Digital Twin Predictive Maintenance Systems

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Researchers examine existing research to identify trends and potential avenues for future exploration.

Who should read this paper?

Anyone who is interested in the current state of Digital Twins in the marine industry will be interested in this study. A Digital Twin may be viewed as a virtual model (influenced by real-world data) to address unforeseen scenarios. It can be used to replicate what is happening to an actual product in the real world and offers real-time feedback. In general, any simulation that is representative of a real-world operation is an instance of a Digital Twin; for example, a ship navigation simulator.

Why is it important?

This study draws insights from twelve data clusters (resulting in 1,074 papers). It not only uncovers significant growth in interest from 2016 to 2023, but also synthesizes key findings from the evolution of Digital Twins. By employing bibliometric techniques, the study maps country collaborations, illustrating international research networks in this field. Moreover, it highlights the most cited papers, underlining influential contributions and their impact.

This comprehensive review offers a unique perspective on the development, collaborations, and key research themes in the context of Digital Twins Predictive Maintenance Systems in the maritime industry. It offers researchers and decision-makers comprehensive and up-to-date knowledge. Findings can be used to assist in establishing prospective research directions for Digital Twin Predictive Maintenance Systems in the maritime industry advancement.

About the authors

Abdelmoneim Soliman obtained his B.Eng. in mechanical engineering in 2016 from the Arab Academy for Science, Technology, and Maritime Transport (AASTMT). He also explored a mechatronics major through courses. Mr. Soliman is presently completing his B.Tech. in engineering and applied science from the Marine Institute of Memorial University, NL. His research interest is in integrating advanced technologies (e.g., artificial intelligence, machine learning, and Digital Twins) in the operational phase of marine vessels.

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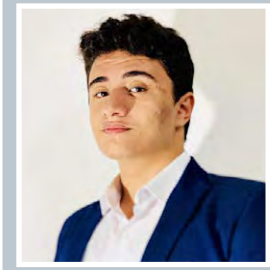

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A BIBLIOMETRIC REVIEW OF RESEARCH PUBLICATIONS ON DIGITAL TWIN PREDICTIVE MAINTENANCE SYSTEMS IN THE MARITIME INDUSTRY

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ABSTRACT

This bibliometric review delves into the topic of "Digital Twin Predictive Maintenance System in the Maritime Industry," examining existing research to identify trends and potential avenues for future exploration. Through analysis of 12 data clusters (consisting of 1,074 publications) from maritime sources, this study uncovers significant growth in interest from 2016 onwards and synthesizes key findings from the historical evolution of Digital Twins. The review highlights various research clusters, including advancements in Digital Twin technology, Smart Manufacturing applications, and the integration of Blockchain. By using bibliometric techniques, the study maps country collaborations and illustrates international research networks in this field. It also highlights the most cited papers, underlining influential contributions and their impact. This comprehensive review offers a unique perspective on the development, collaborations, and key research themes in the context of Digital Twin Predictive Maintenance Systems within the maritime industry.

Keywords: Digital Twin (DT); Predictive maintenance system; Maritime industry; Industry 4.0; Bibliometric; Digital Twin Predictive Maintenance System (DTPMS); Artificial intelligence (AI); Internet of Things (IoT); Total publications (TP); Total citations (TC)

1. INTRODUCTION

In recent years, technological advances on the Internet of Things (IoT), data analytics, artificial intelligence (AI), and data acquisition techniques have paved the way for the full realization of Industry 4.0, and for its many applications to emerge, which totally changed how some industries managed their business [Attaran et al., 2023; IBM, n.d.].

Digital Twin (DT) is one of those technologies that has utilized the recent changes to the extent that it has become the centre of interest for both industry and academia alike [Fuller et al., 2020]. A Digital Twin may be conceptualized as a virtual model (influenced by real-world data) to address unforeseen scenarios. It can be used to replicate what is happening to an actual product in the real world and offers real-time feedback. In general, any simulation that is representative of a real-world operation is an instance of a DT; for example, a ship navigation simulator.

The global market size for DT was valued at USD 3.1 billion in 2020 [Report Linker, 2020]. It has been projected to grow from USD 10.1 billion in 2023 to 110.1 billion by 2028 at a compound annual growth rate of 61.3% [Report Linker, 2024]. (With such anticipated growth, one can only expect DT applications to become more popular in the future.) By perusing those industries which contributed the most to the world DT economy alluded to earlier, the automotive and transport sector were at the top of the list; they contributed more than 20%. There were other industries with large contributions also; for example, the agriculture, aerospace, and energy industries [Report Linker, 2024].

Seven key applications of DT in a variety of industries are: in design or planning or both, optimization, maintenance, safety, decision-making, remote access, and training. It may be an invaluable resource for businesses to boost their productivity, efficiency, and competitiveness [Singh et al., 2021].

In this section, we will briefly discuss the concept behind DT, its potential in the maritime industry, and present an overview of the increasing adoption of DT technology in predictive maintenance.

1.1 Reasons Behind the Increasing Adoption of Digital Twin

At a first glance, it could be assumed that DT is not fully implemented yet. However, one sees the increasing adoption of DT being made possible because of the decreasing costs of technologies that enhance both IoT and the DT, and the recent advances in IT infrastructures and Data Analytics. Moreover, the recent disruptions that the world has gone through (especially the COVID-19 pandemic and the war in Ukraine) may have also contributed immensely to the increasing adoption of DT because researchers were able to devise transformative solutions to vulnerabilities that were shown in the previously adapted methods [Attaran et al., 2023].

DT's potential is vast and, despite it being relatively new, one can find its adaptations in many technologies and domains ranging from healthcare to smart cities and manufacturing [Bilberg and Malik, 2019]. In the following subsection, we will briefly discuss Digital Twin's potential adoption in the maritime industry and its already established applications.

1.2 Digital Twin and the Marine Industry

The marine industry is a broad and multifarious industry with a diverse economy ranging from the reservation and utilization of marine resource to seawater distillation to the enhancement of the coastal tourism, and to the more industrial based applications like the shipbuilding and offshore marine industries. So, it is apparent that DT has found its way to enhance the above listed fields [Lv et al., 2023A].

Predictive maintenance is an important application of DT, and it could improve the marine industry immensely. Many algorithms and applications were proposed concerning this matter. For instance, VanDerHorn and colleagues proposed a model that could monitor and estimate the remaining service time of an active ship. These models could aid in the operational and planning side (of an active ship) to monitor and detect fatigue failures [VanDerHorn et al., 2022]. It should also be noted that the recent adoption of machine learning with DT has leveraged the applications of DT in predictive maintenance as several scholars have proposed models in that aspect; for example, Ren et al. proposed comprehensive equipment-centric DTs through the combination of DT and several machine learning algorithms [Ren et al., 2022]. It could be said that DT's usage in ship maintenance focuses on fault prediction and failure prevention through predictive maintenance [Lv et al., 2023A], which is the aim of this paper.

The operational cost of maintaining aging marine vessels can get expensive if manufacturers stop fabricating the spare part(s) necessary for refurbishing. Furthermore, the health and safety of the crew on board these aging vessels could be impaired because technicians – who are responsible for performing the periodic inspection of machines as part of a planned maintenance program – make errors. For instance, these technicians may be unable to predict where the excessive wearing of the mechanical parts is located or when the failure has occurred. Consequently, the maintenance processes will be reactive; so, it will not be started until after the failure has occurred. This could increase the possibility of injuries on board a marine vessel. Correspondingly, this impediment will reflect on the business side of marine companies because that means the shutdown of the mechanical systems of ships until every suspected piece of equipment is maintained, which further amounts to increasing the maintenance cycle of these vessels. Here, the application of DT as a predictive maintenance tool would play a significant role.

How is this predictive maintenance and monitoring process achieved? To monitor the performance of critical components on a marine vessel or offshore platform, sensors are installed. The data from the sensors are then acquired using specialized data acquisition procedures. This process is epitomized in Figure 1. These acquired data are then transported to the appropriate on-land sites. Figure 2 depicts a synopsis of this intricate data transfer mechanism. Referring to the illustration, at location *D*, the data acquisition system acquires information from the sensors installed on the object(s). These data are then transmitted to the appropriate satellite, designated *S*. From there,

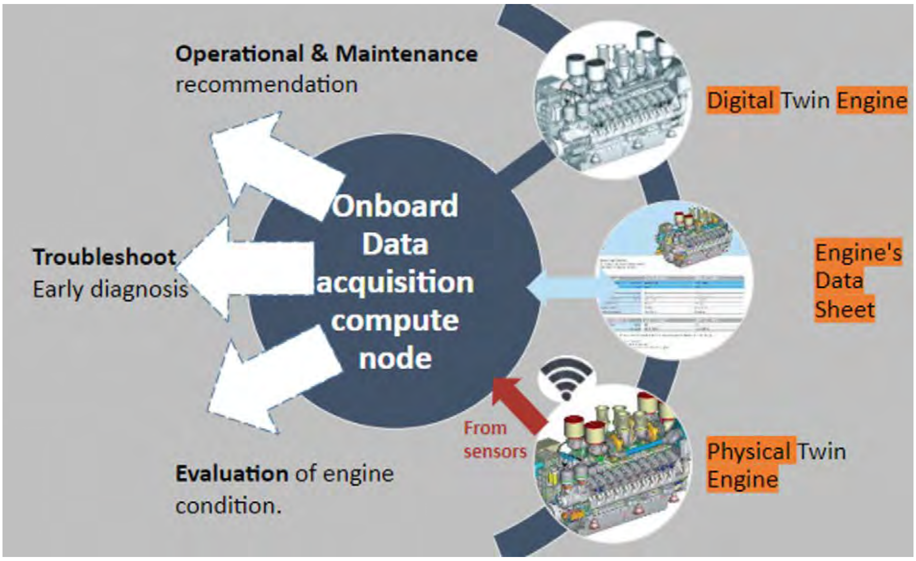


Figure 1: An overview of the data acquisition process.

Figure 2: An overview of the data transfer mechanism.

the data are then routed through an onshore radar antenna (*R*) to a cloud storage, designated *CS*. Data stored there can then be accessed by the on-land information processing centre (IPC). At the IPC, a digital model, also called a DT, runs simulations or analytical models to assess the state of the object. Here, potential improvements are generated and relayed back to the object on the vessel.

1.3 Future Trends

Several trends are expected to shape the future of DTs in the maritime industry [Fuller et al., 2020]:

- ***Technological Advancements.*** The evolution of IoT, AI, and edge computing will enhance DT capabilities, enabling comprehensive data collection, real-time analysis, and informed decision-making.
- ***International Collaboration.*** Collaborative initiatives among countries and stakeholders will be critical for successful DT integration in maritime operations. Engineers, data scientists, experts, policy-makers, and governments must collaborate across borders to develop DT solutions for maritime challenges.
- ***Research Gap.*** A significant research gap exists in the Digital Twin Predictive Maintenance System (DTPMS) in the maritime industry. As DTs are adopted in maritime contexts, there will be a need for predictive maintenance strategies tailored to the complexities of maritime equipment and changing environmental conditions.

1.4 An Overview of this Paper

This paper is a bibliometric review that aims at answering questions about the contemporary trends in DT's research and to provide an in-depth overview of the current state of the academia, the latest trends in DTs, and the proposed future directions concerning DT's adaptation in the marine industry.

2. LITERATURE REVIEW

2.1 Historical Background

The concept of DTs finds its origins in the early instances of complex simulations and modelling of real-world systems. One of the earliest recorded instances of utilizing complex simulations to address real-world challenges can be traced back to the Apollo 13 mission in 1970. During this mission, NASA faced a critical situation when an unexpected explosion damaged the spacecraft, and the spacecraft deviated from its intended course. Swift action was needed to ensure the safe return of the astronauts to Earth.

NASA employed high-fidelity simulators and modified them in real time to mirror the damaged conditions of the spacecraft. This practical application, though not explicitly called a Digital Twin, exhibited the fundamental characteristics of a DT; that is, a virtual model influenced by real-world data to address unforeseen scenarios [Boy, 2020].

2.2 Evolution of Digital Twins

The evolution of the DTs concept has been marked by key milestones that span multiple industries and applications. This timeline highlights examples of pivotal moments in its development [Singh et al., 2021]:

- ***1991 Imagining Mirror Worlds***. David Gelernter introduced the concept of "Mirror Worlds." In this vision, software models replicate reality by using information from the physical world as input. Although not explicitly called DTs, this idea set the stage for virtual representations of physical entities [Gelernter, 1993].
- ***2002 Emergence of the DTs***. The concept of DTs emerged in relation to product lifecycle management (PLM) at the University of Michigan. Michael Grieves introduced the initial model known as the "Mirrored Spaces Model." This model emphasizes real space, virtual space, and a linking mechanism for data exchange between the two [Grieves and Vickers, 2016].
- ***2003 Agent-Based Architecture for PLM***. Kary Främling and colleagues proposed an agent-based architecture featuring virtual counterparts or agents associated with product items. This approach addressed the inefficiency of transferring production information via paper in PLM, which laid the groundwork for digital representations of physical entities [Främling et al., 2003].
- ***2006 Evolution to Information Mirroring Model***. Grieves' conceptual model evolved from the "Mirrored Spaces Model" to the "Information Mirroring Model." This evolution places greater emphasis on bidirectional linking mechanisms and introduces the concept of multiple virtual spaces for a single real space, thus setting the stage for more complex DT structures [Schleich et al., 2017].
- ***2010 DT Defined***. NASA introduced the term "Digital Twin" in its technological roadmap. DT is described as an integrated

multi-physics, multi-scale simulation of a vehicle or system. It leverages physical models, sensor data, fleet history, and more to mirror its real-world counterpart [Shafto et al., 2010].
- ***2010's Application Diversification***. Building on NASA's lead, the US Air Force adopted DTs technology for aircraft design, maintenance, and predictive capabilities. This expansion demonstrates the versatility of DTs beyond aerospace [Gockel et al., 2012]. The term "Digital Twins" gains popularity and broadens its scope, reaching industries beyond aerospace. Manufacturing, energy, healthcare, and more explore the potential of DTs for enhancing operations and decision-making.
- ***Present and Beyond***. The concept of DTs continues to evolve and expand, encompassing a wide array of applications. This includes machines, products, processes, and even complex biological systems. Interest and research in DTs technology persist, with ongoing efforts to refine and adapt its applications for an increasingly digital world [Singh et al., 2021].

2.3 Components of Digital Twins

DTs consist of interconnected components that drive dynamic and data-driven capabilities, resulting in virtual replicas for real-time insights, predictive analytics, and optimization [Grieves, 2005].

Digital Representation and Data Integration: DTs rely on accurate digital models mirroring physical entities [Tuegel, 2012; Gockel et al., 2012], achieved through data integration from sensors, IoT devices, and historical records. This sustains synchronization, empowering DTs to adapt and make informed decisions.

At various levels of scale, DTs are generally structured hierarchically [Tao et al., 2019]:

- **Unit level**. Smallest manufacturing unit, e.g., equipment or material. Unit-level DT mirrors physical twin's aspects.
- **System level**. Combines unit-level DTs in a production system. Enhances data flow and resource allocation. Complex items like aircraft can be system-level DTs.
- **System of Systems level**. Links system-level DTs. Facilitates collaboration across enterprise areas, integrating product life cycle phases.

Real-Time Monitoring and Simulation: DTs excel in real-time monitoring, allowing stakeholders to analyze physical entity behaviour virtually. Continuous data flow from sensors offer immediate feedback. Real-time simulation permits risk-free testing and prediction, aiding issue identification and prompt decision-making. (Refer to Figures 1 and 2.)

In most Digital Twins, three interaction levels can exist [Kritzinger et al., 2018]:

- ***Digital Model***. Manual data exchange – changes not mirrored between physical and digital objects.
- ***Digital Shadow***. Automatic data flow from physical to digital format – changes reflected one-way.
- ***Digital Twin***. Automatic bidirectional data exchange – changes in one object affect the other.

IoT and Sensor Integration: IoT and sensors are fundamental in collecting real-world data for DTs. Sensors provide crucial information and facilitate updating of the digital model in real time. This ensures accuracy, enhancing real-time simulations, analytics, and efficiency optimization [Tao et al., 2017].

Analytics and Machine Learning: Analytics and machine learning elevate DTs from descriptive models to predictive and prescriptive tools. Analytics process data, unveiling patterns. Machine learning enables predictive and prescriptive analytics, predicting behaviour and suggesting actions. Continuous data streams improve accuracy, enabling predictive maintenance and operational optimization [Tao et al., 2017].

2.4 Applications of Digital Twins in Marine Industries

DTs have revolutionized industries by offering a wide array of transformative applications. From manufacturing to healthcare, DTs have reshaped how processes are managed, monitored, and optimized. Within the maritime sector, DTs bring their own set of innovative possibilities [Smogeli, 2017]. Examples of these include:

- ***Predictive Maintenance Strategies***. DTs revolutionize maintenance by employing predictive analytics through continuous sensor-based monitoring. Potential failures are predicted, enabling initiative-taking maintenance scheduling, asset longevity, and minimized operational disruptions [Ibrion et al., 2019].
- ***Vessel Performance Optimization***. DTs optimize vessel performance by simulating real-world conditions. Virtual replicas allow for continuous monitoring and analysis, enhancing engine efficiency, propulsion, fuel usage, and navigation strategies. Marine operators can identify efficient operational configurations, energy-saving tactics, and route optimization [Smogeli, 2017].
- ***Smart Fleet Management***. DTs centralize data for fleet-wide insights. Real-time integration of vessel positions, fuel consumption, weather, and scheduling empower data-driven decisions, elevating fleet performance, route planning, and fuel management [Rudrusamy et al., 2023].
- ***Offshore Asset Management***. DTs replicate offshore assets, enabling real-time monitoring of structural integrity, equipment health, and safety. Data from sensors informs asset management through early issue detection and optimized asset utilization [Golestani et al., 2023].
- ***Maritime Training and Simulation***. DTs offer a risk-free training platform for maritime professionals. Navigation, manoeuvring, and emergency scenarios can be practiced, enhancing skills and decision-making capabilities [Smogeli, 2017].
- ***Autonomous Vessel Development***. Autonomous vessels benefit from DTs for testing navigation algorithms and decision-making processes. Real-world scenario simulations expedite autonomous integration into maritime transportation [Lv et al., 2023A; Mauro and Kana, 2023].
- ***Maritime Incident Analysis***. DTs aid post-incident analysis by recreating events in a virtual environment. Insights into incident factors facilitate preventive measures and enhance safety practices [Lv et al., 2023B].

2.5 Challenges and Barriers

The integration of DTs into industries is not without its challenges and barriers. In the maritime sector, these obstacles manifest in many ways [Singh et al., 2018]:

- ***Novelty***. The adoption of DTs faces hurdles due to uncertain value perceptions, limited successful cases, and evolving technologies like 3D simulations, IoT, and AI. Infrastructure and software enhancements are necessary [Bulygina, 2017].
- ***Time and Cost***. Developing DTs is resource-intensive, requiring time, expert personnel, and substantial funds. High expenses are incurred for detailed modelling, simulations, computational power, sensor integration, and IT infrastructure [Gabor et al., 2016]. (But this is also a benefit compared to using the in-situ equipment being simulated.)
- ***Lack of Standards***. The lack of industry-wide frameworks and standards impedes the adoption of DT. Standardizing interfaces, data flows, models, and data itself are crucial. The absence of clear regulations for innovative technologies adds to the challenge [Wagner et al., 2019]. It should be noted, however, that, recently, ISO issued a series of standards (ISO 23247) that deals with a Digital Twin framework for manufacturing. It is a generic framework [Shao et al., 2023].
- ***Data Challenges***. Challenges involve data privacy, ownership, transparency, and sharing due to company policies and societal views. Data silos, interoperability issues, and cybersecurity risks affect DT performance and data handling [Singh et al., 2018].
- ***Lifecycle Mismatch***. DTs face compatibility issues with long-lifecycle products, risking software obsolescence and vendor lock-in. Balancing product and technology life cycles is essential [Goasduff, 2018].

3. RESEARCH QUESTIONS

This research embarked on an expedition to address the following questions:

- How has the research output and citation impact on the DTPMS in the maritime industry evolved over time?
- Which countries, authors, and institutions are leading in the research and publication output on DTPMSs in the maritime industry?
- What are the countries' collaboration patterns among researchers working on DTPMSs in the maritime industry?
- What is the pattern of authorship in the field of study?
- What are the most influential sources and research areas on the maritime industry's DTPMS?
- What are the emerging research trends and future directions?
- What are the leading author keywords on the maritime industry's DTPMS?
- What are the most cited publications in the field?

4. RESEARCH METHODS AND TOOLS

This in-depth mapping study included the following methods and tools.

4.1 Methodology

Bibliometrics is a quantitative study method

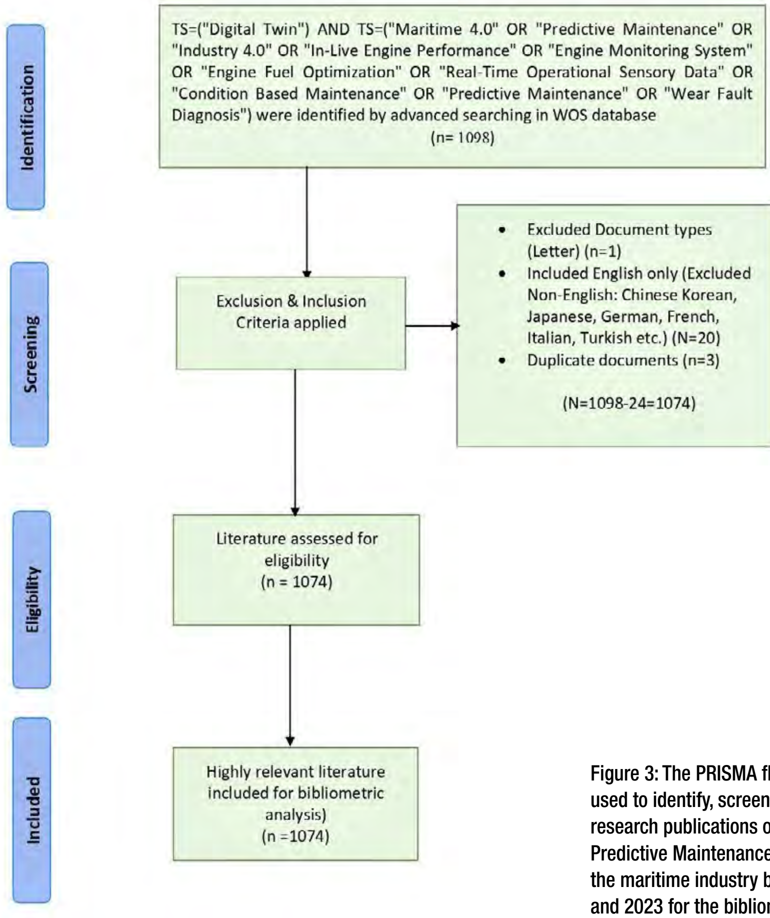


Figure 3: The PRISMA flow diagram used to identify, screen, and include research publications on Digital Twin Predictive Maintenance Systems in the maritime industry between 2016 and 2023 for the bibliometric analysis.

used to analyze and rate scientific literature. It uses statistical and mathematical methods to measure and evaluate various parts of scholarly writings, such as the number of publications, the number of citations, authorship patterns, the impact of a journal, and networks of collaboration [Ball, 2018]. In the subject of library and information science, bibliometric methods are used extensively. Scientometrics is a sub-discipline of bibliometrics that deals with examining scientific publications.

This study employed the bibliometric method to assess the research productivity on DTPMSs in the maritime industry research. This technique, also known as science mapping, represents the relationship between disciplines, domains, specialties, documents, and authors. The present study focused on bibliometric indices such as yearly growth of literature, productive country and organizations, prolific authors, significant sources, author keywords, collaborative country, most cited research papers, exploring research themes, etc. A synopsis of the process is illustrated with a PRISMA flow diagram in Figure 3.

4.2 Search Query

The following search query was framed

in the advanced search box of the Web of Science database to retrieve the bibliographic data [Clarivate Analytics, 2023]. TS = ("Digital Twin") AND TS = ("Maritime 4.0" OR "Predictive Maintenance" OR "Industry 4.0" OR "In-Live Engine Performance" OR "Engine Monitoring System" OR "Engine Fuel Optimization" OR "Real-Time Operational Sensory Data" OR "Condition Based Maintenance" OR "Predictive Maintenance" OR "Wear Fault Diagnosis").

4.3 Date of Data Extraction

The search was started on May 14, 2023, at the King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia. Using the mentioned search query, 1,098 research papers were found.

4.4 Inclusion and Exclusion Criteria

Exclusion and inclusion criteria were applied in the initial search results of 1,098 documents. The analysis eliminated a single research paper from the category of type of publications (Letter). The study only included English papers and omitted 20 non-English language publications (Chinese, Korean, Japanese, German, French, Italian, Turkish, etc.). Furthermore, the authors removed three duplicate publications from the analysis. Finally, 1,074 research papers were chosen for final analysis.

4.5 Data Analysis

All the selected 1,074 research papers have been downloaded in different file formats and analyzed with bibliometric analysis tools such as VOSviewer [van Eck and Waltman, 2010], Biblioshiny [Aria and Cuccurullo, 2017], HistCite, BibExcel [Persson, 2016], and Microsoft Excel.

5. RESULTS AND DISCUSSION

Table 1 presents the quantitative information about the various aspects of the DTPMS in the maritime industry research publications between 2016 and 2023. The dataset includes 1,074 papers published in 508 different sources such as books, reviews, book chapters, journals, and others. These publications received a total of 21,006 citations, indicating their impact and influence within the scholarly community. Each publication, on average, received 19.56 citations. These indicate the impact and visibility of the publications within the scholarly community.

The analysis shows an annual growth rate of 62.04% and average publication age of 2.18 years. The analyzed 1,074 publications comprise 39,561 references. This metric indicates the number of external sources cited within the analyzed publications. The analysis identified 997 keywords plus and 2,843 author keywords. These keywords are specific terms or phrases chosen by the authors to represent their research themes or concepts. A total of 3,432 authors participated in producing 1,074 publications. This includes first authors, co-author, and corresponding authors. Among the total number of authors, there are 38 authors who are responsible for single-authored publications. The analysis also reveals that there are 40 single-authored publications in total. On average, each publication had 4.03 co-authors, and 27.09% of the publications involved international collaboration.

Table 1: Main information about the data – time span 2016-2023.

Description	Results
Sources (Journals, Books, etc.)	508
Documents	1,074
Total Citations (TC)	21,006
Annual Growth Rate %	62.04
Document Average Age	2.18
Average Citations per Doc	19.56
References	39,561
Keywords Plus (ID)	997
Author's Keywords (DE)	2,843
Authors	3,432
Authors of Single-authored Docs	38
Single-authored Docs	40
Co-authors per Doc	4.03
International Co-authorships %	27.09

Table 2: Yearly growth of publications and citation trends on Digital Twin Predictive Maintenance Systems in the maritime industry between 2016 and 2023. TP = total publications. TC = total citations.

Publication Years	TP	TC	TC/TP	h-index
2016	3	433	144.33	3
2017	17	2,430	142.94	13
2018	43	2,289	53.23	19
2019	133	5,459	41.05	36
2020	196	4,609	23.52	38
2021	299	4,447	14.87	35
2022	300	1,292	4.31	16
2023	83	47	0.57	4

5.1 Yearly Growth of Publications and Citations Trends

Table 2 and Figure 4 show the yearly growth of publications and citation trends on DTPMS in the maritime industry between 2016 and 2023. The analysis reveals that 2016 published the first research papers in the field with three publications and 433 citations. From 2019 to 2022, the number of publications was more than 100. There was a noticeable increase in output in 2017 from 2016 to 2017 (i.e., from three to 17 articles) and in citations (433 to 2,430). The total citations/total publications (TC/TP) ratio remained high, suggesting a high mean citation count for each publication. The h-index rose from 3 to 13, indicating the presence of highly cited works. The number

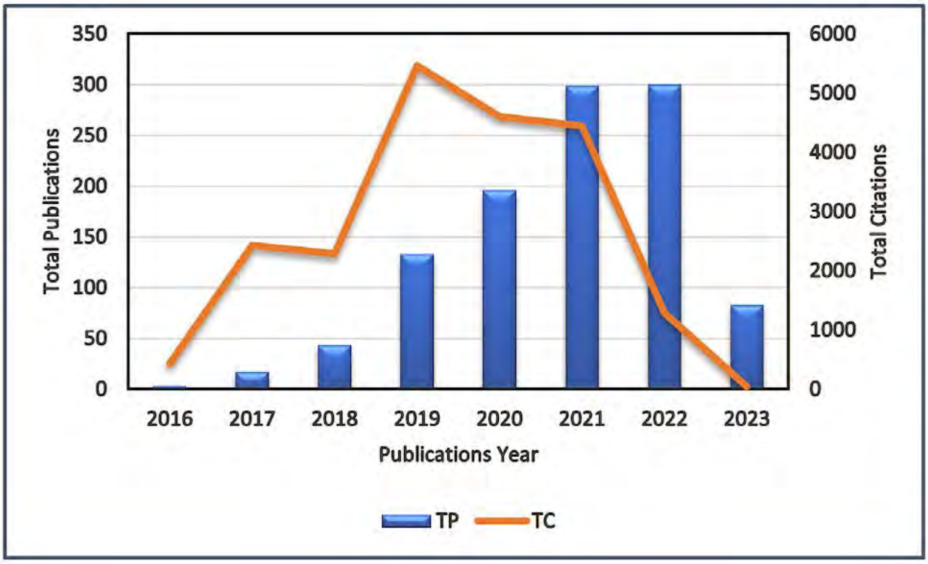


Figure 4: Yearly growth of publications and citation trends on Digital Twin Predictive Maintenance Systems in the maritime Industry between 2016 and 2023.

Table 3: Types of publications on Digital Twin Predictive Maintenance Systems in the maritime industry between 2016 and 2023. TP = total publications. TC = total citations.

Rank	Types of documents	TP	TC	TC/TP	h-index
1	Article	519	13,123	25.29	59
2	Proceedings Paper	436	4,275	9.81	31
3	Review	111	3,471	31.27	29
4	Editorial Material	6	101	16.83	4
5	Book Chapter	2	36	18.00	2

of articles climbed to 43 in 2018. Conversely, the number of citations declined to 2,289. From 2019 to 2021, publications increased steadily, while citations fell. The analysis shows that the year 2022 had the most research publications with 300 publications and 1,292 citations, 2021 with 299 publications and 4,447 citations, and 2020 with 196 publications and 4,609 citations. Articles and citations dropped dramatically in 2023 to 83 and 47, respectively. As a result, the TC/TP ratio and h-index fell to their lowest levels in the whole era. The year 2023 is not a complete year, as data were taken in May 2023 – expecting more publications and citations by the end of the year. The analysis recorded that 2019 received the highest number of total citations with 5,459, followed by 2020 with 4,609, and 2021 with 4,447 citations. The year 2020 has the highest h-index with 38, meaning there were at least 38 publications with more than 38 or more citations, followed by 2019 with 36 h-index and 2021 with h-index of 35.

5.2 Types of Publications

Table 3 illustrates the types of publications on DTPMS in the maritime industry between 2016 and 2023. The following types of papers

Table 4: Top 10 most productive sources in Digital Twin Predictive Maintenance Systems in maritime industry publications between 2016 and 2023. TP = total publications. TC = total citations. JIF = journal index factor.

Rank	Sources	TP	TC	h-index	JIF	Country	Publisher
1	Applied Sciences-Basel	42	531	13	2.83	Swiss.	MDPI
2	IFAC Papers online	32	590	10	0.2	UK	Elsevier
3	IEEE Access	31	2,714	14	3.47	USA	IEEE
4	Sensors	31	327	11	3.84	Swiss.	MDPI
5	Journal of Manufacturing Systems	24	862	13	9.49	UK	Elsevier
6	International Journal of Production Research	17	744	11	9.01	UK	Taylor & Francis
7	Sustainability	16	265	9	3.88	Swiss.	MDPI
8	International Journal of Advanced Manufacturing Technology	15	274	7	3.56	UK	Springer
9	Processes	15	267	6	3.35	Swiss.	MDPI
10	Journal of Intelligent Manufacturing	11	579	7	7.13	NLD.	Springer

are considered in the current analysis: Article, Proceedings Paper, Review, Editorial Material, and Book Chapter. The analysis reveals that many of the researchers in the field preferred to publish their work as "article" with 519 publications and 13,123 citations, followed by "proceedings papers" with 436 publications and 4,275 citations, "review" with 111 publications and 3,471 citations, "editorial material" with six publications and 101 citations, and "book chapter" with two publications and 36 citations. The analysis shows that most of the citations were received by articles with 13,123, followed by proceedings paper with 4,275, and review with 3,471. Regarding the highest average citation per publication (TC/TP), the review received the highest TC/TP with 31.27, followed by the article with 25.29, and the book chapter with 18.

5.3 Productive Sources

Table 4 depicts the top 10 most productive sources of DTPMSs in the maritime industry between 2016 and 2023. The table shows that five sources contributed more than 20 publications each. The journal *Applied Sciences-Basel* (journal impact factor (JIF) = 2.83) from Switzerland, published by MDPI, contributed the highest number of research papers with 42 publications and 531 citations; followed by IFAC Papers online (JIF = 0.2) from the UK, published by Elsevier, with 32 publications and 590 citations; *IEEE Access* (JIF = 3.47) from USA, published by IEEE, and Sensors (JIF = 3.84) from Switzerland, published by MDPI, with 31 publications each and 2,714 and 327 citations respectively; and *Journal of Manufacturing Systems* (JIF = 9.49) from the UK, published by Elsevier, with 24 publications and 862 citations. Springer-published *Journal of Intelligent Manufacturing* (JIF = 7.13) from the Netherlands was the least productive source among the top 10 with 11 publications and 579 citations.

Regarding the most citations, *IEEE Access* received the highest number of citations with

Table 5: Top 10 most productive affiliations on Digital Twin Predictive Maintenance Systems in maritime industry publications between 2016 and 2023. TP = total publications. TC = total citations.

Rank	Affiliations	Country	TP	TC	TC/TP
1	Research Libraries	UK	41	1,001	24.41
2	Polytechnic University of Milan	Italy	24	1,146	47.75
3	RWTH Aachen University	Germany	22	489	22.23
4	Centre National De La Recherche Scientifique	France	20	801	40.05
5	N8 Research Partnership	UK	16	217	13.56
6	Fraunhofer Gesellschaft	Germany	15	125	8.33
7	Norwegian University of Science Technology	Norway	14	293	20.93
8	Beihang University	China	13	2,400	184.62
9	White Rose University Consortium	UK	13	203	15.62
10	University of Auckland	New Zealand	12	912	76.00

2,714, followed by *Journal of Manufacturing Systems* with 862 citations, and *IFAC Papers* online with 590 citations. Among the top 10 most productive sources are four each from the UK and Switzerland, and one each from the USA and Netherlands. The analysis also reveals that among the top 10 sources, MDPI published four; two each were from Springer and Elsevier; and one each was from IEEE and Taylor & Francis. A similar top three productive sources in the research of Digital Twin and health management were reported by De Oliveira Ribeiro et al. [2022].

5.4 Productive Affiliations

Table 5 depicts the top 10 most productive affiliations on DTPMS in maritime industry publications between 2016 and 2023. Among the top 10 most productive affiliations, researchers from Research Libraries of the UK were the most productive affiliation with 41 publications and 1,001 citations, followed by Polytechnic University of Milan, Italy, with 24 publications and 1,146 citations, RWTH Aachen University, Germany, with 22 publications and 489 citations, Centre National De La Recherche Scientifique, France, with 20 publications and 801 citations, and N8 Research Partnership, UK, with 16 publications and 217 citations.

Among the top 10 productive affiliations, the University of Auckland, New Zealand, was the least prolific, with 12 publications and 912 citations. The analysis reveals that Beihang University, China, was the most cited affiliation, with 2,400 for 13 publications, followed by Polytechnic University of Milan, Italy, with 1,146 citations for 24 publications. Fraunhofer Gesellschaft was the least cited affiliation and the least average citation per publication, with 125 citations and 8.33 TC/TP, respectively. Beihang University also has the highest average citation per publication (TC/TP) with 184.62. The analysis reveals that among the productive affiliation, three are from the UK, two are from Germany, and one each is from Italy, France, Norway, China, and New Zealand.

5.5 Productive Country

Table 6 illustrates the top 10 most productive

Table 6: Top 10 most productive countries on Digital Twin Predictive Maintenance Systems in the maritime industry between 2016 and 2023. TP = total publications. TC = total citations.

Rank	Country	Continent	TP	TC	TC/TP
1	Germany	Europe	173	3,294	19.04
2	China	Asia	121	5,791	47.86
3	Italy	Europe	118	2,780	23.56
4	USA	North America	94	1,426	15.17
5	England	Europe	71	1,600	22.54
6	Spain	Europe	69	775	11.23
7	France	Europe	59	1,092	18.51
8	Brazil	South America	44	574	13.05
9	Norway	Europe	34	464	13.65
10	India	Asia	33	291	8.82

Table 7: Top 10 most productive research areas on Digital Twin Predictive Maintenance Systems in the maritime industry between 2016 and 2023. TP = total publications. TC = total citations.

Rank	Research Areas	TP	TC	TC/TP
1	Engineering	725	16,913	23.33
2	Computer Science	398	9,289	23.34
3	Automation Control Systems	173	3,855	22.28
4	Chemistry	94	923	9.82
5	Operations Research Management Science	93	2,420	26.02
6	Telecommunications	91	3,071	33.75
7	Materials Science	88	773	8.78
8	Physics	65	818	12.58
9	Science Technology Other Topics	59	1,009	17.10
10	Instruments Instrumentation	53	457	8.62

countries on DTPMS systems in maritime industry publications between 2016 and 2023. The analysis shows that among the top 10 most prolific countries, 60% (n = 6) of countries are in Europe, followed by two countries from Asia, and one each from North America and South America. Among the top 10 leading countries, three contributed over 100 publications each. Germany was identified as the most productive country on DTPMS in maritime industry publications, with 173 publications and 3,294 citations, followed by China with 121 publications and 5,791 citations, Italy with 118 publications and 2,780 citations, the USA with 94 publications and 1,426 citations, and England with 71 publications and 1,600 citations. India was the least productive country in the list, with 33 publications and 291 citations.

Regarding the most cited countries, China also received the highest citations with 5,791,

Table 8: Top 10 most prolific authors on Digital Twin Predictive Maintenance Systems in maritime industry publications between 2016 and 2023. TP = total publications. TC = total citations.

Rank	Author	Affiliation	Country	TP	TC	h-index
1	Xu X	University of Auckland	New Zealand	10	944	8
2	Lu Y	University of Auckland	New Zealand	9	828	6
3	Zhang C	Xi'an Jiaotong University	China	9	254	5
4	Zhang Y	Rochester Institute of Technology	USA	8	372	7
5	Fumagalli L	Politecnico di Milano	Italy	7	958	6
6	Liu Y	Dalian University of Technology	China	7	315	5
7	Dolgui A	IMT Atlantique	France	7	582	4
8	Leng J	Guangdong University of Technology	China	6	631	6
9	Liu C	Xi'an Jiaotong University	China	6	832	6
10	Liu Q	Guangdong University of Technology	China	6	633	6

followed by Germany with 3,294 citations and Italy with 2,780 citations. India was the least cited country in the list, with 291 citations and 8.82 TC/TP. University-affiliated institutions in China received the highest average citation per publication, with 47.86, followed by universities in Italy, with 23.56.

5.6 Productive Research Areas

Table 7 represents the top 10 most productive research areas on DTPMS in maritime industry publications between 2016 and 2023. The analysis shows that Engineering ranks first, with 725 articles and 16,913 citations, for a TC/TP ratio of 23.33. Computer Science ranks second with 398 articles, 9,289 citations, and a TC/TP ratio of 23.34. With 173 publications, 3,855 citations, and a TC/TP ratio of 22.28, Automation Control Systems takes third place. Despite having fewer publications (94), Chemistry receives 923 citations, resulting in a lower TC/TP ratio of 9.82. Operations Research Management Science ranks fifth with 93 articles, 2,420 citations, and a TC/TP ratio of 26.02. Telecommunications, Materials Science, Physics, Science Technology Other Topics, and Instruments Instrumentation contributed with 91, 88, 65, 59, and 53 publications, respectively.

Regarding citation trends on productive research areas on DTPMS in maritime industry publications, Engineering, Computer Science, and Automation Control Systems were the top-cited research areas with 16,913, 9,289, and 3,855 citations, respectively. The bibliometric study sheds light on the comparative performance of various research disciplines based on publication and citation metrics, demonstrating these subjects' relative impact and influence within the scholarly landscape.

5.7 Prolific Authors

Table 8 optimizes the results from the evaluated of the top 10 prolific authors on DTPMS in maritime industry publications between 2016 and 2023. This bibliometric table provides a summary of these top 10 productive authors' publications and citation impacts, highlighting their research output and importance within their respective fields of study.

Xu X from the University of Auckland in New Zealand is the top-ranked author, with 10 publications, 944 citations, and an h-index of

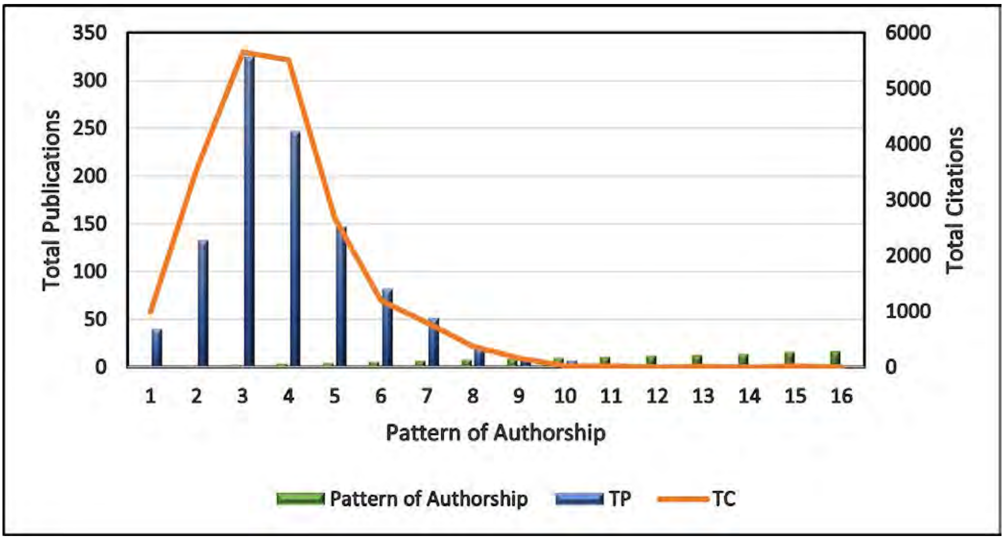


Figure 5: Authorship pattern.

8. Lu Y, also from the University of Auckland, comes close behind with nine publications, 832 citations, and an h-index of 6. Zhang C from China's Xi'an Jiaotong University is third, with nine publications, 254 citations, and an h-index of 5. Zhang Y from the Rochester Institute of Technology in the United States comes in fourth place, with eight publications, 372 citations, and an h-index of 7. Fumagalli L from Italy's Politecnico di Milano takes fifth place with seven publications, 958 citations, and an h-index of 6. Liu Y and Dolgui A have seven publications each, and Leng J, Liu C, and Liu Q have six publications each. Fumagalli L from Politecnico di Milano in Italy received the highest citation with 958, followed by Xu X from the University of Auckland in New Zealand with 944 citations and Liu C from Xi'an Jiaotong University in China with 832 citations.

5.8 Pattern of Authorship

Figure 5 portrays the authorship pattern of the DTPMS in maritime industry publications between 2016 and 2023. This figure illustrates that authorship patterns ranged from 1 to 16. The analysis reveals 96% (TP = 1,034) of the publications were contributed by more than one author, and only 4% (TP = 40) of the publications were contributed by a single author. This indicates that authors preferred collaborative works in the fields. Furthermore, the figure shows Pattern 3 is the most common authorship pattern, with 325 publications and 5,655 citations. Alade et al. [2022] also reported a similar pattern of authorship in their *Journal of Superconductivity and Novel Magnetism* publication. Pattern 4 is close behind, with 247 publications and 5,518 citations. Pattern 2 has the third highest frequency, with 133 publications and 3,552 citations.

The authorship patterns, numbered 5 to 17, show a decrease in publications and citations, indicating fewer common authorship patterns in the given context. It is worth noting that Pattern 12 has only one publication and no citations. This bibliometric diagram sheds light on the collaborative nature and productivity within the investigated research field or dataset

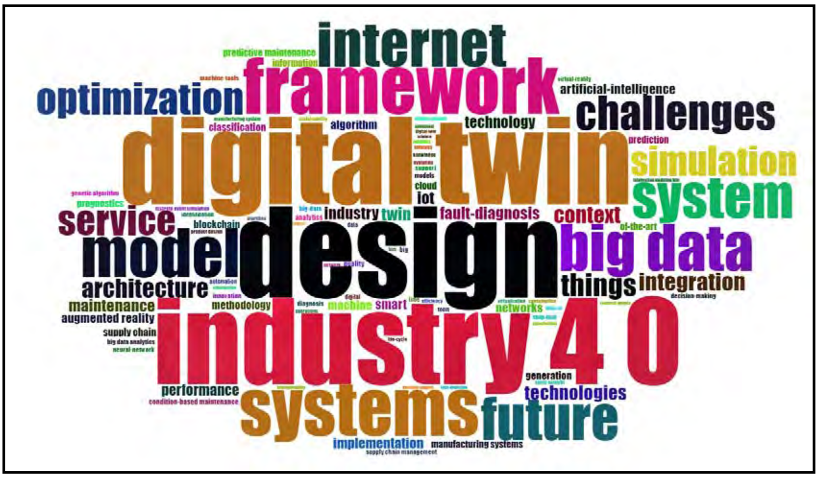


Figure 6: Word Cloud of title keywords from Biblioshiny software 5.9. Mapping and visualizing the co-occurrence of author keywords.

by revealing the distribution and frequency of various authorship patterns.

5.9 Analyzing the Word Cloud from Title Keywords

A title keyword Word Cloud is a visual depiction of the most common or relevant keywords taken from the titles of a group of papers or publications. The Word Cloud indicates the frequency or relevance of specific words used in the titles in this context.

This visualization technique offers a quick and effortless way to identify the major themes or topics in the document titles. As can be seen in Figure 6, the most used terms are “design” (159), “digital twin” (153), and “industry 4.0” (151), emphasizing their importance and ubiquity in the subject. “Framework” (98), “systems” (96), “model” (85), “big data” (81), “internet” (79), and “future” (76) are all noteworthy terms. These terms denote the most important research themes in the field, including design methodologies, DT technology, advancements in Industry 4.0, system modelling and management, Big Data Analytics, internet applications, cyber-physical systems, optimization techniques, and simulation methodologies.

Based on the Word Cloud, potential research areas for the future include supply chain management advancements, Industry 4.0 challenges, optimization methods, Big Data Analytics, IoT integration, and AI advancements. Research gaps should be prioritized, and these areas should be investigated to progress in these fields.

Figure 6 captures the co-occurrence of author keywords in the field of DTPMS in maritime industry publications, using the VOSviewer software. The frequency and patterns of author-assigned keywords in research articles and publications are called co-occurrence. It entails finding correlations and associations between terms that appear in the same publications. Author keyword co-occurrence can reveal the interconnection of subjects, themes, and concepts in a research domain. This study might reveal common research areas, emerging trends, interdisciplinary connections, or clusters of associated concerns, offering a holistic view of the research environment and guiding future research. A minimum of 10 author keywords were considered for the present analysis. From the 2,675 author keywords, 62 keywords met the criteria. The selected 62 keywords were grouped in five clusters/themes and represented in assorted colours, as illustrated in the figure:

- **Cluster 1 (Red)**. This cluster comprises 20 author keywords. The main research theme of this cluster is *Smart Manufacturing and its Integration with Advanced Technologies*. The leading topics in this cluster include smart manufacturing, IoT, AI, cyber-physical systems, blockchain, big data, sustainability, deep learning, smart factory, cloud computing, digital transformation, intelligent manufacturing, additive manufacturing, data analytics, literature review, robotics, condition monitoring, and cyber-physical production systems.
- **Cluster 2 (Green)**. This cluster includes 16 author keywords. The main theme of this cluster is *Digital Transformation*. The leading research topics of this cluster comprise Digital Twin, Industry 4.0, asset administration shell, IoT, digitalization, automation, interoperability, cyber-physical production system, cyber-physical systems (CPS), virtual commissioning, OPC UA, ontology, and virtualization.
- **Cluster 3 (Blue)**. This cluster consists of 12 author keywords, and *Industrial Processes, Digitalization, and Advanced Technologies* are the major research themes in this cluster. This cluster's leading study topics are predictive maintenance, Digital Twins, machine learning, DT, monitoring, anomaly detection, cloud manufacturing, edge computing, sensors, and industrial IoT.
- **Cluster 4 (Yellow)**. This cluster comprises 10 author keywords. The main research theme of this cluster is *Advancing Manufacturing Processes*. The leading topics include simulation, manufacturing, digital manufacturing, production, optimization, manufacturing systems, review, framework, modelling, and systematic literature review.
- **Cluster 5 (Purple)**. The main themes of this cluster are *Digital Technologies and Simulation in Manufacturing* and the leading topics in this cluster include Industry 4.0, virtual reality, augmented reality, discrete event simulation, and maintenance.

Figure 7 displays the leading occurred author keywords such as Digital Twin (n = 463), Industry 4.0 (n = 183), Industry 4.0 (n = 170), smart manufacturing (n = 80), internet of things (n = 72), predictive maintenance (n = 70), Digital Twins (n = 65), artificial intelligence (n = 61), simulation (n = 59), machine learning (n = 47), cyber-physical systems, manufacturing, blockchain, asset administration shell, IoT, big data, industrial internet of things, and virtual reality. N.B.: The weight of an item determines the size of its circle, with heavier items having larger circles.

5.10 Bibliographic Coupling of Documents

Bibliographic coupling is a technique employed in bibliometrics and information science to analyze the relationships between scientific documents based on their shared citations. It is a type of co-citation analysis focused on the bibliographic references cited by various documents, instead of the documents themselves. By analyzing the

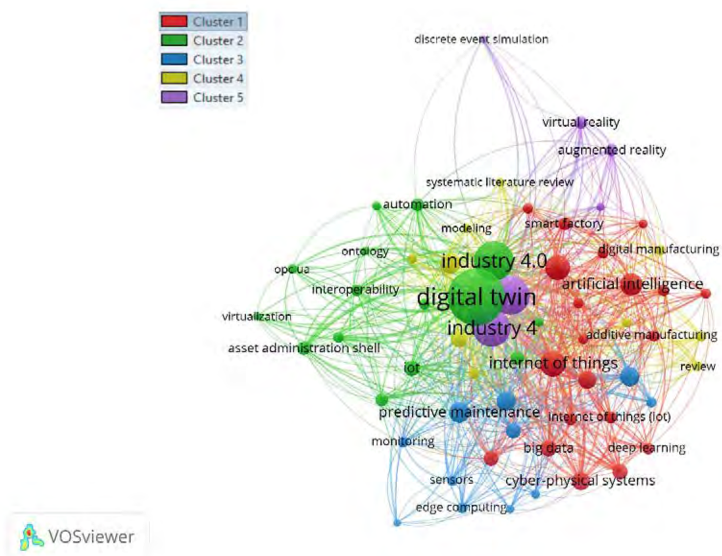


Figure 7: Mapping and visualizing the co-occurrence of author keywords using the VOSviewer software.

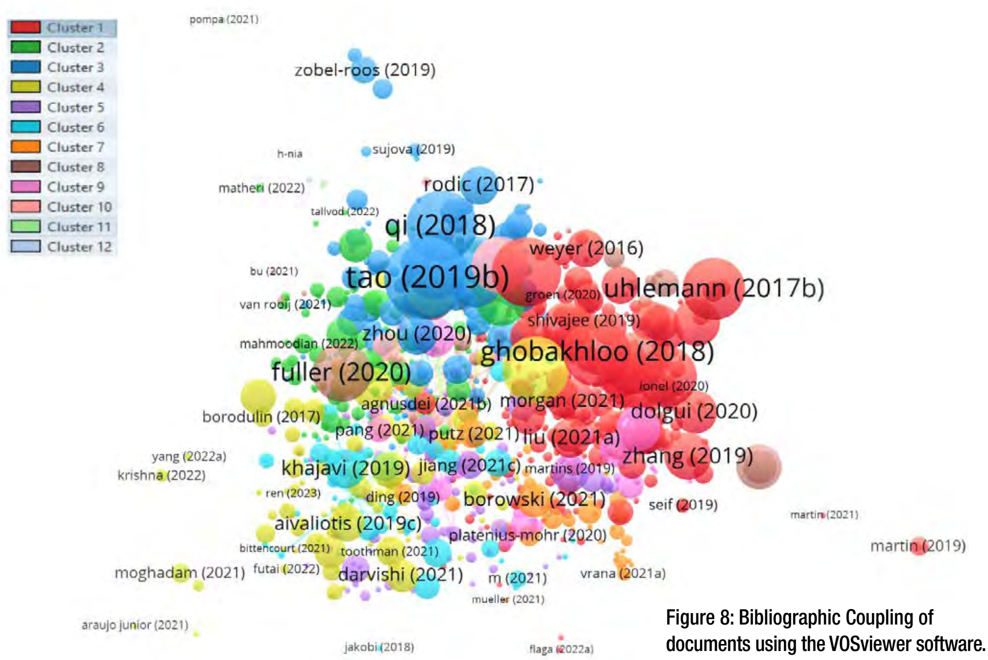


Figure 8: Bibliographic Coupling of documents using the VOSviewer software.

bibliographic coupling network, researchers can gain insight into various scientific thematic similarities and interrelationships of the documents. It can aid in identifying clusters or groups of related research and disclose patterns of knowledge diffusion or research collaboration within a field. Figure 8 (bibliographic coupling) was generated using the VOSviewer software. Minimum (0) number of citations of a document were considered for analysis. Out of the documents, 1,074 meet the thresholds. The documents with the greatest total link strength will be selected. A total of 1,000

Table 9: Significant themes or clusters or both on Digital Twin Predictive Maintenance Systems in maritime industry publications between 2016 and 2023. TP = total publications. TC = total citations.

Cluster /Team	TP in Cluster	TC in Cluster	Most Cited Publication in Cluster			
			TC	Title	Year	Author
Cluster 1	291	7,893	536	A review of the roles of Digital Twin in CPS-based production system	2017	Negri
			501	The future of manufacturing industry: a strategic roadmap toward Industry 4.0	2018	Ghobakhloo
			411	The Digital Twin: realizing the cyber-physical production system for Industry 4.0	2017	Uhlemann
Cluster 2	142	1,290	242	Review of Digital Twin applications in manufacturing	2019	Cimino
			91	Digital Twin: origin to future	2021	Singh
			87	An architecture of an intelligent Digital Twin in a cyber-physical production system	2019	Talkhestani
Cluster 3	112	4,539	819	Digital Twin in industry: state-of-the-art	2019	Tao
			571	Digital Twin and big data towards smart manufacturing and Industry 4.0: 360-degree comparison	2018	Qi
			424	Digital Twin-driven smart manufacturing: connotation, reference model, applications, and research issues	2020	Lu
Cluster 4	105	2,029	479	Digital Twin shop-floor: a new shop-floor paradigm towards smart manufacturing	2017	Tao
			145	A digital-Twin-assisted fault diagnosis using deep transfer learning	2019	Xu
			102	Prototyping a Digital Twin for real time remote control over mobile networks: application of remote surgery	2019	Laaki
Cluster 5	83	652	119	A review on blockchain technologies for an advanced and cyber-resilient automotive industry	2019	Fraga-Lamas
			58	Adaptive federated learning and Digital Twin for industrial internet of things	2021	Sun
			51	Digital Twin to improve the virtual-real integration of industrial IoT	2021	Jiang
Cluster 6	83	818	133	Digital Twin: vision, benefits, boundaries, and creation for building	2019	Khajavi
			68	Differentiating Digital Twin from digital shadow: elucidating a change in basic assumptions to expedite a smart, sustainable built environment	2021	Sepasgozar
			63	The 'how' of benefits management for digital technology: from engineering to asset management	2019	Love

publications were selected, and all the selected publications were grouped into 12 clusters/themes, which are discussed below and shown in Table 9:

- ***Cluster 1 – DT in Industry 4.0***. This is the largest cluster in terms of total publication (TP = 291) and total citations (TC = 7,893). The theme of this cluster is DT in Industry 4.0. The most cited publication in this cluster is entitled *A review of the roles of Digital Twin in CPS-based production system* by Negri et al. [2017] with 536 citations, followed by *The future of manufacturing industry: a strategic roadmap toward industry 4.0* by Ghobakhloo [2018] with 501 citations.
- ***Cluster 2 – Advancements in DT***

Table 9: continued

Cluster /Team	TP in Cluster	TC in Cluster	Most Cited Publication in Cluster			
			TC	Title	Year	Author
Cluster 7	69	519	93	Digitization, Digital Twins, blockchain, and industry 4.0 as elements of management process in enterprises in the energy sector	2021	Borowski
			60	Ether Twin: blockchain-based secure Digital Twin information management	2021	Putz
			38	Modular fault ascription and corrective maintenance using a Digital Twin	2018	Vathoopan
Cluster 8	54	1,309	348	DT: enabling technologies, challenges, and open research	2020	Fuller
			186	Experientable Digital Twins-streamlining simulation-based systems engineering for Industry 4.0	2018	Schluse
			143	A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin	2020	Luo
Cluster 9	40	756	173	Blockchain-empowered sustainable manufacturing and product lifecycle management in Industry 4.0: a survey	2020	Leng
			133	Digital Twin as a service (DT SaaS) in Industry 4.0: an architecture reference model	2021	Aheleroff
			98	Blockchain-secured smart manufacturing in Industry 4.0: a survey	2021	Leng
Cluster 10	15	525	326	Digital Twins and cyber-physical systems toward smart manufacturing and industry 4.0: correlation and comparison	2019	Tao
			77	Exploring the potential of operator 4.0 interface and monitoring	2020	Peruzzini
			62	Digital Twin for the oil and gas industry: overview, research trends, opportunities, and challenges	2020	Wanasinghe
Cluster 11	4	201	196	A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives	2019	Lim
			4	Machine learning techniques in emerging cloud computing integrated paradigms: a survey and taxonomy	2022	Soni
			1	A digital shadow cloud-based application to enhance quality control in manufacturing	2020	Santolamazza
Cluster 12	2	1	1	Nonlinear observer design for guidance and traction of railway vehicles	2020	Heckmann
			0	Predictive maintenance in railway systems: mbs-based wheel and rail life prediction exemplified for the Swedish iron-ore line	2022	H-Nia

Technology. This is the second largest cluster in total publications with 142 publications, while the fifth largest in total citations with 1,290. The most cited paper in this cluster is *Review of Digital Twin applications in manufacturing* by Cimino et al. [2019] with 242 citations, followed by *Digital Twin: origin to future* by Singh et al. [2021] with 91 citations.

- ***Cluster 3 – DT Technology for Smart Manufacturing and Optimization in Industry***. This is the third largest cluster in total publications with 112 publications and second highest cluster in total citations with 4,539. The primary theme of this cluster is Digital Twin Technology for Smart Manufacturing and Optimization in Industry. The most cited publication in this cluster is *Digital twin in industry: state-of-the-art* by Tao et al. [2019] with 819 citations, followed by *Digital Twin and big data towards smart manufacturing and industry 4.0: 360-degree comparison* by Qi and Tao [2018] with 571 citations.

- ***Cluster 4 – DT Applications for Smart Manufacturing and Predictive Maintenance***. This is the fourth largest cluster in total publications with 105 publications, and third largest in terms of total citations with 2,029. This theme deals with DT Applications for Smart Manufacturing and Predictive Maintenance. The most cited paper in this cluster is *Digital Twin shop-floor: a new shop-floor paradigm towards smart manufacturing* by Tao and Zhang [2017], with 479 citations, followed by *A digital-twin-assisted fault diagnosis using deep transfer learning* by Xu et al. [2019] with 145 citations.
- ***Cluster 5 – Leveraging Blockchain and DT Technologies for Advanced Industrial IoT and Manufacturing***. This is the fifth largest cluster with 83 publications and 652 citations.
- ***Cluster 6 – Exploring DT Applications and Benefits in Construction Industry***. This cluster also comprises 83 publications and 818 citations.
- ***Cluster 7 – Digital Transformation and Blockchain-enabled DTs for Efficient Management in Energy and Construction Sectors***. Includes 69 publications and 519 citations.
- ***Cluster 8 – DT: Technologies, Challenges, and Integration for Industry 4.0***. Comprises 54 publications and 1,309 citations.
- ***Cluster 9 – Encompass the Utilization of Blockchain and Digital Twin Technologies in Industry 4.0***. This cluster includes 40 publications and 756 citations.
- ***Cluster 10 – DT, Cyber-physical Systems, and Smart Manufacturing in Industry 4.0***. This cluster comprises 15 publications and 525 citations.
- ***Cluster 11 – DT in Product Lifecycle Management and Business Innovation, Machine Learning Techniques within Cloud Computing Paradigms***. This cluster includes only four publications and 201 citations.
- ***Cluster 12 – Nonlinear Observer Design for Railway Vehicle Guidance and Traction, and Predictive Maintenance in Railway Systems***. This is the smallest cluster with two publications and a single citation.

5.11 Examining Most Cited Papers

Table 10 presents the top 10 most cited research papers on DTPMS in maritime industry publications between 2016 and 2023. Among the top 10 most cited papers, the citation ranged from 348 to 819. The analysis reveals that four research papers received more than 500 citations:

1. *Digital Twin in Industry: State-of-the-Art* authored by Tao et al. [2019] in IEEE *Transactions on Industrial Information* received the highest total citations with 819.
2. *Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison* authored by Qi and Tao [2018] in *IEEE Access*, which received 571 citations.
3. *A Review of the Roles of Digital Twin in CPS-based Production Systems* authored

Table 10: Top 10 most cited research papers on Digital Twin Predictive Maintenance Systems in maritime industry publications between 2016 and 2023. TC = total citations.

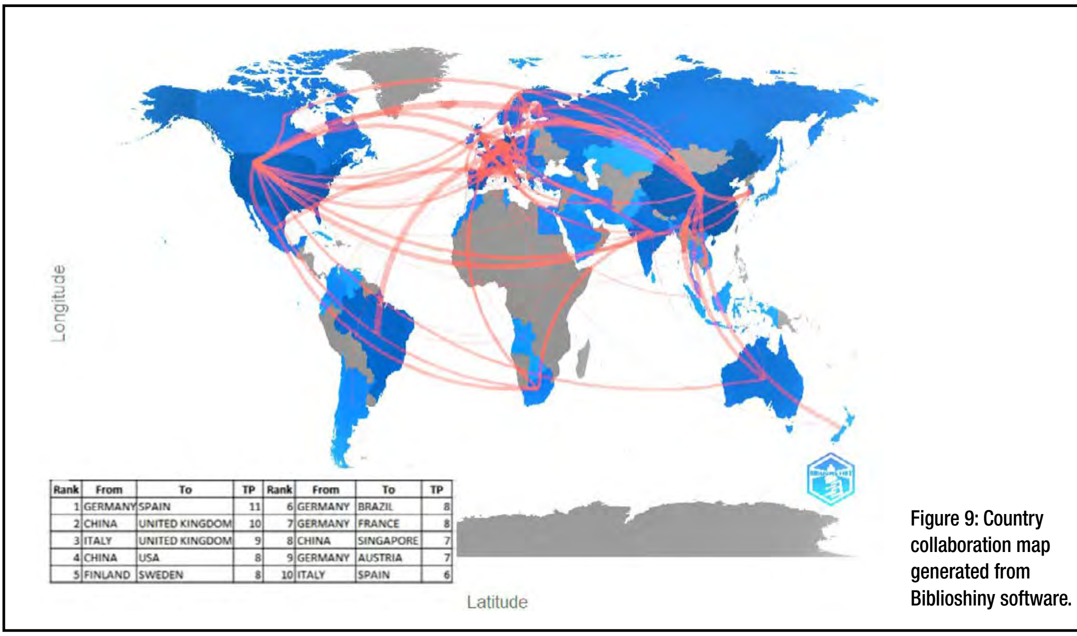
Rank	Title	Author	Year	Source	TC	TC/Year	Normalized TC
1	Digital Twin in Industry: State-of-the-Art	Tao, F	2019	IEEE Trans Ind Inform	819	163.8	19.5
2	Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison	Qi, Q	2018	IEEE Access	571	95.17	10.73
3	A Review of the Roles of Digital Twin in CPS-based Production Systems	Negri, E	2017	Procedia Manufacturing	536	76.57	3.75
4	The Future of Manufacturing Industry: A Strategic Roadmap Toward Industry 4.0	Ghobakhloo, M	2018	J Manuf. Technol Mgmt.	501	83.5	9.41
5	Digital Twin Shop-floor: A New Shop-Floor Paradigm Towards Smart Manufacturing	Tao, F	2017	IEEE Access	479	68.43	3.35
6	Digital Twin-driven Smart Manufacturing: Connotation, Reference Model, Applications, and Research Issues	Lu, Y	2020	Robot Comput - Integr. Manuf.	424	106	17.29
7	The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0	Uhlemann, Thj	2017	Procedia CIRP	411	58.71	2.88
8	Scanning the Industry 4.0: A Literature Review on Technologies for Manufacturing Systems	Alcacer, V	2019	Eng. Sci. Technol	402	80.4	9.57
9	A Digital Supply Chain Twin for Managing the Disruption Risks and Resilience in the Era of Industry 4.0	Ivanov, D	2021	Prod Plan Control	375	125	23.95
10	Digital Twin: Enabling Technologies, Challenges and Open Research	Fuller, A	2020	IEEE Access	348	87	14.19

by Negri et al. [2017] in *Procedia Manufacturing*, which has 536 citations.

4. *The Future of Manufacturing Industry: A Strategic Roadmap Toward Industry 4.0* authored by Ghobakhloo [2018] in *Journal of Manufacturing Technology Management* with 501 citations.

Tao and Zhang [2017] published *Digital Twin Shop-floor: A New Shop-Floor Paradigm Towards Smart Manufacturing* in *IEEE Access* with 479 citations. The article *Digital Twin: Enabling Technologies, Challenges, and Open Research* by Fuller et al. [2020], published in IEEE Access, was the least cited paper in the list, which received 348 citations.

N.B.: These publications have received much attention and citations in the scientific community, suggesting their importance and influence in the fields of Digital Twins, smart manufacturing, Industry 4.0, and other related areas.



Rank	From	To	TP	Rank	From	To	TP
1	GERMANY	SPAIN	11	6	GERMANY	BRAZIL	8
2	CHINA	UNITED KINGDOM	10	7	GERMANY	FRANCE	8
3	ITALY	UNITED KINGDOM	9	8	CHINA	SINGAPORE	7
4	CHINA	USA	8	9	GERMANY	AUSTRIA	7
5	FINLAND	SWEDEN	8	10	ITALY	SPAIN	6

Figure 9: Country collaboration map generated from Biblioshiny software.

5.12 Country Collaboration

In the bibliometric study, the country collaboration map (i.e., Figure 9) depicts collaboration trends among different countries, based on the number of co-publications (TP) between any two countries. The analysis shows that Germany and Spain have collaborated on 11 co-publications, suggesting that the two countries have a good research collaboration, followed by China and the United Kingdom which have collaborated on 10 co-publications, indicating a substantial research collaboration. Italy and the United Kingdom have worked together on nine co-publications, showing a fruitful scientific partnership; China and the United States have collaborated on eight co-publications, indicating a significant research partnership between these two countries; and Finland and Sweden have worked on eight co-publications, reflecting the two countries' strong research connection. Italy and Spain have the least collaboration in the top 10 list, with six co-publications.

Regarding the number of co-publications across countries, the rankings show the most prominent cooperation. It sheds light on international research collaborations and networks in the topic studied by the bibliometric study.

6. CONCLUDING REMARKS

This study employed a bibliometric performance analysis of the Digital Twin Predictive Maintenance System research in maritime industry publications between 2016 and 2023. Based on the 1,074 publications from the Web of Science, this research explored the yearly growth of publications, productive authors, affiliations, countries, most relevant journal, most cited papers, and evaluated author keywords and leading research themes in the field of DTPMS in maritime industry publications.

The finding shows that the DTPMS (in maritime industry publications) has grown exponentially in terms of productivity and citations since 2016. The year 2022 contributed the highest number of research papers with 300 publications, while 2019 received most of the citations with 5,459. In terms of the most relevant sources, *Applied Sciences-Basel* is the most productive with 531 publications in the field. At the same time, *IEEE Access* is the most impactful source on DTPMS in maritime industry publications.

Based upon the reported results and evaluations, three authors, Xu X, Lu Y, and Zhang C, were the most prolific authors, while Fumagalli L is the most impactful author in the field. Germany (TP = 173) is identified as the leader in producing the highest research in the field, while China is the most impactful country in total citations with 5,791. Research Libraries of the UK (TP = 41) is the most prolific affiliation, while Beihang University, China, is the most cited affiliation with a TC of 2,400.

Engineering contributed the most publications and citations in terms of research area. Three-authorship is the most common authorship pattern, with 325 publications and 5,655 citations. The analysis shows that Germany and Spain have collaborated on 11 co-publications, suggesting that the two countries have a good research collaboration.

The analysis also explored 12 research themes on DTPMS in maritime industry publications, namely:

1. Cluster 1: DT in Industry 4.0
2. Cluster 2: Advancements in Digital Twin Technology
3. Cluster 3: DT Technology for Smart Manufacturing and Optimization in Industry
4. Cluster 4: DT Applications for Smart Manufacturing and Predictive Maintenance
5. Cluster 5: Leveraging Blockchain and DT Technologies for Advanced Industrial IoT and Manufacturing
6. Cluster 6: Exploring DT Applications and Benefits in Construction Industry
7. Cluster 7: Digital Transformation and Blockchain-enabled DTs for Efficient Management in Energy and Construction Sectors
8. Cluster 8: DT Technologies, Challenges, and Integration for Industry 4.0
9. Cluster 9: Encompass the Utilization of Blockchain and DT Technologies in Industry 4.0
10. Cluster 10: DTs, Cyber-physical Systems, and Smart Manufacturing in Industry 4.0
11. Cluster 11: DT in Product Lifecycle Management and Business Innovation, Machine Learning Techniques within Cloud Computing Paradigms
12. Cluster 12: Nonlinear Observer Design for Railway Vehicle Guidance and Traction, and Predictive Maintenance in Railway Systems

Furthermore, the concept of DTs, with its origins dating back to the Apollo 13 mission in 1970, has resurged in recent years due to technological advancements like 3D simulations and IoT. Its historical importance and ability to bridge the physical and digital realms make it a crucial tool in addressing contemporary challenges across industries, including the maritime sector. This study is an early attempt to investigate the conceptual framework, driving forces, and theoretical underpinnings of the DTPMS in the maritime industry, which offers current researchers and decision-makers comprehensive and up-to-date knowledge. Researchers can use the findings of this study in developing prospective future research directions for Digital Twin Predictive Maintenance Systems in the maritime industry advancement.

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