How does Prognostics and Health Management (PHM) develop in the engineering domain: A bibliometric analysis with critical review

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Research article

How does Prognostics and Health Management (PHM) develop in the engineering domain: A bibliometric analysis with critical review

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A R T I C L E I N F O

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A B S T R A C T

In recent years, Prognostics and Health Management (PHM) have been considered in broad industrial areas to improve the effectiveness of maintenance activities. In chemical engineering domains, PHM is regarded to have big potential for reliability and safety management of complex systems. In this study, a bibliometric analysis has been conducted to explore the evolution of PHM by retrieving 2351 publications from the Web of Science Core Collection (Retrieve date: 12/05/2023). Science mapping techniques are applied to visualize the results. This study helps to reveal research hotspots and development trends of PHM, with a particular focus on chemical engineering. As for the results, PHM has become a multidisciplinary topic. Its research in chemical engineering domains has gained increasing attention in recent years. By integrating advanced models like neural networks and digital twins, PHM can complement traditional approaches, offering real-time insights that improve operational strategies. In the future, PHM progress will focus on multidisciplinary applications with stronger collaboration between academia and industry, with more potential to address practical challenges.

1. Introduction

Owing to the development of sensing technologies, big data processing, and computing capabilities, the paradigm shift in reliability engineering has broadened the acceptance of Engineering of Asset Management (EAM). As a burgeoning concept, Prognostics and Health Management (PHM) has become a key discipline within asset management programs [1]. PHM is now widely applied in fields such as military aviation, battery and energy systems, production scheduling, and other industrial scenarios [2–4]. PHM can be viewed as consisting of two primary components: Prognostics (P) and dynamic Decision-Making (DM) [5]. By estimating the Residual Performance Lifetime (RPL) or Remaining Useful Life (RUL) of the structures, systems, and components (SSCs), maintenance actions/plans can be scheduled to mitigate the impact of predicted failures [3,6]. This mechanism may enable continuous asset tracking and monitoring, providing significant benefits for asset management. Researchers are developing various PHM approaches, for example, PHM based on physical methods requires detailed knowledge of equipment degradation processes to predict failure behaviors using explicit mathematical models [7]. However, when degradation models cannot be precisely described, PHM becomes more challenging [2]. In the current Industry 4.0 era, emerging technologies like the Internet of Things (IoT), artificial intelligence (AI), and Big Data

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analytics support to development of data-driven PHM approaches. These technologies enhance data collection and management allowing for the extraction of implicit features in components and systems [6]. As PHM evolves, more hybrid approaches are developed by integrating advanced methods such as Deep Convolutional Neural Network [8], Data Envelopment Analysis (DEA), Analytical Hierarchical Process (AHP) [6], Digital Twin (DT) [9], etc. Meanwhile, the development of PHM approaches boosts other related studies, like the cost-benefit model [10], data quality [11], and data management strategies [12].

PHM was initially adopted primarily in mechanical domains, mechanical structures or components are highly focused on such as rolling bearings and turbofans [9,13]. The advancements of PHM applications in certain fields encourage researchers to explore its potential in other fields. In safety-critical industries like chemical engineering domains, system failures can have severe consequences for human lives and property. For instance, as pointed out by Chalgham et al. [14], on average, 287 oil and gas pipeline incidents occur annually in the United States, resulting in 14 fatalities and 59 injuries. PHM is seen as a promising solution in such contexts to guarantee the reliability of pipeline systems. Although PHM techniques have already been applied in some cases from chemical engineering domains, like in lithium-ion batteries [2], nuclear power systems [15], and subsea systems [16], the technological and regulatory gaps hinder the implementation of PHM in complex industries [15]. More research is needed in areas such as failure models, uncertainty analysis, prognostic performance evaluation, and the verification and validation of PHM algorithms and models. Furthermore, more comprehensive methods are required to integrate a holistic view of system operation, maintenance, and decision-making processes.

Given the challenges and opportunities, the research goal of this study is to explore and summarize the current research progress in PHM and to identify patterns in its development across engineering domains. According to PHM's current advancements in mainstream applications, its potential in chemical engineering domains will be further explored and discussed. To achieve this, this study conducts a bibliometric analysis to visualize the research themes and trends, examining existing publications to provide an overview. This analysis helps trace the historical development of PHM research, predict future trends, and map out research activities and collaborations [17]. Moreover, by unfolding a comparison analysis of PHM advancements between general engineering domains and chemical engineering domains, PHM's state-of-the-art in chemical engineering fields is expected to be summarized, which inspires further research in related areas. The study follows four research questions: (1) What are the main characteristics of PHM research in engineering and chemical engineering domains? (2) How does the PHM research develop in the whole period? (3) How does PHM benefit engineering research from a macro perspective? (4) How do PHM advancements in mainstream fields inspire its development in chemical engineering domains? The novelty of this study lies in uncovering the development trends and research hotspots in PHM through the analysis of a large volume of publications. Additionally, it explores the emerging application of PHM in the field of chemical engineering. By conducting a comparison analysis, the patterns observed in broader domains may provide insights that inspire advancements within chemical engineering.

The paper is organized as follows: Section 2 contains the research framework and methods applied in this study. Section 3 analyzes the development trends of PHM and compares its advancements between chemical engineering and wider engineering domains. Discussions, conclusions, and future perspectives are expanded in Section 4.

2. Research framework and methods

2.1. Database built

Publications from various database sources are commonly focused on establishing the required database, like Scopus, Web of Science (WoS), etc. The bibliometric analysis could be conducted based on either one or multiple sources with aids of analysis tools for tracking trends and measuring research impacts [18,19]. Considering the large number of publications related to PHM, this study starts from the publications on the Web of Science Core Collection due to its availability of standardized citation records over a longer period, which supports to explore the citation network of the target topic. To benefit the trend analysis of PHM applications in general engineering fields, and its development trends in the chemical engineering field through comparison analysis, two databases have been built as an Engineering Database and a Chemical Engineering Database by selecting different Web of Science Categories. Firstly, the flowing search query was running to establish the Engineering Database "(TS=("Prognostics and Health Management") AND SU=("Engineering"))". "TS" indicates the topics (title, abstract, and keywords) while "SU" indicates the subject areas. Then, the results were refined by Document Types ("Article," "Proceeding Paper," "Review Article," and "Early Access"). As of 12/05/2023, a total of 2351 publications were retrieved. To establish the Chemical Engineering Database, 2351 publications from the Engineering Database were further refined by narrowing down to Web of Science Categories as "Engineering Chemical", resulting in 57 available publications.

The earliest publication found in the Engineering Database is a proceeding paper of the IEEE Conference on Decision and Control in 1996, entitled 'Monitoring, diagnostics and prognostics of operating machinery through the national information infrastructure (NII)' [20]. All information on publications in the dataset is exported in plain text attached with their titles, authors, keywords, abstracts, and references, and are used for further analysis. Previously, engineering fields have employed bibliometric analysis in conjunction with WoS data retrieval, to recognize the development pattern of relative topics, like microplastics and indoor microplastics [21,22], artificial intelligence in renewable energy [23], risk analysis of oil and gas pipelines [24]. Such successful applications contribute to the establishment of the research framework in this study.

2.2. Research framework

The research framework of this study is illustrated in Fig. 1, where the analysis process consists of five steps, and the results are visualized through science mapping techniques. Firstly, using the Engineering Databases from the Web of Science Core Collection, a performance analysis is conducted to explore fundamental characteristics such as the number of publications (NP), the number of citations (NC), publication types, research areas, and highly cited publications and journals, which serve as the bibliometric indicators. Secondly, an analysis of the publication's background information (including countries/regions, institutions, and authors) is carried out. This part includes citation and cooperation analysis to identify the most influential countries/regions, institutions, and authors. The third step involves conducting a burst detection analysis on authors, references, countries, and institutions to identify periods of intense research activity and sudden increases in publication frequency. This helps in staying informed about the latest trends and advancements in PHM research. Next, a keyword analysis is performed to visualize the co-occurrence, critical terms, and developments of keywords along the timeline. The most important topics, as indicated by the keywords, are critically reviewed. Based on the results above, how PHM benefits reliability and asset management programs is discussed from the perspective of general engineering fields. Finally, the comparison analysis contributes to the current state of PHM applications in chemical engineering domains and suggests future directions for their growth.

3. Results

In this section, the analysis of the Engineering Database is expanded from section 3.1 to 3.4. How PHM benefits asset management is explored in the part 3.5. The comparison analysis on Chemical Engineering Database is shown in the part 3.6. The limitation of this study is discussed in section 3.7.

3.1. Performance analysis

This section comprises two analyses: general performances of publications regarding NP, NC, types and research areas, and highly cited publications; and performances of journals in which PHM-related papers are published. Journal analysis aims to explore the citation relations between citing and cited journals.

3.1.1. General performance

Fig. 2 displays the number of publications and citations of PHM-related studies in engineering domains from 1996 to 2023 (by the retrieval date). The publications grow constantly with time going by, from only one publication in 1996 to 264 by the end of 2022. The first citation appeared in 2000 and grew relatively slowly before 2012. Then, a dramatic increase appears from 331 in 2012–10514 in 2022 without any fluctuation. In 2023, nearly 100 papers have already been published before the end of May, with more than 3000 citations. The publication and citation performance indicate that engineering-based PHM research has gained more and more scholarly attention in recent years. Specifically, the paper entitled '*Prognostics and health management design for rotary machinery systems-Reviews, methodology and applications*' [25] gains the highest NC number of 874, with an average citation number per year (AC) of 87.4. In this paper, Lee et al. presented the relationship between PHM and machinery systems and provided a systematic approach to design the PHM system and select proper tools. According to their discussions, PHM is suitable to the scenario with a certain level of system

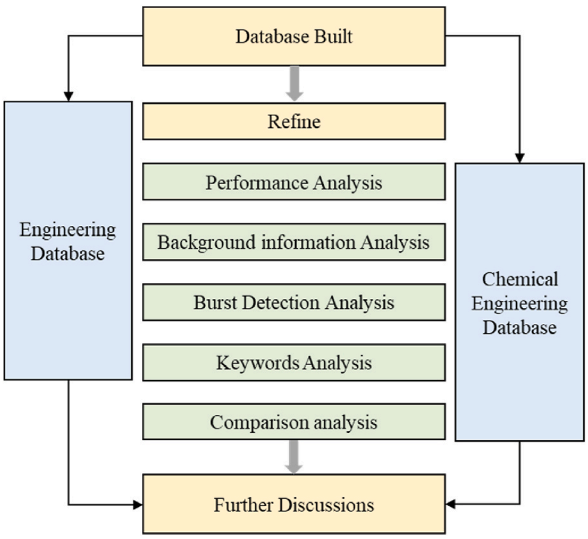

Fig. 1. Research framework.

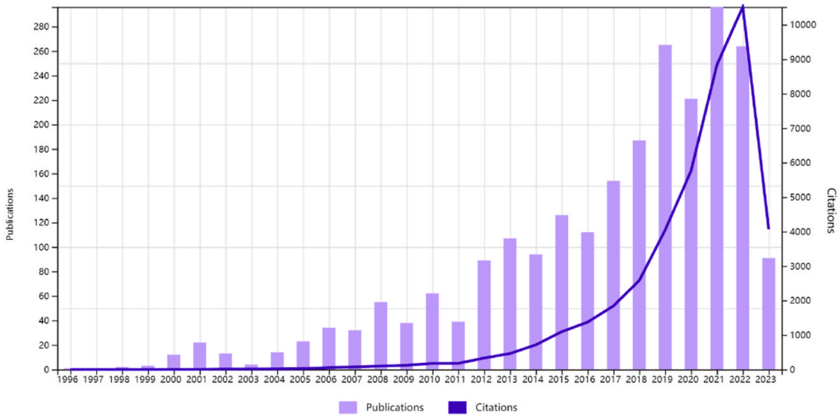

Fig. 2. The number of Publications and Citations from 1996 to 2023.

uncertainty and complexity. Positive attitudes were held in this study towards the future of PHM, by developing self-maintenance, resilient systems, and engineering immune system (EIS) as next generations. The paper entitled '*Digital Twin in Industry: State--of-the-Art*' [26] gains the highest AC with 164.2, with an NC of 821. Though this paper mainly focuses on the industrial application of DT, it points out that PHM is the most popular application area of DT. The benefits of DT to PHM methods are summarized to be four aspects: more accurate models, multisource and big data, back-and-forth interactions between physical entities and corresponding virtual models, and decision-making for more rational maintenance strategies. However, the limitation is also obvious, high-value equipment is always focused in such research, which hinders the applicability of DT in PHM.

Based on document types from the WoS (Table 1), the majority of publications are articles (1243, 51.36 %). Proceeding Papers account for nearly the same proportion (1053, 43.51 %), meaning that PHM-related studies are attractive at conferences. The small number of Review Articles (95, 3.93 %) may suggest that PHM research is still in the period of developing its expertise by concentrating on novel problems.

Fig. 3 summarizes the top 10 popular research areas according to the NP. PHM gains more attention in *Engineering Electrical Electronic* (1150), with the dominant proportion (48.71 %) from 70 involved research areas. Other 69 research areas account for 51.29 %, revealing that researchers are trying to explore more potential of PHM in multidisciplinary engineering domains.

3.1.2. Journal performance

This section analyzes journal performances by exploring relations of disciplinaries. The disciplinary distribution and citation trajectories are visually revealed by journals' citation trajectories. Citation relations between citing and cited journals can reflect the main research topics and the macro knowledge flows in the field [27]. Disciplines reflected by citing journals are displayed on the left side of the overlay map, meaning the target (applications). Disciplines based on cited journals (on the right side) represent the knowledge source (theories, prior research) [28]. Fig. 4 displays the citation trajectories of PHM studies after analyzing 663 journals from the database, 16 and 18 clusters are respectively extracted to form the target and source disciplines, and lines between them with different colors reflect the citation paths. Primary citing trajectories are evidently revealed by four red lines. Specifically, they are from '*Mathematics, Systems, Mathematical*' to respectively '*Environmental, Toxicology, Nutrition*', '*Chemistry, Materials, Physics*', '*Mathematical, Mathematics, Mechanics*', and '*Systems, Computing, Computer*'. Besides, disciplines like '*Molecular, Biology, Genetics*', '*Health, Nursing, Medicine*', '*Economics, Economic, Political*', etc. are also considered as knowledge foundations in some PHM studies, implying that engineering-based PHM research tends to improve along multidisciplinary directions.

3.2. Analysis of countries/regions, institutions, and authors

This section analyzes publications from three perspectives: countries/regions, institutions, and authors. The results contribute to 1) finding out the most productive countries/regions, institutions, and authors through statistics, and the most influential authors through citation analysis. 2) collaboration networks of institutions and authors.

Table 1
Distribution of publication types.

Document Type	Number	Percentage
Articles	1243	51.36 %
Proceeding Papers	1053	43.51 %
Review Articles	95	3.93 %
Early Access	29	1.20 %

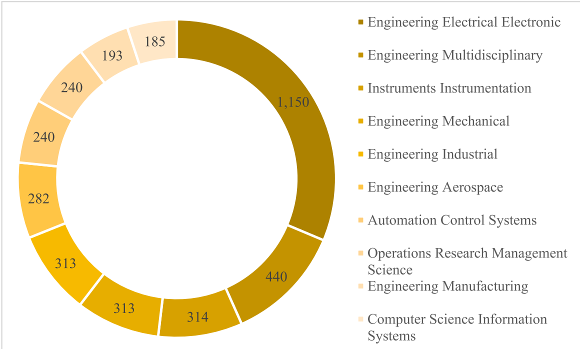

Fig. 3. The top 10 PHM research areas.

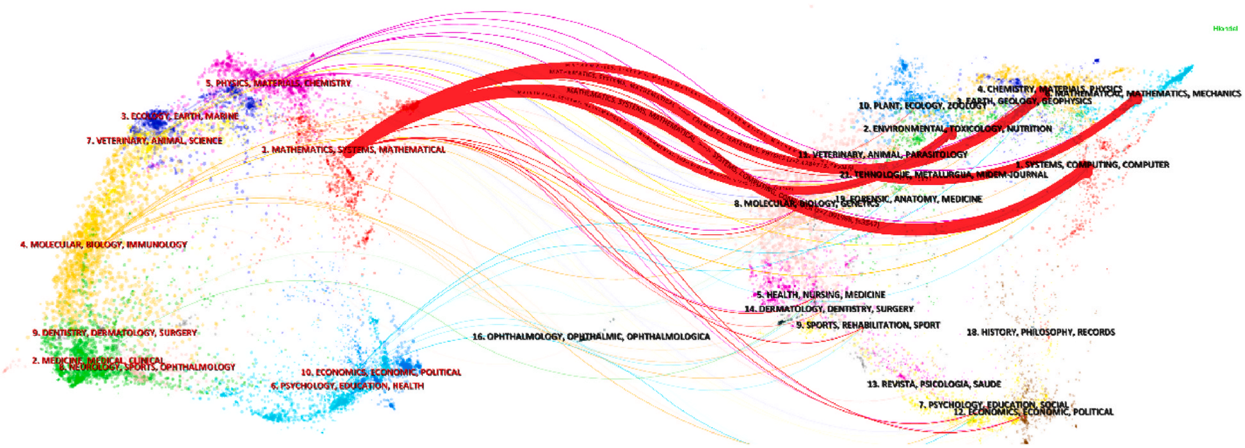

Fig. 4. Citation trajectories of engineering-based PHM studies.

3.2.1. The most productive countries/regions, institutions, and the most productive/influential authors

Based on the NP, the top 10 productive countries/regions, institutions, and authors are summarized in Table 2. *China* and *the USA* are the top two productive countries, having the highest publication numbers (1000 and 725). This is followed by *France* (175), *England* (128), *South Korea* (128), *Italy* (108), and *Canada* (96). Most productive institutions are universities, like the *University of Maryland* (124), *Beihang University* (122), *Université de Franche-Comté* (65), *University of Technology of Belfort-Montbéliard* (59), *Politecnico di Milano* (53), and *Harbin Institute of Technology* (47). Two institutions on the list are non-university institutions: *Centre national de la recherche scientifique* (83) and *NASA* (51). According to the results, PHM research is more concentrated in East Asia, Europe, and North America.

Table 3 summarizes the most conductive and influential authors based on NP and NC of their publications. Most productive authors are from universities, others may be from laboratories, companies, and research institutions, e.g., Kai Goebel and Noureddine Zerhouni. Some productive authors are also influential (high NC), like Xiaosheng Si, Jay Lee, Michael Pecht, and Enrico Zio. They could be regarded as having remarkable contributions in this domain. Besides, some authors in the list co-work with each other. For example,

Table 2
Top 10 productive countries/regions and institutions.

Country/Region	NP	Institution	NP
China	1000	University of Maryland	124
USA	725	Beihang University	122
France	175	CNRS	83
England	128	UFC (Franche Comte)	65
South Korea	128	UTBM (Belfort M.)	59
Italy	108	Research Libraries UK	54
Canada	96	Politecnico di Milano	53
Germany	52	NASA	51
Australia	41	Udice (French)	48
Netherlands	41	Harbin Inst. of Tech.	47

Table 3
Top 10 conductive and influential authors according to citation number.

Productive Author	NP	Influential Author	NC
Pecht, Michael	59	Si, Xiaosheng	280
Zerhouni, Noureddine	45	Lee, Jay	279
Goebel, Kai	41	Lei, Yaguo	269
Lall, Pradeep	41	Saxena, Abhinav	248
Zio, Enrico	34	Pecht, Michael	217
Lee, Jay	31	Li, Xiang	212
Si, Xiaosheng	27	Jardine, Andrew K.S.	206
Hu, Changhua	23	Saha, Bhaskar	198
Liu, Datong	23	Wang, Dong	155
Medjaher, Kamal	23	Zio, Enrico	141

Bhaskar Saha shares some publications with Abhinav Saxena, they are co-working on topics like distributed prognostics algorithms [29], uncertainty representation and management [30], etc. He also co-worked with one productive author, Kai Goebel, on communication issues in prognostics algorithms [31] and electronics components in avionics systems [32]. The results imply that PHM research is not limited to the academic circle, it gains attention from researchers, engineers, and other practitioners.

3.2.2. *Cooperation networks of institutions and authors*

Figs. 5 and 6 visually display the cooperation networks of institutions and authors. Each node in the figure represents an institution or authors, and the size of the node represents their collaboration strength with others [23]. Some productive institutions/authors analyzed in section 3.2.1 are explored playing key roles in the cooperation network, like the University of Maryland and Michael Pecht. Apart from the institutions listed in Table 2, other institutions are also regarded as proactive in collaborative PHM projects, such as Cranfield University (the United Kingdom), Beihang University (China), and Politecnico di Milano (Italy).

Reflected by a high density of lines surrounding the node in Fig. 6, Kai Goebel, Michael Pecht, and Jay Lee have intensive cooperation with other authors, forming three large clusters. Authors in the same cluster have stronger collaborative connections and may focus on similar or highly related topics. For example, three influential authors: Michael Pecht, Xiaosheng Si, and Enrico Zio have stronger connections, by further targeting their work, all of them have achieved prominent progress in data-driven models and prognostic algorithms. Kai Goebel and Jay Lee are from other clusters. They focused on asset management and applied AI and machine learning (ML) techniques in PHM applications. Besides, some authors from small networks may contribute to a larger network. For example, the network of Kai Goebel is also connected to the network of Pradeep Lall, who started to work on PHM of electronic devices at an early time [33]. By tracing back to the year when institutions/authors were active based on the color bar, Kai Goebel, Michael Pecht, and Carl S. Byington started PHM research at an earlier time, where research of Kai Goebel and Michael Pecht still remains in the spotlight. Authors like Jay Lee and Xiaosheng Si are centered in other clusters and are continuously cited by current research. By visualizing the collaborative networks of authors, it is possible to locate different directions, catch the development trends and hotspots, and focus on the representative work in PHM research.

3.3. *Burst detection analysis*

This section concentrates on the burst detection analysis of cited authors, references, countries, and institutions. The algorithms

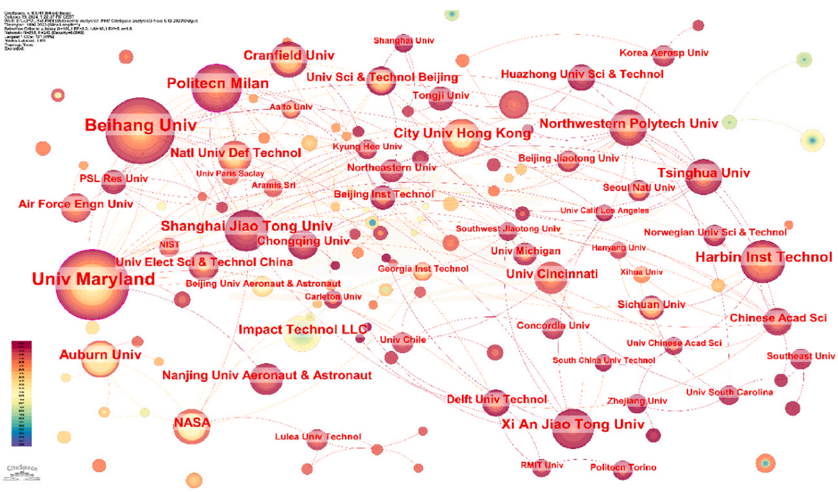

Fig. 5. The cooperation network of institutions.

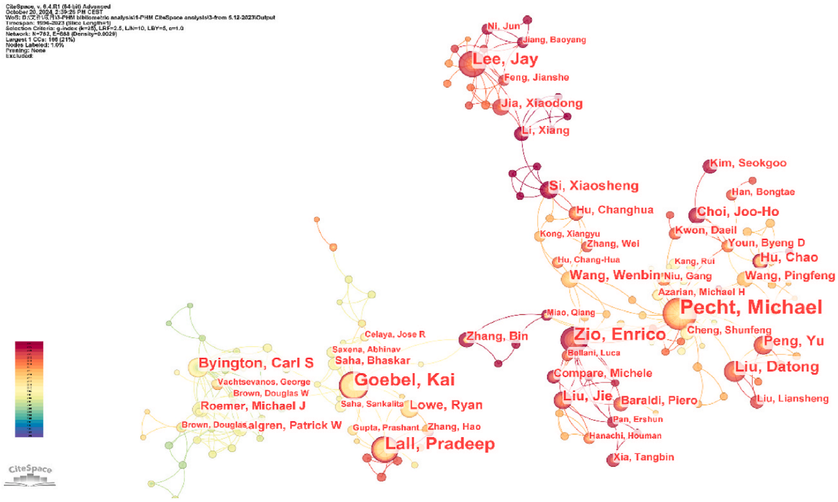

Fig. 6. The cooperation network of authors.

used in burst detection aim to detect changes in the burst variable with reference to others in the same population over a period of time. The burst is a surge of the frequency of a term/article in the references, which helps to explore research frontiers at each time along the developing timespan, and the burst strength indicates the quantified magnitude of its influence [34,35].

Table 4 shows the top 10 cited authors with the strongest bursts from 1996 to 2022. Michael Pecht ranks first with a burst strength of 30.54, which means that once he published his research in 2009, he had a great influence on other scientists, and this lasted 8 years. The following author is Andrew Hess, whose burst strength is 28.04, and also got high attention once his research was published in 2004. Some authors' research was not directly dug out by others at the beginning, like Bhaskar Saha and Sanjeev Arulampalam. The explosion periods were 2 and 5 years later than the publication time.

Table 5 displays the top 10 cited references with the strongest bursts from 1996 to 2022. The work from Lee et al. [25] has the highest citation burst strength (41.34), and a comprehensive PHM study for rotary machinery systems has been conducted. It is also the PHM research with the highest NC, as discussed in section 3.1.1. The second and third strongest burst references are from Michael Pecht and Si et al., with citation burst strengths of 26.19 and 24.97. Pecht [36] discussed in detail some physics-based models in electronics prognostics. In the research of Si et al. [37], statistical data-driven approaches were divided into two models relying on either direct or indirect observed state information. One challenge discussed by Si et al. is to evaluate the effect of subjective information, like the expert knowledge applied in designing physics-based models. Another work from Michael Pecht was published in

Table 4
The top 10 cited authors with the strongest citation bursts.

Authors	Year	Strength	Begin	End	1996–2022
M. Pecht	2009	30.54	2009	2017	
A. Hess	2004	28.04	2004	2014	
B. Saha	2008	23.02	2011	2017	
P. Lall	2006	22	2006	2015	
N.M. Vichare	2007	19.57	2007	2016	
J. Gu	2008	18.73	2008	2013	
X. Li	2009	17.94	2020	2022	
S.F. Cheng	2010	17.76	2010	2016	
M.S. Arulampalam	2008	16.12	2013	2018	
J.J. Wang	2020	15.91	2020	2022	

Table 5
The top 10 cited references with the strongest citation bursts.

Labels	Year	Strength	Begin	End	1996–2022
Lee J. 10.1016/j.ymssp.2013.06.004	2014	41.34	2016	2019	
Pecht M. 10.1002/9780470061626	2008	26.19	2009	2013	
Si X.S. 10.1016/j.ejor.2010.11.018	2011	24.97	2013	2016	
Saha B. 10.1109/TIM.2008.2005965	2009	16.5	2011	2014	
Vichare N.M. 10.1109/TCAPT.2006.870387	2006	15.88	2007	2011	
Miao Q. 10.1016/j.microrel.2012.12.004	2013	15.31	2015	2018	
Pecht M. 10.1016/j.microrel.2010.01.006	2010	15.18	2011	2015	
Sikorska J.Z. 10.1016/j.ymssp.2010.11.018	2011	14.77	2013	2016	
Lei Y.G. 10.1016/j.ymssp.2017.11.016	2018	14.74	2020	2022	
He W. 10.1016/j.jpowsour.2011.08.040	2011	14.22	2013	2016	

2010, with a strength of 15.18. In this study, Pecht and Jaai [7] worked on combining model-based and data-driven approaches, to perform a better prognosis of remaining useful life for electronics-rich systems. Overall, the citation burst appeared no more than 2 years after these ten references had been published, which probably means that researchers in the PHM field can rapidly target the frontiers and hotspots.

As for countries/regions, the USA (123.68), England (6.79), Spain (4.92), Netherland (4.75), and Sweden (4.3) are the top five with strong citation bursts (see Table 6). The USA had overwhelming strength, and its intensive influence lasted for almost 15 years. The research in England and Spain started also at the early time, but the burst appeared respectively 13 and 15 years later. Besides, the citation burst of Sweden is still developing. In terms of institutions, the company: Impact Technology LLC had the highest citation burst strength (17.34), but it was mainly at the early period of the PHM research. The latest citation burst happened from 2013 to 2017, it is the Cranfield University with a strength of 9. Based on the results, it is reasonable to point out that frontiers and hotspots of

Table 6
The top 5 countries/regions and institutions with the strongest citation bursts.

Countries/Regions	Year	Strength	Begin	End	1996–2022
USA	1998	123.68	1998	2012	
England	2000	6.79	2013	2015	
Spain	2002	4.92	2017	2020	
Netherland	2010	4.75	2015	2017	
Sweden	2009	4.3	2019	2022	
Institutions	**Year**	**Strength**	**Begin**	**End**	**1996–2022**
Impact Technol LLC	2001	17.34	2001	2010	
Univ Maryland	2004	14.27	2009	2013	
NASA	2008	10.58	2008	2012	
Auburn Univ	2006	9.9	2010	2012	
Cranfield Univ	2011	9	2013	2017	

engineering-based PHM mainly occur in the USA and Europe, and it has been transferred from other institutions to universities.

3.4. Keyword analysis

The identification of the main topics in PHM research is aided by keyword analysis, which is visualized through the co-occurrence network, citation burst, and clustering development in the timespan.

547 keywords are summarized from the database, Fig. 7 shows their co-occurrence network, each node represents one keyword. The highly concentrated keywords from PHM studies over the time span are indicated by a few large nodes that are visible. Some keywords reveal the main research goals, such as 'prognostics', 'health management', 'prediction', and 'maintenance', etc. These research may be related to 'system' and 'model', focusing on 'reliability', 'feature extraction', and also 'algorithm', etc. The color fading from the center to the periphery of these nodes means that such keywords are still proactive in the current research. Some keywords are rather recent, like 'charge estimation', 'artificial neural network', 'regression', etc. The color of the connection lines between them is lighter compared with it between the aforementioned big nodes, which also means their novelty. These keywords reveal the current trend of battery-targeted research and the application of artificial intelligence.

Meanwhile, burst detection on keywords supports to identify the 'burst term' that has shown a surge of usage during the selected time interval. A quantified result is shown in Table 7. 17 keywords have been detected having a usage surge from 2013 to 2019 in the cited articles. Keywords with strong citation burst (strength) indicate how references influence the study of PHM. For example, the word 'health management' had the highest strength of '8.35'. Several following keywords are 'residual life', 'management', and 'prognostics', which pointed out the purpose of PHM research. The keywords 'electric vehicle', 'electronics', and 'system' stressed the research object while 'particle filter' was one popular method applied in PHM research from 2015 to 2017. Besides, the researcher mainly focused on the study of 'parameter' and 'algorithm' for better 'maintenance' and 'reliability'. The word 'reliability' had the longest burst period (2006–2018). However, there are no bursts of keywords appearing after 2020, two reasons might be reasonable towards this result. The first one relates to the selection of the time window. Since the built database focuses on a large time window (1996–2023), keywords' performance on citation burst might not be prominent since 2020. Moreover, combining the development trend of PHM, PHM attracts more attentions since 2019 (Fig. 2) and has been applied to multidisciplinary, which might also affect the formation of citation bursts in a specific field.

Highly related keywords are clustered by clustering analysis. Fig. 8 displays the development of clusters from a timeline perspective. Nine clusters are mostly identified, and their labels are determined by using log-likelihood ratios (LLR) to select the terms of citing publications. The clusters 'transfer learning', 'health management', and 'deep learning' appeared at an early time, 'data models' appeared quite late. 'fault diagnosis,' 'reliability engineering,' and 'health monitoring' are popular topics in the PHM research, as keyword distributions in these clusters are relatively even since they appeared. Clusters like 'transfer learning,' 'lithium-ion battery,' and 'deep learning' have intensive keyword nodes in the latest periods, these topics may have received more attention lately.

In order to build a connection between keywords and corresponding topics, Table 8 summarizes the typical topics from PHM research according to extracted trending keywords. Three topics are focused based on Drissi's research [5]: Prognostics (P), Decision-making (DM), and the coupling between P and DM. By reviewing the critical papers related to them, the main problems focused and techniques applied in such topics are described.

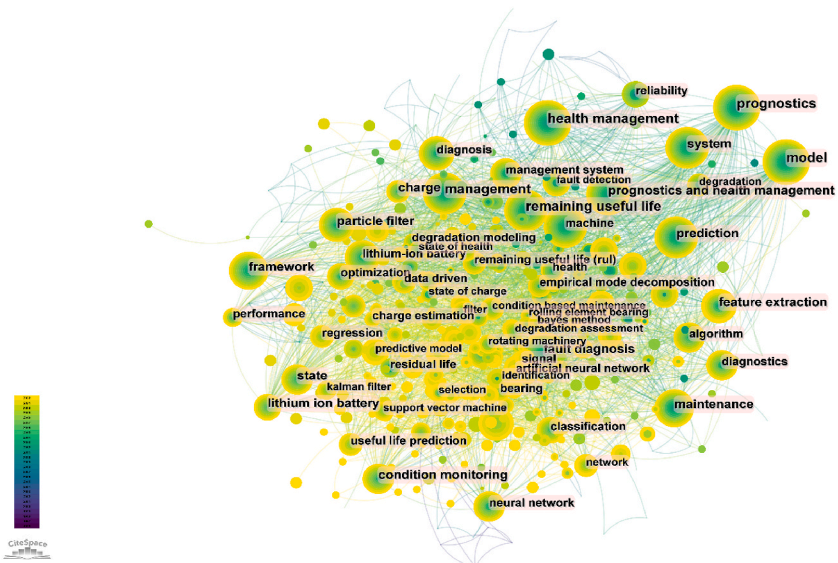

Fig. 7. The co-occurrence network of keywords.

Table 7
Keywords with the strongest citation bursts.

Keywords	Year	Strength	Begin	End	1996–2022
health management	2009	8.35	2011	2015	
residual life	2012	7.13	2012	2018	
management	2009	7.04	2013	2018	
prognostics	2010	6.95	2013	2014	
electric vehicle	2016	5.75	2016	2018	
reliability	2006	5.59	2006	2018	
particle filter	2013	5.57	2015	2017	
electronics	2010	5.52	2010	2015	
design	2011	5.33	2017	2019	
system	2009	5.31	2012	2016	
parameter	2014	4.7	2014	2019	
health	2013	4.5	2013	2017	
condition-based maintenance	2013	4.13	2013	2015	
failure	2017	3.91	2017	2019	
framework	2013	3.67	2014	2016	
state of charge	2014	3.46	2014	2015	
algorithm	2013	3.33	2015	2017	

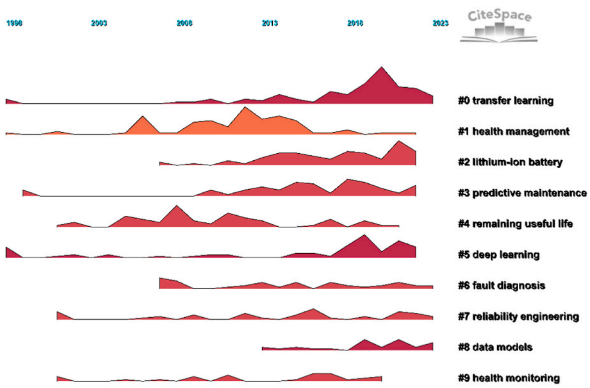

Fig. 8. Clustering development in the timespan.

3.5. *PHM from a macro perspective*

Currently, PHM is discussed by some researchers as having advantages from the perspective of reliability engineering, especially asset management [14,41]. PHM stresses enhanced diagnostic techniques, prognostics, and decision-making processes in health management to guarantee system reliability [42]. Jolfasei et al. [43] highlight the pivotal role of failure prognostics and RUL

Table 8
Typical PHM topics summarized from keywords and critical reviewing.

Topic	Keyword	Description	Publication samples
Prognostics (P)	residual life, degradation modelling, failure diagnose, remaining useful lifetime, data driven, deep learning, artificial neural network, support vector machine, data model.	'Prognostics (P)' are considered a process of predicting the future condition and performance of a system, based on current and historical data. The main research in this topic is about designing predictive methods, with the application of broad techniques like deep learning, artificial neural networks, feature extraction techniques, filter techniques, support vector machines, and so on. Data-driven models are widely applied in this topic, the choice of different techniques is different based on the type of data: run-to-failure historical data or conditional monitoring data.	Si et al. [37]; Pecht [36]; Pecht and Jaai [7]; Omri et al. [6]
Decision making (DM)	condition-based maintenance, optimization, risk management, cost benefit analysis.	'Decision making' refers to the process of making informed choices about system maintenance and operations, based on prognostic information. Key methods include decision trees, Bayesian networks, optimization algorithms (such as genetic algorithms, linear programming), multi-criteria decision analysis, etc. Researchers also focus on evaluating maintenance strategies using the designed predictive methods, such as comparing priorities among alternatives and taking maintenance costs into account.	He et al. [10]; Compare et al. [3]; Hu et al. [38] Bhat et al. [39]
Coupling P and DM	digital twin, system, health management, prognostic and health management,	The 'Coupling' of these two aspects involves integrating prognostic data and methodologies into the decision-making process, aiming to optimize maintenance strategies and enhance system performance and reliability. The reconciliation between models and reality is highlighted. This often involves systems engineering approaches, feedback control loops, and the use of simulations and digital twins to simulate and evaluate the impact of decisions.	Drissi et al. [5]; Negri et al. [4]; Peng et al. [9]; Guo et al. [40]

estimations for critical engineering assets, with the primary goals of enhancing safety, minimizing downtimes, and reducing maintenance costs. The integration of PHM also complements traditional Reliability Centered Maintenance (RCM) by embedding data-driven analysis, which automates conventional risk analysis techniques such as Failure Modes and Effects Analysis (FMEA) [44]. Payette and Abdul-Nour discuss the relationship between PHM and the classical reliability framework of Reliability, Availability, Maintainability, and Safety (RAMS) [1]. In addition to leveraging historical data for modeling, as RAMS does, PHM utilizes sensor-generated data to enable continuous monitoring.

According to their study, PHM and RAMS are complementary, sharing similar goals in asset management. The key difference between them lies in decision-making. Particularly, RAMS strategies are typically employed at the tactical level, supporting long- or medium-term organizational decisions, whereas PHM focuses on operational strategies that inform medium-to short-term, as well as real-time, decision-making. PHM's direct interaction with assets provides more details regarding asset health and performance.

3.6. Comparison analysis for chemical engineering-based PHM

The adoption of PHM concepts and approaches is seen as both highly beneficial and challenging in chemical engineering domains, particularly when dealing with complex systems [15]. In this section, the development trends of PHM research within the chemical engineering field are explored by a comparison analysis. A total of 57 publications from the Chemical Engineering Database are analyzed. By comparing the development of PHM in chemical engineering with its progress in broader engineering domains, insights from other disciplines may be transferred to the chemical engineering field, providing inspiration and guiding future developments. This comparison may also help forecast the future trajectory of PHM within chemical engineering.

3.6.1. Performance analysis

Table 9 shows the annual publication and citation performance of CEPHM, and Fig. 9 compares them with the performances of engineering-based PHM. By the retrieval date, the highest NP of chemical engineering-based PHM (CEPHM) is in 2021, with 11 publications. Though there are fewer PHM publications in this field, it is evident that the NC of CEPHM keeps an increasing trend. Comparing CEPHM's performance with broader domains, the start of CEPHM research is quite late (16 years later). The proportion of research on CEPHM in terms of publications and citations remains relatively small. However, with an increasing trend in citation performances, a significant potential for growth is expected in this area in the future.

Table 10 summarizes the categories of 57 CEPHM publications. In addition to the overall category of 'Engineering Chemical', a majority of the publications also fall under the 'Energy Fuels'. Notably, the top five publications with the highest NC are all related to research on lithium-ion batteries. This indicates that current CEPHM research remains concentrated within a relatively narrow scope.

3.6.2. Keyword analysis

The results of the keyword analysis are presented by a co-occurrence network, illustrating the frequencies, relationships, and freshness of the keywords (Fig. 10). From the network, three categories of keywords can be identified.

1) Keywords that appeared early age but remain highly relevant today:

Table 9
The number of publications and citations of CEPHM (till the retrieval date).

Year	NP	NC	Year	NP	NC
2012	1	0	2018	2	143
2013	18	8	2019	4	190
2014	4	26	2020	1	195
2015	2	61	2021	11	280
2016	1	102	2022	9	389
2017	1	92	2023	3	178

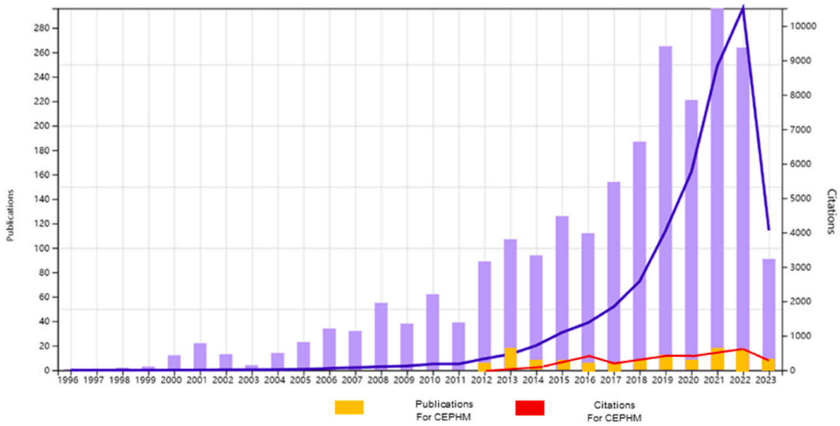

Fig. 9. The comparison between CEPHM and engineering-based PHM.

Table 10
Categories in CEPHM.

Category	No.	Percentage
Engineering Chemical	57	100.00 %
Energy Fuels	25	43.86 %
Engineering Multidisciplinary	17	29.83 %
Chemistry Multidisciplinary	5	8.77 %
Environmental Sciences	4	7.02 %
Automation Control Systems	1	1.75 %
Engineering Environmental	1	1.75 %

Keywordssuch as ‘remaining useful life’, ‘management system’, ‘prognostics’, ‘model’, and ‘system’ locate centrally in the network. These keywords are similar to the trending keywords identified in other disciplines (as discussed in Section 3.4), indicating that the research goals of CEPHM are closely aligned with those of broader PHM studies. This suggests that systematic concepts, methods, and perspectives from other fields are likely to apply to chemical engineering systems as well.

2) Keywords that are not highly focused on currently:

Keywords such as ‘K-nearest neighbor’, ‘kernel regression’, and ‘naïve baye’ are mainly connected by yellow lines, indicating that they were the focus of early CEPHM research. These keywords reflect the primary methods initially adopted, but over time, researchers might have shifted their attention to other techniques.

3) Keywords that are currently burgeoning:

Keywords such as ‘hybrid’, ‘machine learning’, ‘algorithm’, ‘performance’, and ‘gaussian process regression’ represented by dark red nodes, are relatively new and gaining attention. Similar to trends in the broader PHM domain, researchers are increasingly focusing on hybrid methods, incorporating artificial intelligence techniques to improve performance.

3.6.3. The PHM in chemical engineering VS. The broader engineering domain

Table 11 summarizes the comparison results between CEPHM and general engineering-based PHM. From the table, it is evident that although PHM gained attention later in the chemical engineering domain, its citation performance has steadily increased. Research on both general PHM and CEPHM is particularly popular in East Asia, Europe, and North America, with a focus on developing suitable models and maintaining complex systems. Additionally, the application of artificial intelligence is seen as having significant potential in the PHM field. However, unlike general PHM research, which has been explored across various multidisciplinary directions, CEPHM remains primarily focused on lithium-ion batteries, despite some studies addressing applications in power systems and subsea systems.

Fig. 10. Keywords co-occurrence network in CEPHM.

Table 11
Comparisons between CEPHM and engineering-based PHM.

	Engineering-based PHM	CEPHM
Publication performance	The first research started in 1996, after 2011, the number of publications increased steeply.	The first research started in 2012, and it keeps a relatively low annual frequency.
Citation performance	Since 2011, the number of citations has increased steeply.	The number of citations keeps on increasing since 2012.
Research category	Multidisciplinary research directions.	More focus on energy fuels, especially the lithium-ion battery.
Network of countries	The study on engineering-based PHM is more concentrated in East Asia, Europe, and North America.	
Network of institutions	Initially mainly focused by other institutions, and then transfers to universities.	Mainly focused by universities.
Network of authors	Huge and complicated author networks can be found, three big clusters are defined and centered by Kai Goebel, Michael Pecht, and Lee Jay. There are also many small clusters.	Only two small clusters are gathered by Chao Hu and Xiaosong Hu, both of them work on the capacity research about lithium-ion batteries.
Keywords	Keywords like ‘remaining useful life’, ‘management system’, ‘prognostics’, ‘model’, and ‘system’ are stressed by researchers in both engineering-based PHM and CEPHM. And they share other similar keywords like ‘machine learning’ and ‘neural network’, which means the potential of applying artificial intelligent methods.	

4. Discussion and conclusion

4.1. The development of engineering-based PHM

This study provides a macro perspective on the development of engineering-based PHM. Since 1996, PHM research has gained increasing attention and steadily developed. The research initially began in the USA and influenced the research in other countries/regions. Currently, China and the USA are the two most influential countries in PHM research. However, Europe and the USA have consistently been at the forefront of innovation, where research frontiers and hotspots have emerged throughout the development timeline. Europe and the USA are likely to continue leading the advancement of PHM research, and China has the potential to play an increasingly significant role. Besides, the advancements in PHM are driven by contributions from both academic researchers and industrial practitioners, highlighting its broad potential for application.

The development of PHM has primarily originated from mathematics, systems, and computer-related disciplines, gradually expanding into fields such as physics, ecology, biology, and economics. The substance of the PHM is revealed by the most concentrated keywords 'prognostics', 'prediction', 'predictive model,' and 'maintenance.' Essentially, engineering-based PHM builds upon physical knowledge, information, and data from industrial scenarios, emphasizing the integration of advanced computing methods and technologies to merge big data with models for predictive health management. As a field that is highly related to reliability engineering, risk assessment, safety engineering, etc., academic research in PHM has rapidly expanded in these fields. However, there are still limited implementations of PHM approaches by industry asset managers and reliability experts [43]. This hinders organizations from incorporating short-term and real-time decision-making horizons into asset management frameworks.

4.2. The development of CEPHM

The Chemical Engineering Database contains fewer recorded publications, with the majority being excluded, reducing the total from 2351 to just 57. One possible reason for this gap, compared to broader PHM research, could be the relatively late start of CEPHM research. The potential of PHM in chemical engineering remains unrealized and could be explored beyond its current focus on lithium-ion batteries. Another contributing factor may be the challenges of chemical engineering, such as complex, non-standard processes and the diversity of specialized equipment in process industries. These complexities make it difficult to implement dynamic monitoring strategies, establish reliable behavior models, and consider proactive maintenance activities.

Even with the mentioned difficulties, the steady increase in annual citations highlights the significant potential of CEPHM. Machine learning and optimization methods are particularly popular in this field. Among the highly cited publications, models such as support vector machines, particle swarm optimization, k-nearest neighbor regression, and naive Bayes have demonstrated strong capabilities in estimating RUL. Similarly to general PHM studies, the adoption of advanced techniques will benefit CEPHM by enabling more precise modeling, accurate fault diagnosis, and effective decision-making. In addition, improved measurement strategies are crucial in chemical engineering scenarios, particularly when considering the challenges of data availability, quality, and reliability. Therefore, the integration of optimized sensor networks and data acquisition methods would be another important direction of CEPHM.

4.3. Limitations

The selection of the data source and analyzed information represent the first limitation of this study, as the literature retrieval was restricted to the Web of Science Core Collection. Although previous sections have explained the rationale for choosing this database, some relevant publications may have been omitted. Notably, when analyzing the citation trajectories of PHM-related literature in this study, some cited references may originate from other databases, which mitigates the impact of this limitation. Another limitation is the limited discussion on PHM applications across different fields. This study aims to explore research hotspots and overall development trends, which lacks detailed analysis of PHM in specific fields, such as risk assessment, safety analysis, etc.

To provide a more comprehensive overview of PHM development, it would be necessary to include additional database resources such as Scopus, Google Scholar, and other collections from WoS. Besides, more information such as funding sources/agencies is meaningful to be analyzed from the perspective of bibliometric analysis. However, incorporating multiple databases and information would introduce challenges in data management, such as duplication checks, eligibility assessments, and potential issues with data integrity due to the lack of standardization across different sources. These aspects should be further addressed in future research.

4.4. Conclusion and future perspective

Engineering-based PHM research is still in its developmental phase, and its improvements are expected along multidisciplinary lines. In recent years, PHM has gained increasing attention in general engineering domains, including Chemical Engineering, where its integration into reliability engineering and asset management has been explored by many scholars. PHM has the potential to complement traditional reliability approaches like RAMS by offering short-term, real-time insights that enhance operational strategies. Future directions include exploring PHM's potential across other engineering fields and integrating advanced models like neural networks and digital twins. Stronger collaborations between academia and industry are also anticipated. Industrial applications of PHM can address practical challenges and furtherly refine the PHM paradigm. For Chemical Engineering, in particular, the development space of PHM remains promising. For specific applications not directly transferable from other fields, the research of PHM will still be based on the discipline of mathematics and systems, and be applied to more fields through continuous improvement.

CRediT authorship contribution statement

Huxiao Shi: Writing – original draft, Methodology, Conceptualization. **Jie Geng:** Methodology, Formal analysis. **Micaela Demichela:** Writing – review & editing, Supervision.

Data availability statement

Data will be made available on request.

Declaration of competing interest

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

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