

# Artificial Intelligence as a driver for Prescriptive Maintenance: Limitations

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## Abstract

*The primary objective of this study is to investigate the contemporary impediments hindering the widespread adoption of prescriptive maintenance within the framework of Industry 5.0 technology. This endeavour encompasses a comprehensive analysis of the fundamental elements of the prescriptive maintenance concept, juxtaposed with a review of the latest advancements in academic and industrial realms. The industrial viewpoint is substantiated through the formation of a focused group comprising ten maintenance officers representing diverse industrial sectors. Furthermore, the study endeavours to provide actionable recommendations aimed at surmounting the identified limitations.*

## 1 Introduction

The global economy has undergone significant changes due to the combined forces of globalization and technological development. Consequently, supply chain management (SCM) for companies has evolved into a complex process. Presently, it is common to observe companies operating in one part of the world while having manufacturing facilities scattered across the globe. Technology plays a pivotal role in manufacturing and supply chain processes, minimizing the time gap for information flow at a nominal cost and enhancing customer service efficiency [1]. Within the supply chain (SC), logistics assumes a crucial role, translating the management's supply chain policies into practical action. Despite the revolutionary impact of technology on supply chains, there are inherent limitations to the development of logistical infrastructure, with improvements reaching a certain threshold. While information can traverse at the speed of light, the physical movement of goods is subject to its own time constraints [2].

Although the SCM is a critical success factor for an organization, it relates to its manufacturing capabilities. These capabilities are influenced by the maintenance strategy, which can significantly hinder the operational availability of equipment. Recent advancements in maintenance modelling, driven by data-centric methodologies like machine learning (ML), have opened a wide array of applications. In the manufacturing industry, managing functional safety throughout the product life cycle while containing maintenance costs poses a significant challenge [3]. A pivotal approach in tackling this challenge is predictive maintenance (PdM). Given the substantial volume of operational data generated by modern vehicles, ML emerges as an ideal tool for implementing PdM. Despite the extensive coverage of PdM and ML applications in manufacturing systems in various review papers, there is currently no comprehensive survey specifically addressing ML-based PdM for automotive systems [4].

The natural progression for predictive maintenance involves embracing a state-of-the-art approach to asset management, leveraging advanced analytics and machine learning to anticipate maintenance requirements and optimize equipment performance. This advanced strategy is termed prescriptive maintenance. Unlike merely pinpointing potential issues, prescriptive maintenance provides concrete recommendations for maintenance actions and operational adjustments [5].

Prescriptive maintenance leverages a combination of machine learning (ML) and artificial intelligence (AI) alongside the Industrial Internet of Things (IIoT) to provide precise recommendations for equipment maintenance. This integration encompasses technologies that scrutinize historical data, formulate assumptions, conduct tests, and iteratively analyse data. Through intricate algorithms, the software autonomously identifies and learns from data trends, efficiently recognizing and understanding data patterns. The machine learning process continuously reassesses models (files trained to recognize specific patterns) and data to accurately forecast what something will do at speeds unachievable by human analysts. Ultimately, prescriptive maintenance determines the potential outcomes of different actions and proposes the best approach [6].

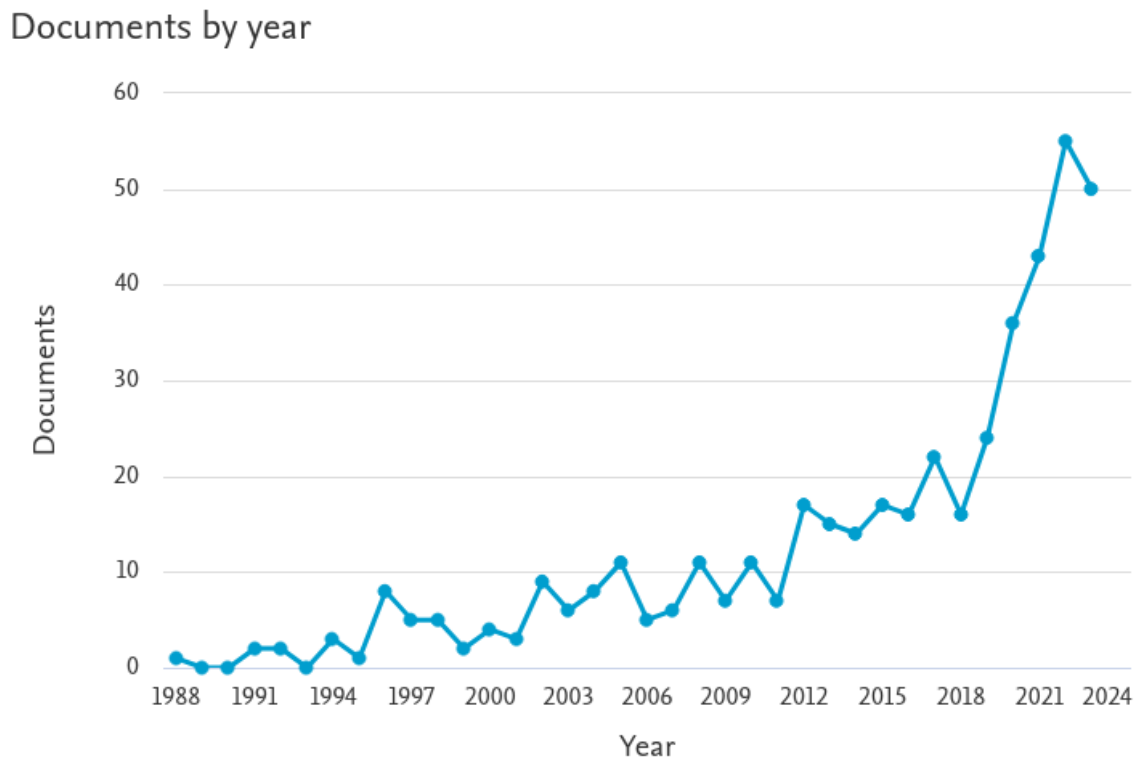
From a pragmatic standpoint, there is a notable incongruity in the maturity levels of theoretical maintenance management approaches as outlined in the literature [7]. While certain companies, particularly those operating in highly automated and technologically progressive sectors like the semiconductor industry, actively employ many of the cutting-edge approaches available, a significant majority of companies—particularly small and medium-sized enterprises—fail to consistently capitalize on the existing opportunities [8]. Therefore, it does make sense to further analyse the limitations to the progress of the concept, both from the applied perspective, but also from the technological dimension.

The sections proposed to address this goal are first, an estate of the art about the topic and related fields. The next section will be devoted to identifying the potential barriers and the last section addresses the Discussion and Conclusions.

## 2 State of the art

The literature review for the main concept “prescriptive maintenance” exhibits an increasing interest through time (See **Figure 1**)

**Figure 1.** Academic interest in the prescriptive maintenance concept.

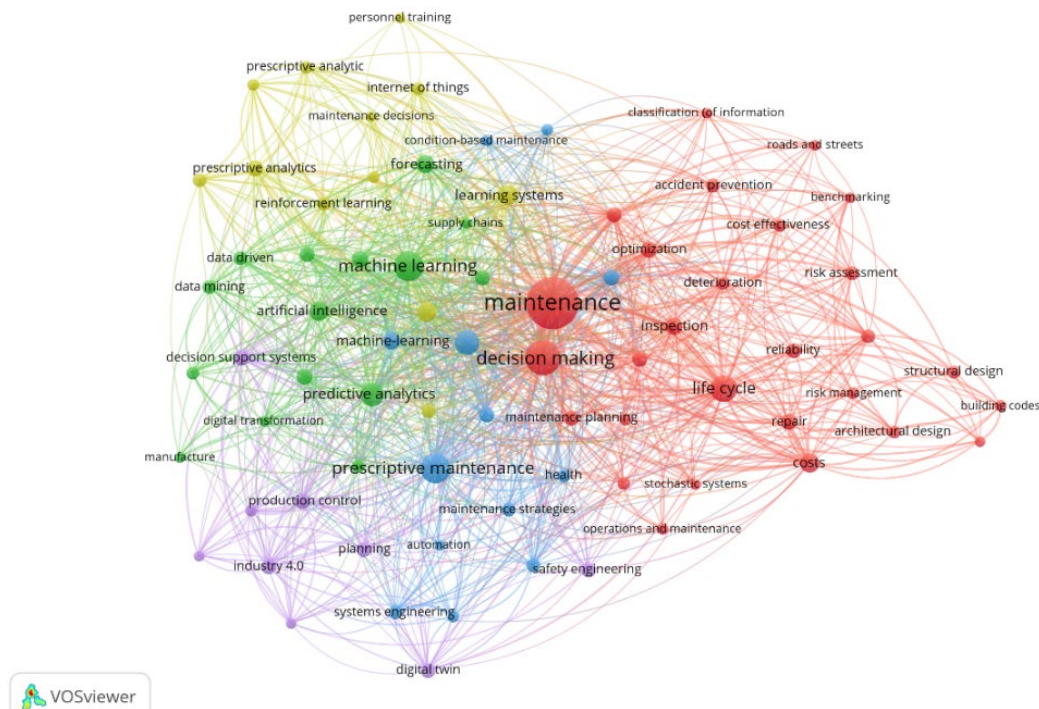


Source: Scopus.

When we analyse the co-occurrence of keywords as presented in **Figure 2**, it becomes clear the different clusters of factors related to the main one.

It becomes clear the connection between prescriptive maintenance with a different cluster, but strongly connected, where general maintenance, risk, inspection and safety, costs, design and life cycle are the key factors. This cluster accounts for asset management as well. In closed connection to those two, the cluster for AI, machine learning and predictive analytics is strongly connected to the application to prescriptive analytics, learning systems, reinforcement learning, internet of things and maintenance decisions. Finally, but importantly, a significant cluster related to prescriptive maintenance involving I4.0, planning, production control and digital twin is found.

**Figure 2.** Associated concepts to be considered according to the literature.



Source: Self elaborated by using VOS viewer tool®.

However, when the search includes the term barrier, the total number of papers jumps from 201 until just four, where just one conference paper from 2022 addresses the problem, where the focus looks in proposing a strategy to identify the action plan based on previous similar situations. This means that more research is needed to accurately identify the practical limitations for expanding the vision, because the identified ones and the promoted solutions have been not enough powerful.

### 3 Analysis of potential barriers

The contribution from [9] provides an analysis of barriers for adoption of predictive and prescriptive maintenance in aviation sector. They understand the Prescriptive Maintenance (PcM) as a concept that takes the PdM prediction that could improve the maintenance scheduling one step further by using the prediction to suggest optimized maintenance actions considering the entire ecosystem of aviation. These authors focus their attention in barriers for massive acceptance of PdM, from a literature review and a focus group with 24 experts in the field. They have highlighted five big topics as relevant barriers,

- Complexity of Prediction,
- Validation, Safety Assurance, and Regulatory Challenges
- Cost of Adoption
- Impact Estimation
- Data Availability, Quality, and Ownership

The work [6] makes a proposal for bridging the missing link between the maintenance literature and in industrial maintenance, to achieve an acceptance by the planner/operator using data-driven approaches. The authors recognize the ambiguity of the PcM and they proposed to identify five functional capabilities for characterising maintenance: Prediction capability, Optimisation capability, Adaptation capability, Learnability to continuously learn from former experiences, and Capability of intelligent actions and self-direction to (completely) automatise maintenance workflow and decision-support systems. They understand PcM to integrate descriptive, diagnostic, and predictive analytics, enabling them not just to comprehend past occurrences but also to forecast the probability of future events and the potential impacts of various decision alternatives (linked to maintenance strategies) on both the physical (machine) space and the related business processes.

Other authors identify decision support methods (equivalent to decision-making and recommendation methods in the literature), with PcM, respectively [10] but they do not look specifically on reasons for the limited support in the implementation.

Other industry specific studies [11], [12] or geographical studies such as [13] have been done, where lack of commitment from top managers as well as limited and overallocated resources or attitude, culture and training become relevant barriers, where different definitions are provided for the PcM concept, as presented in [14].

Theoretically, the adoption of PcM strategies can elevate the decision-making process for maintenance professionals, facilitating more efficient planning and execution of maintenance tasks. Consequently, this leads to reduced downtime and an extended lifespan for assets. The intelligent utilization of data-driven insights places prescriptive maintenance at the forefront of contemporary maintenance methodologies [15]. In this context machine learning and artificial intelligence not only predict future failures but also identify potential solutions.

A frequent limitation for PdM and PcM approaches is related to lack of balanced datasets. The absence of enough failure data is important because it is a basic input for carrying out model training, and the costs of implementing monitoring, associated with specific maintenance strategies, continue to be an obstacle to the implementation of this type of strategies strongly dependent on data.

The analysis of the literature as well as a focus group involving ten maintenance responsible technicians from different industry sectors allow us to recognize the need for a function-oriented description of the meaning of PcM, clarifying what is part of the PdM and what is not included in there. To this end, a proposal for a flexible framework covering such functional description can be a clear need, providing benefits by standardizing the concepts.

Another relevant issue potentially hindering the development of PcM is the generalization capabilities of the data-based models, normally trained with limited set of data and mainly strongly unbalanced. Most of the papers reporting good behaviour of modelling techniques relaying on data are limited to specific datasets and they fully ignore the need for continuous learning. Indeed, federated learning are not very much described in connection with PdM or PcM, although they are critical components.

Therefore, additional efforts are required from the academia and from developers in order to bring robust and resilient self-guided systems able not just to elaborate prognosis depending on asset's current status and different future operating conditions, but also to independently assess the accuracy and introduce close loop asynchronous leveraging measures, while they become enough transparent to explain what fine tuning operations have been performed, how efficient they became and how stable the global system becomes. These improvements can help to get involved the Maintenance responsible at the organizations. Indeed, by this way top managers will be more supportive to consider the new approaches, because they can find business benefits by making more realistic the production scheduling, by integrating asset maintenance planning with production decisions.

Finally, but yet importantly, there is an additional aspect but very relevant which is the management dimensions linked to the maintenance strategy, because PcM can be an excellent opportunity for changing specific business models, where asset ownership is transferred from final business owners to equipment manufacturers or OEMs, which move themselves to a Product Service System (PSS) business model as described in [16].

## 4 Conclusions

Based on the findings elucidated in the study, several scientifically significant conclusions can be drawn:

- **Emergence of Academic Interest in PcM:** The increasing attention garnered by Prescriptive Maintenance (PcM) within academic circles underscores its potential for value creation across diverse industries and geographic regions.
- **Scarcity of Industrial Implementations:** Despite growing academic interest, industrial implementations of PcM remain limited, with only a minimal number of management analyses addressing the underlying reasons or barriers. This scarcity underscores the need for further empirical research and practical applications to bridge the gap between theoretical advancements and real-world deployment.

- Identification of Barriers: While barriers to Predictive Maintenance (PdM) have been extensively studied, the adoption of PcM introduces new challenges, exacerbating existing barriers and necessitating a nuanced understanding of their underlying causes.
- Polyhedral Perspective of Practical Realizations: The findings from the focus group of maintenance technicians highlight the multifaceted nature of understanding PcM in practical settings. Participants' diverse perspectives underscore the need for standardized definitions and frameworks.
- Role of Standardization and Expectation Management: The study reveals a critical need for standardization in defining PcM and managing stakeholders' expectations. Addressing misalignments and discrepancies in understanding can enhance the feasibility and effectiveness of PcM initiatives.
- Identification of Managerial and Technological Barriers: Barriers to PcM deployment encompass both managerial and technological dimensions. Managerial challenges include aligning organizational objectives and incentivizing adoption, while technological hurdles centre on the maturity and stability of critical components, such as AI models, essential for PcM implementation.
- Potential of New Business Models: The potential of innovative business models, such as Product-Service Systems (PSS), can incentivize PcM adoption. By externalizing current assets and adopting a pay-as-per-use model, decision-makers can enhance economic performance.

In conclusion, the findings underscore the complex interplay between academic interest, industrial implementation, and practical challenges in realizing the full potential of PcM. Addressing identified barriers and leveraging innovative approaches, such as standardized frameworks and novel business models, are essential for unlocking the transformative benefits of PcM in Industry 5.0 contexts.

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## List of abbreviations and definitions

AI	Artificial Intelligence
IIoT	Industrial Internet of Things
ML	Machine Learning
PcM	Prescriptive Maintenance
PdM	Predictive Maintenance
SCM	Supply Chain management