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Unlocking the potential of predictive maintenance for intelligent manufacturing: A case study on potentials, barriers, and critical success factors

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ORIGINAL ARTICLE



Unlocking the Potential of Predictive Maintenance for Intelligent Manufacturing: a Case Study On Potentials, Barriers, and Critical Success Factors

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Abstract Predictive maintenance (PdM) is a data-driven maintenance strategy that aims to avoid unplanned downtimes by predicting the remaining lifetime of maintenance objects. Thus, unnecessary replacements of spare parts and critical process disturbances due to breakdowns can be avoided. Despite the widely recognized advantages of this technology, the number of successful applications in practice is still very limited. Our study aims to address the theory-practice gap by conducting a comprehensive case study involving 15 expert interviews with industry professionals to uncover critical factors that hinder the successful implementation of PdM. Our findings shed light on the underlying reasons for a hesitant PdM implementation, including challenges related to digital readiness, data quality and accessibility, technological integration, and maintenance organization. By providing an in-depth analysis of these factors, our study offers valuable insights and guidelines to improve the implementation success rate of PdM in the industrial context. Based on the empirical findings, we present critical implementation factors and develop a framework with ten propositions that aim to dismantle barriers in the industrial application process of PdM and stimulate further research in academia.

Keywords Predictive maintenance · Condition monitoring · Case study · Industry 4.0 · Digitalization · Implementation · Success factors

 $\textbf{JEL} \hspace{0.1cm} L60 \cdot O14 \cdot O32$

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1 Introduction

The fourth industrial revolution, also known as Industry 4.0, includes the implementation of digital technologies in the manufacturing sector. The related challenges aim for cost reduction, improved efficiency, and optimized utilization of resources (Alenizi et al. 2023; Kagermann et al. 2013). Simultaneously, today's supply chains are growing in complexity and are, therefore, more susceptible to disturbances. Reacting to these transformations, supply chain management increasingly requires stable and resilient processes with minimal delays or downtimes. To meet these requirements, predictive maintenance (PdM) has emerged as a critical area of interest in contemporary manufacturing management. This maintenance strategy aims to enhance maintenance practices by leveraging data-driven insights to predict and prevent equipment failures, ensuring minimal downtimes, low maintenance costs, and optimal asset performance (Schwendemann et al. 2021). Conventional strategies such as reactive and time-based maintenance lead to premature substitution of spare parts or unplanned downtimes. Consequently, long shutdown times or high costs for maintenance measures and spare parts can arise. Condition-based maintenance (CBM) faces this problem by constantly monitoring the current states of maintenance objects. PdM extends this approach by calculating the remaining useful life which allows for early indication of necessary maintenance measures and spare parts are replaced in advance of a breakdown. As a result, failures can be avoided in an early stage, which is particularly beneficial in interlinked processes with bottleneck machines and for equipment with very expensive spare parts. In particular, indirect maintenance costs, which represent opportunity costs due to occurred breakdowns, can be reduced to a minimum (Busse et al. 2019).

Despite the widely recognized potentials of PdM in enhancing operational efficiency and reducing downtime, the number of successful implementations in industry remains disproportionately low. The study of Haarman et al. (2018) shows that 60% of the surveyed European companies have tangible plans for PdM implementation, whereas only eleven percent successfully completed this task. These numbers highlight an enormous gap between planning and reality that needs to be addressed. Even though PdM shows a high potential for prescient maintenance management and stable production processes without unplanned breakdowns, there is a lack of successful industrial implementations (Srivastava and Mondal 2016; Welte et al. 2020) that go beyond investigations under laboratory conditions. In order to understand the reasons for the low implementation rate and to develop solutions, empirical research methods are appropriate, as highlighted in previous publications. Passlick et al. (2021) investigate Internet of Things-driven business models for maintenance and state a lack of empirical research in the field of PdM. Furthermore, van Oudenhoven et al. (2022) call for more practice-oriented research in the field of PdM implementation and advocate the development of more propositions. The study of Hoffmann and Lasch (2023) also highlights the need for empirical research to elaborate more on the reasons for a small number of successful PdM applications and analyze critical implementation factors.

To face this research gap, a qualitative case study is conducted in this paper, which allows for a rich exploration of real-world scenarios, offering a contextualized understanding of the potentials and challenges maintenance managers face in harnessing the full potential of predictive maintenance. Several related empirical case or interview studies have been published in the literature, considering CBM and PdM. However, they focus either on a single country or a specific industry. This concentration means that the diverse needs of different regions and sectors are not sufficiently taken into account.

A case study conducted by Tiddens et al. (2022) examines the motivation behind choosing specific PdM methods in practice. Therefore, 13 Dutch companies are examined regarding experience-based, reliability statistics, stressor-based, degradation-based, and model-based remaining useful life prediction. Robatto Simard et al. (2023) reviewed expectations and concerns about PdM in the Canadian mining industry by surveying seven mobile equipment experts in gold and diamond mines. Giada and Rossella (2021) conducted a case study with three companies to exploit the challenges and barriers of PdM implementation in the Italian machinery industry. Wagner and Hellingrath (2019) interviewed six German industry experts, predominantly management consultants. They developed a five-step process model for PdM projects based on theory and empirical insights. Grooss (2024) conducted a case study with four small and medium-sized Danish enterprises regarding the digitalization of maintenance processes. van Oudenhoven et al. (2022) extracted ten propositions from academic literature regarding the behavior of decision-making in PdM and conducted an interview study to verify these propositions with a strong focus on technology acceptance.

Addressing these shortcomings, our paper complements existing publications by the following contributions:

- We investigate 15 European companies of different sizes and seven varying sectors.
- We add a more practice-oriented perspective on opportunities and barriers to the existing literature.
- We establish propositions about further research in the field of PdM implementation.
- We develop solution approaches and provide a framework of requirements for a successful PdM implementation in practice.

Our paper follows a two-step approach. First, we aim to clarify potentials and barriers of PdM as a data-driven maintenance strategy in practical industrial applications. Therefore, we use qualitative interviews to derive empirical insights into the actual state of maintenance management in the investigated companies and the practical implementation of data-driven maintenance by examining potentials, barriers, and success factors in industrial companies. Second, we establish suggestions that intend to establish further research in this area. Furthermore, we want to stimulate support from academia and external institutions for the practical implementation of PdM. To achieve this, we consider the following specific research questions:

RQ1 How can PdM improve the targeted maintenance outcomes?

RQ2 How do barriers obstruct the successful implementation of PdM in practice?

RQ3 How can key success factors and external support allow for a successful implementation of PdM?

RQ4 How can existing barriers be addressed in a framework to support a successful PdM implementation and exploit future potentials?

The remainder of the paper is organized as follows: Section 2 includes an overview of existing maintenance strategies, PdM potentials, implementation barriers, and critical implementation factors in the academic literature. In Section 3, we outline the qualitative research methodology of this study, followed by Section 4, in which we present the findings of the interview study according to the first three research questions. Section 5 presents a framework with ten propositions regarding PdM implementation and potentials, according to research question four. Furthermore, we intend to provide maintenance practitioners with implications and point out further research directions based on the empirical insights of the study. Section 6 concludes with a summary of the study.

2 Theoretical Background

2.1 Maintenance Strategies

Before large data amounts and respective technologies were available, maintenance management was solely based on two conventional strategies. *Corrective* or *reactive maintenance* is the oldest and most straightforward procedure. It implies that necessary repairs are only conducted in the case of a failure occurrence and measures cannot be planned and scheduled in advance. As it can cause long downtimes, this strategy is feasible for objects that are not critical for the process and safety. The *time-based preventive maintenance* strategy is grounded on periodic inspections or replacements of parts to avoid breakdowns. Maintenance scheduling is based on manufacturer specifications and experience (Erbe et al. 2005; Ruiz-Sarmiento et al. 2020).

Data-driven maintenance strategies are becoming increasingly important since conventional approaches are not feasible to reach the high requirements of today's industrial process reliability. The approach of *CBM* includes constant or discrete monitoring of features that indicate the health state of an object. Consequently, faulty or conspicuous components can be replaced before a critical failure occurs (Erbe et al. 2005; Jardine et al. 2005; Mehta et al. 2015). While CBM offers a good starting point for data-driven maintenance, this strategy does not estimate the future state. Addressing this shortcoming, *PdM* aims to predict the remaining useful life of components so maintenance objects can be replaced in advance of a failure and the wear reserve can be used to the best possible extent, which also expands the level of maintenance schedulability. PdM enhances the sensor measurements and data analysis approaches of CBM by applying Artificial Intelligence (AI) and big data evaluation methods, which have made huge progress in the past years (Feng and Shanthikumar 2018; Hashemian and Bean 2011; Hoffmann and Lasch 2023; Selcuk 2017). In addition to industrial applications, CBM and PdM is used in other

Potential	References
Equipment avail- ability and pro- cess stability	Ansari et al. (2019), Arora and Rabe (2023), Davari et al. (2021), Gugaliya and Naikan (2020), Lai et al. (2019), Lee et al. (2011), Meddaoui et al. (2023), Sadegh Kouhestani et al. (2022), Selcuk (2017), Soualhi et al. (2022), Sun et al. (2010), Turnbull and Carroll (2021), Zio (2022), Zonta et al. (2020)
Reduced mainte- nance costs	Arora and Rabe (2023), Davari et al. (2021), Gao et al. (2018), Gugaliya and Naikan (2020), Jezzini et al. (2013), Kim et al. (2016), Lai et al. (2019), Lee et al. (2011), Meddaoui et al. (2023), Selcuk (2017), Soualhi et al. (2022), Sun et al. (2010), Turnbull and Carroll (2021), Zonta et al. (2020)
Extended life- time of spare parts and ma- chines	Arora and Rabe (2023), Gugaliya and Naikan (2020), Jezzini et al. (2013), Lai et al. (2019), Sun et al. (2010), Traini et al. (2021)
Schedulability of maintenance activities	Fink et al. (2020), Fink et al. (2020), Langone et al. (2015), Selcuk (2017)
Environmental protection	Ansari et al. (2019), Ingemarsdotter et al. (2021), Selcuk (2017)

 Table 1
 Academic view of PdM potentials

areas where fatal failures must be avoided, especially in aviation (Verhagen and De Boer 2018; Verhagen et al. 2023). The term *prescriptive maintenance* implies a more holistic approach that fuses data of PdM with information of the production planning and resource management to allow for data-driven decision-making in the complex maintenance management processes (Ansari et al. 2019).

2.2 PdM Potentials

The literature especially highlights the following potentials of PdM, which are summarized in Table 1. The main benefit of PdM is an accurate prediction of failures, implying that necessary maintenance measures can be initiated at an early stage and unplanned downtime can be avoided. As a result, plant availability is increased and process stability is improved. Reduced downtime also leads to reduced maintenance costs, particularly due to the avoidance of unplanned breakdowns and better plant utilization. In addition, by predicting the remaining useful life, wear parts can be used to their maximum potential, saving material and labor costs compared to timebased maintenance. Ongoing monitoring also helps to prevent equipment damage, resulting in a longer service life and higher residual value. Based on an accurate prediction of the remaining useful life, necessary maintenance activities can be scheduled in advance and as a positive environmental effect, waste is reduced due to the optimal usage of spare parts.

2.3 Barriers and Critical Success Factors of PdM

The small number of practical PdM applications indicates a variety of barriers in planning and implementation. The academic literature points out several obstacles that academia and practice are facing (see Table 2).

Barrier	References
Implementation effort/unclear return on investment	Arora and Rabe (2023), Gao et al. (2018), Gugaliya and Naikan (2020), Inge- marsdotter et al. (2021), Lai et al. (2019), Meddaoui et al. (2023), Omri et al. (2020), Zonta et al. (2020)
Missing data and machine parameter	Ansari et al. (2019), Arora and Rabe (2023), Cheng et al. (2022), Gao et al. (2018), Ingemarsdotter et al. (2021), Lai et al. (2019), Lee et al. (2011), Molęda et al. (2023), Omri et al. (2020), Paprocka et al. (2021), Sadegh Kouhestani et al. (2022), Shin et al. (2021), Theissler et al. (2021), Traini et al. (2021), Vallim Filho et al. (2022), Wen et al. (2022), Zio (2022)
Data privacy con- cerns	Ansari et al. (2019), Ingemarsdotter et al. (2021)
Necessary reorgani- zation	Ansari et al. (2019), Ingemarsdotter et al. (2021)
Lack of capacity and skilled workers	Ansari et al. (2019), Arora and Rabe (2023), Cheng et al. (2022), Gao et al. (2018), Ingemarsdotter et al. (2021), Lai et al. (2019), Molęda et al. (2023), Omri et al. (2020), Sun et al. (2010)
Missing knowl- edge about PdM advantages	Arora and Rabe (2023), Ingemarsdotter et al. (2021), Lai et al. (2019), Sun et al. (2010)
Reluctance from employees	Ansari et al. (2019); Ingemarsdotter et al. (2021), Theissler et al. (2021)
Data storage	Ingemarsdotter et al. (2021), Molęda et al. (2023)
Robustness, under- standability, and transferability of data-based models	Ansari et al. (2019), Cheng et al. (2022), Davari et al. (2021), Ingemarsdotter et al. (2021), Lee et al. (2011), Molęda et al. (2023), Sadegh Kouhestani et al. (2022), Soualhi et al. (2022), Theissler et al. (2021), Wen et al. (2022), Zhai et al. (2021), Zio (2022)

Table 2 Academic view of PdM implementation barriers

As a data-driven maintenance strategy, PdM relies on several Internet of Thingstechnologies (Dalzochio et al. 2020; Errandonea et al. 2020). First and foremost, sensors are needed to collect data on system parameters that indicate the system's condition. Large amounts of data are typically collected and analyzed using big data approaches or AI methods. The investment in these technologies is comparatively high. Due to the unclear payback period, companies consider the investment risks too high and do not implement them. While factory-installed sensors can measure machine parameters, data collection is not readily available for some systems. Furthermore, PdM requires a capable and secure IT-infrastructure to handle and store the large data amounts. The scholarly literature shows several barriers on the organizational level of maintenance too, for example necessary restructuring, lack of skilled labor for implementation, missing knowledge about the advantages and effects of PdM, and reluctance from employees.

Furthermore, the following critical success factors are discussed in the academic literature. A company-wide vision and strategy for PdM is essential to ensure a consistent and efficient implementation approach (Grubic et al. 2009; Ingemarsdotter et al. 2021). Pilot projects can be used to avoid the financial risk of large investments and to gain initial experience with a small investment of resources (Omri et al. 2020). PdM is a technology that requires specialists from different fields. Interdisciplinary cooperation is therefore essential for successful implementation (Cheng et al. 2022;

Gao et al. 2018; Ingemarsdotter et al. 2021; Lai et al. 2019; Selcuk 2017; Zonta et al. 2020). As a result, user-friendly applications are required that enable smooth collaboration between people and the system (Ingemarsdotter et al. 2021; Molęda et al. 2023; Omri et al. 2020; Shin et al. 2021).

3 Methodology

3.1 Case Study Research Design

This paper aims to uncover existing potentials and barriers of PdM implementation in industrial companies and provide maintenance managers and scholars with critical success factors and a guideline for this task. Therefore, we conducted a multiple case study based on semi-structured interviews with industrial maintenance experts. The empirical research method for this study is described in the following.

Implementing PdM is a complex task that is rarely based on a general structured process model due to its many application variants. Conducting expert interviews allows for obtaining a comprehensive picture of potentials and hurdles in implementation from the users' point of view, which is a common approach to investigate technology applications (Brandtner et al. 2021; Chew et al. 2018; Lutz et al. 2019). The potentials of PdM are evident in the scholarly literature (see Section 2.2). However, the number of successful implementations still remains behind expectations (Feldmann et al. 2018; Haarman et al. 2018; Welte et al. 2020). To provide academia with empirically substantiated theory in the context of PdM implementation, the structured multiple case study approaches from Eisenhardt (1989) and Yin (2018) were chosen for this study, whereas semi-structured and guideline-based expert interviews serve as input data. Comparing the different interviewed organizations as multiple cases enables us to derive substantiated insights (Yin 2018).

The methodological process is split into case study designing and planning, collecting data, data analysis, and reporting (Yin 2018). The research questions were initially defined based on the analyzed research gap in Section 1. The sampled case selection was executed across different sectors in European operations and logistics. The company size spectrum varies between small and medium-sized enterprises and large international companies listed in the EURO STOXX 50. The companies' sizes are classified according to the European Commission's definition of small and medium-sized enterprises from 2003 (European Commission 2003). We focused on a broad distribution of industries, resulting in insights into seven distinct industry sectors.

Following theoretical sampling strategies, the interview partners were selected by their position and experience in maintenance. Therefore, plant and maintenance managers were consulted. The characteristics of the sector, company size, position of the interviewees, and years of maintenance experience are compiled in Table 3. To ensure insights into potentials, barriers, and critical implementation factors, we considered both types of cases with and without a successfully implemented PdM strategy, considered as polar cases (Eisenhardt and Graebner 2007).

Table 3 Partic	cipants of interview study			
#	Industry	Size	Position of Interviewee(s)	Maintenance Experience (Years)
SEMI 1**	Semiconductor	Large	Maintenance Engineer	20-30
SEMI 2*	Semiconductor	Large	Maintenance Coordinator	>30
SEMI 3**	Semiconductor	Large	Maintenance Engineer	15-20
SEMI 4*	Semiconductor (R&D)	Medium	Chief Maintenance Officer	15-20
AUTO 1	Automotive	Large	Chief Maintenance Officer	20–30
AUTO 2	Automotive	Large	Maintenance Engineer	5-10
LOG 1**	Rail and truck logistics	Large	Process Manager for Diagnostics	15-20
LOG 2*	Rail logistics	Small	Maintenance Engineer	5-10
MECH 1*	Mechanical engineering	Large	Sales Manager of Maintenance Services+Development Engineer (2 in- terviewees)	5-10/10-15
MECH 2	Maintenance services	Large	Project Manager of Maintenance Services	10-15
CHEM 1**	Chemical industry	Large	Plant Manager	5-10
CHEM 2**	Chemical industry	Large	Chief Maintenance Officer	20–30
FOOD 1	Food industry	Medium	Chief Maintenance Officer	>30
FOOD 2	Food industry	Small	Plant Manager	<5
ELEC	Electronics industry	Medium	Chief Maintenance Officer	20–30
<pre>* currently im] ** successfully</pre>	plementing PdM / implemented PdM			

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In total, 15 in-depth interviews were carried out based on the interview guide in Appendix, which contained four sections. Initially, the interviewees were introduced to the topic and asked for general information about the company, the partner's position, and the years of maintenance experience (1). Thereupon, the currently applied maintenance strategies and reasons for this strategy mix were discussed (2). Afterwards, the achieved maintenance results and priorities, breakdown occurrence, as well as direct and indirect maintenance costs were enquired (3). In the last section, we discussed implementation barriers and preconditions to implement PdM (4). The guide also provided the interviewees with an overview of the topic in advance and helped to ensure the comparability of the data collected. The guide does not contain predefined answer options, so ad-hoc or further questions are possible during the interview to explain matters more detailed. The semi-guided expert interviews lasted 43 min on average, which led to a primary source of more than 150 transcribed text pages.

The task of coding and content analysis was conducted by two independent coders using the software MAXQDA 2022 according to the guidelines of Mayring (2015). The main categories of the code-system were developed deductively based on the research questions, the structure of the interview guide and a comprehensive literature review considering potentials, barriers and critical implementation factors in scholarly literature. Therefore, we searched for peer-reviewed articles in the databases ScienceDirect, Emerald, and Web of Science up to 2023.

Further codes were developed inductively during the coding process, which aims to enrich the existing literature with new evidence from practice. This deductive-inductive approach ensures that all relevant information from the interviews is included in the final evaluation and presentation of the results. It is oriented towards the grounded theory approach according to (Suddaby 2006) and aspires to address the theory-practice gap in the research area. The code system is presented in Appendix B. A theoretical saturation was reached after 15 analyzed cases as further interviews generated no more additional insights (Guest et al. 2006).

Since the coded transcripts were used as primary sources, interview accompanying notes of the interviewers, documents provided by the interviewees, and general information about the surveyed companies (e.g., annual accounts and websites) were included in the data set for triangulation and verification of the results.

A major goal of this study is to extract cross-case relations to allow for general statements and propositions about the implementation of industrial PdM. Consequently, the potentials, barriers, and critical implementation factors of PdM application stated by the interviewees were identified and classified. Afterwards, this information was aggregated to build general statements and recommendations for scholars and industry considering future research demand and critical implementation factors.

3.3 Quality Criteria of the Case Study

The following quality criteria for qualitative case studies according to Yin (2018) were considered to ensure a high quality of the examination. Firstly, reliability is a precondition for the reproducibility of the study. Therefore, a transparent research procedure is required. We prepared a research protocol, archived all relevant data for the study and described the research procedure in detail. Internal validity is characterized by the logical representation of cause-effect relationships in the research data. A systematic and transparent comparison is necessary to exploit patterns in the data, which is ensured by the structured evaluation with the code system. External validity describes the transferability and generalizability of the research findings. Therefore, interview partners from different industries and different company sizes were selected. In addition, the views of both, PdM applicators and service providers, were considered. Hence, the selective case selection allows for theory building within the scope of this study (Eisenhardt 1989). Construct validity is guaranteed when the correct research methods are applied to answer the research questions. Consequently, the interview partners were informed in advance about the guide and anonymization of the persons and companies was assured so that the interviewees could also express themselves critically about facts without risking any consequences (Yin 2018).

4 Findings

In the following subsections, we provide insights into the potentials, barriers, and critical factors for the successful implementation of PdM in industry according to the first three research questions and interview questions.

4.1 Potentials of PdM Considering Maintenance Outcome

4.1.1 Process-related Benefits

Every expert expressed the superior importance of *equipment availability* within the maintenance management. This key figure represents the highest target in most analyzed organizations. Availability is predominantly characterized by the mean time to repair, reaction time, and resource disposability (AUTO 1, SEMI 4). With the help of PdM, machinery failures can be predicted in advance, and necessary maintenance measures can be scheduled. Furthermore, unplanned downtimes can affect subsequent process steps which lead to disruptions and high losses, especially in flow shops:

"We had a major malfunction that meant we didn't build a single car body for almost three days. This, in fact, led to delays in the entire car production" (AUTO 2).

Compared to less advanced maintenance strategies where the object's current state is unknown, such as corrective or time-based maintenance, PdM offers a high potential to prevent unplanned downtimes. Therefore, the reaction time is minimized, resource availability can be ensured, and the mean time to repair is reduced as the maintenance staff can prepare themselves for an upcoming repair. The experts highlight the opportunity to carry out pending maintenance activities during unproductive times (e.g., weekend or night-shift) (MECH 1), set-up times (CHEM 1), and while mobile equipment is in the vicinity of the workshop (locomotives) (LOG 2).

As PdM can be seen as an extension of CBM, it involves *continuous monitoring* of maintenance objects. Therefore, ad-hoc failures can also be diagnosed and the system provides a 24/7 observation of the objects (SEMI 2). Consequently, failures such as line breaks can be detected when there is no active production. PdM is also frequently used in industries where the production has to run constantly and 24/7 as it is too costly and energy-consuming to shut down a plant and start it up again:

"Constant monitoring is all the more important in industries where processes are highly interlinked and a plant cannot simply be shut down, as is the case with one of our customers in the paper industry" (MECH 2).

PdM enables constant monitoring of critical equipment and, therefore, ensures process stability, which is highly relevant for interlinked and vulnerable processes. When failures or breakdowns occur, errors can affect the product quality and lead to rejects or scrap:

"Suitable objects for predictive maintenance are vacuum pumps because the failure of the pump causes damage to the product in the plant, leading to discarding of a wafer" (SEMI 2).

Furthermore, a constantly known state of maintenance objects also affects risk management in a positive manner. In particular, processes without redundant machinery carry a high risk of downtime throughout the production chain, which can be mitigated by an appropriate data-based maintenance strategy (FOOD 1).

The large amount of data also allows *easy indexing* of equipment conditions based on multiple sensor data (SEMI 2, CHEM 1). These indices can be used for a graphical dashboard that provides a good overview of the condition of the entire maintenance objects.

4.1.2 Organizational Benefits

Remaining useful life prediction makes it possible to predict precisely when a failure will occur, which enables good schedulability of necessary maintenance measures well in advance. In particular, compared to reactive maintenance and CBM, PdM allows good planning of required resources such as personnel, spare parts, and tools (MECH 2). In time-based preventive maintenance, planning scheduled maintenance measures is comparatively easy as intervals are fixed. However, this maintenance strategy harbors the risk of unplanned breakdowns and emergency reactions. In comparison, PdM can detect failures in advance with sufficient time for resource planning. This characteristic makes PdM the maintenance strategy with the best plannability. In addition, the amount of data available allows for an easy transition to *automated work scheduling* of maintenance activities, reducing manual and error-prone planning (SEMI 1, AUTO 1).

Legal requirements and corporate efforts to improve *health and safety* at work continue to grow, which is underlined by the following statements:

"Among the three main objectives of maintenance–plant availability, cost efficiency, and safety of people and the environment–the latter is the most important for us" (ELEC).

"Safety of employees and environment is by far our highest priority" (CHEM 2).

PdM enables numerous safety applications in industrial environments, for example, preventing the leakage of toxic gases (SEMI 3), hazards in train traffic for passengers or employees (LOG 1), chemical substances (SEMI 4), and rotating equipment (CHEM 1).

The potential of *environmental protection* is discussed two-fold by the interviewees. One aspect is to ensure that no harmful substances are released into the environment. In the same way as in occupational health and safety, this is ensured by using CBM or PdM to continuously monitor facilities with hazardous substances and to detect leaks at an early stage (CHEM 2, SEMI 3). On the other hand, PdM has further positive ecological effects as fewer spare parts have to be produced and transported and less waste is produced due to the optimal utilization of the wear reserve.

The continuous monitoring and storage of system parameters enables extensive root cause analysis in the event of failures. On the one hand, such run-to-failure data is very valuable for training and optimizing remaining useful life algorithms (Lei et al. 2018). On the other hand, it can be used to create a *knowledge database* for maintenance staff, including fault indicators and causes (LOG 1). Such a database is also used to categorize and visualize defects. In this way, it is possible to monitor both the focal points or leading causes of errors and to implement prioritized improvement measures (FOOD 1) strategically.

4.1.3 Cost-related Benefits

In order to examine the impact of PdM on costs, a division into direct and indirect maintenance costs is necessary. *Direct maintenance costs* include all the expenses related to the actual maintenance measures, such as spare parts, human resources, and additional materials. The experts express far-reaching benefits in reducing manual work and the associated saving of labor in operational maintenance (CHEM 2). Two major factors cause this reduction. Compared to time-based preventive maintenance, PdM leads to fewer maintenance measures since the wear reserve is fully used and parts are not replaced so often (SEMI 1), which leads to reduced material costs. Furthermore, PdM requires fewer employees on standby since the risks of unplanned failures and breakdowns are minimal. Since spare parts can be procured on demand and less stock has to be held, storage costs are reduced (MECH 1).

Indirect maintenance costs are opportunity costs that arise due to breakdowns. Particularly in manufacturing companies, where very tight process windows must be maintained, individual system failures can lead to costly scrap and reduced output, resulting in lost revenue. Therefore, accurate condition prediction of bottleneck objects is supportive of avoiding high follow-up costs (SEMI 2). Furthermore, production downtimes can lead to delivery failures (MECH 2). As a result, very high contractual penalties can be claimed by customers (MECH 1). To avoid such events in case of a breakdown, costly ad-hoc measures are necessary, as expressed by one interviewee:

"We once had a very special part flown in by charter plane and then collected from the airport by a helicopter" (CHEM 2).

PdM can also *extend the equipment's lifetime* by reducing or eliminating major damage and replacing only worn parts. In addition, expensive replacement investments can be reduced and the lifecycle costs decrease (MECH 2, SEMI 3) (see 4.1.4).

4.1.4 Strategic and Competitive Advantages

When used in its entirety, PdM delivers profound benefits to the structure and organization of factories. Constantly monitoring and predicting conditions can reduce redundancies and overcapacities in critical production processes, which allows a *leaner production layout* with less spare capacity. By making more efficient use of existing capacity, higher output can be achieved through optimized availability. As a result, production floor space is reduced. Similar effects can be completed in warehousing and logistics. Making maintenance more predictable and reducing the risk of unplanned downtimes means fewer spare parts need to be held in stock, *freeing up valuable storage capacity and capital*. These savings also have positive ecological impacts, as continuous condition monitoring also detects worn components and abnormal resistances, *preventing excessive power consumption* (SEMI 2).

The implementation of PdM always involves the use of data acquisition methods and sensors. The vast amount of data can be used strategically by equipment manufacturers to optimize future versions of machines and to identify weak points through *installed base information* (SEMI 2). In addition, sales potential can be created by offering customers and users individually tailored *after-sales services* that take the condition of the plant and the operating conditions into account. This is of particular interest to companies that outsource maintenance services.

Many companies become more aware of the products' *lifecycle costs*. PdM can reduce maintenance costs considerably, which enables manufacturers and service providers to generate a competitive advantage and *differentiate* themselves. Interviewee MECH 1 reported that some customers already include lifecycle costs in the tender for new equipment and contractually reserve the right to renegotiate prices after a few years if the planned lifecycle costs are unmet.

Furthermore, the interviewee observes that customers have ever less in-house maintenance expertise. Therefore, in the future, the company would like to equip all new facilities with sensors for PdM in order to facilitate maintenance for the customer or offer it as a *comprehensive maintenance service* (MECH 1).

On the one hand, offering comprehensive maintenance solutions can strengthen customer loyalty, which can also lead to *additional revenue*:

"For us, it is also additional potential, an opportunity to earn money with a corresponding application. Not only with the material that we sell, but also with a monitoring product" (MECH 1).

4.2 Barriers and Obstacles

4.2.1 Process-related Barriers

Maintenance structures have been developed in many companies over several decades, and good results are achieved with more straightforward maintenance strategies. All interviewees stated that time-based maintenance is the predominant approach in their organizations and that some assets are still maintained reactively with a run-to-failure strategy. Many employees have acquired extensive knowledge and experience over many years and know the specifics of the facilities very well. As a result, many plants achieve *high availability without any condition monitoring* (SEMI 1, AUTO 1, LOG 1, ELEC). Consequently, some companies do not need complex data-driven maintenance systems.

"Once we've reached an availability of 97%, PdM will be necessary to gain additional 2.5% of availability. But we are not at this point yet" (AUTO 1).

Since availability is based on the extensive experience of employees, comprehensive knowledge management is crucial. Furthermore, it has to be noted that a focus on availability alone ignores the cost savings from reduced maintenance activities and less needed spare parts.

A major inhibiting factor is data privacy concerns, whereas several subcategories can be identified. Firstly, data manipulation is a critical aspect of SEMI 1. The interviewee fears that existing datasets can be changed, resulting in incorrect thresholds or learning values that lead to wrong forecasts or decisions. Another risk is the unintentional transfer of data, in which process and system data from sensitive production steps can be accessed. The risk of external intrusion in the networking of plants is too high for the companies (AUTO 1). The criteria of production safety have the highest priority, and the risk of know-how loss is considered too high, which is why PdM techniques haven't been implemented yet. In addition, the internal requirements for IT security are so restrictive that these technologies cannot be installed in some surveyed companies at present (SEMI 1, AUTO 1). Furthermore, one expert expressed vital concern that the direct connection of sensors and actuators could be a gateway for hacking, which is particularly problematic because such an attack could directly threaten human life and limb. Furthermore, lengthy approval processes make introducing data-driven maintenance techniques very timeconsuming (LOG 1).

The process of PdM implementation is lengthy and time-consuming. First, a concept must be developed, and then the sensors must be procured and installed. After that, suitable evaluation programs are required, which must also be compatible with existing maintenance information systems. Some of these process steps need particular expertise that is not always available in-house. Therefore, companies are often dependent on external know-how. Once these processes are complete, problems with *false or missed alarms* are to be expected at the beginning. Accuracy then increases over time as the amount of data increases. The PdM system cannot be relied on blindly, especially at the beginning of its use, because there is *no run-to-failure data* from which the system can identify which anomalies lead to breakdowns (LOG 1, CHEM 1).

4.2.2 Organizational Barriers

On a company level, maintenance is still *not seen as a strategic component* of operations and logistics but as a necessary support process that must be carried out costefficiently. There is a missing understanding of PdM in responsible departments of the company. As a result, investment in this non-value-adding area is given lower priority, which in turn inhibits innovation (AUTO 1, LOG 1, FOOD 2). Furthermore, large organizations *lack a company-wide strategy* to develop and implement new technologies, which causes inefficiency:

"Within the numerous divisions of the company, many employees deal with the technologies such as CBM or PdM. That means that everyone is doing something and then you find out that another division of the company has already developed a similar solution. But they didn't know about each other, they don't talk to each other" (LOG 1).

Another constraint is the *lack of capacity* to do sufficient work on new technologies. Operational tasks and problems often dominate and there is not enough time to deal with the strategic development of maintenance (AUTO 1). One interviewee stated that a new department would be needed to develop and implement PdM dedicated solely to this issue across the company (SEMI 2).

Deploying PdM requires extensive sensing, signal processing, programming, machine learning, and IT infrastructure expertise. In all these areas, there is a severe *shortage of skilled workers* in Europe, and only a few companies can fully handle these tasks with internal staff. In particular, a shortage of programmers significantly hampers the introduction of new maintenance technologies (AUTO 1, MECH 2). This shortage forces companies to rely on *external specialists*, increasing costs, dependencies, and reducing the ability to react quickly to changes and problems. On the other hand, such an outsourcing solution makes it possible to implement initial PdM projects with a calculable effort without acquiring and employing their own specialized staff, which leads to greater flexibility (SEMI 2, AUTO 1, CHEM 1).

Some organizations experience *reluctance from employees* when introducing new technology in maintenance. To increase acceptance, respondents see the need to clearly communicate the benefits and achieve positive results with small projects (AUTO 1, MECH 2). This problem is accompanied by *missing knowledge about PdM advantages* (CHEM 1) and management's exaggerated ideas about the benefits of PdM (LOG 1). Consequently, meaningful metrics are needed to evaluate successful PdM applications (Velmurugan and Dhingra 2015). The survey of maintenance professionals revealed that no or only *very rudimentary KPIs* have yet been implemented to assess the maintenance results. Three companies have not yet im-

plemented KPIs (SEMI 2, SEMI 4, FOOD 2). In all the others, maintenance is evaluated based on equipment availability. One company also measures the *Mean Time Between Failure* (SEMI 3). FOOD 1 additionally uses *Overall Equipment Efficiency*, mainly implemented in production, to draw conclusions about maintenance effectiveness. It can be concluded that no specific KPIs have been used so far to adequately record and evaluate the results of different maintenance strategies, which consider, for example, direct and indirect maintenance costs simultaneously.

4.2.3 Cost-related Barriers

As mentioned in section 4.1.3, PdM has a far-reaching impact on maintenance costs. Hence, this fact also causes barriers to a successful implementation. In most surveyed companies, investments in data-driven maintenance systems are only approved if there is a relatively short payback period. As the positive effects on maintenance cannot be measured in the short term but only in the medium to long term, the problem of an *unclear return on investment* arises (SEMI 1) compared with the risk of sunk costs:

"I see the risk in the level of investment in PdM, with the risk of not achieving higher machine availability or reliability in the end. Then it will quickly turn out to be nonsense" (MECH 2)

Interviewee LOG 1 claims that positive effects on downtimes and maintenance costs cannot be expected within five years of the beginning of the implementation project. Consequently, the management does not authorize investments as PdM is perceived as disproportionately risky and unprofitable, caused by the comparatively high investment costs (AUTO 1) and doubts about measurable added value in more increased availability.

PdM shows a *diminishing marginal benefit* with increasing investment in complex maintenance systems. New plants often already have extensive sensor technology and data transmission media installed that can be used for PdM, which reduces investment costs considerably. Older plants, however, are not always equipped with condition monitoring sensors. The *cost of retrofitting* this infrastructure is very high and uneconomical, so PdM is often only viable for newer plants (SEMI 1, CHEM 1, MECH 2).

Another barrier is the additional *cost of expanding the IT infrastructure*. Many companies do not have sufficient capacity to exchange large amounts of data; in some cases, there is not enough bandwidth available for mobile applications (AUTO 1). The costly *storage of large amounts of data* is another limiting factor that leads to additional investments in a more extensive server infrastructure or cloud-computing solutions (AUTO 2). A further cost-related barrier is represented by *running costs of the systems' maintenance*. One interviewee described previous experiences with similar software-based processes in the company. Over time, these have led to major compatibility problems when new hardware or related software versions are introduced.

"For example, we had small programs created by working students. The working student is gone, the programs exist, but how are they maintained if something happens? Not every program is compatible. It's also quite a big job to maintain and customize the software. One should definitely not underestimate this if we are now embarking on Internet of Things- solutions" (SEMI 1)

In addition, lock-in effects lead to costly product support from vendors (SEMI 1). Additional costs don't come from the sensors themselves but from connecting them to systems with developed evaluation routines (AUTO 1) and creating the necessary infrastructure (LOG 1), which is also a major drain on human resources.

4.2.4 Technological Barriers

PdM requires sophisticated information systems and must be seen as a holistic approach with numerous interfaces to other systems and sections in the company. In this context, the maintenance experts have outlined several technological barriers. *Compatibility problems* represent a major hurdle for the companies. In the past, many software solutions in other areas of SCM have been developed in isolation and have not been integrated into the overall IT infrastructure. Thus, maintaining software products is very difficult, resulting in individual products becoming incompatible with newer devices or new versions of connected systems. Once the plant is equipped with condition monitoring sensors from the equipment manufacturers, the connection of sensors to the companies' systems is another critical factor where compatibility problems can arise. Therefore, interfaces must be clearly defined and standardized (SEMI 1, SEMI 2).

Equipment manufacturers usually provide recommendations on maintenance intervals and maintenance actions for time-based or usage-based maintenance. Such *manufacturer specifications for CBM and PdM* are often missing. As a result, users cannot rely on predefined thresholds for condition-based operation but must gain the necessary experience over a more extended period. As a result, positive effects on maintenance costs will occur later and unplanned breakdowns will occur regardless of CBM systems (SEMI 1, AUTO 1). It is expected that equipment manufacturers generate more revenue from the sale of frequently replaced worn parts and, therefore, are not motivated to support customers in implementing CBM or PdM. However, it can be assumed that the necessary information on failure behavior is available.

Plant users have very different requirements for condition monitoring. Often, the systems must be retrofitted with sensors during their lifetime to use PdM. Retrofitting is sometimes difficult because of limited installation space and the *lack of open interfaces* to integrate the sensors into the existing system architecture (SEMI 1).

The operator of mobile maintenance assets mentions another hurdle related to the existing public *mobile network infrastructure*. Due to the poor coverage of 5G networks in rural areas, real-time monitoring in operating trains does not work in full coverage and data exchange is delayed or canceled. For this reason, the company currently postpones major investments in PdM (LOG 1).

4.3 Key Success Factors of Implementation and External Support Opportunities

Analysis of the barriers to PdM adoption shows many reasons for the low adoption rate. In the following, critical success factors that should enable the implementation of a PdM strategy are discussed. In addition, we analyze which external support offers are helpful to support companies in implementing PdM.

4.3.1 Organizational Success Factors

Implementing PdM is a very complex challenge, both technologically and organizationally. To master this task, experts from different areas have to work together. A key factor in the organization is conducting implementation projects with an interdisciplinary team, which makes it possible to understand the complex interrelationships of plant design, failure behavior, data collection, data evaluation, and forecasting and to develop suitable solutions. Furthermore, appropriate solutions must be evaluated concerning their economic efficiency to reduce the total maintenance costs (MECH 1).

Smaller implementation projects can gain initial PdM experience with limited resources. Such *lighthouse projects* make it possible to evaluate the effort and benefits of PdM and, if the results are positive, to create a higher level of acceptance among colleagues and management. Based on this experience, other projects can follow and mistakes can be avoided in the early stages. At the maintenance management level, it is possible to assess which technologies are suitable for the PdM application area and where there is potential for further improvement. In that way, a risk-minimal entrance into the field of PdM can be found, laying a solid foundation for further implementation projects (AUTO 1).

Interviewee SEMI 2 experienced a tradeoff between agility in small and mediumsized enterprises and financial opportunities of large companies combined with economies of scale in implementing new technologies. In large and financially strong companies, decisions for PdM are made more frequently, while these take longer to implement. On the other hand, implementation projects at small and mediumsized enterprises are often postponed due to excessive costs and risks but can be implemented much faster when the project starts. As a critical success factor, it can be deduced that a *courageous entry* into the technology with manageable risks is necessary. At the same time, PdM is then implemented with a high level of *agility* (SEMI 2, LOG 1).

The monetary benefit of PdM is challenging to calculate, and the advantage only materializes after a few years in case critical failures are avoided. It is primarily unknown what the consequential costs of such a failure would have been. For this reason, implementing PdM is initially seen as a cost driver. To overcome this problem, it is necessary to have a *basis for evaluating the long-term cost-benefits of PdM* on maintenance costs, which is not addressed adequately in the existing research literature (CHEM 1).

Many companies do not sufficiently consider indirect maintenance costs (see 4.1.3). However, the actual advantage of PdM can only be determined by a *holistic cost calculation* that takes into account both direct and indirect maintenance costs:

"One has to follow a holistic approach and ask the question: if a plant is down for four hours, what costs does that cause beyond the direct maintenance costs? Do I perhaps have any delivery problems with the customer, etc.?" (MECH 2).

4.3.2 Technological Success Factors

A wide range of plant and machinery can be maintained predictively. The vast array of options makes devising and implementing plug-and-play solutions challenging. All companies surveyed that have employed PdM have had to configure the technological solutions independently and integrate them into current systems. One of the interviewed companies, which employs many maintenance objects of the same kind, has instituted a *laboratory-style testing field*. This field is utilized to test solutions on a small scale before deployment on the entire fleet. By doing so, both software and hardware requirements are met and start-up issues are reduced (LOG 1).

Moreover, one can acquire valuable experience, which can prove beneficial for subsequent undertakings. Such experience necessitates a comprehensive knowledge repository archived in a knowledge base. Additionally, interviewee MECH 2 highlights the importance of fault documentation in establishing limits for CBM and PdM.

4.3.3 External Success Factors

The interviewees are aware that research in the field of PdM is already much more advanced than practical implementation. More technology transfer from research institutions to practice is required to overcome the low application of PdM. Interview partner AUTO 1, therefore, calls for more *academic cooperation*:

"Funding might not be a bad thing. If somebody could help with the implementation of PdM, to find a solution together through a research association, through a cooperation agreement with a university or something like that, that would help us" (AUTO 1).

In addition, CHEM 1 achieved economies of scale in introducing PdM by *sharing the development costs* through cooperation with other companies in the same industry. The expert also points out that the necessary sensor technology and evaluation software are still expensive and that implementation will only become attractive for many companies if prices continue to fall.

5 Discussion

The following section intends to interpret and discuss the case study findings by exploiting relationships between the different categories. We provide ten propositions



Fig. 1 Framework of propositions regarding PdM implementation and potentials

regarding measures to overcome the analyzed barriers and how PdM will influence maintenance management in the future. Furthermore, we discuss managerial and research implications based on the interview findings.

5.1 Framework and Propositions

The framework in Fig. 1 shows relationships between the grouped barriers, critical implementation factors, and potentials. They are organized vertically according to their internal or external characteristics. We exploit related critical implementation factors after grouping the inductively and deductively determined barriers. Based on those relationships, we formulate five propositions (P1–P5) on overcoming the obstacles and successfully implementing PdM. Furthermore, we state five propositions (P6–P10) about future PdM potentials and their influence on maintenance and supply chain management. The propositions intend to encourage further research in the field of PdM implementation and to remove obstacles in practice systematically.

The interviewees stated that a lack of strategy hinders the introduction of PdM. Our results suggest that the management should define the implementation objectives, which can be approached in a structured manner. The concept phase can be simplified and implementation standardized using a structured policy and process. It should be noted, however, that the large number of different maintenance objects makes developing a uniform standard difficult. Another issue arises from the limited availability of employees to take care of the strategic maintenance orientation alongside their operational activities. To tackle this challenge, pilot projects can be implemented by smaller teams for the introduction and testing of PdM in agile environments.

P1: A structured implementation process and laboratory-level implementation initiatives can address the problem of lacking deployment strategies and limited

capacity to obtain initial PdM implementation exposure with a reasonable number of employees.

Such laboratory-scale implementations also allow for a mitigation of misinvestment risks and an evaluation of the implemented hardware and software before PdM is scaled up to larger dimensions. The positive results from introducing PdM can only be expected over a more extended period of time as the favorable effects mainly result from avoiding breakdowns, which cause high opportunity costs.

P2: The high initial investment and running expenses of PdM solutions impede its broad industrial implementation, and an excessive focus on return on investment leads to a disregard for long-term advantages. Thus, comprehensive cost estimation and long-term cost-benefit analysis models are required.

PdM requires large volumes of sensor and machinery data, which are analyzed via big data technologies or AI and transmitted in interconnected networks. Therefore, PdM relies on technologies assigned to the Industrial Internet of Things (Taşcı et al. 2023). On the other hand, companies are lagging behind in the digital transformation, which is particularly the case for small and medium-sized enterprises.

P3: Companies with limited digitalization are unlikely to adopt PdM in the near future due to a lack of necessary IT infrastructure. Hence, digital transformation can be seen as a precondition for PdM.

Some interviewees expressed concern about the shortage of skilled workers available in the labor market to fulfill the diverse tasks of digitalization, including the implementation of data-driven processes such as PdM. Additionally, many companies face resistance to technological innovations within their workforce. Some employees associate the introduction of AI with job losses. This misconception can only be dispelled through transparent information and knowledge transfer.

P4: Comprehensive information about PdM advantages, as well as a focus on education and training, helps to overcome several implementation barriers for PdM, for example, reluctance from employees, missing knowledge about PdM benefits, the shortage of PdM-specific skills and external experts.

In existing publications, researchers expressed concerns about the absence of validation methods for current models and data to enhance the robustness and comprehensibility of PdM models. On the other hand, industrial companies have numerous potential application cases for theoretically developed models that could be validated and tested in real scenarios.

P5: There is a need for structured collaboration between academia and companies regarding the implementation of PdM, which would boost the efficiency of development processes, reduce costs, and address the challenge of missing internal and external specialists.

The presented propositions indicate several recommendations for practitioners to approach PdM implementation or lay the foundations to exploit the potential of datadriven maintenance, particularly to create a digital infrastructure and the dedicated start via pilot projects. In addition, the following propositions highlight the benefits of PdM that the interviewees consider most relevant for the future:

P6: PdM offers high sales potential for machine manufacturers and maintenance service providers, as the technology enables them to differentiate from their competitors and build stronger customer relationships.

P7: When applied to maintenance objects that have a high criticality on the process or require expensive spare parts, PdM reduces the overall maintenance costs.

P8: PdM enables the streamlining of organizational processes. An automated work organization in prescriptive maintenance is conceivable through a holistic connection to adjacent areas, such as ordering and shift planning.

P9: PdM is a core component of the Industrial Internet of Things. It enables more stable processes and helps to reduce supply chain risks.

P10: PdM positively affects social and economic sustainability due to higher machine safety and reduced spare parts consumption.

5.2 Managerial Implications

The findings of this study intend to support practitioners in implementing PdM to those maintenance objects where it generates added value and leads to reduced overall costs.

PdM should be considered a long-term investment in process stability. The financial benefits may not be immediately apparent in reduced running costs but in preventing damage and indirect maintenance costs resulting from critical failures. Therefore, PdM is an essential component of the company's risk management strategy, acting as an insurance policy against damage caused by unplanned downtime. To quantify this added value, it is necessary to perform *holistic cost calculations* that consider the reduced risks and opportunity costs.

On the other hand, PdM is not a panacea for maintenance obstacles. Instead, it is recommended to implement it in a targeted manner for critical systems where failures must be prevented due to safety concerns, process stability, or indirect maintenance costs. Additionally, it is essential to note that PdM cannot function as a standalone solution and requires *thorough integration into the maintenance organization*. The implementation of PdM is often hindered by an inadequate IT infrastructure and a shortage of programmers and AI specialists, which are required to connect to existing application systems and meet the need for extensive IT expertise. These issues are not unique to PdM and are common obstacles for many technologies in the Internet of Things-environment. Additionally, the reluctance of many employees to embrace new technologies is a major issue in practice. This problem is also evident in the challenge of implementing purely top-down approaches when employees do not accept them. One solution is to *provide comprehensive information* to dispel prejudices and demonstrate the benefits for users.

If maintenance is considered as a service offered by plant manufacturers and service providers, there is high potential for the *utilization and commercialization of PdM*. The widespread use of sensors in running plants can provide valuable information about failure behavior and usage patterns, which can be used to develop future plant generations, so-called installed-based information. Furthermore, service contracts can lead to strong customer relationships and long-term sales in the after-sales phase.

To mitigate the risk of malinvestment and sunk costs, conducting pilot projects on a smaller scale is recommended. This approach allows initial experience to be gained with a smaller project team and for initial results to be validated. If these pilot maintenance objects on a larger scope. It is reasonable to assume that introducing this technology is associated with high costs, mainly due to the demands on IT infrastructure. However, economies of scale will considerably decrease marginal costs for implementing it on additional objects. One different approach to reduce implementation costs is to collaborate with other companies, which allows for pooling of resources to compensate for the lack of specialists.

5.3 Academic Implications

This study can substantiate several findings of previous research in the field of PdM implementation. Evidence exists regarding the economic benefits of PdM, the need for high-quality data, the focus on human und know-how, missing IT infrastructure, and a need for more skilled data analysts. However, further relevant aspects of PdM implementation could be identified by considering different regions and industries. These include enhanced safety for humans and the environment, differences between small and large companies in managing the digital transformation, including the implementation of PdM, and cooperation among companies. The study also revealed several directions for further academic research.

In addition to the mentioned partnerships between companies, collaborating with research institutions holds great potential. They have a high level of technological expertise and can provide support, particularly in parameterizing algorithms for anomaly detection and remaining useful life forecasting. *Interdisciplinary cooperation* is assumed to lead to a more efficient implementation of PdM, allowing for the utilization of synergy effects between partners.

A major obstacle regarding the decision to implement PdM is unclear monetary benefits, which is caused by difficult measurement and prediction of indirect maintenance costs. To overcome this issue, *holistic calculation models* that take the benefits of reduced direct and indirect maintenance costs into account, are required. The latter include the impact of equipment failures on complex supply chains and the cost of supply disruptions. From the practitioner's point of view, maintenance management also lacks *specific KPIs* that measure the impact of PdM, thus allowing proper monitoring and benchmarking of maintenance results against other maintenance strategies.

The development and parameterization of algorithms is a major technological challenge in implementing PdM. There is a need for further research into models and solutions that *prioritize ease of application* in practice, which is also claimed by Vogl et al. (2019). In this context, self-optimizing approaches that can be implemented by maintenance staff without in-depth programming knowledge need to be further explored.

Implementing data-driven technologies always carries some risk of data manipulation and loss. Many respondents consider these risks to be greater than the potential of PdM and are concerned about over-dependence on cyber-physical systems. Consequently, further research is needed to *improve data security, build resilient systems*, and protect them from unwanted external access. There are also major overlaps with the research topic of cyber-security. Governments should also take a greater interest in introducing PdM, as this maintenance strategy can improve ecological (lower resource consumption) and social sustainability (occupational and environmental safety). Furthermore, *funding interdisciplinary research projects* helps closing the gap between the evident benefits of PdM and the small number of practical implementations.

6 Conclusion

This paper intends to expand existing research about PdM potentials and add a more practical perspective on the future of this technology. Furthermore, our objective was to gain new empirical insights into the barriers to PdM implementation and shed light on the reasons for the small number of successful applications. In contrast to existing publications, 15 European companies from seven industry sectors and varying sizes were examined. The study revealed, that the differences between small and large companies are bigger than the differences between the industry sectors and regions.

Regarding the first two research questions, the experts expressed high expectations of PdM regarding system availability, process stability, maintenance planning, cost reduction, and sustainability. In particular, high investment costs and risks, a lack of strategic understanding of maintenance, and insufficient information and expertise were identified as barriers. In some organizations, PdM is part of a series of open-ended digitalization projects that are not being implemented with the necessary consistency, mainly due to inadequate IT infrastructure and a lack of internal specialists.

According to research question three, several approaches are exploited to overcome those barriers. A major implementation factor is cooperation, both intercompany and between companies and research institutions. Furthermore, lighthouse projects with small and interdisciplinary teams allow first experiences, reduce the risk of sunk costs, and prepare upscaling of PdM in a company. We mapped the relationships between barriers, critical success factors, and potentials in a framework, according to research question four, and established ten propositions on the future development of PdM and its successful implementation. Furthermore, several research directions were revealed based on the empirical data to stimulate academia with further achievements in the area of PdM and to develop solutions for a broad application in industry.

7 Appendix

7.1 Interview Guide

1 Information about the company and interviewee

- Please describe your company and main field of economic activity.
- What department are you working in and what are your responsibilities?

- What is your experience in maintenance?
- What strategic role does maintenance play in your company?

2 Status quo of maintenance

- What maintenance objects are you responsible for?
- What maintenance strategies are applied for which type of objects?
- What were the major drivers for the currently applied maintenance strategies?
- Which major opportunities do you see regarding the implementation of PdM?

3 Maintenance results and costs

- How do you evaluate the maintenance results and how do you rate your current maintenance results?
- Which maintenance goals have the highest priority?
- What is the average number of critical failures per month?
- Do you track direct and indirect maintenance costs separately and if so, what is the proportion of the two cost components?
- If you have implemented PdM, how did this maintenance strategy affect your maintenance outcomes and costs?

4 PdM implementation barriers and success factors

- What barriers did you face when implementing PdM or which barriers discourage you from implementing?
- What preconditions have to be fulfilled in an organization to implement PdM?
- What success factors are relevant and how can external support contribute to a successful PdM implementation?
- Which future optimization potentials do you see regarding maintenance in general and PdM in particular?
- What topics regarding PdM should be considered in future research?

Conflict of interest M.A. Hoffmann and R. Lasch declarethat they have no competing interests.

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