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*Systematic Review*

# Prescriptive Maintenance: A Systematic Literature Review and Exploratory Meta-Synthesis

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**Abstract**

Prescriptive Maintenance (PsM) transforms industrial asset management by enabling autonomous decisions through simultaneous failure anticipation and optimal maintenance recommendations. Yet, despite increasing research interest, the conceptual clarity, technological maturity, and practical deployment of PsM remains fragmented. Here, we conduct a comprehensive and application-oriented Systematic Literature Review of studies published between 2013–2024. We identify key enablers—artificial intelligence and machine learning, horizontal and vertical integration, and deep reinforcement learning—that map the functional space of PsM across industrial sectors. The results from our multivariate meta-synthesis uncover three main thematic research clusters, ranging from decision-automation of technical (multi)component-level systems to strategic and organisational-support strategies. Notably, while predictive models are widely adopted, the translation of these capabilities to PsM remains limited. Primary reasons include semantic interoperability, real-time optimisation, and deployment scalability. As a response, a structured research agenda is proposed to emphasise hybrid architectures, context-aware prescription mechanisms, and alignment with Industry 5.0 principles of human-centricity, resilience, and sustainability. The review establishes a critical foundation for future advances in intelligent, explainable, and action-oriented maintenance systems.

**Keywords:** prescriptive maintenance; predictive maintenance; systematic literature review; Industry 4.0; Industry 5.0; maintenance decision-support; meta-synthesis; cyber–physical systems

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## 1. Introduction

The introductory section provides background and contextual information on Prescriptive Maintenance (PsM) within the modern industrial analytics and Industry 4.0 domains. Subsequently, previous systematic reviews on PsM are critically appraised to establish a rationale for the study. Lastly, the section defines the explicit research questions and objectives that guide the systematic review.

### *1.1. Background*

The growing demand for intelligent and automated decision-making positioned Prescriptive Analytics (PsA) [1] as crucial in next-generation operational strategies, especially for modern maintenance strategies [2]. As a fusion of data analytics, simulation, and AI (Artificial Intelligence), PsA reduces human intervention by transforming historical and real-time data into optimal decisions [3], considering factors such as time, cost, safety, and energy [3]. Using descriptive and diagnostic logic to detect anomalies, identify root causes, and anticipate failures, PsA enables organisations to move beyond forecasting to recommend concrete, contextual, and automation-oriented actions with minimal human intervention. Consequently, PsA formed analytical groundwork for Prescriptive Maintenance (PsM), translating data-driven insights that directly support operational excellence [4].

As industrial systems grow more complex and interconnected, maintenance strategies, such as Condition-Based Maintenance (CBM) [5] and Predictive Maintenance (PdM) [6], evolved to keep pace with growing operational demands. However, although PdM is beneficial for forecasting failures, it falls short in determining *what* actions should be taken, *when* to take them, and *how* to optimise decisions under limited resources and environmental uncertainty [7]. In response, PsM emerged as the next evolutionary step, offering targeted and optimised interventions that align with business objectives [8–11].

The strategic relevance of PsM is amplified by its alignment with Industry 4.0 (I4.0) technologies (e.g., Internet of Things (IoT) [12], Cyber Physical Systems (CPS) [13], Digital Twins [14]), providing the technical infrastructure for implementing intelligent, distributed, and real-time operational decision-making. Simultaneously, the emergence of Industry 5.0 (I5.0) [15] reinforces human-centricity, resilience, and sustainability as core industrial values [16] and encourages the development of decision-support systems that prioritise collaborative intelligence, environmental awareness, and social responsibility [17].

Understanding that these transformations do not occur in a policy vacuum, several strategic policy frameworks directly shape the scope and deployment of PsM technologies. Namely, the Green Deal [18] places explicit emphasis on energy efficiency and resource optimisation, indirectly promoting the PsM approach, stressing the importance of minimising waste and energy in asset management. The Digital Europe Programme [19] incentivises research and innovation in AI-driven maintenance, which is essential for scalable PsM deployment. Rhetorically, the Artificial Intelligence Act [20] establishes a legal framework to assure trustworthy use of AI in high-risk environments, including industrial systems, guiding PsM development towards transparency and explainability. Despite the convergence of technology and policy, the industrial implementation of PsM remains fragmented.

To facilitate PsM maintenance actions in a sustainable and context-aware manner [21], it is essential to resolve challenges in model integration, real-time decision-making, semantic operability, data quality, and alignment with production goals under resource constraints. Nowadays, such decisions are often neglected due to the current state of demands, productivity paranoia, and energy constraints, especially with organisational silos between maintenance and production planning [22] and the limited scalability of PsM frameworks [23]. Consequently, the full potential of PsM remains largely untapped across industrial settings. To address this gap, we conduct a Systematic Literature Review (SLR) to examine the current research discourse on PsM.

### *1.2. Related Reviews*

Before performing SLR, the overview of related PsM reviews is provided. Although literature reviews on PdM are extensive, comprehensive reviews focusing solely on PsM are sparse and fragmented. For searching related systematic reviews, we performed a search on Scholar using the search strings ("*prescriptive maintenance*" AND ("*systematic literature review*" or "*systematic review*"). However, although not mainly dealing with PsM, we extract several review studies that partially introduce the PsM aspect.

A study by Lepenioti et al. [1] was the first foundational review of PsA; however, it was not in the business context. While they contributed to understanding PsA with AI-based prescriptions, their review did not cover industrial applications. Even so, the primary constructs and functional descriptions seem to serve as groundwork for introducing the analogy into the industrial domain. Some of the early reviews, like [24], examined post-prognostic decision-making models, identifying early-stage prescriptive functions; however, they lack in-depth discussion on the relevance of the prescriptive aspect of PsM practice. Moleda et al. [25] reviewed the evolution of maintenance in the power industry, recognising that PsM integration with Digital Twin significantly improves performance; however, PsM is minimally addressed and without action-based taxonomies. Carvalho et al. [26] reviewed PsM in the biopharmaceutical industry, highlighting challenges of data silos, algorithmic opacity, and low deployment readiness. Although extensive, their contribution is domain-specific and with limited generalisability.

Mallioris et al. [27] systematically mapped PdM under the Industry 4.0 (I4.0) domain, but only acknowledged PsM as a natural extension. Similarly, Shadi et al. [28] tackled the role of Explainable AI (XAI) in energy systems maintenance and included PsM only as a component. Although their work mapped PsM models in the energy context, the focus was primarily on the interpretability rather than the functionality of PsM practice. Burggraf et al. [29] reviewed intelligent maintenance and remanufacturing, highlighting that PsM research is scarce and typically focuses on failure prevention rather than performance assurance.

Recently, Souza et al. [30] examined the association of I5.0 and PsM, suggesting that key challenges companies face are related to human–machine collaboration, Operator 4.0 integration, and sociotechnical transformation. Wesendrup et al. [31] proposed a framework to integrate PsM with production planning and control; however, although their review emphasised planning models and decision variables, the scope was narrow regarding sectors and real-world deployments. Santiago et al. [32] and Fox et al. [33] reviewed data-driven maintenance models in Wind Turbines. While PsM was discussed, their retrieved studies mainly cover renewable energy systems and health prognosis. Lastly, a study by Giacotto et al. [34] is the first review to perform a comprehensive PsM-specific review to date. Their work developed a taxonomy of prescriptive outputs, methods, and architectures while identifying enablers and limitations. However, the review focused heavily on methodological classification, while not sufficiently examining implementation maturity or industry-specific applications.

Collectively, these reviews offer valuable contributions to specific aspects of PsM, including analytics, explainability, planning, and decision-making. However, none have offered a fully integrated synthesis of prescriptive actions and enabling technologies, nor have they clustered PsM knowledge into thematic research areas grounded in practical deployment. This review addresses the gap by providing an application-oriented and decision-centric mapping of the PsM body of expertise with industrial relevance. Hence, infrastructure maintenance, i.e., railway tracks [35], pipeline corrosion [36,37], concrete bridges [38], etc., are described elsewhere [39].

### *1.3. Research Questions and Objectives*

This SLR aims to advance the theoretical clarity of PsM by (i) systematically identifying PsM studies published in the post-I4.0 period; (ii) critically appraising studies dealing specifically with prescriptive aspects and post-prognostic (and diagnostic) recommendations and decision-making; and (iii) identifying research areas and challenges to recommend solution space in PsM practice. To do so, we set the following Research Questions (RQs):

**RQ1:** What applications, methods, and tools are utilised within the PsM body of knowledge?

Understanding the diversity of practical applications, methods, and tools, the motivation behind RQ1 is to enable researchers and practitioners to benchmark existing solutions and recognise areas for improvement. By identifying prevalent practices, technological bottlenecks, and knowledge gaps, the question aims to determine the breadth of real-world use cases, analytical methods, and tools deployed in practical PsM scenarios.

**RQ2**: What activities characterise the prescriptive part of PsM?

A precise characterisation of PsM activities is crucial for delineating PsM from other maintenance practices. By systematically mapping core activities, their automation levels, and operational context, RQ2 aims to clarify what uniquely constitutes PsM. Consequently, RQ2 supports theoretical differentiation and practical operationalisation, which in turn helps practitioners to make better decisions.

**RQ3:** What clusters of research can be identified within the existing PsM?

The motivation behind this approach is to identify thematic areas within PsM research and provide an integrative overview of the field, offering researchers and industry professionals a structured understanding of major research trends, focal areas, and theoretical contributions.

**RQ4**: What are the current challenges and future research agenda for PsM?

Lastly, exploring the current challenges and identifying future research directions are essential for bridging the gap between theoretical advancements and practical scenarios. Namely, by systematically extracting evidence from prior research, RQ4 aims to translate findings into actionable research agendas aligned with I5.0 objectives. RQ4 will drive industry leaders and policymakers in prioritising research investments and strategic decision-making for broader PsM adoption.

The rest of the paper is structured as follows: The Section 2 provides a methodological description of the research protocol and search strategy; the Section 3 analyses metadata, content-based data, and qualitative data. The Section 4 offers an in-depth analytical description of the meta-synthesis results. The Section 5 presents concluding remarks, implications, limitations, and future research directions.

## 2. Methodology

The methodology section describes the search strategy, retrieval of studies, data synthesis, and data analysis of retrieved evidence. The methodological framework consists of six modules (Figure 1). The first module explains the study retrieval process via a Systematic Literature Review (SLR), leveraging the PRISMA (Preferred Reporting in Systematic Reviews and Meta-Analyses) protocol [40]. The second module builds upon an ORS (Objective Review Strategy) [41,42] in order to assure an objective retrieval of studies.

The data extraction module synthesises metadata (titles, abstracts, and keywords), content-based categorical data (e.g., industrial domain, data sources), and qualitative data (e.g., challenges, findings, PsM activities). The following module, i.e., metadata analysis, includes a descriptive analysis of metadata, including word n-grams for bibliographic analysis. This is primarily carried out to gain a general overview of the PsM research discourse.

The analysis of content data includes detailed multivariate and cross-sectional analyses, leveraging factor analysis for allocating clusters of research within the PsM domain. The last module provides an exhaustive discussion of findings in response to the proposed RQs. Based on identified research clusters from content-based analysis, functional descriptions of PsM are provided, contributing to the understanding and development of the PsM research field. Lastly, considering that PsM practice is applied differently across various industrial domains, we exemplify PsM characteristics in four main industrial sectors. Below, we provide a detailed description of each module.

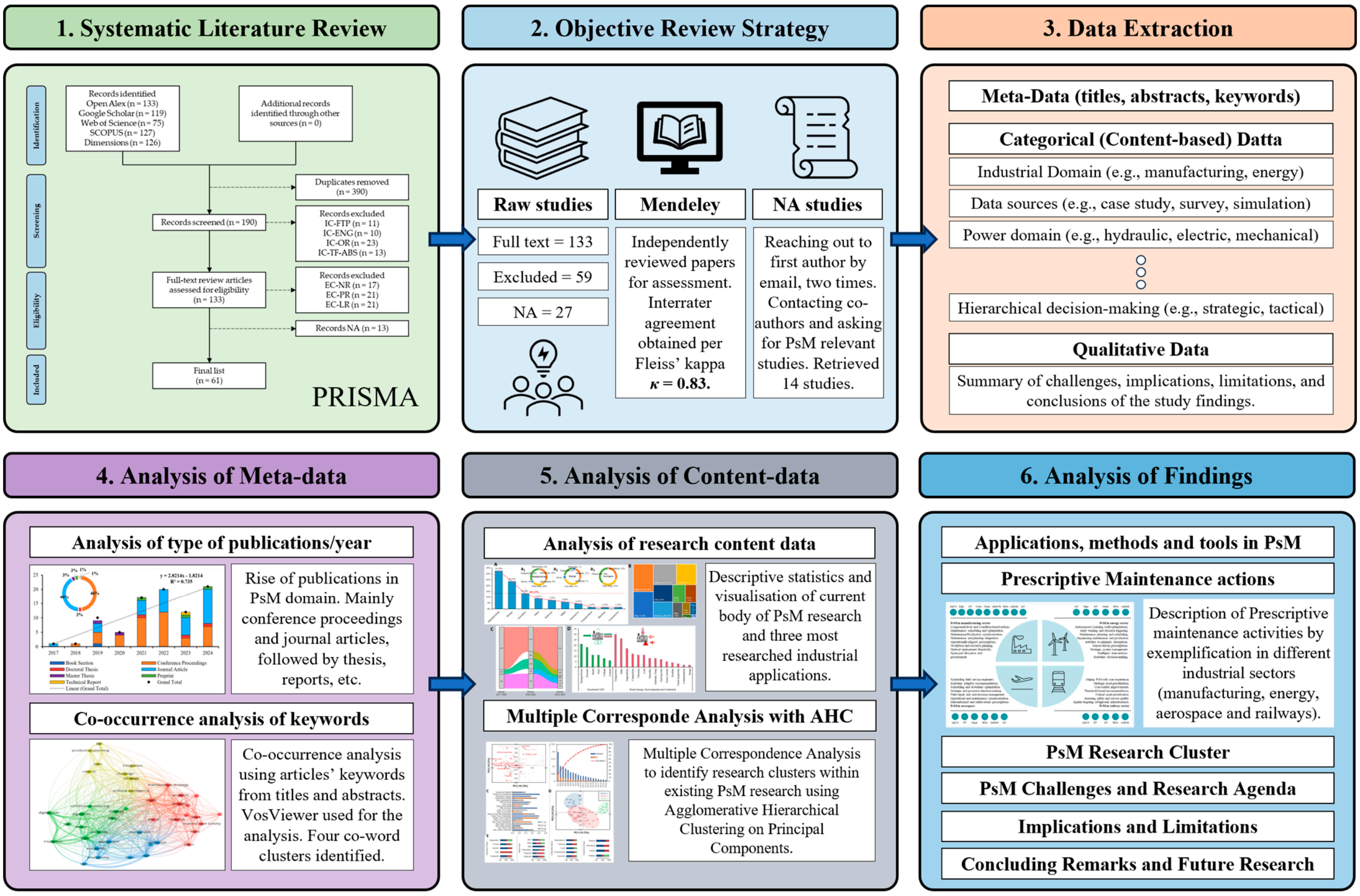


**Figure 1.** Research framework describing the analytical procedure of study retrieval, data acquisition, and meta-synthesis. The framework consists of six modules.

## *2.1. Systematic Literature Review*

The search strings are defined per the proposed RQs (Table 1). Only primary (original) studies are included to respect the PRISMA-SLR protocol. Since PsM is implemented in various industrial applications (e.g., manufacturing, aerospace, energy), there were no limitations in terms of determining the search strings. However, we specifically targeted industrial maintenance, and did not cover facility, infrastructure, and building maintenance. Given the research settings, we considered the PCC (Population–Concept–Context) framework (Table 1) as the most suitable option for constructing search strings.

**Table 1.** The PCC question framework defines the focus of the research question.

| PCC Item | PCC Features | Explanation |
|---|---|---|
| Population | PsM features based on RQ | Includes applications, tools, methods, actions, etc. |
| Concept | Prescriptive maintenance | Studies explicitly deal with the PsM body of research. |
| Context | Industrial maintenance | Facility and infrastructure maintenance are excluded. |

Given the topic's rise and to avoid missing essential studies, we set the following search strings: "*prescriptive maintenance*". The search strategy was limited to titles, abstracts, and keywords to avoid excessive and irrelevant papers. This approach aimed to exclude studies that only cite or reference prescriptive maintenance, ensuring that our studies explicitly address the concept of prescriptive maintenance. In addition, a search alert was set on Google Scholar and SCOPUS for the search string "prescriptive maintenance" in case new articles emerged during the analysis and writing of the paper. The PRISMA flow diagram (Figure 2) explains the process of study retrieval.

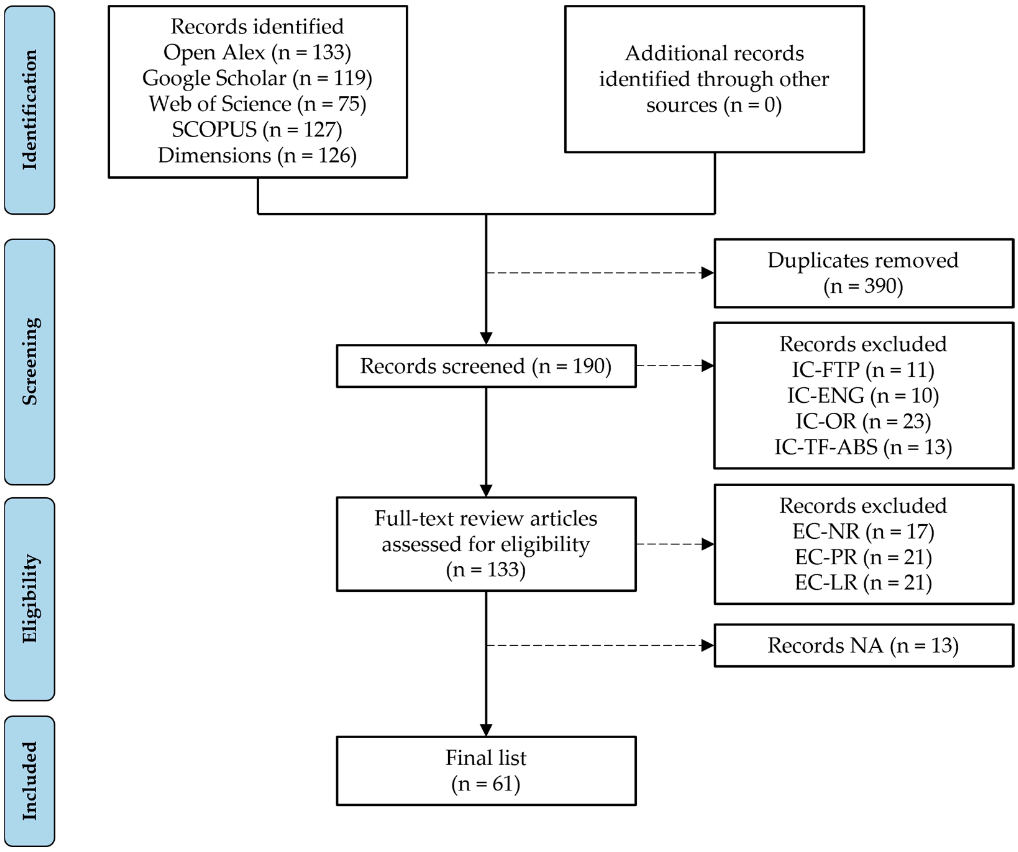


**Figure 2.** PRISMA flow diagram.

Firstly, the search was performed using Harzing's Publish or Perish software (Windows GUI Edition, v. 8.9.4554.8721) to ensure replicability and transparency. Given that Web of Science and SCOPUS APIs (Application Programming Interfaces) could not be obtained, the search within these index bases was performed manually. The eligibility criteria used for the research are explained in Table 2.

**Table 2.** Eligibility criteria for selection and study retrieval.

| Criteria | Sub Criteria | Description of Criteria |
|---|---|---|
| Isolation Criteria (IC) | Full-Text Papers (FTP). | Editorials, posters, or similar records are excluded. |
| | English Language (ENG). | Only articles written in English. |
| | Only Original (OR) studies. | Only primary (not review) studies. |
| | Time Frame-Abstract (TF-ABS) | The time frame spans 2013–2024. |
| Exclusion Criteria (EC) | Loosely Related (LR). | Theoretical, opinion, or roadmap. |
| | Partially Related (PR). | Only refers to PsM and lacks depth. |
| | Non-Related (NR). | Not industrial (e.g., facility, buildings). |

The rationale for proposing FTP's IC (Isolation Criteria) is to include all relevant articles. This includes peer-reviewed original journal articles, conference papers, and book chapters. However, we covered reports and theses if they were deemed valid in rigour by the review panel. Studies written in English were included to avoid misunderstandings in reporting findings. Only primary (original) studies were included, meaning that review (theoretical, systematic, or scoping) studies were excluded. The time frame and abstract criteria consider using only studies from 2013 to capture the evaluation of the Industry 4.0 era. Also, we limited the search to 2024 for the sake of completeness. Lastly, considerable efforts were dedicated to studies conflating PsM with PdM maintenance unless they explicitly address prescriptive actions (e.g., decision-making, optimisation).

The initial search through the index bases resulted in 580 records. After extracting the records and inputting them into Mendeley, we performed duplicate removal on 390 studies. During the screening phase, 57 records were removed due to non-eligibility criteria (FTP = 11, ENG = 10, OR = 23, TF-ABS = 13). The removed records included an extensive list of grants and projects. These records comprise dissemination results of articles and reviews that are currently under review or are expected to be published in the upcoming years. The remaining studies ($n$ = 133) were subjected to EC criteria, and 59 records were removed (NR = 17, PR = 21, LR = 21). Ultimately, 61 studies were included in the final assessment and extraction of pertinent evidence.

### 2.2. Objective Review Strategy

The assessment of included studies was performed by measuring interrater agreement of included studies using Fleiss' $\kappa$ (at least moderate agreement $\kappa$ = 0.61–0.80) [43]. After the screening, the interrater agreement was $\kappa$ = 0.67. Given that the search was performed independently by two authors, all studies were recorded in Mendeley. After the removal of duplicates, 190 records were analysed and discussed to maintain consistency concerning isolation criteria (Table 2). Following the screening, 133 studies underwent an in-depth analysis. In the event of disagreement, the third author intervened to make a final decision. After the screening stage, all three authors provided studies that should be included, eventually reaching an interrater agreement of $\kappa$ = 0.83.

Considering that 27 studies were unavailable for complete textual analysis, several methods were used to contact the authors of the papers that were not accessible. We first tried searching for preprint versions of the paper, and then we contacted the first author at least twice. After the second time, we tried reaching out to the co-authors of unavailable studies. After reaching out, we also kindly asked the authors to share PsM studies or preprints that were potentially missed or omitted by our search strategy, which the authors provided. However, none of the studies were deemed relevant per our eligibility criteria.

During the entire process of retrieving studies, RSS notifications from SCOPUS and Google Scholar identified additional studies; however, all of these studies were published after 2024, and including them would not have ensured the completeness of the SLR. Hence, those studies were recorded and will be extended in our living SLR at the end of 2025. Ultimately, 13 papers were unable to be included due to a closed-access publication policy and a lack of response from the authors. The complete list of both included and excluded studies, including the complete search records in screening, is provided alongside the article in Supplementary Materials.

### 2.3. Data Extraction

The evidence used for the analysis consists of three types of data. Firstly, we rely on the article's metadata to extract word n-grams for bibliometric analysis, which describes the existing PsM research. The word n-grams (e.g., bigrams, trigrams) are constructed from titles, abstracts, and keywords. The content-based data is in categorical form, comprising (i) Research Design (e.g., simulation, case study, survey, framework); (ii) Data Source (e.g., sensor data, synthetic data, maintenance log-data, fault data); (iii) Industrial Sector (e.g., manufacturing, railways, aerospace); (iv) Application Scope (e.g., unit/component, fleet, machine, process, organisation); (v) Condition Monitoring Parameters (e.g., temperature, vibration, pressure, power); (vi) Power Domain (e.g., electrical, mechanical, hydraulic); (vii) Study Focus (e.g., diagnosis, prognosis, risk assessment, strategy selection); (viii) Prediction Data Analysis (e.g., exploratory analysis, Machine Learning); (ix) Optimization Data Analysis (e.g., Reinforcement Learning, Linear Programming); (x) Industry 4.0 Technologies (e.g., IoT, Cloud Computing, Big Data); (xi) Decision Variables (e.g., operational costs, maintenance costs, time); (xii) Systemic and Sustainability Aspects (e.g., economic, environmental, social, technical); and (xiii) hierarchical decision-making level (e.g., strategic, tactical, operational). Lastly, qualitative data comprising challenges, implications, limitations, and conclusions from study findings are included.

### *2.4. Metadata Analysis and Data Coding*

The metadata analysis is performed by exporting RIS (Research Information System) data from the Mendeley library. Hence, no coding was required for metadata, as it can be automatically processed by VosViewer (v.1.6.20) for bibliographic analysis. However, it is essential to note that different combinations of word n-grams are used to obtain the most essential insights using word n-grams. Here, different combinations of word n-grams from titles, abstracts, and keywords are used, and no apparent clusters were observed. Additionally, given the exponential rise of the topic, even after using reference co-citation analysis, we have still not been able to obtain cluster similarity. Only after using 10-word co-citation analysis in VosViewer were we able to cluster properties that are used for the discussion.

### *2.5. Content Data Analysis*

Factor Analysis (FA) is performed to uncover research clusters in the PsM domain. Although different FA methods exist, most are designed for continuous-type data (e.g., Principal Component Analysis). Given that content data is categorical, Multiple Correspondence Analysis (MCA) is used as the most suitable alternative for handling categorical data [44,45]. The analysis is conducted in RStudio (v2024.04.2) of R (v.4.3.3) using *FactoMineR* and *Factoshiny* packages [46]. The first step includes forming an indicator matrix, such that rows correspond to studies $n$ = 61 and Q = 32 (16 variables with outcomes [1, 0], i.e., [present, not present]). The indicator matrix $Z$ of size $n \times Q$ is constructed as:

$$z_{iq} = \begin{cases} 1 \; study \; i \; has \; a \; category \; q \\ 0 \; study \; i \; does \; not \; have \; q \end{cases}. \tag{1}$$

After forming the $Z$ matrix, the Correspondence matrix $P$ is created to normalise $Z$ by $N = \sum_{i,q} z_{i,q} = 16 \cdot 61 = 976$, obtaining row and column mass. For row mass (studies), we calculate $r_i$ = 1/n (studies weighted equally), and for column mass (variables), we calculate $c_q$ = category count $q/N$. Before performing SVD (Singular Value Decomposition), a standardised residual matrix $S$ needs to be obtained by computing deviations from independence:

$$s_{iq} = \frac{p_{iq} - r_i c_q}{\sqrt{r_i c_q}}, \tag{2}$$

where $p_{iq}$ is the element of $P$. Performing SVD on $S$ is as follows:

$$S = U \Sigma V^T, \tag{3}$$

where Σ contains singular values $\sigma_k$ and $U$ and $V$ are left and right singular vectors, respectively. Lastly, estimating the coordination for studies from Principal Components (PCs) $m$ is performed as follows:

$$F = D_r^{-1/2} U\Sigma, \tag{4}$$

where $D_r$ is the diagonal matrix of row (studies) masses. Coordinates for categories is performed as follows:

$$G = D_c^{-1/2} V\Sigma, \tag{5}$$

where $D_c$ is the diagonal matrix of column (categories) masses. Calculating total inertia $T$ is as follows:

$$T = \sum \sigma_k^2, \tag{6}$$

while the first selected $m$ (PCs) explains inertia (variance):

$$m = \frac{\sum_{k=1}^{m} \sigma_k^2}{T}. \tag{7}$$

Estimating total inertia is crucial to explain the dataset's variation (heterogeneity). It can be viewed as analogous to the PCA variance but adjusted for categorical data. Additionally, it is essential to consider this when analysing the quality representation of categories per inspected PC in discussing the factor map. As a final step, we utilise the first two m (PCs) components, as they capture the most variance in terms of performing cluster analysis and grouping similar studies. To do so, we use the Euclidean distance between $i$ and $j$ studies by computing the following:

$$d_{i,j} = \sqrt{\sum_{k=1}^{2} \left( f_{ik} - f_{jk} \right)^2}, \tag{8}$$

where $f_{ik}$ is the coordinate of study $i$ on PC $k$. Lastly, to perform HCPCs (Hierarchical Clustering on Principal Components), Ward's linkage method is used to minimise within-cluster variance:

$$\Delta(A,B) = \frac{n_A n_B}{n_A + n_B} \| \mu_A - \mu_B \|^2, \tag{9}$$

where $\mu_A$, $\mu_B$ are centroids of clusters A and B and $n_A$, $n_B$ are their sizes. To ensure transparency and replicability of the findings, we recommend that the reader perform the analysis using the *FactoMineR* (v.2.12) R package to obtain the same results.

The context of implementation (Application Scope), the functional objectives (Study Focus), the broader value-driven and systemic implications (Systemic and Sustainability Aspects), and the decision-making levels (Hierarchical Levels) are used to map a complex ecosystem in which PsM operates. To do so, we rely on the HCPC-MCA method. This enabled us to offer valuable insights about the evolving field of PsM research.

### 2.6. Analysis of Findings

This subsection includes the extraction and discussion of qualitative data from retrieved studies. This qualitative data consists of the following: definitions used (or referenced) in the paper; PsM type of actions proposed for post-prognostic or post-diagnostic analysis; challenges/problems addressed in the study; implications of the study; future research directions; and study limitations presented by the authors. All of the mentioned qualitative data are extracted and are available in the Supplementary Materials. The PsM actions proposed in the paper are directly used to answer RQ2 and to offer a characterisation of the PsM overall. In addition, the evidence regarding challenges and future research directions is used to answer RQ4, while the definitions used, implications, and limitations are employed to provide a coherent understanding of the perspectives and contextual settings of the findings within the retrieved studies.

## 3. Results

This section provides a comprehensive bibliometric and exploratory analysis to identify trends and thematic areas within PsM literature. Meta-data descriptive analysis (3.1) reveals a notable increase in PsM publications. Bibliometric analysis identifies four distinct clusters, highlighting research interests in maintenance strategy integration, cost–benefit analysis, and integrating Industry 4.0 technologies. Content data analysis (3.2) reveals a shift from purely technical optimisation towards incorporating sustainability metrics. Lastly, the cluster analysis (3.3) distinguishes between operational, managerial, and strategic research discourse within PsM studies, suggesting an evolving and increasingly sustainable research approach.

### *3.1. Meta-Data Descriptives*

Analysis of the PsM publication trend is depicted in Figure 3. Two primary studies were mentioned before 2017 [47,48]. Since then, there has been a lack of primary research explicitly providing practical applications of PsM, and most studies published have been theoretical. The trend suggests a rise of at least 50% in PsM publications ($R^2$ = 0.6925) via journal articles ($n$ = 29, 47%) and conference proceedings ($n$ = 25, 41%).

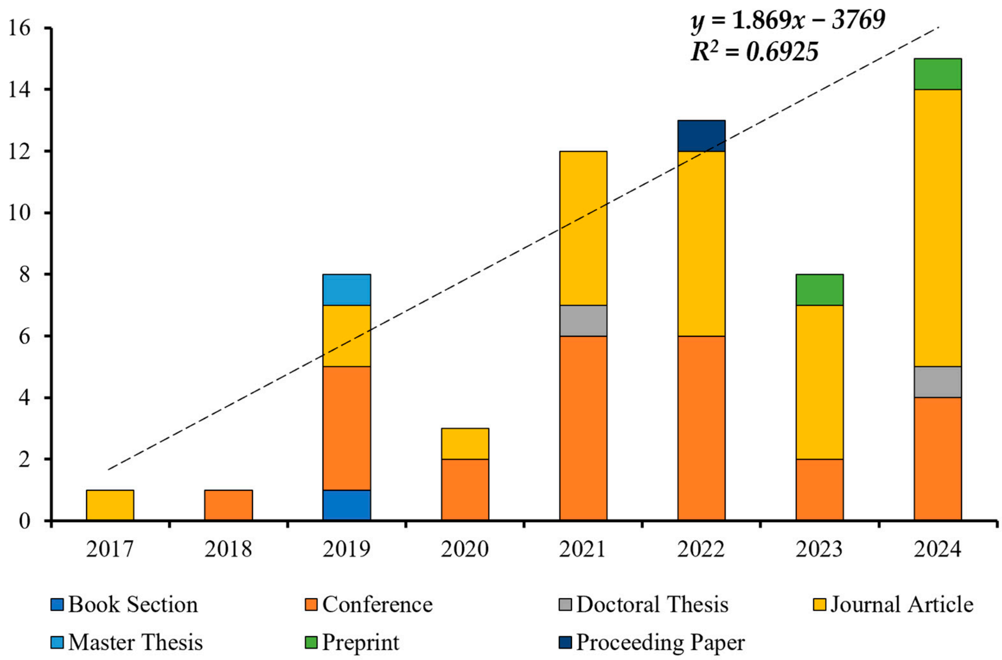


**Figure 3.** Type of publications by year ($x$-axis) and the number of publications ($y$-axis).

The word co-occurrence analysis (Figure 4) was performed in VosViewer (v. 1.6.20). The method involves extracting word n-grams from the title and abstract fields, while ignoring structured abstract labels and copyright statements if they appear. The counting method was complete counting, meaning all term occurrences in a document are counted, i.e., titles and abstracts. A minimum of 10 word co-occurrences was set, and we ended up with 45 terms that met the threshold criteria. The co-occurrence map suggests the presence of four clusters. However, due to the limited word co-occurrence and the use of generic terms, such as strategy, challenge, problem, and control, it was difficult to determine what each cluster could represent regarding the generalisation of existing PsM research. For instance, the yellow cluster (Figure 4) suggests that the research on PsM is centred around production planning and control with maintenance strategy integration. The red cluster suggests general PsM implementations and associated effects, particularly fitting under the domain of Knowledge-Based Maintenance (KBM) [49]. In contrast, the blue cluster suggests a more technical approach to analysing the benefits of PsM in terms of economic costs or optimisation based on decision variables, specifically performed on equipment and component levels. Lastly, the green cluster suggests the high dependability of I4.0 technological aspects in adopting PsM, such as digital twins, the Internet of Things, and sensor and condition-monitoring technology, particularly in prognostics (e.g., RUL estimation) and post-prognostic activities.

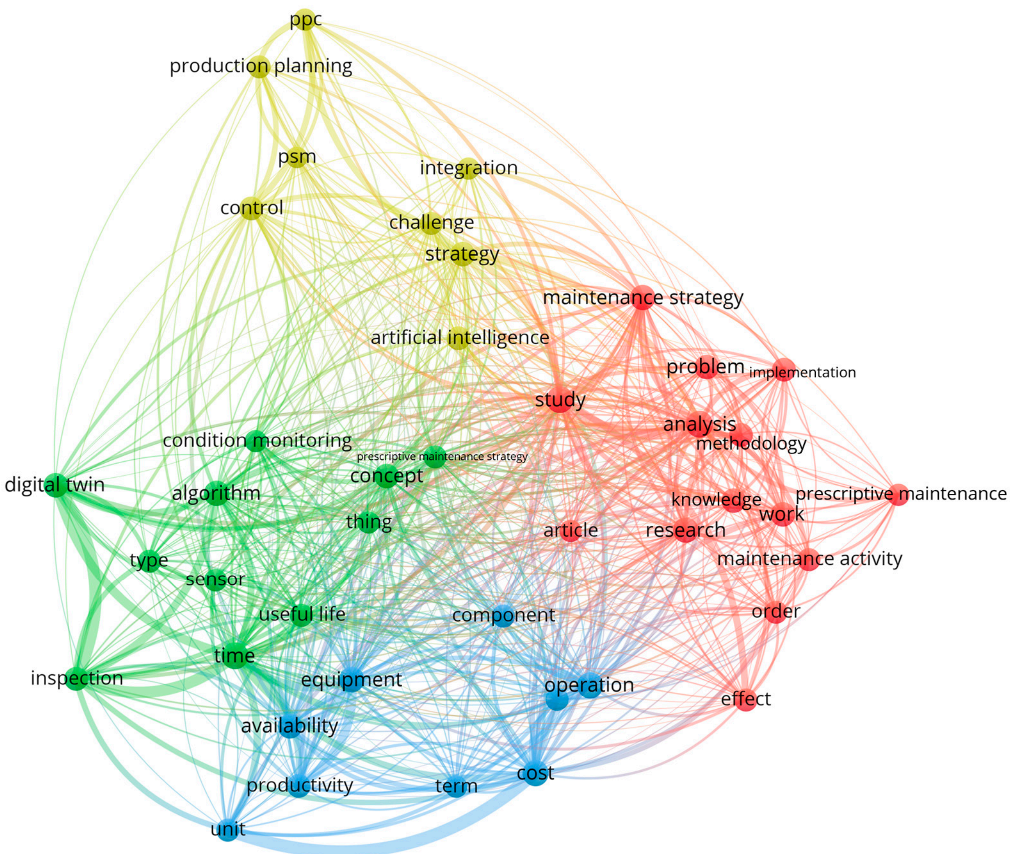


**Figure 4.** Co-occurrence mapping of titles and abstracts (threshold > 10-word co-occurrence).

Although the metadata provided insights about the current body of research on the PsM, the analysis did not offer much in terms of an understanding of PsM research. Consequently, this necessitated an in-depth and exhaustive meta-synthesis of the corpus of studies, employing a study-by-study approach. We first performed descriptive and exploratory analysis, which was followed by factor mapping and clustering of research studies.

### *3.2. Content-Based Data Descriptive and Exploratory Analysis*

The descriptive statistics suggest that most of the PsM studies (Figure 5A) are dedicated to manufacturing (32%), energy (23%), and aerospace (13%), followed by other domains. Accordingly, this suggests that most of the research (69%) is situated around these domains. Next, the research design indicates that 57% ($n$ = 35) of studies rely on a single case study, followed by simulation ($n$ = 33%) and the simultaneous application of PsM frameworks ($n$ = 33%). Looking at specific domains, the evidence shows that 30% of studies in manufacturing (Figure 5$A_1$) rely on theoretical frameworks with validation through a simulation or a case study. In the energy sector, most of the work is performed similarly to that in manufacturing; however, there are more surveys and observational studies (7%). In contrast, the proposed frameworks in the aerospace domain are predominantly based on numerical simulations with case studies (31%). This suggests that scalable PsM applications are still in an infant phase, and more practical study designs are yet to be explored.

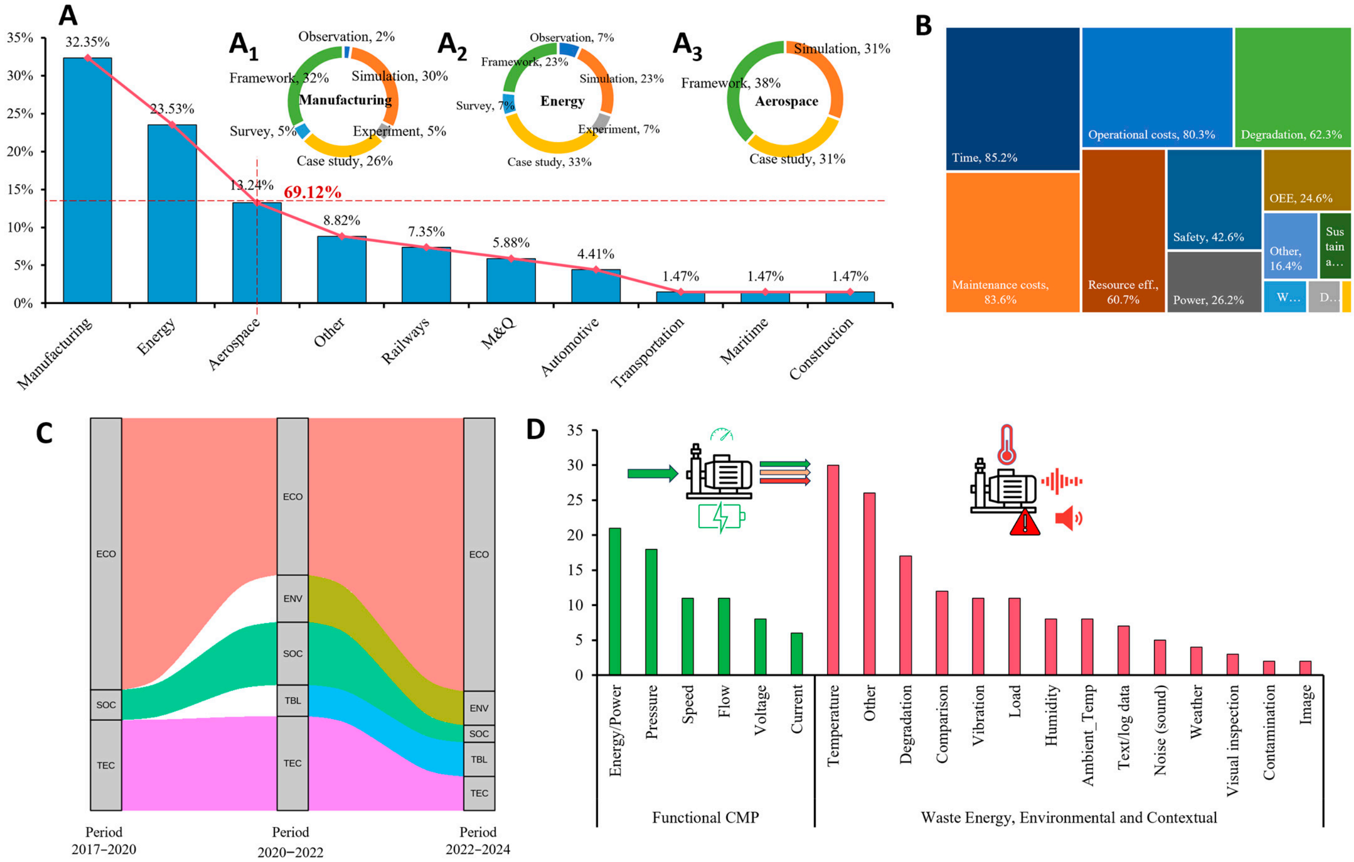

**Figure 5.** Descriptive statistics considering (**A**) the industrial sector, including (**A$_1$**) the research design of manufacturing studies; (**A$_2$**) energy studies; and (**A$_3$**) the research design of aerospace studies. (**B**) Overall key performance metrics considered in the optimisation and decision-making. (**C**) Systematic and sustainability aspects considered for optimising of maintenance activities. (**D**) Condition Monitoring Parameters are functional energy (green) and waste energy (red).

Furthermore, the optimisation metrics (Figure 5B), particularly decision variables used for optimisation of maintenance activities and scheduling, primarily rely on time (85%), maintenance costs (84%), and operational costs (80%), followed by degradation metrics (62%) and resource efficiency (61%) metrics. It becomes apparent that social and environmental aspects are still neglected. For that reason, we performed an analysis of Systemic and Sustainability Aspects (Figure 5C), such as economic (ECO), environmental (ENV), social (SOC), Technical/Technological (TEC), and TBL (Triple Bottom Line—studies that consider economic, ecological, and social aspects). The evidence suggests that, before 2020, there was a lack of TBL and environmental considerations in PsM's decision-making, while a limited number of studies incorporated social aspects (e.g., safety).

Post-2020 studies show that environmental and social elements are being considered in decision-making steps, while TBL aspects are being integrated into optimisation frameworks. This suggests that green initiatives imposed by, for instance, the EU (e.g., the Green Deal) may indicate the presence of this effect. Rhetorically, a rise in sustainable consideration and a drop in technical performance indicators (e.g., availability metrics) are significant. This presumably marks the shift from purely technical performance metrics (e.g., reliability, availability) to product- and user-centric design (e.g., product quality, customer satisfaction, user experience).

Lastly, inspired by the *p-f* curve proposition in the Energy-Based Maintenance (EBM) domain regarding primary (functional) and secondary (waste) energy indicators (see [50]), we devise functional condition monitoring indicators of power variables (e.g., hydraulic, electrical, mechanical) and secondary (waste) emission energy monitoring (e.g., temperature, vibration, sound) parameters (Figure 5D). This distinction aligns with growing interest in leveraging energy signals for condition assessment, as demonstrated in studies dealing with hydraulic power (i.e., pressure and flow) [51] and electrical power (i.e., current and voltage) [52] for estimating the state of the machine or at least comparing input and output signals, such as energy consumption profiles [53].

Across the literature, data-driven condition monitoring often employs degradation metrics (e.g., wear, corrosion) and comparative metrics (e.g., anomaly detection, pattern changes) to estimate remaining useful life (RUL). In PsM research discourse, temperature remains the most frequently used condition monitoring parameter for assessing system health. This is followed by system-specific data ("Others" 43%), energy/power consumption (34%), pressure (30%), speed (18%), flow (18%), load (18%), and others. The preference for emission-based signals, such as vibration, heat, and acoustics, is likely due to their sensitivity and the maturity of the available sensing technologies.

While data-driven approaches dominate the current landscape, there is an emerging body of work emphasising the integration of physics-based models and causal machine learning [54,55]. This shift reflects a broader rationale for evolving from purely data-centric to process- and energy-driven causal decision-making frameworks in PsM. Such integration is expected to enhance decision reliability, reduce model opacity, and improve prescriptive accuracy by incorporating domain knowledge and causal inference mechanisms. A study [56] demonstrates the superiority of causal knowledge graphs over non-parametric ML models in failure classification.

### 3.3. Prescriptive Maintenance Research Clusters

The MCA uncovered latent thematic structures (Figure 6) established by categories of Application Scope, Study Focus, Sustainability Aspects, and Hierarchical Scope. The MCA biplot analysis (Figure 6A) suggest that the first three PCs account for 40% of the total inertia (Figure 6B). Such low variance is common in MCA [57,58], given the high variability of data. To handle low inertia (variance), the correlation coefficient $\eta^2$ (Figure 6C) is introduced. The criteria explain the degree of association between variables and PCs. For the analysis of individual components, we set $\eta^2 > 0.200$. Class categories (red points) below the threshold are marked transparent in the biplot (Figure 6A), suggesting a poor contribution in terms of explaining the PC. Lastly, we use $R^2$ to indicate how well the particular PC represents the category. Additionally, estimates (category coordinates) that describe the location of a modality (category) in reduced space are utilised. The sign and magnitude indicate how a category relates (i.e., influences) to a specific PC.

PC1 explains analytical depth and functional enhancement (e.g., predicting failures, optimising maintenance plans), considering technical and organisational aspects. PC2 reflects the implementation level and managerial scope of PsM practice, i.e., PC2 links large-scale, fleet-, or organisational-level applications with strategic and tactical maintenance planning, particularly dealing with decision-making and strategy selection problems (e.g., resource allocation, maintenance planning). PC3 addresses multi-level integration, where strategic decision-making is informed by operational considerations, reflecting vertically integrated decision-making. The emergence of social aspects suggests that some studies are shifting towards cross-functional collaboration, reflecting the challenges of aligning top-down policies with shop-floor execution. For interpreting PCs, specifically the positive and negative sides of individual PCs, the description of $R^2$ and estimates is provided in Appendix A, considering only statistically significant contributions ($p < 0.05$).

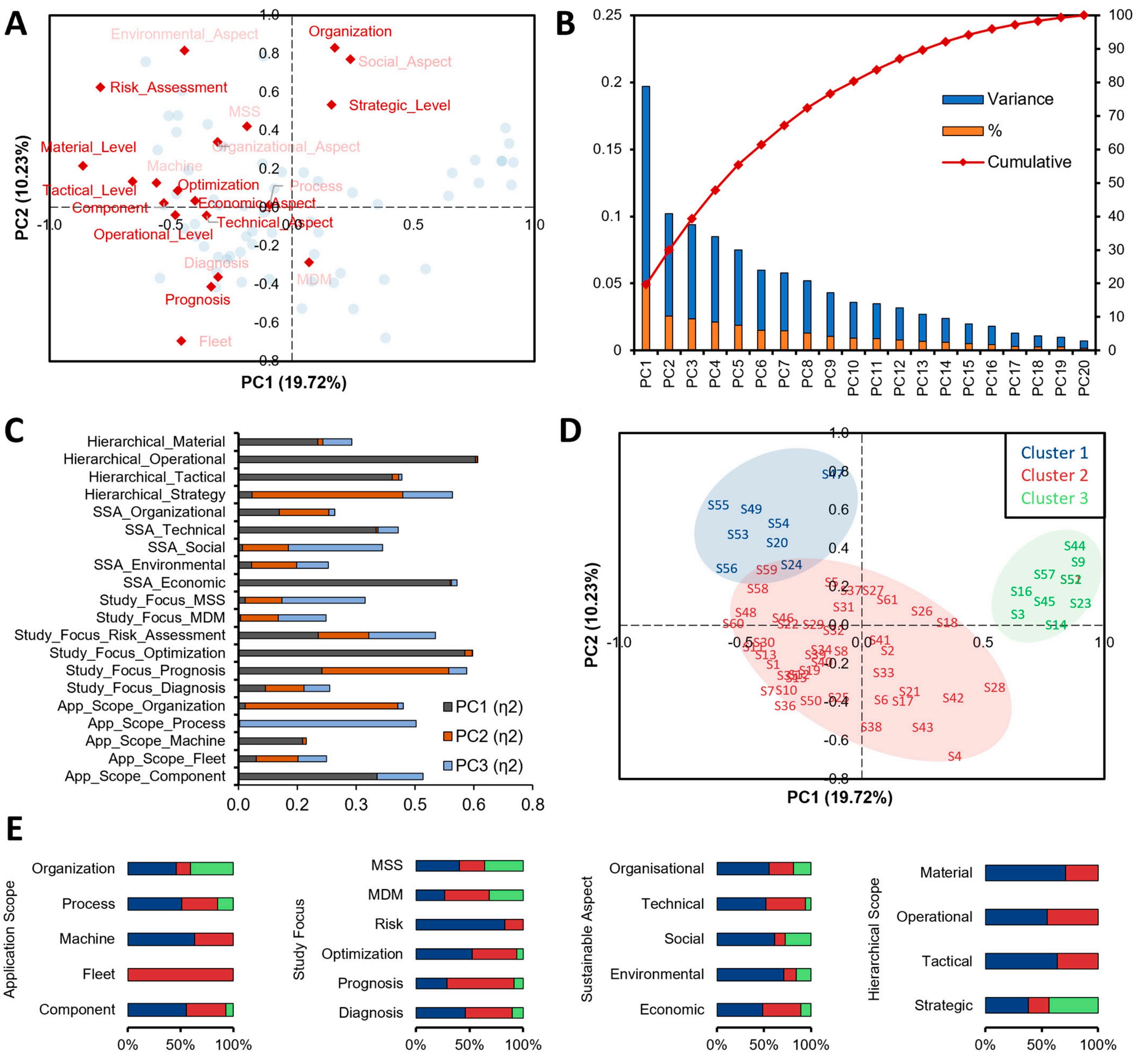

**Figure 6.** Multiple Correspondence Analysis with Agglomerative Hierarchical Clustering on Principal Components. MCA biplot of PC1-PC2 (**A**) positions subcategories (red) and individual studies (light blue). The scree plot (**B**) illustrates the eigenvalues (left y-axis) and the percentage of variance (inertia) for each separate component (right *y*-axis). The bar plot (**C**) explains PCs' contribution (measured by $\eta^2$). The $\eta^2$ explains the proportion of inertia of the categorical variable on the PCs. The $\eta^2 > 0.200$ is a threshold ($\eta^2 < 0.200$ is transparent). The AHC (**D**) represents clusters of research studies. The categories (**E**) used for the analysis show the frequency of class categories and their contribution in terms of explaining the research clusters.

Subsequently, Hierarchical Clustering on Principal Components (Figure 6D) was applied using the first three PCs. For robustness, extended clustering was performed using seven components (cumulative inertia >70%), which yielded no additional substantive differentiation. The analysis suggests clear separability among the clusters, which were further analysed based on their mass contributions and class modalities. Full content-based descriptions of each cluster are detailed in Appendix B and visualised via a line bubble chart.

Cluster 1 (blue) and Cluster 2 (red) exhibit partial overlap, indicating a degree of structural similarity in the configuration of categorical variables. Despite its visual proximity, their internal composition, reflected through class category frequencies (see Figure 6E), reveals substantive differences if we consider alignment with the positive side of PC2 and the negative side of PC1, suggesting Cluster 1's tendency towards operational/material hierarchical level risk assessment with machine and component application scopes, highlighting a bottom-up approach. Cluster 2, on the other hand, aligns more closely with managerial and system-level concerns, centring on fleet-level prognosis and post-prognostic optimisation. Cluster 3 diverges notably from the others, adopting a strategic and conceptual approach to PsM. Dominant modalities include organisational planning, strategic formulation, and survey-based analysis, often detached from technical aspects. Rather than proposing algorithmic and sensor-based solutions, Cluster 3 typically frames PsM with broader discussions on digital transformation, business model innovation, or long-term organisational objectives. This top-down orientation suggests a vision of PsM as a strategic enabler rather than a purely operational function.

## 4. Discussion

This section synthesises the review findings designed to answer each RQ. Section 4.1 examines the range of applications, methods, and tools underpinning PsM. Section 4.2 characterises prescriptive actions and operational decision-making of PsM across a range of industrial sectors. Section 4.3 describes research clusters derived from multivariate factor analysis to form a structured thematic landscape of PsM research. Finally, Section 4.4 identifies prevailing challenges and proposes a solution space to enhance the implementation and scalability of PsM.

### 4.1. Applications, Methods, and Tools

The review reveals that PsM is concentrated primarily within manufacturing, energy, aerospace, and railway domains, where downtime is costly and asset longevity is critical. The prominence of these sectors reflects the maturity of the condition monitoring infrastructure and increased convergence of maintenance with production planning and control [22,59–61]. Although heavily relying on expensive waste–energy sensor data (e.g., temperature, vibration), many are considering alternatives of inexpensive functional–primary power sensors (e.g., flow, pressure) [56]. This translation aligns with an increased focus on physics-driven modelling and causal machine learning, provoking renewed debates on the value of interpretable, context-aware decision models in maintenance [55]. Still, current applications remain anchored in data-driven frameworks, particularly predictive models for prognosis and optimisation of subsequent maintenance actions.

In terms of methods, the PsM landscape is dominated by supervised ML models (Table 3), such as Random Forest (RF), Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs) [62–64]. RF is especially prevalent due to its high classification accuracy and ability to perform feature importance, making it well-suited for root cause analysis and anomaly detection. The models are typically trained on historical failure data or sensor data, which is commonly required to forecast remaining useful life (RUL) or classify failure types.

**Table 3.** Supervised and unsupervised machine learning algorithms used in PsM applications.

| Study | SVM | ANN | RF | DT | kNN | NB | AdaB | kM | XGB | PCA |
|---|---|---|---|---|---|---|---|---|---|---|
| [65] | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | |
| [66] | | ✓ | | | | | | | | ✓ |
| [67] | | ✓ | | | | | | | | |
| [68] | | | | | | ✓ | | ✓ | | |
| [69] | ✓ | | | | | | | | | |
| [70] | ✓ | | | | | | | | | |
| [71] | | | | | | | | ✓ | | |
| [72] | ✓ | | | ✓ | | | | | | |
| [62] | ✓ | | ✓ | | ✓ | ✓ | | ✓ | | |
| [73] | ✓ | ✓ | ✓ | ✓ | | | | | | |
| [74] | | | ✓ | | | | | | | |
| [63] | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | |
| [54] | | ✓ | | | | | | | | |
| [75] | | | | | | | ✓ | ✓ | | ✓ |
| [76] | ✓ | ✓ | ✓ | | | | | ✓ | | |
| [77] | | ✓ | | | | | | | | |
| [64] | ✓ | | ✓ | ✓ | | | | | | |
| [78] | ✓ | | ✓ | | | | | | | |
| [79] | | | ✓ | | | | | | ✓ | |
| [80] | | | ✓ | | | | | | | |
| [61] | ✓ | | ✓ | ✓ | ✓ | ✓ | | | | |
| [81] | | | ✓ | ✓ | ✓ | | ✓ | | ✓ | |

SVM (Support Vector Machine); ANN (Artificial Neural Network); RF (Random Forest); DT (Decision Tree); kNN (k-Nearest Neighbour); NB (Naïve Bayes); AdaB (AdaBoost); kM (k-Means); XGB (eXtreme Gradient Boosting); PCA (Principal Component Analysis).

Complementing ML, the DL models (Table 4) have significantly expanded the scope of prescription for PsM. Namely, based on reviewed studies, key DL architectures—LSTM, CNN, GAN, ESN, and Reinforcement Learning (RL) variants—have been deployed to meet operational targets in PsM frameworks: (i) temporal dependencies and prognosis (LSTM, RNN, ESN) for practical RUL estimation and the ability to model long-term dependencies in time-series data. Dual-LSTM architectures demonstrate high accuracy and real-time feasibility in complex machinery, such as turbofan engines and batteries [72,75]. In contrast, ESNs are suitable for adaptive modelling in environments with noise and constraints of real-time systems [62]. (ii) Spatial–Temporal Feature Extraction (CNN, DNN) is used in extracting spatial features from vibration and thermal data processing for early detection and RUL prediction [64,78]. (iii) Causality and Reasoning (MLP-ANN, ML causal learning) are gaining significant prominence. Causal ML, addressed by Vanderschueren et al. [55], leveraged MLPs in combination with causal inference to predict individualised effects and optimise maintenance schedules, thus handling heterogeneity across datasets. (iv) Generative Learning and Anomaly Detection (e.g., GAN) in the PsM domain are usually employed to simulate rare failure events and generate synthetic training data for imbalanced datasets. GAN is beneficial in classification problems, particularly in cases where failure samples are rare or costly to collect [55,81]. (v) Action-oriented Optimisation (Deep RL)—Deep RL and Transformer networks are becoming an integral part of PsM applications, specifically decision-making layers, by recommending optimal maintenance actions by balancing cost, settings, and operational constraints [9,82–85]. Although commonly used for making cost-effective decisions, Sun et al. [64] demonstrate the applicability of adopting sustainability in PsM decision-making.

**Table 4.** Deep learning algorithms used in PsM applications.

| Study | MLP-ANN | LSTM | DNN | CNN | VAE | TRN | RNN | GAN | ESN |
|---|---|---|---|---|---|---|---|---|---|
| [81] | | | | | | | | ✓ | |
| [78] | ✓ | | | ✓ | ✓ | | ✓ | | |
| [55] | | | | | | | | ✓ | |
| [64] | ✓ | ✓ | | ✓ | | | | | |
| [86] | | | ✓ | | | | | | |
| [75] | | ✓ | | | | | | | |
| [87] | | ✓ | | ✓ | ✓ | ✓ | | | |
| [63] | ✓ | ✓ | | | | | | | |
| [83] | | | ✓ | | | | | | |
| [62] | | ✓ | | | | | | | ✓ |
| [72] | ✓ | ✓ | | | | | | | |
| [65] | ✓ | | | | | | | | |

NOTE: MLP-ANN (MultiLayer Perceptron ANN); LSTM (Long Short-Term Memory); DNN (Deep Neural Network); CNN (Convolutional Neural Network); VAEs (Variational AutoEncoders); TRNs (Transformer Networks); GAN (Generative Adversarial Network); ESN (Echo State Network).

Although Deep RL has been established as a core component in PsM, the interpretability of models, particularly in safety-critical and industrial applications, becomes a significant challenge. Only a few studies address the challenge by introducing XAI for effective human–machine collaboration. Eider et al. [72] proposed a context-aware recommendation system for battery management that integrates XAI principles through natural language. Prescriptive actions, like advising a lower charging rate, are paired with contextual cause (e.g., high state of charge) and human-readable rationale, enhancing user compliance and understanding. Similarly, Petroutsatou et al. [88] emphasise integration of XAI to ensure technical validation and inform replacement versus repair decisions under economic and environmental constraints. Gordon [73] highlights that interpretable ML methods help operators understand when and why specific maintenance actions are recommended, reinforcing decision accuracy.

A significant body of PsM relies on correlation-based ML models for the prediction. These models are often used to answer business-relevant questions, such as "If we perform a certain maintenance action, how will it affect our operational goals?", to inform subsequent decisions. However, the approach has a fundamental challenge, and that is, most of the AI (and ML) approaches in PsM used for classification and regression are purely associative; they can recognise patterns and associate them with a particular label but are unable to distinguish cause from effect. This limitation is critical because the goal of PsM is inherently causal—it attempts to intervene in a system to achieve a desired outcome. To put it in perspective, in a technical value chain, a process fault can originate long before it is detected. The ML algorithm that only *detects* a fault after it has occurred is far less valuable than one that *predicts* it from the earliest process step. Hence, this limits the true detection period and delays preventive actions. The need for a dual-layer architecture, i.e., "Predict-and-Prescribe," combined with causally grounded explainability, positions PsM as a pillar for a sustainable, safe, and cost-effective asset management strategy. Although this depicts the future of PsM, given that it converges neural–symbolic learning, causal inference, and a human-in-the-loop approach to ensure technically robust and socially acceptable solutions, the work is still theoretical.

### *4.2. Prescriptive Maintenance Actions*

The prescriptive dimension of PsM is characterised by the ability to convert predictive insights (e.g., failure diagnosis, RUL) into actionable recommendations. These recommendations outline *what* activities should be taken, *when*, *by whom*, and *under what constraints*.

In contrast to traditional maintenance strategies, PsM extends this pipeline by embedding decision-making logic into the maintenance execution process. This marks a decisive shift from mere prognostics to prescriptive intelligence. To capture this dimension, we show how PsM is operationalised in practice (Table 5).

**Table 5.** Characterisation and exemplification of PsM activities.

| PsM Activity | Characterisation | Example | I4.0 Tools | References |
|---|---|---|---|---|
| Component-level Repair vs. Replace. | Deciding whether to replace or repair a specific part based on degradation and resource constraints. | The compressor blade of a turbofan engine is evaluated using RUL; if degradation is within tolerance, the part is repaired instead of replaced. | AI/ML. | [62,71,73,82,86,87,89] |
| Spare Parts and Workforce Planning. | Spare parts pre-ordering, resource allocation, technician dispatching, and alarm adjustment. | Automate work orders and spare part requests based on sensor anomalies, and dispatch a technician based on their skill and profile. | AI/ML. IoT. Big Data. | [39,54,62–64,75,78,90–93] |
| Prioritisation and Planning. | Workforce optimisation and intelligent scheduling to maximise OEE. | Maintenance tasks are reprioritised dynamically due to unexpected failures. | AI/ML. H&VI. Cloud. | [66,68] |
| Decision Support for Strategic Management. | Selection of alternative strategies (e.g., preventive vs. corrective, outsourcing vs. in-house, scheduled vs. condition-based). | Recommends outsourcing the turbine overhaul based on risk thresholds, technician shortages, or a cost–benefit analysis of the repair. | AI/ML. H&VI. DT. | [60,78] |
| Maintenance-Production co-optimisation. | Synchronising operation and maintenance schedules (e.g., control sequencing, load balancing). | Aligning maintenance with production changeover to minimise disruptions; optimising load to reduce failures. | AI/ML. Edge. H&VI. IoT. Big Data. | [62,66,78] |
| Automated Execution and Self-Regulation. | Self-regulating workflows, feedback loops, and minimal human intervention to prevent stoppages. | The battery management system automatically reduces the charging rate when thermal thresholds are reached, eliminating the need for operator input. | AI/ML. H&VI. Big Data. IoT. Edge. | [62,64,75,78,92] |
| Fleet- and Mission-Level Prescriptions. | Mission planning for fleets, coordinated scheduling, and downtime optimisation. | Scheduling maintenance for an aircraft fleet considering mission, availability windows, and component fatigue. | AI/ML. Cloud. H&VI. Big Data. IoT. | [66,68,81,83,91,92,94] |

Note: AI/ML = Artificial Intelligence/Machine Learning; IoT = Internet of Things; H&VI = Horizontal and Vertical Integration; Edge = Edge Computing; Cloud = Cloud Computing and Connectivity; Big Data = Big Data and Analytics.

The spectrum of PsM activities spans from localised decisions—component repair versus replacement—to systemic interventions including fleet-level scheduling and co-optimisation. This is supplemented by prioritising and planning necessary tools and resources to resolve specific failures using optimal strategies (e.g., corrective vs. preventive). Consequently, the prescriptive part aims to execute actions that will be self-regulated with minimal human interventions. These can be within the operational segment (e.g., adjusting machine settings, reducing speed, or load) [9,95,96], input segment (e.g., resource allocation, spare parts supply, workforce prioritisation) [65,66,68,97], environmental segment (e.g., adjusting env. temperature) [72], and output segment (e.g., modifying production targets or quality criteria) [3]. In contrast to traditional maintenance practices that focus solely on machine-level availability, PsM considers other elements of overall equipment effectiveness, enabled by I4.0 technologies such as AI, ML, and H&VI (Horizontal and Vertical Integration), which are crucial for automating PsM actions. Thus, switching from system-oriented to process-oriented reasoning replaces discrete (static) decisions with continuous (dynamic) prescriptive response actions.

Moreover, the activities are highly dependent on the industrial domain. For instance, in manufacturing (Figure 7), actions are oriented to preventing disruptions in production flows by minimising downtime and aligning maintenance with operational schedules [22,60,98]. Consequently, many have begun integrating maintenance with planning systems that support decisions such as workforce assignment, spare parts forecasting, and production (re)configuration. Implicitly, using H&VI seems crucial for determining the quality of products (or services).

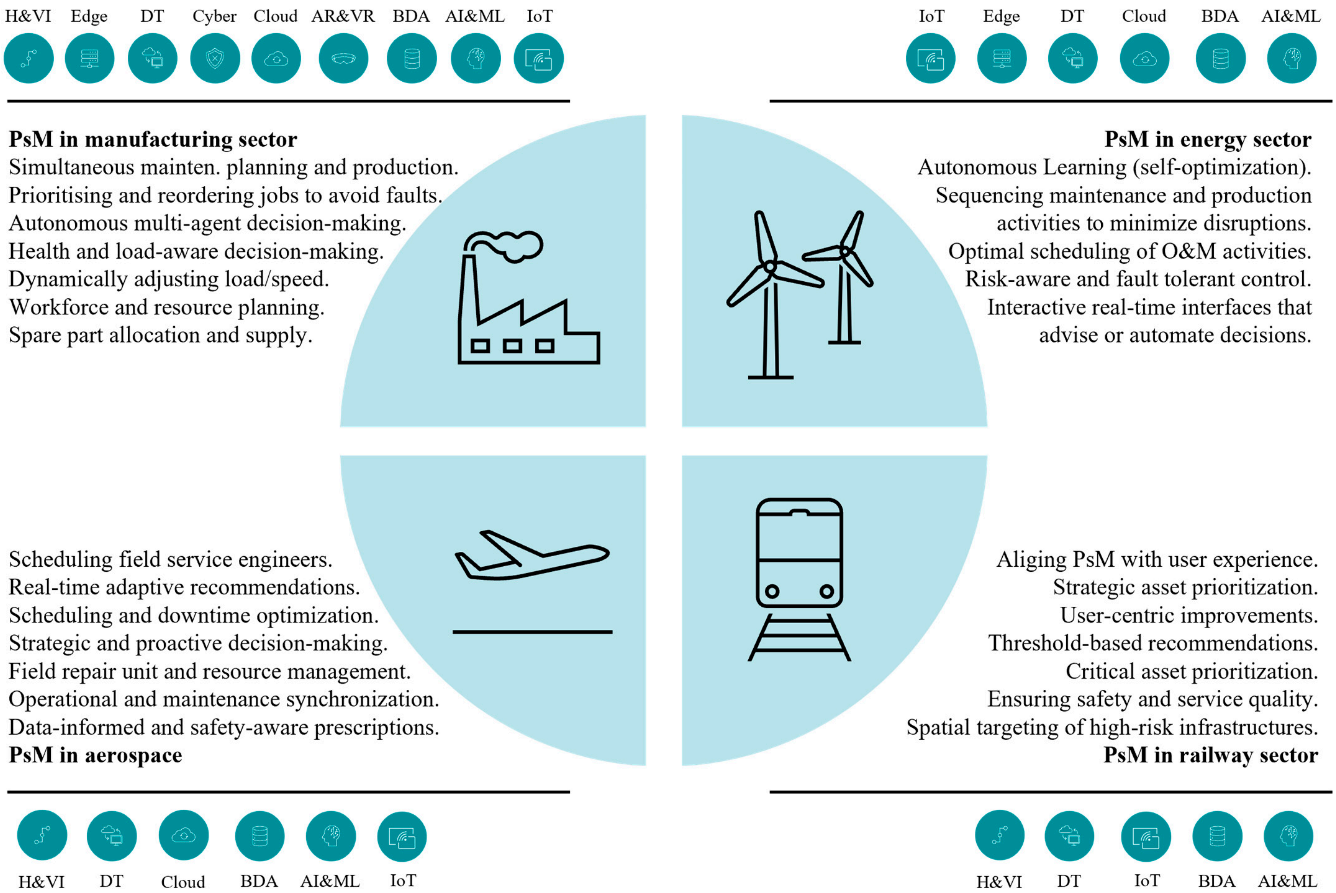


**Figure 7.** Characterisation of prescriptive maintenance activities within four dominant industrial sectors. Industry 4.0 technologies are added based on their presence in the industrial sector.

Unlike manufacturing, the use of PsM in the energy sector exhibits a higher level of autonomy and intelligence, where self-optimising systems rely on real-time data inputs and ML algorithms that trigger early warnings for adapting operations. Prescriptive actions here are sensor-driven and embedded within broader strategic management goals, such as grid stability, load balancing and/or emission reduction. Therefore, sequencing maintenance and operation activities is critical for preventing disruptions. Here, PsM facilitates intelligent and real-time interventions to maintain safety, reliability, and sustainability in volatile operational environments.

In aerospace, PsM actions are driven by mission-critical priorities with a focus on field service engineers [99], flight delay minimisation [100,101], and safety-aware recommendations [91,102]. Prescriptive activities include integrating data from onboard diagnostics, flight history, and sensor logs to offer real-time, adaptive decisions for field repair. This usually considers proactive decisions that align operational goals with maintenance needs to ensure continuity and regulatory compliance. The aerospace domain highlights the importance of synchronising operation and maintenance planning, considering that the cost of failure is exceptionally high [99].

The railway sector shows that PsM activities prioritise user experience, infrastructure safety, and service reliability. Prescriptions are primarily determined by the prioritisation of critical assets and the spatial targeting of high-risk or high-use infrastructure segments. These actions often align with real-time data usage, enabling strategic asset management and user-centric improvement. As with the aerospace domain, PsM activities in railways shift from simple performance metrics (e.g., reliability, availability) to aligning with service quality and safety.

### 4.3. Research Clusters

Exploring latent thematic structures leveraging MCA-HCPC (Figure 6), we identified three distinguishable clusters. Each cluster encapsulates a coherent line of research focus and mainly reflects varying levels of technical maturity, organisational engagement, and systematic integration. The characterisation of each cluster and references are provided in Table 6. Technical integration and real-time diagnostics primarily characterise Cluster 1 and focus mainly on machine- and (multi)component-level analysis. The studies in this cluster primarily focus on the manufacturing and energy sectors, and the prescriptive part of PsM mainly relies on reinforcement learning models and IoT deployments. Applications typically demonstrate the use of AI's potential in operational settings for identifying and preventing failures, ultimately avoiding unnecessary downtime. Another characteristic is that PsM applications, such as frameworks and decision-support systems, thrive in sensor-rich operational settings. However, the enterprise-scale integration and generalisability remain limited, which is where H&VI I4.0 technology plays a crucial role in enabling a Cyber Physical Production System (CPPS).

Cluster 2 mainly focuses on tactical and strategic decision-making. This includes enterprise-level decision-support systems, primarily relying on probabilistic modelling, fuzzy logic, Monte Carlo simulations, and optimisation frameworks. Unlike Cluster 1, the scope is dedicated to fleets and process-wide systems. This considers incorporating not only technical and organisational but also human factors. Here, studies extend beyond operational efficiency to address decision-making at the higher levels and planning under uncertainty, which usually builds upon prognosis models. This cluster fills the gap between operational-level and enterprise-wide decision frameworks by considering the complexities and uncertainty of operational settings. Typical examples are PriMa (Prescriptive Maintenance Model) models [2,103], which comprise multiple functional dimensions and encompass multiple hierarchical decision-making levels.

Cluster 3 primarily describes studies that focus on conceptual frameworks, organisational enablers, and strategic transformation for adopting PsM practices. The methods typically include conceptual models, case-based reasoning, and survey analysis. Primarily, the work here describes socio-technical endeavours and lifecycle thinking. Theoretically, the work discusses the role of human factors, such as workforce dynamics, upskilling, and knowledge management, on organisational and PsM performance. While technically less engaged studies, the studies here mainly focus on broader industrial transformation and analysing the readiness of PsM.

**Table 6.** Cluster characterisation.

| Cluster | Cluster Characterisation | References |
|---|---|---|
| Cluster 1 | Component-level prescriptive decision-making. Use of Deep Reinforcement Learning. Real-time (partially) edge/IoT integration. Multicomponent systems modelling. Hybrid physical-data modelling. Partial consideration of sustainability objectives. | [55,64,73,78,79,84,104,105] |
| Cluster 2 | Focus on prescriptive decision-making at tactical and strategic levels. Incorporates human and organisational factors. Decision-making is considered under uncertainty using data-driven and probabilistic modelling. Strong emphasis on economic (cost) optimisation. Introduction of reference models and maturity frameworks (e.g., PriMa). Scalability through simulation and optimisation for real industrial applications under resource constraints. | [3,7,9,23,49,54,59–63,65–69,71,72,74,75,80–83,85–87,89,91–95,99–101,103,106–112] |
| Cluster 3 | Prescriptive maintenance is considered a strategic enabler, focusing on ecosystem and organisational readiness. It integrates with design (e.g., Design for Maintenance) and planning (e.g., Production Planning and Control). The importance of human and workforce dynamics is emphasised. Stresses PsM as a strategic business enabler. | [22,39,76,88,90,96,97,113,114] |

In summary, the clustering analysis reveals distinctive properties. Firstly, the cluster-based differentiation reveals a pathway from operational PsM (Cluster 1) towards enterprise-level integration (Cluster 2) and ecosystem-level consideration (Cluster 3). It is essential to note that clusters are not hierarchical but complementary. Advanced analytics, as observed in Cluster 1, are ecosystem-level and necessary but insufficient without organisational alignment (Cluster 2) and social–technical support structures (Cluster 3). Additionally, the integration of PsM models across verticals (from shop floor to management) and horizontals (across departments and ecosystems) highly depends on I4.0 horizontal and vertical integration technologies. Rhetorically, for an industrial organisation to manage these I4.0 technological solutions, achieving such a high level of success depends heavily on its organisational digital capacities. It has been reported that the adaptation of metrics outside of the purely technical sphere, like availability (e.g., Maintenance Sustainable Responsibility metric), highly depends on the digital capabilities of maintenance personnel [115].

Still, it remains limited in the literature, which was evident in the PC3 of MCA analysis (Figure 6E), which connects operational insights with strategic decision-making. Lastly, there is a need for causal and prescriptive validation. While prediction is a standard, rigorous, and practical approach, prescriptive validation is underrepresented. This also holds for sustainable and human-centric prescriptions, where contemporary PsM literature considers environmental and social factors (e.g., safety, upskilling) in addition to economic criteria. As a response, we provide a Description Matrix (Table 7) for understanding characteristics and features of each research cluster.

### 4.4. Current Challenges and Research Agenda

Several challenges affect the full-scale adoption of PsM. Although economic considerations dominate optimisation efforts, a notable issue is the underrepresentation of sustainability aspects, namely, environmental and social dimensions. Many studies focus on specific machines or processes without addressing broader organisational or cross-industry applications. Another critical challenge is the low maturity of PsM applications, particularly in manufacturing, where exploratory research and propositional frameworks predominate. Enhancing the human–AI interface through trust-building mechanisms and workforce training will facilitate the adoption of PsM. To bridge the gap between theoretical models and industrial deployment, we translate challenges into targeted research opportunities by offering practical scenarios and solutions.

**Table 7.** Description Matrix of clusters.

| Feature | Cluster 1 | Cluster 2 | Cluster 3 |
|---|---|---|---|
| Focus | Deep learning for real-time actions and risk optimisation. | Maturity models. Prescriptive decision-making rules. | Ecosystem analysis for adoption of PsM. Surveys and interviews. |
| Methods | Deep RL. Neural networks. | Deep RL. Fuzzy logic. Monte Carlo simulation. | Reference modelling. Multicriteria analysis. |
| Granularity | Component and machine-level operational settings. | System/process-level under uncertainty. Integration with production planning and control. | Enterprise-level planning, control, and design integration. |
| PsM Contribution | Prescribes technical actions to prevent degradation. | Prescribes actions based on imperfect/limited observations. | Aligns prescriptions with people, processes, and assets. |
| Data | Operational data. Maintenance logs. Sensors. | Operational data. Failure data. Maintenance logs. Sensors. Synthetic datasets. | Questionnaires and surveys. Qualitative data. |
| Human Factors | Minimal to moderate. Neglect of knowledge in the analysis. | High (technical variability, inspection quality). Knowledge-based maintenance. | Considering (e.g., workforce skill gap, learning, task allocation). |
| Strategic Perspective | Operational efficiency and automation. | Maintenance maturity. Risk–cost trade-off. | Strategic transformation. PsM's role in advancing operational effectiveness. |
| Key Challenges | Data scarcity, generalisation, and explainability. | Partial observations, both simulations and limited case studies. Imperfection. | Knowledge feedback. Workforce scaling. Organisational aspects. |

**Industrial Validation**: Many studies suffer from limited real-world deployment, heavily relying on synthetic datasets and parameters (e.g., HackTheMachine [68], LMS Amesim [54]). Thus, existing work suggests that frameworks remain conceptual and theoretical. As a response, a solution space can be a practical deployment and validation of the PsM model, for instance, on a simple CNC machine, given that it is one of the most utilised industrial assets [116]. Validation setup could include remote sensor condition monitoring (e.g., vibration, current), which is input into the prediction layer (PdM). This model forecasts RUL of the cutting tool using time-series ML (e.g., LSTM). The prescription layer (PsM), relying on DRL, recommends *when* to change the tool, *how* to adjust cutting parameters (e.g., speed), and *whether* to continue to operate or interrupt the batch based on tool performance. Validation would include comparison of two scenarios: (a) with proposed PsM (model) actions and (b) without PsM (e.g., standard preventive maintenance). Relying on tool life extension (%), number of unplanned stoppages, production throughput, and maintenance cost savings as key performance metrics, the proposed PsM model or framework is quantitatively established as valid. As a final step, the outcome can be determined by measurable improvements and by operators' feedback on the interpretability and trust in prescriptions, which can serve as an optional XAI layer. Rhetorically, by combining predictive and prescriptive logic, this approach will demonstrate decision quality, provide quantitative metrics for comparison, and support human-in-the-loop feedback.

**Scalability and Complexity**: Scalability issues persist when transferring frameworks from experimental to complex systems with many components and dynamic constraints. This is often observed in applications where studies demonstrate the PsM application on a single-unit system, which limits the scalability of the PsM model to multi-unit, interdependent systems, using a modular and interoperable design. To demonstrate a potential solution, we exemplify a scenario of a food manufacturing facility that operates a fully automated packaging line comprising interconnected subsystems (bottle filling station → cap screwing unit → label applicator → quality inspection → palletizer). Each subsystem has unique failure modes but is interdependent—a failure in one affects the following. Consider the proposed architecture of a packaging line that is modelled using a microservices-based PsM framework, such as those proposed in [2,103]. However, unlike previous models, here each subsystem has its own containerised PsM module, such as Dockerised service (see [117,118]), handling health monitoring (e.g., vibration, temperature), local fault prediction (e.g., ML trained per subsystem), and local prescriptive action (e.g., adjusting speed, triggering technician alert). A central orchestration layer (e.g., Kubernets) with machine-to-machine support (e.g., MQTT broker—Message Queue Telemetry Transport) coordinates cross-system dependencies, such that it synchronises downtime and reallocates line capacity. Exchanging data using ontology-based semantic models, such as OPC UA (Open Platform Communications Unified Architecture), facilitates interoperability, alongside standardised messaging protocols that ensure communication between subsystems and MES (Manufacturing Execution System). Here, the causal inference layer could identify how failure in one subsystem affects downstream performance (e.g., the capping unit has torque drift). In practical scenarios, this would allow PsM frameworks to be deployed and compared similarly to previous propositions by inspecting states with no PsM (baseline), isolated PsM (per machine), and integrated PsM (full orchestration). This would demonstrate scalability across subsystems, show that causal and semantic integration prevents local optima, which is often observed in isolated PsM models, and would ultimately validate how distributed PsM logic can adapt to system-wide scenarios.

**Prediction-Optimisation Integration**: A critical barrier is the seamless integration of the fault prediction (PdM) and decision-support (PsM) modules, which often encompasses the PsM practice. Nevertheless, the existing body of work usually addresses fault prediction (e.g., RUL estimation) or optimisation separately. To put it in context, we exemplify the case of an end-to-end PsM framework, similar to one proposed by [68], but for the HVAC (Heating, Ventilation, and Air Conditioning) system in a pharmaceutical cleanroom. A central HVAC system, in this case, ensures compliance with air purity, humidity, and temperature. Failures in such environments could potentially lead to production stoppages, batch rejections, regulatory non-compliance, and other issues. A challenging situation arises when standard HVAC systems operate as separate models. One model predicts RUL (PdM model) for estimating the lifespan of HVAC filters and fans. At the same time, another is a static rule-based system for scheduling preventive replacements every $t$ hours of operation (PsM model). The models operating in isolation would lead to suboptimal outcomes (e.g., premature filter replacements, unexpected breakdowns during production peaks). A potential solution space would include an infrastructure of sensors (e.g., monitoring air pressure differentials and airflow velocity), historical data logs (e.g., fault logs), and an operational knowledge base (e.g., technician availability). Integrated architecture in this case would comprise a predictive module, such as an LSTM, for RUL estimation and uncertainty bounds to inform risk-aware decisions. The prescriptive optimisation module could consider MILP (Mixed-Integer Linear Programming) that co-optimises filter replacement schedules, technician availability, and other factors, with various constraints (e.g., regulatory limits, cost of downtime). The last layer, the coordination layer, connects the management system (e.g., MES, CMMS) to ensure the real-time synchronisation of prescriptions with operational constraints, allowing decisions to be made on whether to delay or expedite filter replacement, switch to a backup fan, or resequence batch production. Ultimately, linking asset health with production and maintenance scheduling offers direct feedback to planners/operators with explainable recommendations.

**Data Quality and Infrastructure Readiness**: As often encountered in transitioning from conventional to advanced I4.0 technologies, data-related barriers frequently inhibit PsM implementation. This suggests that sensors generate incomplete, noisy, or unlabelled data; incompatibility exists between legacy systems and outdated infrastructure; and, most notably, the need for edge processing and robust data fusion across maintenance, logistics, and operations. One possible research direction for addressing these issues is the recent development of plug-and-play IoT (see [119]), edge AI tools, and data standardisation protocols across value chains, eliminating the need for manual configurations. Leveraging edge-enabled anomaly detection and semantic interoperability frameworks offers a pathway to PsM adoption, particularly in smaller manufacturing enterprises with limited digital infrastructure.

**Human-Centric and Sociotechnical Issues**: Human expertise and sociotechnical factors remain under-addressed in the literature. Specifically, the lack of operator trust and the skills required for the successful adoption of PsM are the reasons why many have initiated discussions on XAI and bypassing the need for human–machine understanding, thereby potentially circumventing the need for upskilling by relying on DRL algorithms. Additionally, the existing body of work overlooks human-in-the-loop feedback and domain knowledge within the Prescriptive Maintenance domain. Consequently, human–machine co-decision environments, training simulators, and XAI-PsM could bridge digital and human reasoning. Validating PsM models in operator-in-the-loop settings, such that recommendations are accompanied by human-readable information, will enable progressive workforce integration without compromising system autonomy.

**Causal Prescriptive Maintenance**: The existing PsM research primarily focuses on correlation-based ML modelling. The work must move beyond associative ML models, which often contain spurious correlations, towards integrating domain knowledge, often in the form of a causal graph. This way, building a PsM system that is more capable of robust interventions and counterfactual reasoning will add more value to the production chain in terms of precision and resource efficiency. Moving from simple predictions to causally optimised decisions, overcoming the limitations of associative models paired with post hoc explanations, will certainly bridge this gap. Validating causal models through real-world scenarios where maintenance actions are triggered by identified root causes, rather than correlation-based symptoms, would certainly demonstrate superior decision reliability. This has been recently shown by [56], where predicting root cause analysis using knowledge graphs offered a more nuanced understanding of failures, rather than simply relying on the data visualisation outcomes of machine learning models.

**Sustainable- and Energy-Based Prescriptive Maintenance**: Although numerous studies outside the PsM domain address the sustainable aspect of industrial maintenance, most PsM models focus solely on cost optimisation or uptime. The existing work in PsM pays little attention to sustainability metrics, energy usage, and lifecycle costs, as evidenced by the absence of green and circular economy objectives. Some of the possible solutions could include assessing the sustainability aspect, including both environmental–sustainable and social aspects that constitute the I5.0 pillars [56,64,120,121]. Validating psM models using sustainability-aware KPIs, such as $CO_2$ emissions, energy consumption, and material waste, will provide tangible evidence that supports arguments about their contribution beyond operational efficiency, aligning prescriptive actions with broader environmental and social goals.

# 5. Conclusions

## 5.1. Concluding Remarks

The study performs a Systematic Literature Review with a meta-synthesis of prescriptive maintenance research. Here, we have extracted relevant metadata and qualitative evidence comprising applications, methods, tools, and prescriptive actions to describe the existing work of prescriptive maintenance. In addition, meta-synthesis is performed using content-based data, leveraging multiple correspondence analyses with hierarchical clustering. The results identified three major research clusters that characterise the role of PsM in operational (Cluster 1), enterprise-level (Cluster 2), and ecosystem (Cluster 3) contextual settings. The review shows that while data-driven predictive techniques are well-established, the prescriptive layer—aimed at transforming predictive insights to actionable intelligence—lacks empirical validation. In particular, the scalability and generalizability of theoretical models suffer from a lack of practical demonstrations and applicability. Although not to a full extent, we infer that the lack of end-to-end holistic frameworks requires dedicated work on horizontal (across functional areas) and vertical (across decision-making levels) integration. Furthermore, PsM efforts are increasingly aligned with product/service quality and lifecycle performance, rather than traditional maintenance metrics (e.g., availability or downtime alone).

## 5.2. Implications and Limitations

This study's findings offer valuable implications for both researchers and practitioners. The identified gaps underscore the need for interdisciplinary approaches that integrate technical, organisational, and sustainability-focused perspectives for researchers. Developing unified conceptual frameworks and hybrid models can enhance the theoretical and practical relevance of PsM. For practitioners, adopting PsM frameworks presents opportunities for significant cost savings, improved operational efficiency, and enhanced resilience. Addressing the identified challenges, such as limited environmental considerations and low maturity levels, will be critical to realising the full potential of PsM in industrial applications. Contemporary PsM research requires adaptive architectures, causal learning, and semantic interoperability to facilitate context-sensitive decision-making.

Regarding the limitations, data heterogeneity, i.e., low inertia (35%) in MCA analysis, suggests high variability, implying that higher-dimensional patterns exist, which is exacerbated by the reliance on simulations and synthetic datasets. However, this certainly does not downplay our findings, given that the clustering inertia of 70% did not add additional insights in describing existing clusters. The study's exclusion of facility maintenance may limit generalisability to the overall application of PsM. Manual screening of SCOPUS and Web of Science records may introduce selection bias, despite rigorous adherence to the PRISMA guidelines. Lastly, given the exponential number of PsM studies that emerged during the writing process, we limited the studies to those published up to January 2025 to ensure completeness. However, incorporating recent publications, we plan to perform a living systematic review.

## 5.3. Future Research

Considering the rise of PsM research, we aim to expand the clusters with contemporary evidence. Hence, future publications will build upon recent work published, given that many studies have emerged (as monitored by RSS feeds from Google Scholar and SCOPUS). Additionally, our future research will focus on primary studies, particularly on post-prognostic (prescriptive) models that consider social and environmental aspects, leveraging probabilistic and deep reinforcement learning algorithms for autonomous decision-making. Lastly, the analysis will be performed from an Industry 5.0 perspective, considering resilient, human-centric, and sustainability pillars.

**Authors Statement:** The authors used large language models to ensure the manuscript's writing quality. Specifically, Grammarly removes spelling errors and language corrections, while OpenAI's GPT-4 and Open DeepL tools refine sentences. The LLM and AI tools used here are solely used as accelerators for enhancing the writing process, assisting in spelling checks and writing accuracy. These tools are not used to generate new ideas, insights, or sources of intellectual content. All the ideas, comments, and figures originated from and are solely the work of the authors of this manuscript.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| AS | Application Scope |
| BDA | Big Data and Analytics |
| CBM | Condition-Based Maintenance |
| CMP | Condition Monitoring Parameters |
| CPPS | Cyber Physical Production Systems |
| DL | Deep Learning |
| DRL | Deep Reinforcement Learning |
| DS | Data Source |
| DV | Decision Variables |
| H&VI | Horizontal and Vertical Integration |
| HA | Hierarchy |
| HCPC | Hierarchical Clustering on Principal Components |
| I4.0 | Industry 4.0 |
| I5.0 | Industry 5.0 |
| IoT | Internet of Things |
| IS | Industrial Sector |
| MCA | Multiple Correspondence Analysis |
| MDM | Maintenance Decision-Making |
| MES | Manufacturing Execution System |
| ML | Machine Learning |
| MQTT | Message Queue Telemetry Transport |
| ODA | Optimisation Data Analysis |

| | |
|---|---|
| OPC UA | Open Platform Communications Unified Architecture |
| ORS | Objective Review Strategy |
| PC | Principal Component |
| PCC | Population Concept Context |
| PDA | Prediction Data Analysis |
| PdM | Predictive Maintenance |
| PRISMA | Preferred Reporting Items of Systematic Reviews and Meta-Analyses |
| PsM | Prescriptive Maintenance |
| RD | Research Design |
| SF | Study Focus |
| SLR | Systematic Literature Review |
| SSA | Systemic and Sustainable Aspects |

## Appendix A. Description of PCs in MCA by R2

**Table A1.** Description of class categories for PC1.

| Categorical Class-Variables | $R^2$ | *p* Value |
|---|---|---|
| Hierarchical_Operational | 0.60 | <0.01 |
| Study_Focus_Optimization | 0.58 | <0.01 |
| SSA_Economic | 0.54 | <0.01 |
| Hierarchical_Tactical | 0.39 | <0.01 |
| App_Scope_Component | 0.35 | <0.01 |
| SSA_Technical | 0.35 | <0.01 |
| Study_Focus_Prognosis | 0.21 | <0.01 |
| Study_Focus_Risk_Assessment | 0.20 | <0.01 |
| Hierarchical_Material | 0.20 | <0.01 |
| App_Scope_Machine | 0.16 | <0.01 |
| SSA_Organizational | 0.10 | 0.01 |
| Study_Focus_Diagnosis | 0.07 | 0.04 |

**Table A2.** Description of category estimation for PC1.

| Categories | *Estimate* | *p* Value |
|---|---|---|
| Hierarchical_Operational = No_Operational_Level | 0.39 | <0.01 |
| Study_Focus_Optimization = No_Optimization | 0.38 | <0.01 |
| SSA_Economic = No_Economic_Aspect | 0.39 | <0.01 |
| Hierarchical_Tactical = No_Tactical_Level | 0.28 | <0.01 |
| App_Scope_Component = No_Component | 0.27 | <0.01 |
| SSA_Technical = No_Technical_Aspect | 0.30 | <0.01 |
| Study_Focus_Prognosis = No_Prognosis | 0.22 | <0.01 |
| Study_Focus_Risk_Assessment = No_Risk_Assessment | 0.23 | <0.01 |
| Hierarchical_Material = No_Material_Level | 0.24 | <0.01 |
| App_Scope_Machine = No_Machine | 0.19 | <0.01 |
| SSA_Organizational = No_Organizational_Aspect | 0.14 | 0.01 |
| Study_Focus_Diagnosis = No_Diagnosis | 0.12 | 0.04 |
| Study_Focus_Diagnosis = Diagnosis | −0.12 | 0.04 |
| SSA_Organizational = Organizational_Aspect | −0.14 | 0.01 |
| App_Scope_Machine = Machine | −0.19 | <0.01 |
| Hierarchical_Material = Material_Level | −0.24 | <0.01 |
| Study_Focus_Risk_Assessment = Risk_Assessment | −0.23 | <0.01 |
| Study_Focus_Prognosis = Prognosis | −0.22 | <0.01 |
| SSA_Technical = Technical_Aspect | −0.30 | <0.01 |
| App_Scope_Component = Component | −0.27 | <0.01 |
| Hierarchical_Tactical = Tactical_Level | −0.28 | <0.01 |
| SSA_Economic = Economic_Aspect | −0.39 | <0.01 |
| Study_Focus_Optimization = Optimization | −0.38 | <0.01 |
| Hierarchical_Operational = Operational_Level | −0.39 | <0.01 |

**Table A3.** Description of class categories for PC2.

| Categorical Class Variables | $R^2$ | *p* Value |
|---|---|---|
| App_Scope_Organization | 0.39 | <0.01 |
| Hierarchical_Strategy | 0.38 | <0.01 |
| Study_Focus_Prognosis | 0.32 | <0.01 |
| Study_Focus_Risk_Assessment | 0.13 | <0.01 |
| SSA_Organizational | 0.13 | <0.01 |
| SSA_Social | 0.12 | 0.01 |
| SSA_Environmental | 0.12 | 0.01 |
| App_Scope_Fleet | 0.11 | 0.01 |
| Study_Focus_Diagnosis | 0.10 | 0.01 |
| Study_Focus_MDM | 0.10 | 0.01 |
| Study_Focus_MSS | 0.09 | 0.02 |

**Table A4.** Description of category estimation for PC2.

| Categories | *Estimate* | *p* Value |
|---|---|---|
| App_Scope_Organization = Organization | 0.21 | <0.01 |
| Hierarchical_Strategy = Strategic_Level | 0.20 | <0.01 |
| Study_Focus_Prognosis = No_Prognosis | 0.19 | <0.01 |
| Study_Focus_Risk_Assessment = Risk_Assessment | 0.13 | <0.01 |
| SSA_Organizational = Organizational_Aspect | 0.11 | <0.01 |
| SSA_Social = Social_Aspect | 0.15 | 0.01 |
| SSA_Environmental = Environmental_Aspect | 0.15 | 0.01 |
| App_Scope_Fleet = No_Fleet | 0.14 | 0.01 |
| Study_Focus_Diagnosis = No_Diagnosis | 0.10 | 0.01 |
| Study_Focus_MDM = No_MDM | 0.10 | 0.01 |
| Study_Focus_MSS = MSS | 0.10 | 0.02 |
| Study_Focus_MDM = MDM | −0.10 | 0.01 |
| Study_Focus_Diagnosis = Diagnosis | −0.10 | 0.01 |
| App_Scope_Fleet = Fleet | −0.14 | 0.01 |
| SSA_Environmental = No_Environmental | −0.15 | 0.01 |
| SSA_Social = No_Social | −0.15 | 0.01 |
| SSA_Organizational = No_Organizational_Aspect | −0.11 | <0.01 |
| Study_Focus_Risk_Assessment = No_Risk_Assessment | −0.13 | <0.01 |
| Study_Focus_Prognosis = Prognosis | −0.19 | <0.01 |
| Hierarchical_Strategy = No_Strategic_Level | −0.20 | <0.01 |
| App_Scope_Organization = No_Organization | −0.21 | <0.01 |

**Table A5.** Description of class categories for PC3.

| Categorical Class Variables | $R^2$ | *p* Value |
|---|---|---|
| App_Scope_Process | 0.45 | <0.01 |
| SSA_Social | 0.24 | <0.01 |
| Study_Focus_MSS | 0.21 | <0.01 |
| Study_Focus_Risk_Assessment | 0.17 | <0.01 |
| Hierarchical_Strategy | 0.13 | 0.01 |
| Study_Focus_MDM | 0.12 | 0.01 |
| App_Scope_Component | 0.12 | 0.01 |
| SSA_Environmental | 0.08 | 0.03 |
| Hierarchical_Material | 0.07 | 0.03 |
| App_Scope_Fleet | 0.07 | 0.04 |
| Study_Focus_Diagnosis | 0.07 | 0.05 |

**Table A6.** Description of category estimation for PC3.

| Categories | *Estimate* | *p* Value |
|---|---|---|
| App_Scope_Process = Process | 0.24 | <0.01 |
| SSA_Social = Social_Aspect | 0.20 | <0.01 |
| Study_Focus_MSS = No_MSS | 0.15 | <0.01 |
| Study_Focus_Risk_Assessment = Risk_Assessment | 0.15 | <0.01 |
| Hierarchical_Strategy = No_Strategic_Level | 0.11 | 0.01 |
| Study_Focus_MDM = MDM | 0.11 | 0.01 |
| App_Scope_Component = No_Component | 0.11 | 0.01 |
| SSA_Environmental = Environmental_Aspect | 0.12 | 0.03 |
| Hierarchical_Material = No_Material_Level | 0.10 | 0.03 |
| App_Scope_Fleet = No_Fleet | 0.11 | 0.04 |
| Study_Focus_Diagnosis = Diagnosis | 0.08 | 0.05 |
| Study_Focus_Diagnosis = No_Diagnosis | −0.08 | 0.05 |
| App_Scope_Fleet = Fleet | −0.11 | 0.04 |
| Hierarchical_Material = Material_Level | −0.10 | 0.03 |
| SSA_Environmental = No_Environmental | −0.12 | 0.03 |
| App_Scope_Component = Component | −0.11 | 0.01 |
| Study_Focus_MDM = No_MDM | −0.11 | 0.01 |
| Hierarchical_Strategy = Strategic_Level | −0.11 | 0.01 |
| Study_Focus_Risk_Assessment = No_Risk_Assessment | −0.15 | <0.01 |
| Study_Focus_MSS = MSS | −0.15 | <0.01 |
| SSA_Social = No_Social | −0.20 | <0.01 |
| App_Scope_Process = No_Process | −0.24 | <0.01 |

## Appendix B

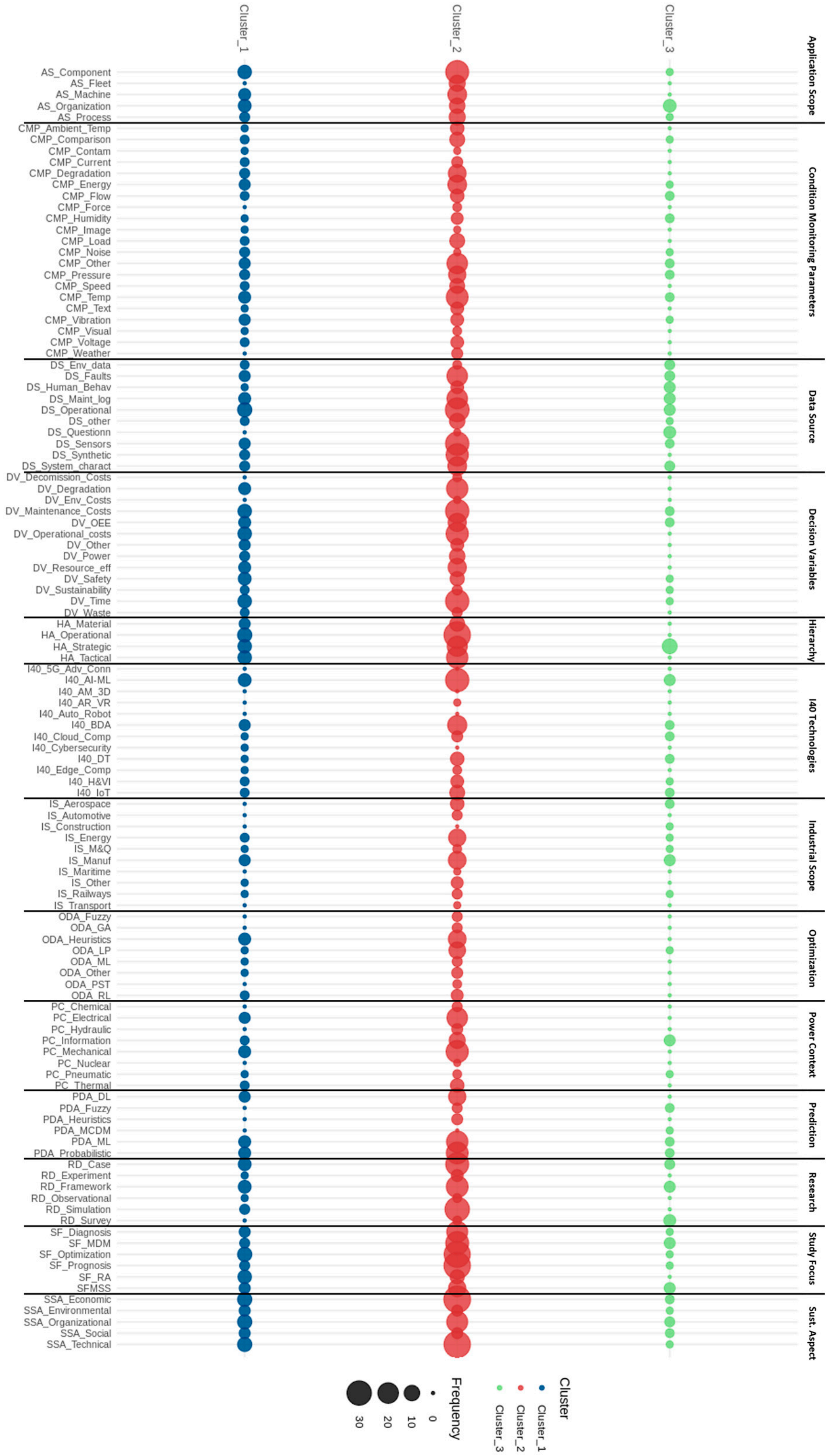

**Figure A1.** Frequency of class categories in research clusters. (Note: AS = Application Scope; CMP = Condition Monitoring Parameters; DS = Data Source; DV = Decision Variables; HA = Hierarchical Aspect; I40 = Industry 4.0 technologies; IS = Industrial Sector; ODA = Optimisation Data Analysis; PDA = Predictive Data Analysis; RD = Research Design; SF = Study Focus; SSA = Systemic and Sustainable Aspects).

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