints, corners of hatches, deck openings, connections of stiffeners, brackets, and other areas of stress concentration. If left undetected, they can threaten hull integrity, reduce structural strength, increase maintenance costs, interrupt operations and in extreme cases cause catastrophic failure. Fatigue analysis has thus become an integral part of ship structural design, classification society requirements, life-cycle management and predictive maintenance.

Academia and industry have been using traditional fatigue assessment methods for decades. These methods predict fatigue life under cyclic loading by S-N curves, Palmgren-Miner linear damage accumulation, rainflow cycle counting, spectral fatigue analysis and finite element analysis. They are good for many engineering applications and are still embedded in the design guidelines of the major classification societies. Their limitation is that they are based on deterministic assumptions and predefined loading scenarios that limit their capability to represent the nonlinear, stochastic and time-varying conditions in which modern ships operate in reality.

The advances in computational mechanics have enhanced the fatigue assessment via high-fidelity numerical simulation. Currently, Finite Element Method (FEM), Computational Fluid Dynamics (CFD), Fluid-Structure Interaction (FSI), hydroelastic analysis and time domain simulation are commonly used, enabling researchers to assess structural response with significantly higher accuracy. These methods generate detailed stress distributions, critical sites for fatigue and account for the interaction between hydrodynamic loading and structural behaviour . Special attention has been paid to hydroelastic effects, such as springing and whipping, as they are of considerable importance for cumulative fatigue damage, especially in large container ships and other flexible hulls.

Numerical simulation is limited by computational cost, model uncertainty, and the need for assumed boundary conditions. Most fatigue analyses are offline with predefined operational scenarios instead of data that updates continuously. As a result the predictions often do not match the actual structural conditions experienced by a vessel in service. This drawback has led researchers to data-driven approaches that can introduce real operational information into fatigue assessment.

Advances in sensing technologies have enabled Structural Health Monitoring (SHM) for marine structures. Modern SHM systems employ accelerometers, strain gauges, displacement sensors, fiber-optic sensors and acoustic emission sensors as well as wireless sensor networks to monitor the structural response during operation. These systems allow engineers to identify abnormal behavior, quantify accumulated fatigue damage and plan maintenance based on the real state of the structure as opposed to time-invariant inspection periods. Maintenance strategy is changing from corrective to condition-based and predictive.

The importance of AI and machine learning in fatigue prediction is growing. Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks and deep learning architectures have demonstrated promising results in fatigue damage estimation, anomaly detection, damage classification and Remaining Useful Life (RUL) prediction. Unlike traditional empirical approaches, these algorithms can capture nonlinear relationships from large operational datasets, which improves predictions under complex environmental conditions.

Despite the advances in predictive capability brought by machine learning, most of the AI-based models on fatigue are black boxes with limited physical interpretability. They are typically trained using lab-scale data or simulation results, as opposed to long-term measurements taken from operational vessels. Questions therefore remain about the extent to which these models generalize and how well they perform in real maritime environments, where operational conditions are highly variable.

Digital Twin technology has recently received attention as a new approach to intelligent ship operation and maintenance. Digital Twin is a digital dynamic twin of a physical asset that is continuously updated with real operational data from the physical asset through sensors and computational models. In ship structural engineering, a Digital Twin can integrate numerical simulation, real-time sensor measurements, machine learning and decision support on one platform that continuously evaluates structural integrity and predicts how fatigue develops over the life cycle of the vessel.

Although there is increasing interest in Digital Twin applications, the research is still dispersed. Most research focus on specific components, such as numerical fatigue simulation, sensor deployment, machine learning approaches, or conceptual Digital Twin frameworks, rather than merging them into a full predictive maintenance system. Few research have combined physics-based structural models with data-driven learning to forecast tiredness in an adaptable and understandable manner. Validation with long-term on-board data is also limited, creating a gap between laboratory research and practical application.

Conventional fatigue analysis, hydroelasticity, structural dynamics, numerical simulation, sensor technology, artificial intelligence and Digital Twin systems are now being investigated, producing a large amount of literature in the last twenty years. The number of publications is growing , but no systematic synthesis has charted the evolution of the field as a whole. Existing reviews have typically focused on particular methods, individual structural elements or single technological developments, but have not provided an integrated perspective on publication trends, thematic change, methodological progression and future opportunities across the field.

To fill this gap, this study performs a Systematic Literature Review (SLR) of the bibliographic metadata of 75 scientific publications published between 2002 and 2026. This review describes the publication trends, thematic development, methodological evolution, bibliometric characteristics and emerging directions of vibration-induced fatigue assessment of ship structures based on the PRISMA 2020 framework. The difference from narrative review is that it uses a systematic and transparent approach that minimizes selection bias and allows reproducibility. What is available is bibliographic metadata, not full text, so the analysis is based on the metadata. This allows a robust descriptive synthesis of the development of the field but avoids unsupported claims about the findings of individual studies.

This review has four contributions. It presents the evolution of vibration-induced fatigue research in ship structures over a span of over two decades. It reflects the current hot topics and the change of approach from traditional fatigue evaluation to intelligent monitoring. It describes the existing gaps which hinder real-time fatigue prediction and predictive maintenance in maritime engineering. Finally, it indicates future directions based on the integration of digital twin technology, structural health monitoring, physics-informed artificial intelligence, multisensor data fusion, and residual useful life prediction for intelligent life-cycle management of marine structures.

The structure of the paper is as follows. Section 2 describes the methodology of the review based on the PRISMA 2020 framework, including the search strategy, inclusion and exclusion criteria, quality assessment, and data synthesis. Section 3 deals with the publication trend analysis, bibliometric characteristics, thematic classification and metadata-based synthesis. Section 4 presents the key findings, research gaps and the assessment of emerging technological developments. Section 5 gives conclusions and proposes future research directions for intelligent fatigue assessment by integrating Digital Twin technology, structural health monitoring and artificial intelligence.

2. Methodology

2.1 Research Design

In this paper a Systematic Literature Review (SLR) is presented to produce a structured and transparent synthesis of research on vibration induced fatigue assessment in ship structures. The methodology was based on the PRISMA 2020 guidelines, widely adopted for improving the transparency, reproducibility and rigor of literature reviews. PRISMA provides a systematic way to identify, screen, select and synthesize relevant studies while minimizing selection bias 22.

This study was conducted under a protocol with pre-defined research questions, explicit eligibility criteria, systematic screening, quality assessment and structured data extraction, unlike a conventional narrative review. Because of the bibliographic metadata nature of the available data rather than full-text articles, the synthesis targeted publication characteristics, thematic evolution, methodological trends, and bibliometric patterns rather than detailed comparison of experimental results. The review followed six sequential stages: formulating the research questions, identifying the literature, screening and assessing eligibility, assessing quality, extracting metadata, and performing qualitative synthesis and bibliometric analysis.

2.2 PRISMA 2020 Review Protocol

The review protocol was designed according to the PRISMA 2020 framework, comprising four principal stages: Identification, Screening, Eligibility, and Inclusion.

Stage 1. Identification

The bibliographic collection yielded relevant literature on vibration-induced fatigue in ship constructions. The first collection includes 75 papers from 2002 to 2026.

The metadata included:

1. Authors
2. Article title
3. Journal
4. Publication year
5. Volume
6. Issue
7. Pages
8. Publisher

This metadata served as the foundation for analyzing publishing trends, categorizing themes, describing bibliometrics, and identifying research gaps.

Stage 2. Screening

The identified records were filtered to exclude publications that fell outside the scope of this review.

Screening considered:

1. Article relevance to ship structural fatigue;
2. vibration-induced structural response;
3. fatigue assessment methods;
4. hydroelastic response;
5. structural health monitoring;
6. numerical simulation;
7. machine learning;

8. Digital Twin.

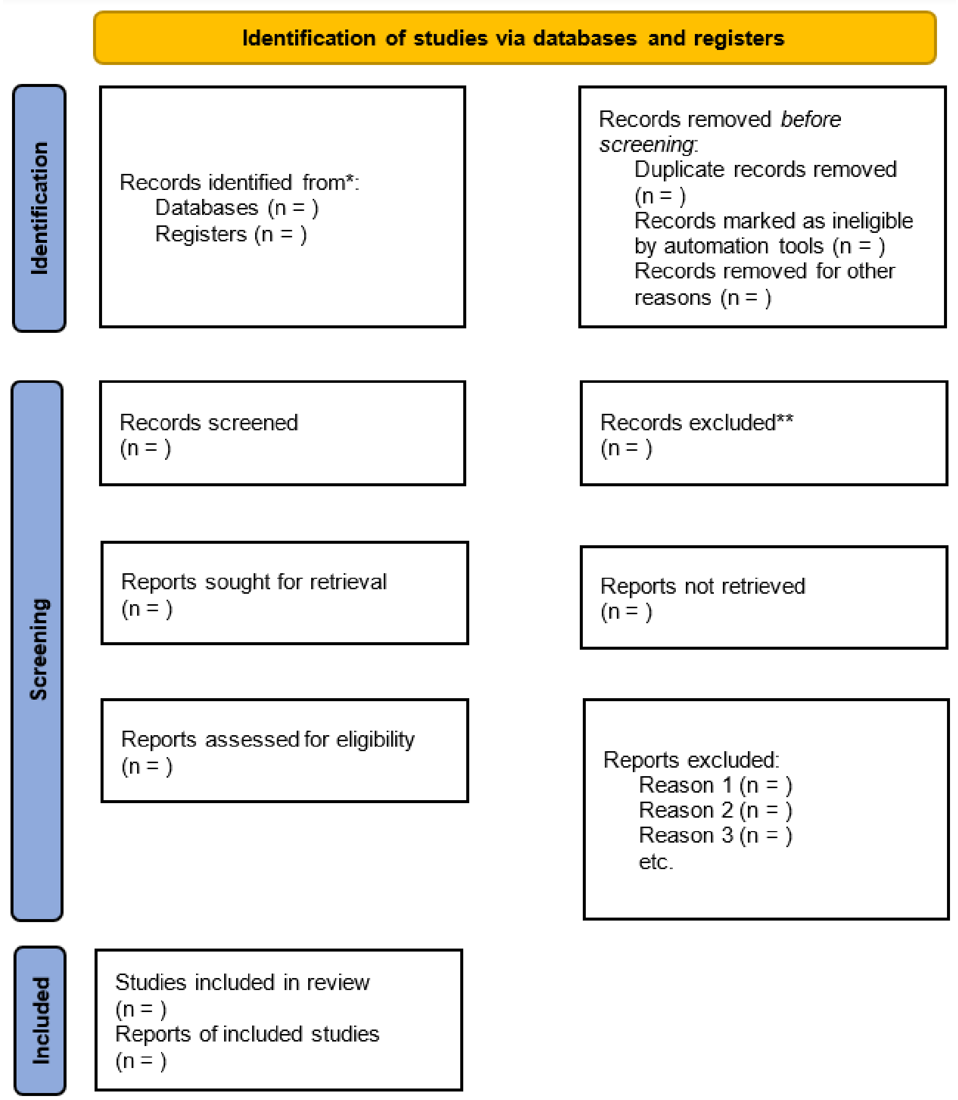
Duplicate records and publications unrelated to marine structural fatigue were excluded.

Stage 3. Eligibility

Eligible studies were reviewed against predetermined inclusion and exclusion criteria. Because this study drew on metadata, the criteria emphasized topic relevance rather than methodological details that appear only in full-text articles.

Stage 4. Inclusion

Only studies that directly address vibration-induced fatigue or closely related structural integrity issues in marine engineering are included in the final synthesis. The resultant dataset of 75 papers served as the basis for all future studies. PRISMA flow diagram (review based on metadata).



2.3 Research Questions

The review was directed by five research questions (RQs) that sought to explore the evolution of vibration-induced fatigue research, from publishing trends to future research prospects.

RQ1

How has research on vibration-induced fatigue assessment in ship structures evolved over time?

Purpose:

1. publication growth
2. annual trends
3. research maturity

RQ2

What are the dominant research themes and methodological approaches employed in vibration-induced fatigue studies?

Purpose:

1. identify major topics
2. classify research methods
3. investigate methodological evolution

RQ3

What bibliometric characteristics describe the existing body of literature?

Purpose:

1. publication distribution
2. journal distribution
3. publisher distribution
4. temporal evolution

RQ4

What research gaps remain in current vibration-induced fatigue assessment studies?

Purpose:

1. identify methodological limitations
2. identify technological limitations
3. identify validation limitations

RQ5

What future research directions can advance intelligent fatigue assessment for ship structures?

Purpose:

1. Digital Twin
2. Structural Health Monitoring
3. Artificial Intelligence
4. Remaining Useful Life prediction
5. Predictive Maintenance

2.4 Search Strategy

The literature search focused on publications addressing vibration-induced fatigue assessment in ship structures and related marine structural engineering topics.

Representative search terms included combinations of:

1. vibration-induced fatigue

2. ship structures
3. fatigue assessment
4. hull girder vibration
5. hydroelasticity
6. springing
7. whipping
8. structural health monitoring
9. machine learning
10. Digital Twin
11. fatigue prediction
12. marine structures
13. structural integrity
14. finite element analysis
15. wave-induced fatigue

Boolean operators were employed to broaden or refine search combinations.

Typical search expressions included:

("vibration-induced fatigue" AND ship) ("fatigue assessment" AND marine structures) ("ship structure" AND fatigue) ("Digital Twin" AND fatigue) ("Structural Health Monitoring" AND ship) ("Machine Learning" AND fatigue prediction) ("wave-induced fatigue" AND hull structure)

The retrieved publications were exported into bibliographic metadata format for further screening and descriptive analysis.

2.5 Inclusion and Exclusion Criteria

Explicit eligibility criteria were established before the review process to ensure consistency and transparency.

Inclusion Criteria

Criterion	Description
IC1	Peer-reviewed journal articles
IC2	Publications addressing vibration-induced fatigue or related ship structural integrity topics
IC3	Studies published between 2002 and 2026
IC4	Publications written in English
IC5	Studies related to marine, offshore, or ship structural engineering
IC6	Publications containing sufficient bibliographic metadata for classification

Exclusion Criteria

Criterion	Description
EC1	Conference abstracts without complete bibliographic information
EC2	Editorials, book reviews, news articles
EC3	Studies unrelated to marine structural fatigue

EC4	Publications outside the predefined time period
EC5	Duplicate records
EC6	Publications lacking essential bibliographic metadata

2.6 Quality Assessment

Although the review was based on bibliographic metadata rather than full-text evaluation, a controlled quality assessment verified that all included studies satisfied a minimum relevance threshold.

Each publication was evaluated according to six quality assessment (QA) criteria.

QA Code	Assessment Criterion
QA1	Clearly related to vibration-induced fatigue
QA2	Relevant to ship or marine structures
QA3	Published in peer-reviewed scientific journals
QA4	Published within the selected period
QA5	Contains complete bibliographic metadata
QA 6	Provides sufficient thematic information through title and publication metadata

The scores for each criterion were as follows:

1 = Yes

0 = No

The total quality score varied from zero to six.

Only publications with a good quality score were used for thematic synthesis.

Because the dataset only included journal papers with comprehensive metadata, each selected study satisfied the minimum quality standard.

2.7 Data Extraction

A standardized data extraction protocol was developed to standardize metadata gathering and assist subsequent analyses.

The retrieved variables are summarized in Table 1.

Table 1. Metadata Extraction Framework

Variable	Description	Purpose
Authors	Author names	Collaboration analysis
Publication Year	Year of publication	Trend analysis
Journal	Source title	Publication distribution
Publisher	Publisher information	Bibliometric description
Article Title	Research topic	Theme classification
Volume	Bibliographic information	Documentation
Issue	Bibliographic information	Documentation

Pages	Bibliographic information	Documentation

Following extraction, the metadata were entered into a review database and analyzed descriptively, temporally, thematically, and qualitatively.

2.8 Data Synthesis

The extracted metadata were synthesized using descriptive qualitative analysis combined with bibliometric summarization.

The synthesis comprised of five analytical steps:

1. Publication Trend Analysis, which analyzes the growth rate and time evolution of the literature.

2. Bibliometric Descriptive Analysis, reporting publication distribution by journals, publishers and years of publication.

3. Thematic Analysis: Studies categorized into major research themes based on title and bibliographic information.

4. Gap analysis in the research, identifying methodological, technological and practical gaps across the literature reviewed.

5. Future Research Agenda, highlighting promising research directions based on observed thematic evolution and identified knowledge gaps.

The dataset consists of bibliographic metadata, not full text articles, so the synthesis addresses the evolution of research, publication characteristics, and the development of themes. Interpretations of experimental findings, quantitative performance comparisons or detailed methodological outcomes are deliberately omitted to maintain validity and transparency.

3. Results

3.1 Publication Trend Analysis

Metadata analysis of 75 publications shows a significant increase in research interest in vibration-induced fatigue assessment of ship structures in the last two decades. Time distribution shows the field’s evolution from a specialized topic to a multidisciplinary one covering structural mechanics, naval architecture, computational engineering, structural health monitoring, artificial intelligence, and Digital Twin technology.

The publications cover from 2002 to 2026, showing the growth of interest in fatigue assessment under dynamic loading. The initial work from 2002 to 2010 was based on the theoretical basis for fatigue damage assessment according to the conventional structural mechanics . Spectral fatigue analysis, S-N curves, Miner's cumulative damage rule and finite element analysis studies were developed during this period for fatigue life estimation . This work provided the engineering basis for structural design and fatigue assessment used by the classification societies.

Between 2011 and 2018, the research concentrated on enhancing numerical accuracy using advanced computational techniques. Wave induced loading, hull girder vibration, springing, whipping and nonlinear structural response associated with hydroelastic effects gained increased attention. Increasing computational resources and simulation techniques have led to an increasing use of finite element modeling, computational fluid dynamics (CFD), and fluid-structure interaction (FSI) approaches .

Between 2019 and 2022, a broader change took place, as researchers began to see the limits of physics-only approaches. In many studies, sensor technology, operational measurements and Structural Health Monitoring (SHM) began to be included in the fatigue assessment. This was in line with the general trend in marine engineering towards condition-based maintenance and continuous monitoring.

The most recent period, 2023-2026, demonstrates the highest diversity and innovation. The publications increasingly investigate machine learning, deep learning, Digital Twin technology, virtual sensing, predictive maintenance and Remaining Useful Life (RUL) prediction. These studies typically aim to complement traditional structural analysis with data-driven approaches for real-time decision-making rather than replacing physics-based methods.

In summary, the publication trend demonstrates three major stages of development:

1. Foundation Phase (2002–2010): Establishment of traditional fatigue assessment procedures.

2. Computational Development Phase (2011-2022): increase in high-fidelity numerical modeling and structural monitoring.

3. Intelligent Monitoring Phase (2023–2026): Implementation of AI-based fatigue prediction, Digital Twin, and predictive maintenance technologies.

The timeline depicts the evolution of vibration-induced fatigue research, from deterministic engineering analysis to intelligent, adaptive, and data-driven structural integrity management.

3.2 Bibliometric Descriptive Analysis

A descriptive picture of the research landscape represented by the chosen publications is provided by the bibliometric analysis. Even if the review solely makes use of bibliographic metadata, some characteristics unique to the field come apparent.

Publication Year Distribution

The annual distribution indicates a progressive increase in output over the review period. Early papers came seldom, but the quantity of studies increased significantly around 2020. This shows that vibration-induced fatigue has become a more pressing issue as ship constructions get more complicated, safety standards tighten, and computational tools increase.

Research Evolution

The chronological development of the literature reveals four major technological transitions:

Research Period	Dominant Characteristics
2002–2010	Conventional fatigue analysis using S–N curves, Miner's rule, and spectral methods
2011–2016	Extensive application of Finite Element Analysis and hydroelastic simulations
2017–2022	Structural Health Monitoring, sensor technologies, and operational measurements
2023–2026	Artificial Intelligence, Machine Learning, Digital Twin, and predictive maintenance

This pattern reflects the gradual convergence of structural engineering and intelligent digital technology.

Publication Sources

Numerous international journals covering naval architecture, marine engineering, offshore engineering, computational mechanics, structural integrity, fatigue analysis, and applied engineering published the reviewed works. This diversity of venues illustrates that research on vibration-induced fatigue is varied and draws on numerous engineering specializations.

Publisher Distribution

According to the metadata, the publications are from a number of globally renowned academic publishers in the fields of structural engineering, computational mechanics, engineering, and nautical sciences. Their inclusion in many journals demonstrates extensive scientific interest in vibration-induced fatigue and its status as a research field worldwide.

Based on article titles and metadata, the reviewed studies fall into several methodological categories.

Based on article titles and metadata, the reviewed studies can be broadly classified into several methodological categories.

Methodological Category	General Research Focus
Analytical approaches	Fatigue theory and structural mechanics
Numerical simulation	FEM, CFD, FSI, hydroelastic analysis

Experimental investigation	Laboratory vibration and fatigue testing
Structural Health Monitoring	Sensor-based monitoring
Artificial Intelligence	Machine learning and deep learning
Digital Twin	Virtual representation and predictive maintenance

The distribution shows a gradual move from conventional analytical methods toward integrated intelligent monitoring systems.

Keyword Evolution

The article titles reveal a clear shift in the terminology researchers use most often. Earlier publications emphasized fatigue assessment, fatigue damage, spectral fatigue, and hull girder vibration.

More recent publications increasingly incorporate emerging technological terms such as:

1. Digital Twin
2. Structural Health Monitoring
3. Machine Learning
4. Deep Learning
5. Remaining Useful Life
6. Predictive Maintenance
7. Virtual Sensing

This shift in terminology reflects the digital transformation underway in maritime structural engineering.

3.3 Theme Analysis

The thematic synthesis grouped the publications into eight research themes according to their primary focus.

Theme 1. Conventional Fatigue Assessment

The largest percentage of papers concerns traditional fatigue life estimation using stress-life connections, cumulative damage theories, and spectral fatigue analysis. These studies establish the theoretical framework for measuring fatigue accumulation under cyclic loads and remain prevalent in engineering practice.

Theme 2. Wave-Induced Fatigue

Fatigue brought on by wave-induced loading is the subject of the second theme. Researchers look into how fatigue accumulation is impacted by irregular waves, nonlinear hydrodynamic stress, shifting sea states, and long-term environmental influences. This study demonstrates that one of the main causes of structural fatigue during vessel operation is environmental loading.

Theme 3. Hydroelasticity and Hull Girder Vibration

A substantial number of publications examine hydroelastic structural response. Common topics include springing, whipping, hull girder vibration, and slamming-induced fatigue. The literature consistently shows that hydroelastic phenomena add substantially to cumulative fatigue damage and should be included in structural integrity assessment.

Theme 4. Local Structural Fatigue

Fatigue of localized parts including welded joints, rudders, shafts, bearings, brackets, and stiffeners has been the subject of numerous research. This study stresses the significance of stress concentration effects, which global structural analysis alone cannot always reveal.

Theme 5. Numerical Simulation

Numerical simulation is one of the dominant methodological themes.

Frequently employed computational techniques include:

1. Finite Element Method (FEM)
2. Computational Fluid Dynamics (CFD)
3. Fluid–Structure Interaction (FSI)
4. Dynamic response simulation

These methods improve understanding of structural behavior under complex operational loading.

Theme 6. Structural Health Monitoring

Research on SHM has expanded considerably in recent years. Typical monitoring technologies include strain sensors, accelerometers, vibration monitoring, and wireless sensing systems. The main goal is continuous assessment of structural integrity during operation.

Theme 7. Artificial Intelligence

Artificial intelligence has become an increasingly prominent topic.

Recent studies investigate:

1. Artificial Neural Networks
2. Machine Learning
3. Deep Learning
4. anomaly detection
5. fatigue prediction

These approaches aim to improve prediction accuracy while lowering computational cost.

Theme 8. Digital Twin

This week's theme is "Digital Twin," which is new and growing quickly. Most of the current research looks into:

1. A virtual model of a ship.
2. Monitoring in real time.
3. Maintenance that is planned ahead of time.
4. Figure out how much useful life is left.

Digital twin technology is still in its early stages, but it is expected to become more important in smart ship management in the future. All of these ideas point to a move away from linear structural analysis and toward cyber-physical systems that work together to track, predict, and improve the performance of structures over the course of a ship's lifetime.

3.4 Research Gap Analysis

The thematic synthesis reveals several knowledge gaps that continue to limit the practical use of intelligent fatigue assessment.

Gap 1. Fragmentation Between Physics-Based and Data-Driven Models

Most examined papers use either traditional mechanics-based analysis or machine learning on its own. Few studies have combined the two into a cohesive hybrid framework that maintains physical interpretability while obtaining excellent prediction accuracy.

Gap 2. Limited Real-Time Fatigue Prediction

The majority of fatigue models remain offline tools. Continuous real-time fatigue prediction using operational sensor data remains unusual.

Gap 3. Limited Digital Twin Integration

Digital twin research is emerging, but the majority of investigations are still in the conceptual or prototype stages. Few examples show constant synchronization between physical ships and virtual structural models.

Gap 4. Limited Full-Scale Validation

Most published models are validated using numerical simulations or laboratory investigations. Long-term validation of operational ships under actual situations is limited.

Gap 5. Limited Multisensor Data Fusion

Current monitoring systems typically use only one or two sensor types. The fusion of strain, vibration, environmental loading, propulsion parameters, and operational data has not yet been thoroughly investigated.

Gap 6. Explainability of Artificial Intelligence

Most machine learning models operate like black boxes. Explainable Artificial Intelligence (XAI) and Physics-Informed Machine Learning are underrepresented in vibration-induced fatigue studies.

Gap 7. Remaining Useful Life Prediction

Many studies conclude after measuring fatigue damage. Comprehensive Remaining Useful Life prediction that takes into consideration operational uncertainty, environmental variability, and structural degradation remains restricted.

Gap 8. Intelligent Decision Support

Most studies yield engineering signs such as fatigue damage or crack growth. Few integrate these insights into practical maintenance suggestions, inspection scheduling, or operational decision support. Research on vibration fatigue is rapidly shifting toward data-driven, intelligent structural integrity management. However, enabling technologies like digital twins, artificial intelligence, structural health monitoring, and predictive maintenance are regarded as distinct research streams in the articles under review. The lack of an integrated framework that integrates physics-based structural modeling, multisensor monitoring, Digital Twin synchronization, explainable artificial intelligence, and remaining usable life forecast is the biggest gap our investigation identifies. Closing it would enable the development of flexible, dependable fatigue assessment systems for future ship decision support, risk-informed maintenance planning, and real-time structural integrity management.

4. Discussion

4.1 Evolution of Vibration-Induced Fatigue Research

A review of 75 papers shows that research on vibration-induced fatigue in ship frames has changed a lot in the last 20 years. The field began with deterministic fatigue analysis and classical structural mechanics. It has since grown into a diverse field that includes cyber-physical systems, AI, sensor technologies, and computational mechanics. This change is caused by both more working demands on modern marine structures and progress in the science of engineering.

During the first phase, which lasted from 2002 to 2010, research focused on better ways to figure out the damage that comes from repeated cyclic loads. The goal was to find out how long something would last under fatigue using well-known methods like S-N curves, Palmgren-Miner cumulative damage theory, spectral fatigue analysis, and finite element modeling. These methods give classification groups and ship builders a way to think about how to measure fatigue. Fatigue was looked at as a problem that could be solved by making simple assumptions about loads, material properties, and environmental effects.

These old ways of doing things made building structures better, but as boats got bigger and situations at sea got trickier, it became clear that they weren't perfect. Waves that are hard to predict, propulsion systems, hydroelastic response, slamming, and maneuvering are just some of the things that make loads on container ships, LNG carriers, offshore platforms, and high-speed vessels very nonlinear. Most of the time, deterministic models don't show how complicated the structural response is when it's actually used.

A lot of powerful computer techniques were used during the second part. As computers got faster and more powerful, they made it possible to make high-fidelity models that showed complex structural dynamics more correctly.

The Finite Element Method (FEM), Computational Fluid Dynamics (CFD), and Fluid-Structure Interaction (FSI) are all useful ways to look into how stress builds up, deforms, and causes wear under real-life loading conditions.

During this time, people had a good understanding of hydroelastic processes like whipping and springing. In earlier studies, it was often thought that the response would be almost static. However, later studies found that hydroelastic vibration adds a lot to the damage from fatigue, especially in large, flexible hulls. These results changed the way we think about fatigue by showing how important it is to consider both static and dynamic structural interaction.

Another big change came when design-based fatigue testing gave way to operating structural integrity management. Later research focused on keeping track of how well structures worked over the course of their operational life cycle. Earlier research, on the other hand, was more concerned with figuring out fatigue life during the planning stage. This is in line with the general direction in the industry toward performance-based asset management, risk-informed maintenance, and life-cycle engineering. This trend has moved faster thanks to Structural Health Monitoring (SHM). Better sensors, such as strain gauges, accelerometers, fiber-optic sensors, and portable monitors, were always checking the response of the structure. Instead of relying on regular inspections or assumptions about how much weight something could hold, researchers started looking into fatigue using actual operational measurements. In order to predict fatigue, static calculations were replaced by dynamic condition monitoring. Another change was how quickly digital technology grew after 2020. More and more, machine learning, deep learning, and data analytics are being used to make forecasts more accurate by finding nonlinear relationships in operational data. These algorithms can be trained on measurable response, while classical empirical models need governing equations for each loading situation. This feature is helpful in marine settings where practical uncertainty, changing environmental conditions, and random loads have a big effect on how structures behave.

With the progress of Digital Twin technology, numerical models, sensor networks, operational data, and predictive algorithms can now all be put together in a single cyber-physical framework. Digital twins are more than just numerical models. By synchronizing virtual and physical representations, they allow for real-time review and planned maintenance. The literature review shows that digital twin applications are still in their early stages. However, they are the next step in the study of vibration-induced fatigue.

The chronology illustrated in this review highlights a gradual transition from deterministic fatigue assessment to intelligent structural integrity management. This change has been driven by advances in computational mechanics, sensing, artificial intelligence and digital engineering. Their convergence is changing fatigue assessment from a static calculation to a dynamic decision-support process that continuously evaluates structural health over a vessel's operational life.

4.2 Methodological Evolution and Technological Transformation

The methodological changes in the reviewed literature reflect the wider technological change in marine engineering and intelligent manufacturing. Although conventional approaches still play an important role in the field of structural design and regulation, modern research is more interested in adaptive, data-based and integrated approaches, which are able to cope with the complexity of modern ship operation.

In the past, fatigue assessment was performed by analytical and numerical methods based on classical mechanics. The main framework for structural life estimation included S-N curves, Palmgren-Miner cumulative damage theory, rainflow cycle counting and spectral fatigue analysis. These were simple to implement and provided acceptable accuracy under well-defined loading. Their use by classification societies confirmed their importance to ship design.

Deterministic models assume that we can define parameters beforehand to describe the loading, the material behavior, and the environmental influence. These assumptions become restrictive for ships operating in variable sea states, changing operational profiles, and uncertain environmental conditions. So the researchers looked for numerical methods that could better capture these complexities.

The most widely used computer method for evaluating fatigue is finite element analysis. Fatigue-critical areas were better understood thanks to the comprehensive stress distributions and localized behavior provided by FEM. Fluid-Structure and Computational Fluid Dynamics Interaction modeling enabled researchers study hydrodynamic loading that was previously difficult to quantify. These developments improved the capacity for prediction and made structural optimization more effective.

But physics-based models takes a lot of computing power and often needs exact boundary conditions. Also, the loading assumptions that are used in numerical models might not properly show how things work in the real world. Because of these problems, there is more interest in using observational data to study tiredness.

When Structural Health Monitoring was put in place, simulation-based analysis was mostly replaced by measurement-based review. Instead of just using numbers to guess how fatigue will affect something, SHM systems give you constant information about how structures react in real life. By measuring strain, vibration, displacement, acceleration, and environmental loads in real time, sensors make models that are only based on computations less uncertain.

A new method for predicting weariness was introduced using artificial intelligence. Machine learning approaches such as Artificial Neural Networks, Support Vector Machines, Random Forests, Convolutional Neural Networks, and Long Short-Term Memory networks can find complex nonlinear connections directly from operational data. Instead of simulating every physical encounter, these algorithms use statistical learning to figure out how predictions are related. Because of this, they often get better computing performance in situations that change.

The review also demonstrates that traditional engineering has not been superseded by artificial intelligence. The two collaborate more and more. While machine learning provides adaptive prediction, uncertainty management, and real-time analysis, physics-based models provide mechanistic insight, interpretability, and regulatory assurance. In particular, Physics-Informed Machine Learning, which incorporates governing physical concepts into data-driven algorithms to increase robustness and interpretability, has gained attention as a result of this combination.

The newest change is the rise of Digital Twin technology. A Digital Twin is not a standalone simulation or a single machine learning model. It synchronizes physical assets and virtual models using real-time sensor data. The cyber-physical integration offers the possibility of a continuous structural assessment, on-line fatigue prediction, Remaining Useful Life estimation, anomaly detection and maintenance optimization within one digital environment.

The publications reviewed show that current implementations of Digital Twins are still fragmented and often only cover a single component, e.g. sensor integration, virtual sensing or a predictive algorithm. Fully integrated Digital Twin ecosystems combining structural mechanics, multisensor monitoring, artificial intelligence, operational databases, uncertainty quantification, and engineering decision support are still rare. The technological transformation is therefore not yet finished.

This review describes the evolution of methodology from the traditional deterministic engineering calculation to intelligent cyber physical systems. It is unlikely that any single technique will dominate the future of vibration-induced fatigue assessment. This will consist of the development of decision-support frameworks that incorporate computational mechanics, structural health monitoring, explainable artificial intelligence, Digital Twin technology and predictive maintenance to improve the structural reliability and operational efficiency in the life cycle of marine structures.

4.3 Research Gaps and Scientific Contributions

The review shows that the scientific knowledge on fatigue caused by vibration on ship structures has significantly developed during the last two decades. Important advances appear to have been achieved in analytical fatigue assessment, numerical simulation, hydroelastic modeling, structural health monitoring (SHM), machine learning, and, most recently, Digital Twin technology. However, the metadata synthesis suggests that these streams of research have developed in parallel, resulting in fragmented progress rather than a holistic structural integrity management framework. The main challenge for future research is this fragmentation.

Data-driven methods and physics-based models are still very far apart. Classical fatigue evaluation is still based on structural mechanics, finite element analysis, spectral fatigue analysis, and fracture mechanics. Even though these methods are accepted by engineering design standards and give a clear physical interpretation, they aren't very good at showing how a ship works in a dynamic environment because they use simplified conditions and assumptions about how much weight the ship is carrying.

Machine learning, on the other hand, uses algorithms to look for complex, nonlinear patterns in operational data. This makes it very good at making predictions. Artificial neural networks, long short-term memory (LSTM) networks, and convolutional neural networks (CNN) are some examples of deep learning models that have been used to identify fatigue and find damage. But most of these predictors are "black box" models that are hard to understand,

and they don't always match up with structural mechanics. The study makes it clear that we need mixed systems that have the strength of physics-based analysis and the adaptability of artificial intelligence.

The second gap is that real-time tiredness prediction isn't used very often. Most of the studies that were looked at use offline modeling or post-processing of measured data to guess how much fatigue damage will happen. These methods help with understanding, but they can't keep track of how much fatigue is building up during operation. For predictive maintenance and making practical decisions, you need to use current data for adaptive online assessment.

The study also points out that the use of digital twins in marine structural engineering is still not very advanced. Most of the articles focus on certain parts of the Digital Twin, like prediction algorithms, virtual models, or integrating sensors. Real ship structures that are constantly linked to virtual ones are still hard to find in full-fledged ecosystems. A small number of studies have combined finite element models, hydraulic simulations, sensor data, AI, and predictions of "remaining useful life" (RUL) into a single cyber-physical platform, and digital twins are still mostly just ideas.

Another constraint is the validation of operating ship data. Many research use numerical simulations, lab-scale experiments, or benchmark datasets. These are useful for building methodologies, but they do not adequately convey the ambiguity of real-world situations. Sources of uncertainty such as sea-state variability, vessel loading, propulsion characteristics, weather and long term degradation are difficult to reproduce under controlled conditions. Therefore, a large-scale validation using long-term on-board monitoring is required.

The literature also shows that contemporary SHM systems are typically based on single sensor or limited multisensor configurations. Most studies employed strain gauges or accelerometers as a standalone sensor, with very few studies combining multiple sensing modalities such as strain, vibration, displacement, temperature, propulsion parameters, wave loading, and environmental measurement. Monitoring systems, without data fusion, cannot characterize the structural behaviour in complex conditions.

Explainable artificial intelligence (XAI) and Physics-Informed Machine Learning (PIML) are not largely considered. With artificial intelligence becoming increasingly embedded into engineering decisions, transparency and interpretability become increasingly important. Ship operators and regulators need predictive systems where the recommendations can be explained by physically meaningful mechanisms and not just by the statistical correlation. Future systems should embed the governing equations, material behavior, structural constraints and uncertainty quantification in the learning algorithms .

Decision support integration is another gap. Most of the studies end with the estimation of fatigue damage, crack growth or Remaining Useful Life, without translating those predictions into a practical maintenance strategy. Capabilities such as scheduling inspections, prioritizing maintenance, optimizing operations and risk-informed asset management are still under-explored. There is great potential to translate fatigue prediction into actionable engineering intelligence for maritime operations .

The review reports some contributions from these observations. It organizes the evolution of research on vibration-induced fatigue over more than two decades by clustering publications into coherent themes. It tells the story of the transition from deterministic structural mechanics to intelligent cyber-physical systems that integrate sensing and artificial intelligence. It recognizes the absence of unified research directions as the primary obstacle for the widespread adoption of intelligent fatigue assessment. Finally, it provides a conceptual basis for future work on the integration of Digital Twin technology, structural health monitoring, physics-informed artificial intelligence, multisensor data fusion and predictive maintenance.

Unlike studies that summarize individual methodologies, this study offers a systems approach, demonstrating how emerging digital technologies might synergistically change fatigue evaluation from a standalone computation to an adaptive life-cycle management framework. This viewpoint is also utilized to guide researchers in the creation of next-generation intelligent structural integrity systems for marine engineering.

4.4 Future Research Framework toward Digital Twin–AI–SHM Integration

Thematic progression in this review implies that the work should progress from the incremental improvement of individual technologies to an integrated cyber-physical framework that can monitor, predict, and optimize structural integrity throughout a vessel's operational life. Such a framework should integrate advances in computational mechanics, structural health monitoring, artificial intelligence and Digital Twin technology into one decision support ecosystem.

The framework proposed by this review is illustrated in Figure X. It has six interrelated layers that transform raw operational measures into maintenance decisions.

The first layer is the physical structure of the ship, the actual system under cyclic environmental and operational loading. Excitation of waves, vibration of machinery, propulsion systems, hydroelastic effects, cargo loading and maneuvering cause the structure to respond. These loads generate stress cycles that accumulate fatigue damage in structural members.

The second level is multi-sensor structural health monitoring. Future systems should not be based on isolated measurements, but should integrate strain gauges, accelerometers, displacement sensors, fiber-optic sensors, acoustic emission sensors, environmental sensors, propulsion monitoring and voyage information. Continuous acquisition of this data provides a more complete picture of the structural behavior and reduces the uncertainty of any individual sensor.

The third layer is a Digital Twin platform that continuously synchronizes measured data with high fidelity virtual models. The Digital Twin does not rely on offline simulation, but updates the structural states based on the current conditions. This allows to constantly estimate stress distributions, structural response, accumulated fatigue damage and evolving integrity during operation.

The fourth layer is physics-informed AI. Instead of replacing structural mechanics, artificial intelligence should complement it by incorporating the governing equations, material constitutive relationships, fatigue damage models and structural constraints into the learning algorithms. Physics-informed neural networks and hybrid architectures can improve accuracy, while keeping interpretability and regulatory acceptance.

Layer 5: How much doubt there is and an estimate of the remaining useful life (RUL). In addition to the current state, future systems should be able to predict how things will get worse in a number of different operating situations. Bayesian reasoning, probabilistic fatigue models, and uncertainty-aware machine learning could all help make adaptive prediction intervals that are more like real-world settings.

The sixth layer is a smart system that helps people make decisions. Fatigue assessment isn't just about figuring out how much damage has been done; it also helps engineers make decisions. Decision-support modules should be used to turn fatigue forecasts into maintenance schedules, inspection plans, operational ideas, risk assessments, and the best use of resources over the course of a product's life. These skills would allow for predictive repair that cuts down on downtime, improves safety, and makes operations run more smoothly.

The architecture rests on continual feedback between its components. Sensor measurements update the Digital Twin, which delivers refined data to physics-informed learning algorithms. Predictive models then estimate Remaining Useful Life. Operating conditions are altered by maintenance activities, and new operational data enhances prediction through ongoing learning. The typical linear fatigue assessment is very different from this closed loop.

To implement this architecture, a number of enabling technologies must be in place. Standardized onboard sensing architectures ought to guarantee dependable, high-quality data collection. Infrastructure for cloud and edge computing should enable real-time synchronization between digital twin models and physical assets. Explainable artificial intelligence will be needed to promote transparency, regulatory acceptance, and engineering trust. To verify integrated ecosystems under full-scale conditions, collaboration between academia, ship operators, shipyards, classification societies, and technology providers will be required.

The proposed framework is aligned with digital transformation in the maritime sector such as Maritime 4.0, smart shipping, autonomous ships and intelligent asset management. As shipping becomes more data-driven, integrated digital twin, artificial intelligence and SHM systems are expected to play a central role in improving structural reliability, reducing maintenance cost, increasing safety and extending service life.

Future research should therefore investigate explainable, adaptive and validated cyber-physical fatigue assessment systems, that integrate physics-based structural modeling, multisensor monitoring, Digital Twin synchronization and artificial intelligence within a single predictive maintenance platform. This integration is the most promising way forward to next generation intelligent structural integrity management of ship structures and is the main direction identified in this review.

5. Conclusion

This systematic literature review (SLR) investigates the development of vibration-induced fatigue assessment in ship structures based on the bibliographic metadata of 75 publications from 2002 to 2026. This review, guided by the PRISMA 2020 framework, examines publication trends, bibliometric characteristics, thematic advances, methodological shifts, research gaps, and future prospects in this growing discipline. Although the review employed bibliographic metadata and not full text extraction, the findings do offer useful insight into the trajectory of the field and the technological change underway in fatigue assessment.

A look at the trends of publications over the past 20 years shows a clear direction. Early studies mostly used common structural mechanics-based methods for figuring out fatigue, like spectral fatigue analysis, S-N curves, cumulative damage theories, and finite element modeling. These methods are still used in structure design and classification society rules, and they were the basis for figuring out how long something would last under stress. Scientists created detailed models like Computational Fluid Dynamics (CFD), Fluid-Structure Interaction (FSI), and hydroelastic analysis to learn more about how environmental stress affects structures and how they respond to it. Some newer studies have moved away from deterministic analysis and toward intelligent monitoring. Examples of this are machine learning, digital twin technologies, virtual sensing, predictive maintenance, and structural health monitoring (SHM).

We found eight main areas of research in this field: conventional fatigue assessment, wave-induced fatigue, hydroelasticity and hull girder vibration, local structural fatigue, numerical simulation, structural health monitoring, artificial intelligence, and digital twin technology. Because of these ideas, we are moving away from one-way analytical methods and toward multimodal cyber-physical systems that keep an eye on the structural integrity of a ship while it's in service. Fatigue assessment used to be a design-time calculation, but now it's an operating decision support system that combines condition-based and predictive maintenance.

The bibliometric study shows that vibration-induced fatigue is now a research topic that is studied in many fields, such as data science, artificial intelligence, naval architecture, marine engineering, computational mechanics, and structural engineering. Today's ship structures are getting more complicated, as more problems and approaches are being used. This means that review methods need to be more flexible, reliable, and smart. This coming together creates chances for new ideas, but it also shows how important it is to have frameworks that include ideas from many different fields.

One important finding is that gaps in the current system make it harder to use intelligent fatigue evaluation. A lot of different types of research are being done on different topics, such as physics-based models, structural health monitoring, machine learning, and digital twin technology. It's not easy to put these technologies together into a single cyber-physical ecosystem. The review also talks about how there isn't enough long-term operating ship data, how multisensor data isn't properly combined, how Physics-Informed Artificial Intelligence can't be used in all situations, and how little study there is on explainability, uncertainty quantification, and decision support. As a whole, these problems show that there is a lot of room for improvement in figuring out tiredness that goes far beyond what is currently possible.

Because of this, the review says that future studies should focus on Digital Twin, AI, and SHM frameworks that work together. These frameworks should include accurate physics-based models, continuous monitoring by multiple sensors, machine learning that can be explained, RUL prediction, uncertainty-aware modeling, and smart decision support for maintenance in a cyber-physical world that is always in sync. These new technologies shouldn't take the place of traditional structural mechanics; instead, they should be used in addition to it to make accurate, adaptable, understandable, and useful fatigue assessment systems. The main contribution of the review is this point of view, which provides a road map for the next generation of smart structural integrity management in maritime engineering.

Practical Implications

Researchers, ship designers, classification groups, ship operators, and people who make marine technology can all use the data in different ways. The change in methods shows designers and structural engineers how important it is to include dynamic operational loads and hydroelastic response in fatigue evaluation, in addition to deterministic design methods. As Digital Twin and structural health tracking technology improve, they allow operators to switch from time-based to predictive maintenance. This lowers costs while increasing safety and availability.

The review also shows how important it is for classification societies and regulators to have more rules that cover sensor-based monitoring, AI-assisted fatigue prediction, and using Digital Twins. Companies that make maritime technology can use the directions that have been found to create unified platforms that combine structural simulation, sensor analytics, machine learning, and maintenance optimization into decision-support systems that can be used in the field. Together, the effects help the maritime business become more digital, which will make it safer and better for the environment.

Theoretical Implications

The review contributes, in theory, to a synthesis of the evolution of the vibration-induced fatigue research from a systems perspective rather than from a focus on individual methods. The proposed framework views future fatigue assessment as an interdisciplinary cyber-physical process, which integrates structural mechanics, sensing, artificial intelligence, uncertainty modeling and life-cycle engineering. Such perspective broadens the conventional fatigue analysis by positioning the Digital Twin-enabled structural integrity management as a unifying framework connecting the previously disconnected research areas.

Moreover, the review also indicates that Physics-Informed Artificial Intelligence is a promising theoretical direction since it combines the interpretability of engineering mechanics and the adaptive learning of modern artificial intelligence. The fusion of these paradigms could improve the accuracy and engineering trust, thus allowing for a broader application of intelligent fatigue assessment in safety-critical maritime applications.

Limitations of the Review

There are some limitations to this review. First, the analysis was based on bibliographic metadata and not on full-text articles, so thematic classification and methodological interpretation were mainly derived from article titles and publication information. This precluded detailed comparison of experimental procedures, datasets, quantitative findings, and performance metrics. Second, the dataset of 75 publications, although sufficient for a descriptive synthesis, may not be representative of the global literature on vibration-induced fatigue in ship structures.

Third, the analysis employed metadata and advanced bibliometric techniques like citation network analysis, co-authorship analysis, co-occurrence analysis of keywords, and bibliographic coupling were not within the scope of the present analysis. Finally, the review did not carry out a quantitative meta-analysis because the meta-data did not contain standardized numerical results that could be aggregated. The findings should be interpreted with these limitations in mind and suggest avenues for future reviews using full text datasets.

Recommendations for Future Studies

Future work should build on this review by performing full text analysis, enabling detailed comparison of methods, datasets, validation procedures and engineering performance across fatigue assessment approaches. Using both bibliometric network analysis and qualitative synthesis together could help us learn more about how people work together, new research groups, and how knowledge changes over time in maritime structural engineering. More research needs to be done on technology to build and test frameworks that combine Digital Twin, AI, and SHM using data from ships that have been in use for a long time and in real life. Some of the most important areas are machine learning based on physics, combining data from multiple devices, figuring out how long something will still be useful when there isn't enough information, artificial intelligence that can be explained, and intelligent decision support for maintenance. Proof on full-size working boats is needed to show that it works in real life and get companies to use it.

Last but not least, tech companies, shipping companies, schools, and shipyards should work together more to quickly put lab research to use in the real world. It is important to work together in this way to make smart systems for managing the integrity of structures. These systems will help Maritime 4.0 by making structures last longer, making ships safer, and lowering the cost of maintenance. Based on the information in this study, research into fatigue caused by vibrations is now entering a new phase. This is because AI, digital engineering, and structural physics are all working together. For better marine structural engineering and for smart, strong, and eco-friendly ship operations in the future, it is best to make cyber-physical fatigue assessment systems that work, can be explained, and are fully integrated.

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