ADOPTION OF AI BASED PREDICTIVE MAINTENANCE TECHNOLOGIES IN THE MANUFACTURING INDUSTRY

A RESEARCH TO DETERMINE AND DEVELOP THE SUITABLE BEST PRACTICES REFERENCE CHECKLIST TO FACILITATE THE ADOPTION OF ARTIFICIAL INTELLIGENCE PREDICTIVE MAINTENANCE TECHNOLOGIES

MOT2910 MASTER THESIS PROJECT

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Adoption of AI Based Predictive Maintenance Technologies in the Manufacturing Industry

Research to determine and develop the suitable best practices reference checklist to facilitate the adoption of artificial intelligence predictive maintenance technologies

by

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Abstract

Predictive maintenance (PdM) is one of the promising technologies coming along with the fourth industrial revolution being pushed by disruptive technologies like Internet of Things (IoT), Artificial Intelligence (AI), robotics and Augmented and Virtual Reality (AR/VR). Adopting PdM potentially allows companies to reduce equipment downtime, increase the safety of their processes, increase revenue and develop additional business models. Although the promises of the technology are extensive, the successful adoption rate of this technology is still relatively slow. This is stemming from PdM's multi-disciplinary nature and "hype" that over-promised its ease of implementation. Organizations are now starting to understand what is needed for efficient implementation, and this helps to manage the expectations about this technology.

The fundamental problems highlighted in this research are the complexity, unclear vision, lack of knowledge and know-how in adopting AI predictive maintenance technologies inside an organization. According to Bain & Company's survey companies in the industrial sector indicated that implementing IoT inside their organization proved to be more complicated than anticipated (Schallehn, Schorling, Bowen, & Straehle, 2019). There is a knowledge gap in the scientific literature, where a lack of best practice methods in terms of predictive maintenance implementation can be identified. Based on the problem highlighted and knowledge gap, the main research question was formulated: "How to facilitate the adoption of Artificial Intelligence-based predictive maintenance technology in the manufacturing industry?".

This study follows a phase-wise approach to obtain the research results. In the first phase, a literature study is conducted to identify the current situation about PdM, what information is available about the factors affecting this technology's adoption and where is the knowledge gap to be filled. Selected factors to focus on with this research are discussed and agreed upon with the researcher and supervisors. In the second phase, the development of the best practices checklist is commenced. The centrepiece of this phase and the research project overall is the set of semi-structured interviews with 11 industry experts with extensive domain knowledge about predictive maintenance to collect best practices in PdM implementation. The insights gathered from the interviews are analysed in-detail in multiple iterations and then that filtered, aggregated information is used to develop the predictive maintenance project reference checklist. In the third phase, expert panel evaluates the practical applicability, generalizability and the validity of the constructed PdM checklist.

Efficient implementation of PdM inside the organization could face numerous barriers and difficulties. Most of these barriers related to technologies using big data could be divided into three categories: technical, organizational and people related (S. Li, Peng, & Xing, 2019). Addressing all of these barriers in those 3 major categories would be unwise since that would not provide sufficient depth of analysis for each one of them. Selection of barriers is based on 3 criteria: the barriers must be relevant and applicable to the adoption of the PdM technologies; there should be a noticeable knowledge gap about how to overcome the barriers; the barriers must be complex enough (affecting multiple layers and stakeholders of the organizations) to fit with the Management of Technology multidisciplinary problem-solving perspective. Based on the information from scientific literature and consultancy reports on PdM, 3 relevant barriers to be focused on are chosen: business case building for PdM; trust in AI-based PdM (lack of trust in big data analytical results) and data management for PdM (the challenge of collecting the data, utilizing it and making sense of it).

The interviews with the industry experts revealed valuable insights about predictive maintenance adoption, factors affecting the implementation and best practices that other companies have followed during the process of PdM realization. The most notable best practice that all the interviewees mentioned was involving all the relevant stakeholders early on. In addition, taking small steps, maintaining PdM platforms, celebrating small successes, showing a broad picture and providing a range for PdM business case were outlined. Furthermore, key factors that emerged from the conducted interviews influencing PdM adoption are delineated and summarized in this research project. These are useful for both practitioners and academic personnel who have an interest in this domain and want to gain further understanding of the dynamics surrounding predictive maintenance projects.

This research project developed best practices reference checklist for predictive maintenance project implementation that supports organizations on high-level in adopting this novel technology by illustrating and bringing awareness to best practices that other organizations have been following during PdM implementation. This reference checklist is constructed to be a holistic, high-level PdM project support tool for the stakeholders proceeding with predictive maintenance implementation for the first time. This means that a detailed analysis of separate nuances is not sought after since that would misalign with the goal of being a wholesome, comprehendible overview of PdM project implementation checklist. Having a clear, structured and holistic perspective allows stakeholders to conveniently follow this checklist commencing and during predictive maintenance projects without being overwhelmed by excessively detailed information.

This best practice checklist based on empirical study comprises a five-phase approach where the enablers and barriers in each phase are mentioned and suggestions on how to deal with them are outlined. These 5 phases are as follows: concept, feasibility, data, PdM algorithm development and operation phase. Furthermore, high-level, structured steps in each phase are laid out to support and offer recommendations to organizations with their PdM activities. In the end of each phase, an overview of best practices and barriers is delineated to recapitulate. In the concluding section of this best practices checklist, a compact, five-page adaptation of this reference checklist is devised for a quick overview of this constructed PdM project support medium and it is advisable to resort back to phases in the checklist itself if the more detailed explanation is needed. This compact version is meant for practitioners in the industry who have strict time limitations and wish to receive information quickly in a condensed format. To the best of our knowledge, such kind of high-level compact overview to assess PdM projects was not existing in the scientific literature. This research project directly investigates and provides a best practices checklist to fill this gap. In addition, this research provided design improvement ideas for different stakeholders to incorporate in their processes/products to facilitate better adoption of PdM. Trust factors affecting the implementation process of predictive maintenance are also outlined, helping companies to better communicate with their clients and internal organization about the benefits and usefulness of PdM.

The developed research output has been preliminarily validated and evaluated by the expert panel that concluded that this best practice checklist indeed supports organizations in adopting predictive maintenance technologies. Furthermore, it was agreed that the output is clear and understandable with a well-structured approach. Coming from the high-level nature of this research, experts agreed that this research is generalizable to other industries.

Main recommendations (for future research) include validating the best practice checklist in practice with multiple organizations inside the industry to correlate usage of this approach and success factor of implementing PdM. Furthermore, the development of additional support tools and frameworks to facilitate efficient implementation of predictive maintenance technologies would yield increased adoption rates of the technology.

This research highlighted important factors contributing to the adoption of predictive maintenance technologies from organizational, people and technology perspectives. This helps to create more awareness about what is needed to consider for better adoption of this technology. Furthermore, a high-level structured overview of best practices checklist supporting PdM implementation is contributed to the scientific and practical domain, filling the previously outlined gap in the literature. In addition, coming from the analysed literature, this research complements the scientific literature on the topic of predictive maintenance by providing original content and additional awareness to the overall academic context regarding the dynamics of this technology’s adoption.

Keywords: Predictive Maintenance, Maintenance, Internet of Things, Technology adoption, Industry 4.0.

Note to the reader

This research provides insights into the dynamics and factors of predictive maintenance adoption. Based on interviews with the industry experts, a best practices reference checklist for PdM project realization is developed. Since this research report is elaborate and provides a considerable amount of information, an overview of the content in this research report is provided in this section. In addition, instructions on how to approach and read this document are outlined.

The first chapter, Introduction provides the background and the significance of this research by introducing maintenance maturity levels and briefly what predictive maintenance is. Then, the problem statement is elaborated on why this research is commenced and the knowledge gap inside the scientific literature is delineated. Coming from the problem statement and knowledge gap in the scientific literature, the main research question is formulated along with sub-questions complementing the main research question. The first chapter is then concluded with a quick recap.

The second chapter, Research Design and Methods provides an overview of the design methodology that this research followed. The utilization of Design Science Research Methodology (DSRM) Process Model (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007) is elaborated on and explained how it is adapted to accommodate this research. Then, design and development are explained by introducing barriers that this research tackles followed by design objectives of the best practices reference checklist. Additionally, research methods that are utilized in this study are elaborated on. In addition, the limitations of the used research methods are outlined. The last paragraph, a brief conclusion summarizes the content in this chapter.

The third chapter, Predictive Maintenance in Industry 4.0 introduces the executed literature study to understand what the state-of-the-art scientific literature about predictive maintenance adoption is and how it could be utilized for the best practices reference checklist development. The insights from the literature study are then concluded in the summarizing paragraph.

The fourth chapter, Investigation Study for Method Development presents how the interviews with the industry experts were constructed and executed. The qualitative analysis framework is introduced to provide an understanding of the methodology used as the foundation to analyse the interviews. Then, a description of how the actual insights gathered from the interviews were analysed by the researcher. Then, the transparency of how the best practices reference checklist was developed is discussed to give a clear idea of how the researcher approached the construction of the checklist on a principal level. Furthermore, findings from the interviews are outlined in this chapter. Best practices and key factors influencing PdM adoption are outlined along with findings that are new and surprising or contrasting. The last paragraph in this chapter concludes the content of this chapter briefly.

The fifth chapter, Developed Best Practices Checklist on the Road to PdM is the most elaborate section of this research report. This is the essential core of this study which introduces the best practices reference checklist to support organizations implementing PdM projects. This checklist comprises of 5 phases: concept, feasibility, data, predictive algorithm development and operation phase. Each section is elaborated on, including best practices, barriers and recommended procedural steps in each phase, bringing awareness on what to potentially expect and consider during PdM project implementation. Then, an overview of the developed reference checklist is provided for quick referencing and summarizing, binding all the previous sections together into one compact table. In addition, design improvement elements for better PdM adoption are outlined along with trust factors affecting the implementation of predictive maintenance. Lastly in this chapter, a comparison between this produced research output in contrast with other scientific approaches is illustrated.

The sixth chapter, Evaluation provides information about the validation of this research output done by the expert panel consisting of 4 authorities in the PdM domain with extensive knowledge about predictive maintenance. Experience of the expert panel is described then followed by the build-up of the expert panel meeting. Findings from the panel discussion are outlined: fulfilment of purpose, generalizability and strengths of the developed best practices checklist, improvement recommendations and validation of this research output. The last paragraph provides a brief summary of this chapter.

The seventh chapter, Discussion consists of notions about the generalizability of this research to other industries. Then, the connection of the findings from this research to the overall academic context is elaborated on. In addition, this chapter discusses the limitations and advantages of this research and developed best practices reference checklist. Opportunities and ideas for future research are then outlined for the scientific community.

The eight chapter, Conclusion brings all the information provided in this research report together. It discusses how this study fills the knowledge gap in the scientific literature and how it supports organizations implementing PdM. Furthermore, this chapter provides answers to the main research question along with the resolution to the formulated sub-questions. Then, the scientific, managerial and societal contribution of this research project is elaborated on. The linkage between the management of technology program and this research is illustrated and discussed. Lastly, the researcher's personal reflection on predictive maintenance and Industry 4.0 is presented.

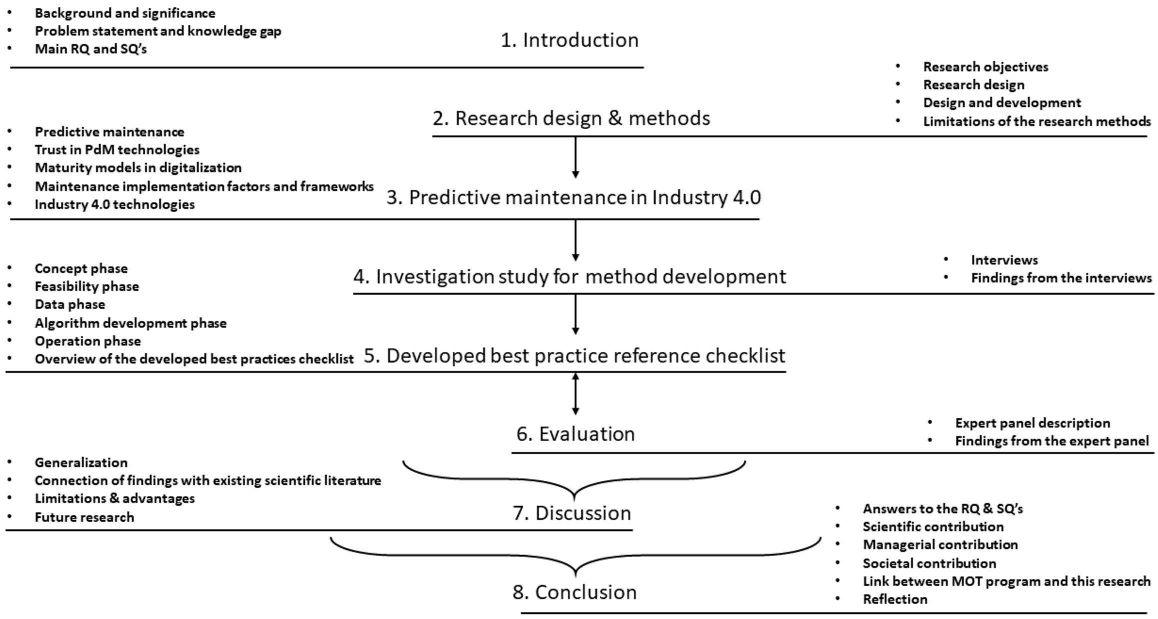

Figure 1: Overview of the content in this research report by chapters

As can be seen, this research report consists of multiple chapters with a considerable amount of information to be worked through. The ideal case is when the reader has the time to read through the whole research report to work through the information thoroughly. However, it is well known that professionals nowadays have tight time schedules and prefer to receive information in the compact form. Henceforth, it is important to mention that chapter 5 consists of the essential core information in this research project. Although chapter 5 can be quite elaborate and needing some time to work through, it would provide the most useful information to the reader. If the reader is under an extreme time constraint, then section Overview of the developed reference checklist for PdM projects provides a compact overview of the developed best practices reference checklist in one table. Alternatively, appendix Overview of Best Practice Checklist road to PdM comprises of all the core information about the checklist which is presented in a more illustrative way. If the reader finds something that needs more explanation and the information is not provided in the overviews, it is advised that they refer to the specific section in the research report for clarification and deeper understanding. Conclusion section provides an overview about the importance of this research for the practitioners and scientific community, it would be advisable to refer to that for quick understanding how to place this research in overall practical/academic context. Wishing a pleasant, informative read ahead!

Contents

List of figures

List of tables

List of definitions and acronyms

AHP – Analytic Hierarchy Process

AI – Artificial Intelligence

AR – Augmented Reality

CPS – Cyber Physical System

CPSaS – Cyber Physical System as Service

DSRM – Design Science Research Methodology

FMEA – Failure Mode and Effects Analysis

FMECA – Failure Mode Effects and Criticality Analysis

ICT – Information & Communication Technology

IoT – Internet of Things

IIoT – Industrial Internet of Things

PBL – Problem Based Learning

PdM – Predictive Maintenance

PMP – Predictive Maintenance Program

Prima-X – Maintenance Reference Model

RCM – Reliability Centred Maintenance

SME – Small to Medium-size Enterprise

SQ – Sub-Question

SSI – Semi-Structured Interview

VR – Virtual Reality

Predictive Maintenance (**PdM**) – the scheduling of maintenance based on indications from different systems – is a valuable asset for any business that relies on asset availability. It minimises the risk of unplanned downtime and assists in predicting future asset performance. By employing predictive models, maintenance assignments can be based on asset condition, asset usage, asset failure modes and asset failures (UReason, 2020).

Asset Performance Management (APM) is the practice of optimising the usage of company's physical assets. That is achieved by combining the asset data collection, integration, visualisation, analytics and interpretation. Industrial organisations mainly benefit from APM solutions by improved product offering, decreased asset downtime, increased asset availability and lower maintenance costs (UReason, 2020).

1 Introduction

There are challenges in adopting Industry 4.0 that companies must address to achieve sustainable competitive advantage. The scarcity and ageing population of engineers, who possess a knowledge of legacy systems along with nearly 20% of the assets used in manufacturing petrochemical and energy sector in the Netherlands are at the end of their life stage (UReason, 2020). Careful decisions need to be made considering operations, maintenance and replacement of those assets. These problems combined with tighter regulation and compliance, higher requirements of asset operations and increasing asset complexity add up to a challenging operational environment for the asset owners.

Predictive maintenance and asset performance management are the new popular word combinations on the forefront of Industry 4.0 that promise to eliminate many operational challenges companies are facing. Technologies like Artificial Intelligence and Machine Learning algorithms allow designing next-generation predictive maintenance solutions that reduce operational costs by eliminating unplanned downtime due to equipment malfunctions and interruptions, improve operational readiness by planning maintenance in a better, more efficient way, help manage risks and provide new opportunities for strategic positioning of the company. Despite the positive aspects that predictive maintenance promises for the asset owners and original equipment manufacturers, adoption rates of these next-generation solutions are still very low.

This research will focus on the adoption of predictive maintenance Artificial Intelligence technologies in the manufacturing industry. It is important to first understand what is understood under the term manufacturing: "*Manufacturing can be defined as the production of merchandise for sale with the help of human resources, machines along with chemical and biological processes*" ("Manufacturing vs Production" n.d.). Coming from the practical experiences and preliminary literature review, there is a definite need for companies to have support in adopting Industry 4.0 maintenance technologies. Failing to adopt these new technologies could result in decreasing safety and quality of production processes and assets, losing the competitive edge to companies adopting new technologies quicker and substantial revenue losses from unplanned downtime. Francisco Betti, head of Shaping the Future of Advanced Manufacturing and Production for the World Economic Forum, mentioned in his article that the world of production faces a "perfect storm" shaped by the Fourth Industrial Revolution and to deal with challenges like growing economic uncertainty and rising trade tensions, manufacturers must develop new capabilities and adapt (Lydon, 2020).

Therefore, coming from the need for adopting the new horizons in the manufacturing industry, the main research question for this study is established: "How to facilitate the adoption of Artificial Intelligence-based predictive maintenance technology in the manufacturing industry?"

The result of this study will help companies to better understand how to overcome specific barriers in the implementation of predictive maintenance strategies and technologies. The academic output would add to the knowledge pool of this specific domain by researching into the adoption rates and challenges, analysing the findings and consequently developing a scientific approach for better implementation of predictive maintenance technologies.

1.1 Background and significance

This study is researching into the problem of slow adoption of predictive maintenance technologies in the manufacturing industry despite the apparent business benefits. Applying predictive models allows maintenance assignments to be based on asset condition, asset usage, asset failure modes and asset failures (UReason, 2020).

There are four levels on maintenance maturity levels leading up to the predictive maintenance 4.0 (UReason, 2020). Prescriptive maintenance and digital twins are more advanced, complex solutions from predictive maintenance, however analysing their application is out of the scope of this research. Each maintenance maturity level corresponds to the respective maintenance strategies used to determine the asset health, from visual inspections to complicated predictive algorithms.

Table 1 gives a compact overview of the characterizing attributes of maintenance maturity levels. As can be seen from Table 1, the first level of maintenance maturity, visual inspections, is quite simple and do not require digital capabilities from the organization. Moving further towards higher maintenance maturity levels, the technical complexity coupled with them increases accordingly, demanding greater competences from the companies. The fourth level, predictive maintenance requires strong digital IT/OT infrastructure and bringing in new capabilities to the organization by employing additional data scientists. This illustrates the increasing complexity of implementing PdM in contrast to the lower levels of maintenance maturity, which means that companies would greatly benefit from shared best practices in the industry regarding predictive maintenance implementation to prevent avoidable mistakes during the process.

Table 1: Different levels of maintenance maturity inside the organization. Adapted from: (Haarman et al., 2018)

Capability	1. Visual Inspections	2. Instrument Inspections	3. Real-time condition monitoring	4. PdM 4.0
Processes	- periodic inspection (physical) - checklist - paper recording	- periodic inspection (physical) - instruments - digital recording	- continuous inspection (remote) - sensors - digital recording	- continuous inspection (remote) - sensors and other data - digital recording
Content	-paper-based condition data - multiple inspection points	- digital condition data - single inspection point	- digital condition data - multiple inspection points	- digital condition data - multiple inspection points - digital environment data - digital maintenance history
Performance Measurement	- visual norm verification - paper-based trend analyses - prediction by expert opinion	- automatic norm verification - digital trend analyses - prediction by expert opinion	- automatic norm verification - digital trend analyses - monitoring by CM software	- automatic norm verification - digital trend analyses - prediction by statistical software - advanced decision support
IT	- Backlogs saved on PC	- embedded instrument software	- condition monitoring software - condition database	- condition monitoring software - big data platform - wifi network - statistical software
Organisation	- experienced craftsmen	- trained inspectors	- reliability engineers	- reliability engineers - data scientists

According to PwC's market report (Haarman et al., 2018), adopting PdM will bring along 9% of uptime improvement of assets, 12% of operational cost reduction, 20% of lifetime extension of ageing assets and 14% of risk reduction regard to health and environment. However, one of the main findings of PwC's report was the fact that only 11% of the organizations studied have adopted some levels of predictive maintenance, showcasing low adoption rates. Furthermore, McKinsey & Company have gathered insights (Table 2) about how lighthouse manufacturers reap the distinctive benefits of being frontrunners in the industry (De Boer, Leurent, & Widmer, 2019). For example, Table 2 shows that adopting novel digital technologies like predictive maintenance could yield factory output increase anywhere from 10-200% along with other benefits of being a front-runner. These values illustrate obvious incentives to adopt these Industry 4.0 technologies in the manufacturing industry, yet the industry is slow to respond in adopting these innovations successfully which makes this research valuable in examining why organizations are rather reluctant to implement PdM despite the benefits it brings along.

Table 2: Impact of Fourth Industrial Revolution use cases on select KPIs in Lighthouse factories. Adapted from: **(De Boer et al., 2019)**

Theme	KPI improvements	Impact range observed
Productivity	Factory output increase	10-200%
	Productivity increase	5-160%
	OEE increase	3-50%
	Quality cost reduction	5-90%
	Product cost reduction	5-40%
Agility	Energy efficiency	2-50%
	Inventory reduction	10-90%
	Lead time reduction	10-90%
	Time to market reduction	30-90%
	Change-over shortening	30-70%
Customization	Lot size-reduction	50-90%

1.2 Problem statement and knowledge gap

The principal problems highlighted in this research are the complexity, unclear vision, lack of knowledge and know-how in adopting AI predictive maintenance technologies inside an organization. According to Bain & Company's survey companies in the industrial sector indicated that implementing IoT inside their organization proved to be more complicated than anticipated (Schallehn et al., 2019). Rise of big data and IIOT are providing new horizons on how to more efficiently utilize assets and improve products by adding digital capabilities to them. Developments in sensor technology, 5G connectivity, edge computing and edge analytics together with approximately 20 billion devices connected by 2020 leave little room to doubt the potential for technology to greatly enhance efficiency – a trend which IoT will have to manage (Schallehn et al., 2019). However, these new opportunities reveal alternative possibilities for alternative business models and operational excellence, the lack of expertise, proven methods and overall uncertainty in a rather conservative manufacturing industry withholds companies from adopting novel Industry 4.0 technologies at a faster rate. The report from McKinsey notes that while many manufacturers have made strides towards technological transformation, over 70% of the companies in the manufacturing ecosystem are falling further behind with their Fourth Industrial Revolution efforts by attempting to implement advanced manufacturing technologies without realizing acceptable returns on investment or measurable improvements in operational key performance indicators (De Boer et al., 2019). The genuine challenge for PdM lies in the areas of process and decision support and service/business model. Here, far-reaching innovations, mindset changes and business model disruptions will be required in the years to 2023 and beyond, which few companies have fully got to grips with as yet (Feldmann, Buechele, & Preveden, 2018).

This is stemming from the knowledge gap in the scientific and industrial domain, where a lack of best practice methods in terms of predictive maintenance implementation can be identified.

Furthermore, a comprehensive overview is not present about the potential barriers and enablers in adopting these maintenance technologies.

The purpose of the study is to understand the factors that contribute to the adoption rates of these technologies, unveiling the reasons for the relatively slow adoption rates. After understanding the factors, enablers and barriers to the adoption, the most relevant ones are chosen for further in-depth analysis. Based on the knowledge gained from the previous steps, a suitable approach for the adoption of AI predictive maintenance technologies will be developed that enables to overcome these barriers more easily. The research will try to fill the knowledge gap by addressing the need for better understanding and delineation of enablers and barriers in predictive maintenance adoption.

This is useful for both the practitioners and scientific community because of the added value in terms of extended knowledge about the enablers and barriers of the technology adoption and developed best practices checklist that will support the implementation process of predictive maintenance. The developed approach to PdM projects could potentially ease the complex implementation procedures, allowing companies to cut costs, avoid failures in predictive maintenance projects and better understand the necessary steps and direction towards successful adoption on technological and organizational levels. Only by transforming your corporate culture, evolving from a "traditional" to a "digital" company, will you be able to provide maximum benefit to your clients in the area of predictive maintenance – and consequently extract maximum value for your company in the longer term (Feldmann et al., 2018).

This research will not focus on the development of mathematical methods and models that determine which maintenance strategy to adopt dependent on separate classes of assets. In addition, this developed best practices reference checklist aims to be a high-level PdM support tool, meaning that detailed analysis of separate nuances is not sought after since it is out of the limited time scope of this project. Furthermore, predictive maintenance is part of the Industry 4.0 revolution, however, this study will not concentrate on in-depth analysis of other technologies more than delineating correlation and connections between them and predictive maintenance technologies adoption.

1.3 Main research question and sub-questions

The main research question for this thesis is as follows:

“How to facilitate the adoption of Artificial Intelligence-based predictive maintenance technology in the manufacturing industry?“

Sub-research questions (SQs) that support the main research question are listed below:

SQ1: What is the relevant State-of-the-Art literature that supports PdM adoption method development?

SQ2: How can we develop a method that is suitable to support the adoption of AI PdM technologies in the manufacturing industry?

SQ3: How can we validate the method applicability in supporting the adoption of these technologies?

SQ1 aims to delineate and understand the technological, organizational enablers and barriers in adopting AI predictive maintenance technologies by using literature research. Furthermore, the literature review will provide the first input to the best practices checklist design and development by making use of work done in this research domain. This will provide enough understanding about the domain itself and uncovering knowledge gaps that could be filled with further research.

SQ2 is fully focused on the method development itself. Semi-structured interviews with the industry experts will be the main input for the design of the best practices method. Knowledge from the interviews will be transformed into tangible, practical steps to aid the adoption of predictive maintenance AI technologies inside the organization.

SQ3 will try to evaluate the developed method in its applicability in supporting the adoption of these technologies. This will be done using an expert panel consisting of industry professionals with extensive knowledge about this domain to provide an in-depth examination of the method during the design and development phase until the end.

1.4 Conclusion to the introduction

Predictive maintenance potentially brings along considerable benefits with its adoption, but the industry is slow to respond to its implementation. This provides the foundation for this research that aims to uncover the reasons why the adoption rates to predictive maintenance are still relatively low and support organizations in overcoming these reasons. The knowledge gap in the scientific literature has been identified: there is a lack of best practice approaches to predictive maintenance implementation along with a comprehensive overview of the whole process. Based on these notions, the main research question has been formulated: “How to facilitate the adoption of Artificial Intelligence-based predictive maintenance technology in the manufacturing industry?“.

2 Research Design and Methods

2.1 Research objectives

The objective of this study is to investigate the underlying factors contributing to the adoption rates of predictive maintenance AI technologies in the manufacturing industry and develop the best practices reference checklist to make the adoption more efficient. Exploration of enablers and barriers to the technology adoption on technological, organizational and human layers will contribute to the body of knowledge of technology adoption of emerging and breakthrough technologies that are novel and waiting for widespread commercialization. The developed best practise reference checklist would potentially aid companies in the manufacturing industry in adopting predictive maintenance technologies and contributing to the scientific knowledge pool in understanding the dynamics of this technology adoption for both managerial and scientific relevance.

2.2 Research design

This research will adopt the Design Science Research Methodology (DSRM) Process Model (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007) as a foundation on which to build the research design. The researcher believes that applying DSRM methodology leads to the desired research output since it entails phase-wise approach to the overall project, each step logically connecting to the next one, allowing to surely build towards the formulated research goal. The DSRM model (Figure 2) includes six steps: problem identification and motivation, the definition of the objectives for a solution, design and development, demonstration, evaluation, and communication. This model will be tailored to the specific elements of the study, linking the aforementioned six steps to practical stages undertaken in the research itself (see Figure 3).

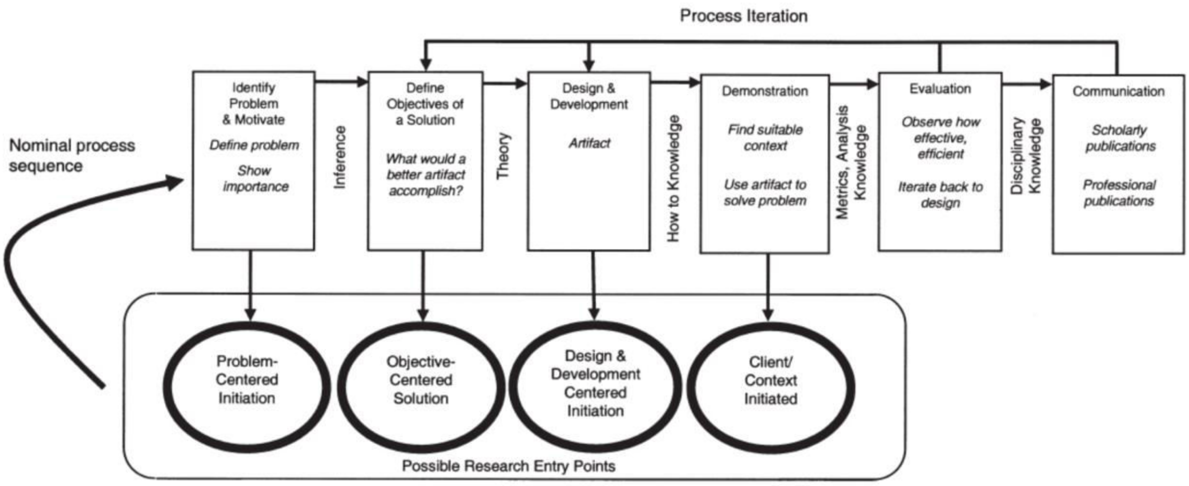

Figure 2: DSRM cycle (Peffers et al., 2007)

The first stage in the research „Identify problem & motivate“ will be completed by preliminary literature review on the topic of predictive maintenance and its adoption, where the goal is to understand the background of the domain and identify knowledge gaps in the current scientific knowledge base. This step has already been undertaken and knowledge gaps in terms of delineation of barriers and enablers together with best practice PdM implementation methods have been recognized. Furthermore, expertise from the company UReason provides useful in-depth insights into the maintenance domain itself. Additionally, review of the market reports about predictive maintenance allows to better illustrate the importance of the predictive maintenance for the companies, assuring the validity of the study for managerial relevance.

In the second step “Define objectives of a solution” a more elaborate literature review and research will be undertaken to fully understand the delineation of factors contributing to the technology adoption rates. This will provide the foundation for the preliminary design focus of the improved adoption method that is aiming to aid companies with overcoming the selected adoption barriers.

The third stage of “Design and development” will comprise semi-structured explorative and qualitative interviews with industry experts. These interviews will try to explore the enablers and barriers to PdM technology adoption in the manufacturing industry. Furthermore, potential best practices and/or failures together with approaches used in relation to predictive maintenance implementation will be investigated. This acquired knowledge will be the cornerstone to method development, coming straight from the need of the practitioners. Gathered data will be used to make connections between the different factors contributing to the adoption of PdM and organizational readiness to implement PdM.

The fourth stage “Demonstration” will revert to the iterative process of interviews with the industry experts that will be part of the expert panel who will provide continuous feedback on the method under development. The best-case scenario would be to find a company that would follow the guidelines of the developed method fully or use partial fragments of it at least. This could potentially be achieved by using any of the use cases that UReason is working on to gather feedback during the implementation.

The fifth stage “Evaluation” will analyse if the developed method is an improvement from the previous methods and would be suitable to facilitate efficient predictive maintenance adoption inside the industry. The evaluation is done by an expert panel consisting of industry professionals with extensive work experience and domain knowledge.

The last stage “Communication” will provide publications for the scientific community and the practitioners. The knowledge acquired of the barriers, enablers and other factors will be transformed into reports, which will be shared alongside the best practices reference checklist to the community that contributed to the research.

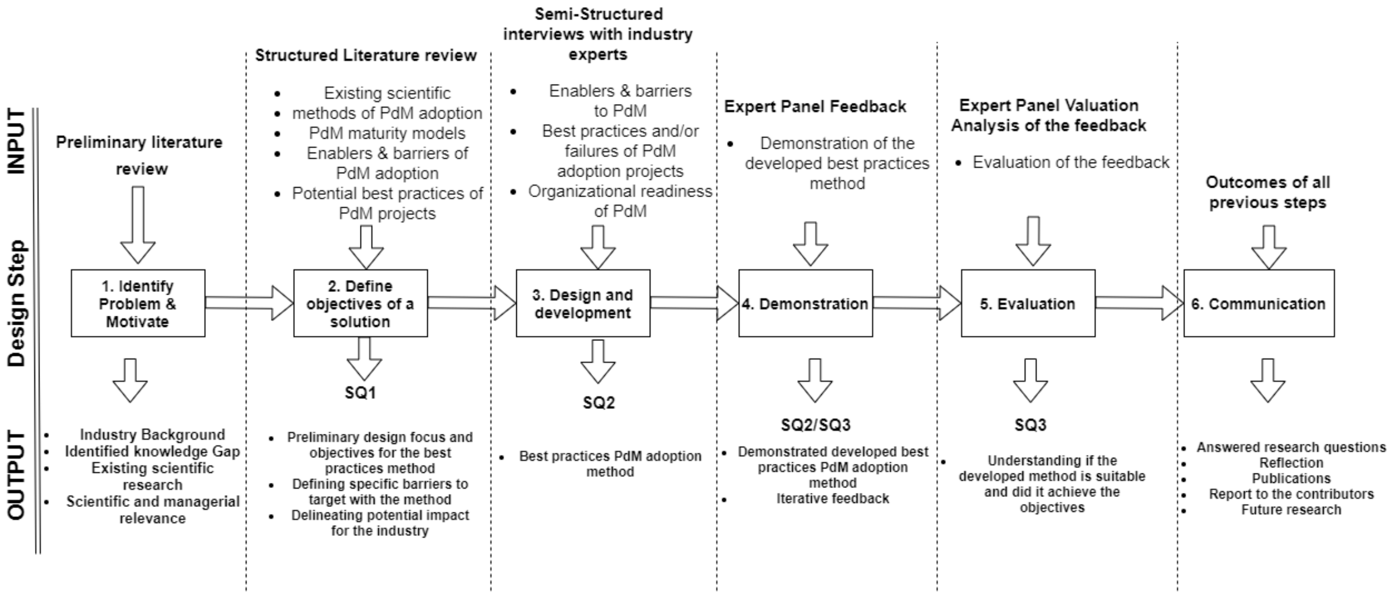

Figure 3: Research flow steps

2.3 Design and development

2.3.1 Barriers to be tackled

Predictive maintenance is a complex technology that addresses change across the entire organization that seeks to integrate it into their business processes. Efficient implementation of PdM inside the organization could face numerous barriers and difficulties. Most of these barriers related to technologies using big data could be divided into three categories: organizational, people and technical related (S. Li et al., 2019). Overview of these barriers, brief description of them and further breakdown of elements attributing to them could be seen in Table 3. Organizational barriers are listed as follows: lack of understanding and planning; lack of top-level management; lack of departmental collaborations and alignment; fail to identify big data analytical needs. People related barriers include lack of qualified consultants; lack of in-house data scientist; lack of trust in big data analytical results; user resistance. Technical barriers are listed as follows: immature CPS and IoT development; poor big data set; poor big data management; information security threats. Furthermore, consultancy report about the PdM adoption in the manufacturing companies revealed that the main three main reasons for not implementing Predictive Maintenance in the organizations were: No good business case/not relevant (63%), no data/not enough data available (23%) and lack of data analytics capabilities (8%) (Haarman et al., 2018). Both resources together provide a sufficient array of barriers to choose from to be focused on in this study.

Table 3: Overview of barriers to big data-related technologies. Adapted from: **(S. Li et al., 2019)**

Perspective	Barrier	Brief description	Element
Organization	Lack of understanding and planning	Organizations do not possess the necessary knowledge about big data and how to commence with digital big data projects strategically	Concept complexity
			Smart factory development cycle
			Multiple vendors
			Insufficient knowledge
	Lack of top management commitment	Top management support (financial, strategic et cetera) for innovation projects is crucial for their success	Lack of consolidated business model
			Limited understanding
			No clear vision
			Support needed in the right time
	Lack of departmental collaborations and alignment	Different departments in organization compete for resources, have contradicting goals and conflicting interests, which cause misalignment, consequently hampering projects.	Data owned by multiple departments
			No holistic vision
			Conflicted goals and interests
			Cross-functional product lifecycle
			Lack of a communicational plan
	Fail to identify big data analytical needs	Organizations lack the knowledge and capabilities how to utilize their big data and fail to identify the analytical needs of their processes	No focus on “smart” vs “big” of data
			Data collected with no specific purposes
			Lack of knowledge and understanding
People	Lack of qualified consultants	Industrial big data related projects require consultants with extensive skillset who can be difficult to find and recruit	New concepts to IT consultants
			Limited knowledge
			Limited experience
			Lack of industrial standards

Perspective	Barrier	Brief description	Element
	Lack of in-house data scientist	Highly skilled data scientists are rare and in high demand, making finding suitable candidate difficult	Difficult to hire a data scientist
			Difficult to identify training needs
			Difficult to explain the usefulness of analytical results
	Lack of trust in big data analytical results	Practitioners inside organizations can have trouble trusting the insights from big data analytical results	Conflicted interests in big data usage
			Difficulty in interpreting results
			Quality of analytical results
			Experience vs machine analysis
	User resistance	Personnel is cautious about new technologies they do not understand and might feel that they might become obsolete	Unfamiliarity
			Job security
Technical and Data	Immature CPS and IoT development	Having strong IT/OT infrastructure is the cornerstone to smart automation, but the cost and technical complexity can hold companies back from acquiring that infrastructure	Weak technical infrastructure
			Insufficient support from vendors
			High investment cost
			Poor CPS and machine integration
			Lack of accuracy in machine control
	Poor big data set	Big data sets are gigantic in volume and contain very different forms and formats which can be near impossible to understand if not labelled, structured and maintained correctly	The complexity of real-time data
			Poor consistency of data from the source
			Poor consistency in data cleaning
	Poor big data management	Organizations lack the knowledge which data should be collected, how and for how long it should be stored, how to filter it et cetera	Difficult to be managed timely
			Insufficient technical support
			Unclear analytical needs
	Information security threats	Increasing number of devices connected to the IoT networks pose information security threats	Attacks in IoT network
			Big data leakage
			Lack of industrial standards

As illustrated in Table 3 and mentioned in the consultancy report (Haarman et al., 2018), many barriers could hamper the adoption of Predictive Maintenance technologies. From the method design perspective, it would be unwise to try to tackle them all since addressing all these barriers would not provide sufficient depth of analysis for each one of them. Therefore, it is essential to focus the research towards the more relevant barriers to the adoption. Choosing the barriers to tackle was done by using the following criteria:

- The barriers must be relevant and applicable to the adoption of the PdM technologies;
- There should be a noticeable knowledge gap about how to overcome the barriers;
- The barriers must be complex enough (affecting multiple layers and stakeholders of the organizations) to fit with the Management of Technology multidisciplinary problem-solving perspective.

According to these criteria and coming from the listing in Table 3 along with main reasons for companies not to implement PdM from the consultancy report, three of the following barriers were chosen and adapted wording-wise to predictive maintenance perspective for further investigation with reasoning why these were chosen:

1. **Business case building for PdM**
   According to the PwC report (Haarman et al., 2018) the major reason why manufacturing companies are not yet successfully adopting novel PdM technologies is that they are struggling or unable to find an applicable business case. The business case is the cornerstone for PdM technologies – without it, companies would not realize positive business value from adopting PdM. This illustrates the need for proper guidelines on how to formulate the business case for PdM.
2. **Trust in AI-based PdM (Lack of trust in big data analytical results)**
   Lack of trust in big data analytical results, including insights from PdM technologies and its dynamics were constantly mentioned inside the academic literature of stakeholders and different departments in organizations not trusting those new black box AI solutions, the insights they provide and 3rd parties having access to the business-critical data through PdM platforms that they provide (Golightly, Kefalidou, & Sharples, 2018; S. Li et al., 2019; Wagner & Hellingrath, 2019). Trust in these systems has an underlying effect towards most of the factors related to people and organization considering the adoption of the PdM technologies. Therefore, trust in AI-based PdM technologies is deemed to be highly relevant to this research.
3. **Data management for PdM (Poor big data management & poor big data set)**
   Data being the second cornerstone of any next-generation maintenance solutions (Haarman et al., 2018), then the 3rd barrier will tackle the challenge of having the industrial data, utilizing it and making sense of it. This further is broken down into 3 subcategories of providing the necessary digital infrastructure to collect data; what to make of the collected data and how to use it; how to make the data integration possible regarding the fact that there are an extensive amount of solution providers, which could be potentially hampering the integration possibilities.

All these barriers comply with the choosing of the complications criteria by being relevant; this research being potentially able to develop a best-practices reference checklist to aid companies in related to these barriers. The selection was limited to three barriers since they provide enough challenges to be covered and to ensure the sufficient depth of the analysis regarding each of the barriers. Some of the barriers in the list were out of the scope because of their far-reaching complexity. For example, the potential challenge of “Changing organizational culture” is consisting of too many elements and factors contributing to this, hence making guidelines for that would prove to be excessively complex. However, the chosen barriers and their analysis could potentially inter-relate and be part of more convoluted impediments towards the predictive maintenance adoption.

2.3.2 Design objective

The desired output of the analysis is to develop a supportive tool, checklist for organizations that are looking to implement predictive maintenance technologies and need an assessment point for the PdM project. The aim is to stay on high-level to provide a compact overview of the adoption process since covering the nuances in deeper detail is out of the scope for this research and heavily depends on the respective organization implementing the technology, making it extremely difficult to provide one concrete approach that fits for all. This developed checklist must be:

- Support organizations in implementing PdM more effectively;
- Clear and understandable;
- Provide a compact overview on high-level;
- Be logically structured;
- Cover the adoption from technical, organizational and people perspectives;
- Bring awareness to the important factors influencing the implementation.

2.3.3 Research methods

This research uses qualitative approaches to answer research questions. These methods are literature study, explorative semi-structured qualitative interviews coupled with expert panel feedback for method validation. These qualitative research methods are chosen to accommodate the distinct **phases** of this scientific study (see Figure 4). Phase 1 and 2 (Literature study and interviews with industry experts) are the input on which the best practices checklist is built upon. Phase 3 (expert panel) evaluates the output of the previous phases for its applicability to facilitate more efficient PdM technologies adoption.

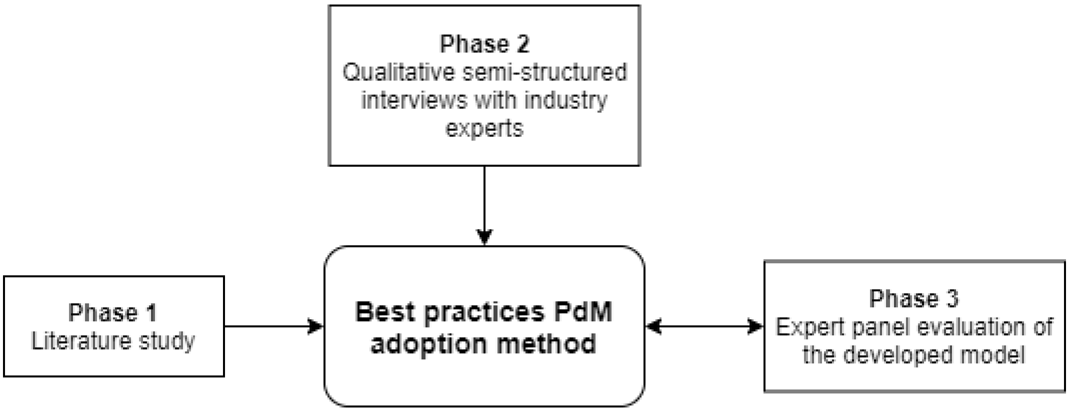

Figure 4: Phases diagram

Literature study helps to gather the information needed to develop an understanding of "effective" adoption of predictive maintenance including the factors like enablers and barriers to it. Furthermore, the literature study supports in analysing the current implementation methods developed by the scientific community to supplement the method development. This approach is using secondary data to develop the correct understanding of the current situation in the scientific community of the predictive maintenance domain and its adoption. Literature study is elaborated more on in Predictive Maintenance in Industry 4.0.

Interviews with the industry experts are qualitative, semi-structured and explorative in nature to understand and gather in-depth information about the phenomena of predictive maintenance adoption inside the manufacturing industry on a technological and organizational level. These interviews are conducted within specific target groups: general management including ICT officials, maintenance management and maintenance personnel. Companies are chosen from different manufacturing industries. People chosen for interviews have different levels and durations of work experience. The initial aim is to have at least a minimum of 10 individuals in total chosen for the interviews from each target group. These interviews are done online using proven platforms (Microsoft Teams or Skype for Business) and then recorded using specific software provided by the Windows itself to then be transcribed for deeper analysis. The interview process is illustrated in more detail in the section of Investigation Study for Method Development.

Interviews are the cornerstone of this research project from which the necessary insights and knowledge is derived to develop the best practices reference checklist to support realizing predictive maintenance projects. The method of analysis for the interviews is content analysis, where the documented information (interview transcriptions) is analysed, filtered and utilized for the checklist construction. The semi-structured approach allows to steer the interviews in the wanted direction, focusing on the domains chosen but leaving necessary room to navigate between emerging interesting topics if there is a potential need for that. Interviewing experts with extensive knowledge from different industries potentially enables to acquire novel information and structure it accordingly into the best practice checklist for the industry and scientific domain to benefit from.

The expert panel is composed of individuals taking part in the interviews who are offered the opportunity to be part of the expert panel in the later stages that provide feedback and validation to the best practices method under development. Access to those industry experts comes from UReason's network or from contacting the companies directly. The expert panel and the evaluation process is expanded more in the Evaluation section.

2.4 Limitations of the research methods

This research design may encounter a couple of potential barriers in the process of carrying it out. Taking into consideration that this study is heavily reliant on the input from the industry experts, the initial stage of finding suitable individuals who are willing to share their knowledge and foremost, their time, could prove to be the first challenge. To cope with this barrier, a good analysis of the current network of UReason will be undertaken to pin-point relevant individuals. This will provide the first touchpoint with the potential experts through a mutual linkage, which would hopefully increase the level of interest of the participants. Furthermore, providing them with the outcomes of the research in terms of report and method should be a substantial incentive to participate in this study. Additional examination of the existing scientific and available consultancy literature will provide supplementary input.

Another dynamic to research outcome will be the information quality gathered from the industry experts in terms of best practices for predictive maintenance adoption. Without good information quality, it will be difficult to develop a suitable method that will make the adoption more efficient. Well-structured interviews will be used to extract relevant information. Consultancy reports on successful cases will provide an additional medium for quality assurance and cross-checking. Furthermore, in-house expertise of UReason will be utilized for the method development.

Next barrier could be finding a company to test out the method in a practical environment. This is due to the limited time scope of the research project and as stated beforehand, having a partial case study would be an added benefit to the validation stage. Potential workaround for this barrier would be the option to implement the developed method to any of the ongoing or starting projects that UReason is commencing. This would still allow to test out and validate the method, not on an overall organizational level, but at least on the project level if possible.

The research will be conducted by one researcher, meaning that during the coding part of the interviews inter-coder agreement will not be cross-checked. This leaves heavy reliance on the perception of the researcher on coding and interpreting the results of the interviews. Research conducted is highly qualitative and exploratory in its nature by investigating and revealing best practices used inside organisations related to PdM. Having expert panel validation in the end-phase of the method development will allow feedback on these findings, interpretations, the method itself and their validity.

2.5 Research design conclusion

This research adapts the Design Science Research Methodology (DSRM) Process Model (Peffers, Tuunanen, Rothenberger, & Chatterjee, 2007) to reach its set goals. Barriers to big data-related technologies are illustrated in the scientific literature and can be divided into three categories: organizational, people and technical related (S. Li et al., 2019). Tackling them all would be out of the scope of this research project; therefore, it is important to focus on a couple of these. Based on selection criteria, 3 barriers were chosen: business case building for PdM; trust in AI-based PdM (lack of trust in big data analytical results) and data management for PdM (the challenge of collecting the data, utilizing it and making sense of it). Design objectives for this research are outlined: Support organizations in implementing PdM more effectively; Clear and understandable; Provide a compact overview on high-level; Be logically structured; Cover the adoption from technical, organizational and people perspectives; Bring awareness to the important factors influencing the implementation. Methods used for this research are literature study, semi-structure interviews with the industry experts and utilization of expert panel to evaluate this research.

3 Predictive Maintenance in Industry 4.0

This literature review is focused on the adoption of predictive maintenance technologies along the lines of Industry 4.0 movement. In detail, the mission is to determine relevant State-of-the-Art literature that supports PdM adoption method development by figuring out what the factors and attributes are that hold companies back in adopting these new technologies that provide considerable opportunities for better operational excellence and cost reduction. The focus is on manufacturing and process industry, where there are major costs due to unplanned downtime in the process flows, which could cost companies millions of euros in a short timeframe. This literature review would be the foundation of knowledge from where the method is developed. Recent investigations show that especially the sub-domains quality management, maintenance and production planning strongly interact and jointly determine the achievement of the desired production performance, equipment availability and product quality (Nemeth, Ansari, Sihn, Haslhofer, & Schindler, 2018)

The read publications could be mainly distributed into four categories: a compact description of predictive maintenance along with trust in PdM technologies; maturity models regarding digitalization, including maturity models in digitalization; maintenance programs and strategy decision models; Industry 4.0 technologies and overview of them.

3.1 Predictive maintenance

The fourth industrial revolution is being pushed by exceptionally fast advancements in technologies like Artificial Intelligence, big data analytics, robotics, Internet of Things and Augmented/Virtual Reality. Artificial Intelligence is one of the novel technologies that have the potential promise to change our lives by improving healthcare, increasing the efficiency of agriculture, contributing to climate change mitigation and adoption and improving the efficiency of production systems through predictive maintenance for example (European Commission, 2020).

Predictive maintenance (PdM) illustrates a maintenance technique that relies on new technological advances in terms of monitoring and analyzing machine conditions by analyzing the available data that is collected by sensors. This collected data is the basis for advanced AI predictive algorithm development. These algorithms can identify and estimate upcoming machine failures by real-time data processing. Insights coming from these PdM techniques provide improved support for maintenance decision-making (Wagner & Hellingrath, 2019). To attain accurate predictions, PdM is usually based on a set of actions that notify about the current, and preferably also the future state of the physical assets. These developed PdM algorithms and techniques use asset data such as condition and loading data or experience, to detect or predict changes in the physical conditions of the equipment (Tiddens, Braaksma, & Tinga, 2018). A high-level overview of PdM can be seen in Figure 5.

Organizations in asset-intensive industries turn their focus towards predictive maintenance to decrease unexpected failures of their physical assets since it is one of their primary operational risk to their business (Tiddens et al., 2018). Unexpected downtime could critically disrupt complex manufacturing supply chains, bearing high costs due to the limited productivity which can affect the whole supply chain. In addition, extremely competitive market pressures companies to increase the reliability and dependability of their equipment to match with the changing market requirements. Selection of the maintenance techniques is based on data dependencies and ambitioned outcomes of the analyses. Furthermore, criticality and type of asset determine the use of more or less advanced maintenance strategies (Tiddens et al., 2018).

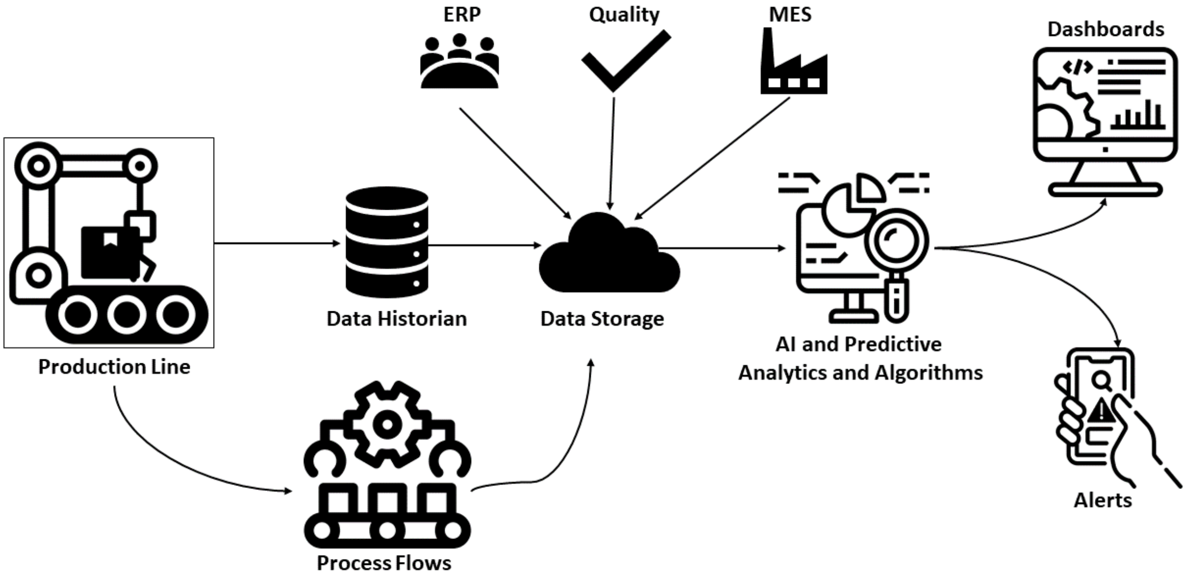

Figure 5: Predictive maintenance operational high-level overview

Adopting predictive maintenance or higher maintenance techniques usually stems from either decision pull or technology push. Decision pull comes from the higher management that is scoping for new techniques and tools that are potentially beneficial to stay ahead of the competition and improve operational capabilities. Technology push comes from the advancements from the technology in the industry, making implementing these new technologies a little bit easier and cheaper, meaning that the organizations are more prone to adopt them into the existing processes in the hopes of operational benefits (Tiddens et al., 2018).

3.2 Trust in PdM technologies

With fast technological advances, the digital solutions become an ever more central part of every aspect of society, including individuals and organizations. This means that the users should be able to trust it since trustworthiness is also a prerequisite for the technology's uptake (European Commission, 2020). IoT adoption enables more detailed and accurate predictive analytics, making asset management processes more trustworthy and allowing for better predictability in risk-based decision-making. This allows decision-making to become partially automated due to increased certainty about when and which action needs to be undertaken for more efficient asset management (Brous, Janssen, & Herder, 2019). This showcases the existing trust towards PdM technology, but there are still some concerns persisting.

One of the biggest trust-related concerns is about different stakeholders having access to performance and business-critical data (Golightly et al., 2018). In addition, "black box" solutions receive amounts of distrust towards them since they often mask important aspects of analytical complexity and being opaque, although it might be the case that some organizations are looking for these levels of simplicity. Furthermore, having multiple "black box" solutions in the maintenance environment could generate uncertainty if the insights from these were comparable and are trusted in the operations. If the elements of these opaque PdM techniques were procured from a different industry, then it was again unclear if threshold or analytical processes were relevant to the process it was now being applied. Lastly, occasionally the "black box" solutions masked fundamental flaws in the development of the technology. This had an immense effect on user implication since without knowing where the data was coming from or how it would be applied or analyzed, the trust levels would decrease sharply, leading to eventual rejection of the novel technology (Golightly et al., 2018). In addition, if the technology is already implemented, but there is a lack of trust in the system, then the advised actions from the predictive maintenance solutions are not followed up on (Tiddens et al., 2018).

Another important factor to consider in developing trust towards the PdM solutions is the importance of balance between overloading the user with all different forms of original and raw data streams and the danger of hiding too much data in the form of simplified dashboards (traffic lights for example). It is essential to show the nature of the data that underpins a decision related to diagnostics and maintenance decisions. The sheer amount of the data could be managed by showing the salient relationships in the data, rather than the original raw data itself (Golightly et al., 2018).

European Commission has laid down decisive directions for the European Union to move towards to related to the Artificial Intelligence and technologies based on that. For example, the EU wants to strengthen and foster the collaboration between SME's and governmental institutions, helping SME's to better adopt AI-related technologies. This is done by establishing Digital Innovation Hubs to support SME's in understanding the opportunities of AI, increasing their trust levels in the technology (European Commission, 2020). Furthermore, it is laid down that AI-related regulations will be improved to accommodate the legislation to new requirements like transparency, traceability and human oversight of the technology. Human oversight from the product design and throughout the lifecycle of the AI products and systems may be needed as a safeguard. In addition, specific requirements will be put in place addressing the safety risks of faulty data at the design stage as well as a mechanism to ensure that the data quality is kept to the higher level throughout the usage of the AI-related products and systems (European Commission, 2020). These requirements and legislation improvements are aimed to ensure the safe usage of AI technologies which in return increases the trust towards them.

3.3 Maturity models in digitalization

This subcategory talks about different maturity models regarding company levels of digitalization and readiness to adopt relevant Industry 4.0 technologies in their organization. Furthermore, barriers and challenges in different maturity stages are touched upon.

Digital transformation, which involves many stakeholders and experts from various backgrounds, is still a relatively novel phenomenon that is demanding an absolute commitment from organisations, making the Industry 4.0 buzz still hard to grasp and reap benefits for the manufacturing companies (Colli et al., 2018). Moreover, the complexity of digital transformation is making it hard for the upper-level management to lay down comprehensive strategies for digitalization of the companies. This problem focus is getting more attention in the scientific community due to the practical need of scientific methods and models that aid management in their implementation strategies. An additional part of the digital transformation of the companies is increasing complexity of production systems and therefore the higher demand for better maintenance management (Nemeth et al., 2018). Furthermore, manufacturing and production are becoming more technology-intensive and physical assets are pushed to maximal uptime (Oliveira & Lopes, 2019). This brings along a paradigm shift from descriptive to prescriptive maintenance, but it is utterly complex to evaluate organizations maintenance maturity levels in systematic terms, especially considering that all industries are different.

Scientists from Aalborg University (Colli et al., 2018) proposed a maturity model that relies on Problem Based Learning in contextualizing the environment and domain where the company is operating in. The maturity model is elaborated upon, divided into 6 maturity stages (none, basic, transparent, aware, autonomous, integrated) in five subcategories (governance, technology, connectivity, value, competence). The classification of subcategories is clear and definite, whereas the evaluation of the company's maturity stages can be quite ambiguous in the sense that they rely on "self-assessment" questionnaires with workshops on the related topics. This leaves some subjective room to interpret the outcomes from the assessments, which could be tackled by providing more detailed benchmarks for each of the stages that they do right now. I believe this maturity model is comprehensible in the sense of elaboration from previous maturity models researched by having a clear-cut approach to contextualize maturity assessment using enhanced PBL model regarding the company's industry domain. However, when it comes to the methodology of applying the maturity model in the company, the steps needed are not elaborated enough in my perspective. They give out general guidance on how these steps should be applied, but it is lacking the in-depth details of how to carry out these steps in the right way. This chasm of missing detailed implementation steps is covered by another maturity model called PrimaX (Nemeth et al., 2018). They determined a scientific gap on integrated data-driven maintenance maturity assessment considering multi-dimensionality of maintenance problems affected by strategic, tactical and operational processes. Implementation of PriMa-X model is clearly illustrated by clear-cut steps by the authors. The implementation entails 5 steps: analysis & diagnosis, prediction model building, prescriptive maintenance decision support, maintenance planning, execution & documentation. In each step, the necessary details are brought forward to successfully carry out each step. Even common challenges in implementation for each step and solutions to them are mentioned in compact tables, which I consider to be extremely valuable.

An aspect to examine deeper is the number of different maturity stages in these maturity models and what elements exactly constitute to these levels. There is an extensive literature overview of already existing operational and maintenance maturity models (Oliveira & Lopes, 2019) that shows the number of maturity stages by average is around 5, which is somewhat compatible with the maturity model by scientists from Aalborg University that proposes 6 maturity stages, but that goes hand-in-hand with predictive and prescriptive maintenance maturity levels in terms of digitalization and data utilization inside manufacturing companies. The interesting part is comparing the measurement classes of different models as well, having some minor differences, but altogether combining comparable multi-variate elements into the overall maturity assessment. This meaning that there is an overall coherence between digital maturity models, allowing practitioners to have a catalogue of maturity assessment approaches to choose from. This research will aim to aid practitioners by providing best practice knowledge to move to higher maintenance-related maturity levels.

3.4 Maintenance implementation factors and frameworks

This section talks about different maintenance-related topics as in implementation processes, factors related to successful deployment and challenges that the companies face in terms of maintenance.

There is a distinctive problem of lacking knowledge and guidance during the predictive maintenance implementation process, therefore companies experience many difficulties for the realization of this proactive maintenance approach. Also, there are only a few efforts regarding a generic methodology independent of a specific application or equipment (Wagner & Hellingrath, 2019). The literature review on their side claims that the process models for predictive maintenance application are very high-level without providing deeper knowledge or focus on complete introduction process and being targeted in specific use-cases, again a phenomenon that was witnessed in previous articles as well. In the academic domain, the scientific output regarding this topic is highly theoretical and lacking expertise in the domain. Furthermore, the human and organizational factors are not covered sufficiently enough in the scientific knowledge pool, which must be analysed in depth knowing very well that most of the times in technology implementation the human factors play a critical role in successful project outcome or a failure (Golightly et al., 2018). This is also delineated that the success of the implementation is dependent on the competency, training, and motivation of people interacting with the asset management systems (Brous et al., 2019).

Predictive maintenance technology implementation is a complex process that takes a lot of time, usually years to adopt in the organizations, human and organizational factors being the most time-consuming and needing a lot of effort to resolve, before the program can take off. This means that the industry needs “best practice” models and frameworks in implementing predictive maintenance technologies inside their companies and this is the knowledge gap that the authors try to fill. Predictive maintenance implementation is divided into five phases: Process model and phases, concept phase, data phase, development phase and operationalization phase (Wagner & Hellingrath, 2019). This is again similar to previous articles that delineated similar phases or stages as well for implementation. Clearly defined implementation phases and listed challenges in each phase provide practical value to the professionals dealing in this domain and as a step further, recommendations how to deal with these challenges is sought after by managerial domain.

3.5 Industry 4.0 technologies

This section talks about industry 4.0 technologies like AI, data analytics et cetera and how these are shaping the companies and the competitive environment. Understanding this technological landscape is important for laying down the role of predictive maintenance analytics in the midst of it.

With the complexity rising due to the advancements in technologies, new combinations of systems are appearing that try to provide classification to these structures. Physical Cyber Systems will streamline the manufacturing and communication on different levels, exchanging MOM – Manufacturing operations management (Buhulaiga, Telukdarie, & Ramsangar, 2019). PCS as a Service is a possibility for stakeholders to utilize for better integration vertically between suppliers and manufacturers and end clients. Industry 4.0 embodies an advanced industrial stage by integrating a set of both emergning and convergent technologies resulting in added value to the whole product lifecycle (Frank, Dalenogare, & Ayala, 2019).

Although comprehensive empirical evidence about the way these Industry 4.0 technologies are adopted in manufacturing companies is not completely demonstrated. This leads to an important question: what are the current Industry 4.0 technologies adoption patterns in manufacturing companies? Authors (Frank et al., 2019) provide a conceptual framework (Figure 6) of Industry 4.0 technologies, classifying them into front-end technologies & base technologies. This framework provides a good understanding of Industry 4.0 concept with its core elements and what are the technological enablers for it, removing ambiguities about this term.

Most of these Industry 4.0 technologies are based on the advancements on big data and its processing capabilities. The challenges companies face in terms of big data analytics and the implementation of that inside the organizations should be examined, illustrated and structured more adequately (S. Li et al., 2019). These barriers could be distributed into 3 main categories: technical, organizational and people. Aligning with previous articles, the organizational and people-related challenges are the most problematic and require the most effort in that sense to overcome. This solidifies the personal impression that technology is here and ready, but the organizations together with the people are not yet ready to embrace a paradigm shift in this technological sense. Only the leading, pioneering companies are willing to step up and innovate, while others are playing the wait & see game to see how successful it is to adopt these technologies, including next-generation maintenance technologies using artificial intelligence etc. This could backfire in the sense of losing competitive advantage in the long run by not acting quickly enough and falling behind.

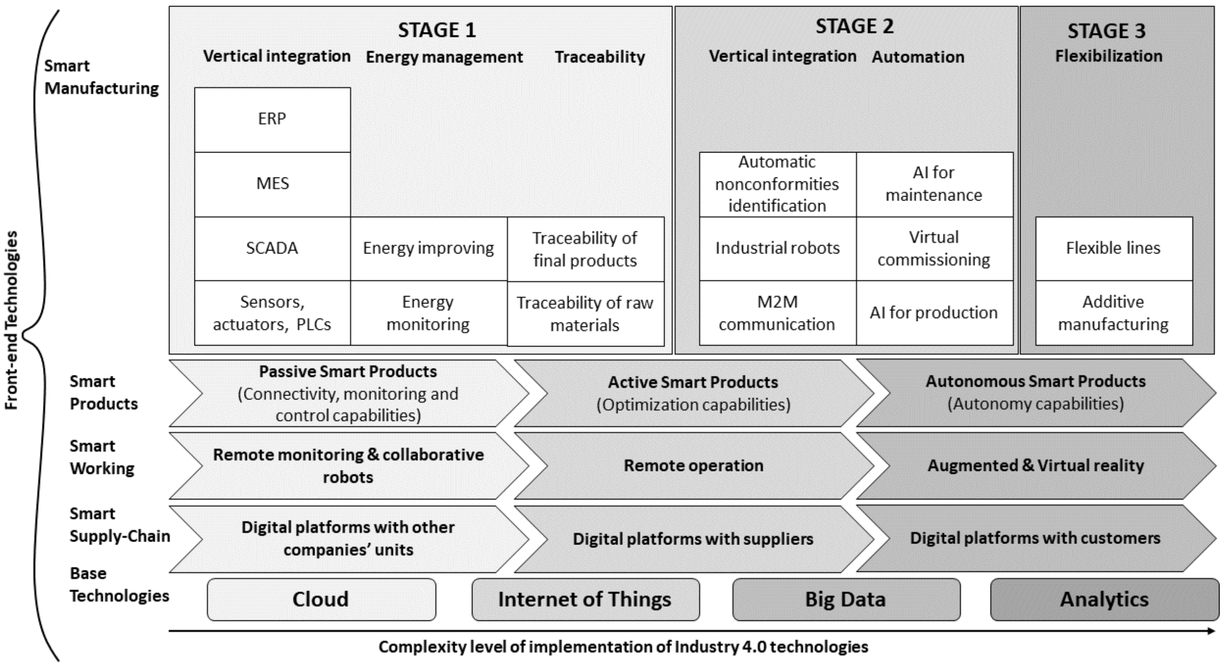

Figure 6: Industry 4.0 Conceptual Framework. Adapted from: (Frank et al., 2019)

3.6 Literature review conclusion

Emerging technologies like Artificial Intelligence, Cloud/Edge Computing, big data analytics and IoT automation manifest in the concept creation of Industry 4.0, which is closing the gap between information technologies and operational technologies. This brings along the development of Physical Cyber Systems that merge traditional manufacturing and new, emerging technologies, meaning rapidly changing competitive environment, forcing manufacturers to adapt quickly or fall behind. Adopting this new paradigm shift does not come without challenges although. Organizations do understand the benefits of this new manufacturing concept and innovation wave but are struggling to implement it inside their company. There are numerous organizational, human and technological barriers that need to be solved before enterprises can move towards maximizing their benefits from Industry 4.0. The method under development aims to support organizations in overcoming some of these barriers in adopting PdM by providing best practices how the organizations in the industry dealt with these hindrances.

4 Investigation Study for Method Development

This section covers the research part that was conducted to examine what factors and elements should be the foundation on which the best practices checklist for supporting PdM adoption is then developed on. First, the illustration of how the interview process went is provided. Second, findings and insights from the interviews are presented from which the building blocks for method development are derived.

4.1 Interviews

Semi-structured interviews (SSI) for this research were developed and commenced by using guidelines from handbook and article that delineate the necessary steps and useful guidelines for conducting research (Newcomer, Hatry, & Wholey, 2015; Turner, 2010). Following paragraphs will cover how the interview questions and guidelines were devised; how the interview respondents were chosen and using which criteria; how the interviews were organized and carried out.

Certain guidelines were followed for devising the interview questions (Turner, 2010):

- Wording should be open-ended (respondents should be able to choose their terms when answering questions);
- Questions should be as neutral as possible (avoid wording that might influence answers, e.g., evocative, judgmental wording);
- Questions should be asked one at a time;
- Questions should be worded clearly (this includes knowing any terms particular to the program or the respondents' culture).

4.1.1 Interview guideline

The general interview guide was developed allowing the researcher to ensure that the main key subjects for this research will be covered during the interviews, but still having the flexibility and degree of freedom to go into deeper discussions on some topics where interesting insights potentially erupt coming from the expertise of the interviewee. The interview is built up in 3 phases – introductory phase to get acquainted between the researcher and the interviewee and to additionally address questions that the interviewee has regarding the study and confidentiality; then the main part of the interview will be focusing on the questions related to the barriers chosen for the research (Business case building for PdM, Trust in PdM technologies, Data management for PdM); concluding section of the interview will go over the topics discussed and leaving some room for the interviewees to add anything they deem relevant to this research. Overview of interview questions can be found in Interview Questions. Furthermore, the interview will follow guidelines for logical sequence flow of the questions to make sure that the agenda falls in place according to the plan (Newcomer et al., 2015). The exact interview questions were then crafted and, as suggested (Newcomer et al., 2015), edited, pretested with colleagues to determine the supposed time-frame of the interview, clarity of the questions and overall coherence.

As mentioned before, the conducted interviews were structured in 3 phases. The first, introductory phase consisted of 5 questions determining what is the position of the interviewee, the industry the company is working in, their personal experience with condition monitoring and predictive maintenance solutions and how they evaluate from their personal perspective the effect of PdM technologies on the organization. The second, main part of the interview focused on the chosen 3 barriers for this research. The section of business case building for PdM examined what was the process of business case building inside the organizations, who were the stakeholders involved, what were the major sticking points and key takeaways during that process and how could business case building be done better in the future. Section of trust in PdM technologies focused on inquiring about organizational trust in this novel technology, how do third party solutions affect the trust factor, how correct functioning of PdM platforms is ensured, how data and dashboarding should be displayed, how does PdM affect decision-making and what measurements could be undertaken to increase trust in these technologies. Last section of the main part, data management for PdM investigated what is the relevant IT/OT for PdM realization, what are the enablers and barriers on getting to that level of digitalization, what capabilities and tools the organization uses for working with data, what are the processes and best practices to utilize data efficiently, how could integration between systems be enhanced and how data management could be done better. The last phase, final concluding questions aimed to summarize points made previously, focus on the main ideas and allow the interviewee to discuss anything important that was not mentioned already.

4.1.2 Choosing the participants

This research aimed to interview at least minimally 10 industry experts to gather in-depth insights about PdM adoption and best practices. Interviewees for this research were chosen by their expertise and position inside the company. Interviewees were either from general management including ICT officials, maintenance management and maintenance personnel. Selection of experts was distributed across different industries and in addition, the selection was distributed between the role of the company: *Original Equipment Manufacturer*, *Asset Owner* or *Maintenance Repair Operations* company. For improvement of generalizability and perspective terms, some of the interviewees were chosen from different industries than manufacturing – academia, transportation and consultancy. This ensures that the insights were collected from multiple perspectives of companies with differentiating business drivers. Furthermore, all the interviewees had different levels of work expertise regarding PdM technology to diversify the sample. Although, persons with extensive industry experience were preferred to retain their knowledge about best practices gathered over their working years.

4.1.3 Interview process

Interviewees were approached on LinkedIn after the initial screening of their expertise. The connection request was sent with a small introductory message to potential participants. After the connection was accepted more elaborate message was sent to them discussing details of the research and asking for their interest to participate. After an initial showcase of interest, the participants were sent 3 documents by email: an overview of interview questions to help them prepare, one-pager about the research and its aims, informed consent form discussing confidentiality and how the data will be used regarding this research. The informed consent form was signed digitally by the researcher and the interviewee. In total 11 interviews were conducted. The expertise, industry and position of the interviewees are illustrated in Table 4. Interviews were mostly done using Microsoft teams, where the interview was recorded for transcription using Otter software for further analysis. Interviews lasted from 1 to 2 hours, 1 hour and 20 minutes on average.

Table 4: Interviewee position, the industry where the company operates in and experience related to maintenance

Position	Industry	Experience related to maintenance (including PdM)
Maintenance Engineer Rotating Equipment	Agriculture	25 years
Corporate Lead Maintenance & Equipment Reliability	Chemical	32 years
Maintenance and Reliability Strategy Manager	Mining	30 years
Business Unit Manager	Chemical	5 years
Global Product & Growth Leader	Energy	10 years
Professor Maintenance Engineering	Academia	40 years
Research and Development Manager	Transportation	17 years
Principal Consultant	Consultancy	38 years
Asset Management Consultant	Manufacturing	14 years

Professor in Maintenance	Academia	30 years
Senior Asset Management Consultant	Consultancy	16 years

During the interview, some sections were focused more and discussed further in-detail than others. This was due to the fact that the interviewee had more experience and knowledge in that domain. However, all the sections of the interview structure were covered in an evenly distributed manner over all the interviews. It is worth mentioning that on average (23 years) the interview participants possessed extensive experience in this domain, illustrating and assuring the high quality of the sources where the information was collected from.

4.1.4 Interview analysis methodology

This research is qualitative and exploratory in its core. The inductive approach is used to investigate connections and elements related to predictive maintenance implementation. Meaning that the researcher will use the conducted interviews with the industry experts as the foundation to derive insights and build a best-practices method from the acquired results and interpretations. Qualitative data can provide deep insights into explaining how programs, policies or technology adaption works or fails to work by having compelling accounts of success and failure (Newcomer et al., 2015). Following understandable framework and concise steps in the qualitative data analysis would allow this research to be reproducible to some extent, discarding changing variables like interviewees and their experience participating in the study for example.

4.1.5 Qualitative analysis framework

For analysing the qualitative data, the researcher turned to PPOIISED framework (Newcomer et al., 2015). PPOIISED stands for Purposes, Paradigms, Options, Interpretations, Iterations, Standards, Ethics and Displaying. This framework (Table 5) comprises series of questions about a variety of key analysis issues in each of these categories, although the researcher might need to move around the framework and revisit questions during the actual analysis phase. The researcher considered these guiding questions in-detail and used them as a roadmap through the analysis. It is recognized that qualitative data analysis is both rigorous and creative process and that the analysis methods should be chosen to best suit the context, resources and the skill set of the researcher conducting the evaluation. This framework illustrates that good qualitative analysis finds a fine balance between exploring the data to its deepest depths and meeting deadlines, so the research strategies used are focused on the action while having a sense of assurance based on a systematic approach and considered choices (Newcomer et al., 2015).

Table 5: The PPOIISED framework for the analysis of qualitative data (Newcomer et al., 2015)

Category	Questions
Purposes	• What sort of evaluation is being undertaken? • What kinds of questions is the analysis seeking to answer? • Who are the intended users of this analysis, and what are their preferred ways of receiving information?
Paradigms	• What questions about reality, knowledge, and power are reflected in the approach?
Options	• What are realistic options for analyzing this qualitative data? • Will this analysis be linked to the analysis of other data?
Interpretations	• How can interpretations be checked? • What are reasonable ways to categorize the data?
Iterations	• What iterations should be built into the analytical process?

Standards	• What standards should guide qualitative data analysis? • What strategies should be used to meet the standards for quality • analysis?
Ethics	• What ethical issues might arise in the analysis, and how should they be addressed?
Displaying	• What data displays would be useful during analysis? • What data displays would be useful for reporting?

4.1.6 Analysing the interviews

In the used framework for analysing the qualitative data, *interpretation* is referring to making meaning out of the data by understanding the concrete pieces of data, categorizing the data and identifying the overall patterns. During the analysis, it is important to take into account what is seen or heard during the interview while drawing contextual information to make sense of the data presented (Newcomer et al., 2015). The research followed the guidelines illustrated in the framework to draw insights from conducted interviews.

The researcher followed outlined steps (Figure 7) in processing and analysing the data: transcription of the interviews, categorizing and coding the data in the interviews, networks were generated for connections between different codes and quotations and code co-occurrence was analysed to reveal additional, potentially surprising insights that were otherwise unseen. The researcher used software designed for qualitative research support – ATLAS TI 8.

1. **Transcription of the interviews** – The conducted interviews were transcribed using the AI based transcription tool Otter.ai which enhanced the process considerably. Although it is worth mentioning that each of these interviews was double-checked word-by-word to make sure that any data was not lost in the process. This meant that the transcription process took an extensive amount of time and effort.
2. **Categorizing and coding the data** – Transcriptions were loaded into AtlasTI software where they were analysed. Relevant quotations from the interviews were marked with a code. The researcher did not use any predetermined codes since the study is exploratory and every piece of data could potentially lead to useful insights into method development. Then all the codes were categorized into code groups depending on their content. All of the codes and code groups were commented to clearly understand what each code/group stands for so other researchers could grasp them with ease if needed. In total there were 632 quotations, 127 codes and 14 code groups which illustrate the extensive collection of qualitative data available for analysis.
3. **Network generation and data analysis** – Networks in ATLAS TI were created to understand the linkages between the codes, code groups and quotations leading to new insights from the data. These insights and linkages were the building blocks for the best practice checklist developed.
4. **Analysing the code co-occurrence** – Researcher created smart codes to run the analysis of code co-occurrence (Figure 8) revealing before unseen connections between quotations and codes.
5. **Iterative filtering of the data** – During this data analysis phase researcher did multiple iterative loops to double-check the accuracy of connections made between the quotations, codes and code groups. Furthermore, the insights derived from the initial data were filtered in multiple steps to make sure that the foundation for the method development was high in quality and focused. This means that the best practices checklist is consisting of aggregated data to be as compact as possible considering the size of the initial data collected from the interviews.

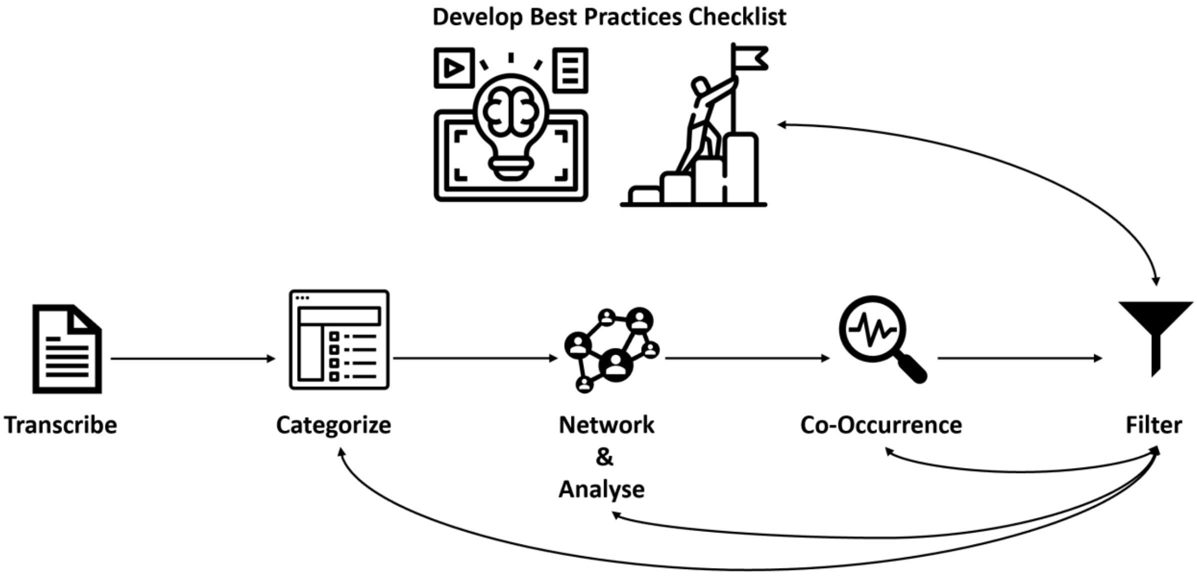

Figure 7: Illustrated steps during the data analysis phase

		Smart: Barriers 39	Smart: Best-Practice 48	Smart: Business Case 85	Smart: Company PdM Elements 163	Smart: Concerns 37	Smart: Convincing 181	Smart: Enablers 84	Smart: Integration 56
Smart: Barriers	39		1 (0.01)	7 (0.06)	4 (0.02)	2 (0.03)	3 (0.01)	7 (0.06)	6 (0.07)
Smart: Best-Practice	48	1 (0.01)		8 (0.06)	8 (0.04)		35 (0.18)	6 (0.05)	
Smart: Business Case	85	7 (0.06)	8 (0.06)		23 (0.10)	2 (0.02)	32 (0.14)	8 (0.05)	3 (0.02)
Smart: Company Pd...	163	4 (0.02)	8 (0.04)	23 (0.10)		5 (0.03)	59 (0.21)	38 (0.18)	8 (0.04)
Smart: Concerns	37	2 (0.03)		2 (0.02)	5 (0.03)		2 (0.01)	2 (0.02)	5 (0.06)
Smart: Convincing	181	3 (0.01)	35 (0.18)	32 (0.14)	59 (0.21)	2 (0.01)		39 (0.17)	11 (0.05)
Smart: Enablers	84	7 (0.06)	6 (0.05)	8 (0.05)	38 (0.18)	2 (0.02)	39 (0.17)		21 (0.18)
Smart: Integration	56	6 (0.07)		3 (0.02)	8 (0.04)	5 (0.06)	11 (0.05)	21 (0.18)	
Smart: IT/OT Infra	51	5 (0.06)		3 (0.02)	7 (0.03)	3 (0.04)	2 (0.01)	13 (0.11)	10 (0.10)
Smart: Org Change	76	4 (0.04)	5 (0.04)	6 (0.04)	21 (0.10)	2 (0.02)	47 (0.22)	11 (0.07)	3 (0.02)
Smart: Participant	35		1 (0.01)				2 (0.01)		
Smart: Procedures	75	5 (0.05)	1 (0.01)	4 (0.03)	8 (0.03)		9 (0.04)	10 (0.07)	3 (0.02)
Smart: Stakeholders	109	2 (0.01)	13 (0.09)	9 (0.05)	17 (0.07)		34 (0.13)	11 (0.06)	1 (0.01)

Figure 8: Code Co-occurrence analysis to detect potential unobvious connections

4.1.7 Transparency of the best practice checklist development

Important notion regarding developing the best practices checklist is how the researcher developed it. As mentioned before, the checklist is composed of highly aggregated data from the interviews. Data was filtered iteratively in multiple rounds by the researcher using his interpretation of the value of the data and volume of participants that mentioned similar underlying ideas during the interviews. From each quotation in the interviews, the underlying idea was identified and other quotations with the same core meaning were examined to include additional perspectives/elements that support to illustrate the key idea further. The researcher did not add any information into the checklist that was only based on his own opinion and not mentioned in the interviews. This means that all the insights are based on empirical research from the interviews. These insights were then combined into a structured best practices checklist towards PdM implementation to generate awareness about the enablers and barriers that affect the adoption of predictive maintenance technologies.

4.2 Findings

The findings from the research will be presented below by being structured in the code groups. The information will be presented as raw data, meaning that there is no added altered opinion or perception from the researcher. Since most of the essential data is present in the developed best practices checklist, then the research findings with the raw information will be introduced in a compact way to limit the length of the report. A high-level overview of themes can be found in Figure 9. The connections illustrate how different trends dynamically affect and link to each other, providing general structure how these trends attribute to the adoption of PdM.

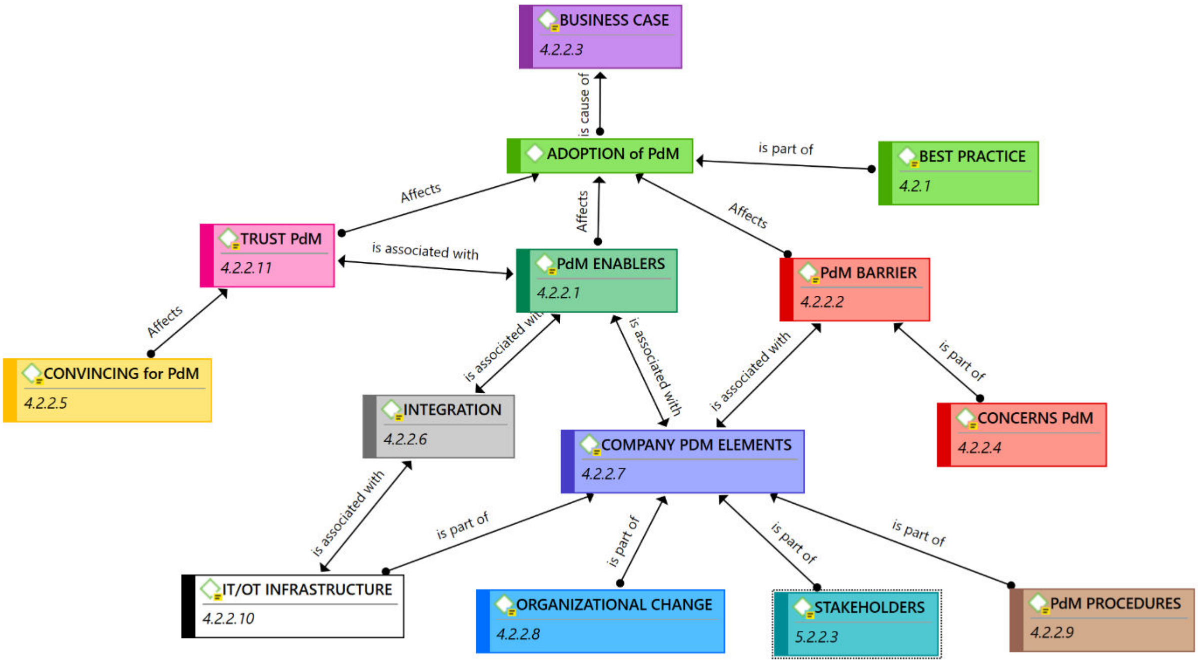

Figure 9: High-level overview of code groups (with subchapters) contributing to the adoption of PdM

In the end of each subparagraph in this following section is a figure illustrating the findings in a compact overview. These figures showcase the codes that the researcher used to analyse and filter the information from the interviews. Each emerging idea/notion in the interview transcripts was allocated a specific code to investigate the trends and connections across the interviews. It is important to mention that the letter "G" on the illustrations stands for *grounded* which is showcases how many different quotations are linked to that code to give some insight into the occurrence of different codes. Furthermore, each of the code has brief introductory comment attached to them which gives an idea about the essence of the code. Connections between the codes and the major theme showcase their relation to each other, relation is worded on the connecting arrow. Interpreting these figures along with Figure 9 allows to conceive a hierarchical structure of elements from the lower levels contributing to the themes that attribute to the adoption of predictive maintenance technologies.

4.2.1 Best practices

A clear illustration of best practices that the organizations in the industry followed to implement PdM was deemed important for this research. This is the reason why each of them is highlighted in a separate paragraph; an overview can be found in Figure 10.

The term *best practice* is elaborated more in the section of Best practices checklist, where the best practice reference checklist development is commenced, although it is important to mention that in this section best practices are the reflection of judgements from the experts that interviews were conducted with, meaning that during the interviews correspondents were inquired about the best practices their organization is utilizing relating to PdM and its implementation. Each organization is unique with different operating environments, but overall matching trends across the interviews could be noticed and aggregated into this following section. Furthermore, these best practices correspond with scientific literature (Golightly et al., 2018) where similar recommendations were illustrated for better PdM project realization. Further elaboration with connection to the existing scientific literature can be found in Connection of findings with existing scientific literature.

4.2.1.1 Stakeholder involvement

The most important best practice mentioned was stakeholder involvement from the early stages of the predictive maintenance adoption. This meant including relevant people to the meetings regarding the PdM project from the work-floor (the end-user), middle management (maintenance manager) and top-level management (decision-makers). Involving the stakeholders from the beginning ensured that the entire organization is better aligned with this new project and maintenance strategy. Furthermore, it saved effort and time since there was not a need to approach different layers of personnel separately each time. Detailed overview of the stakeholders can be found in 5.2.2.3 Stakeholders.

4.2.1.2 Take small steps

It became apparent from the interviews that implementing predictive maintenance should be a stepwise approach. This meant that the adopting PdM should be a longer process where organizations have time to slowly adapt to working with this new technology, in iterative phases. Bringing in PdM into the company in a contrasting, sharp manner provided a lot of resistance from the inside of the organization.

4.2.1.3 Maintaining PdM platforms

It was mentioned that constant improvement and maintenance of PdM platforms is essential to the success of the solution. Having quality and feedback loops to improve the algorithm’s accuracy was deemed high of importance. When the environment, where the PdM algorithms were trained, changed, then it is important to update/re-train the algorithms with the new information/data.

4.2.1.4 Celebrate small successes

In a couple of interviews it was mentioned that celebrating small successes is important for PdM adoption. This creates more traction of this technology inside the organization, making it easier to convince others of its success by making it apparent and celebrating it. Furthermore, this provided a motivational increase for the project team and invited others to “jump on the train”, being part of the success.

4.2.1.5 Illustrate the potential impact of PdM to the client organization

Showcasing the bigger picture to the client organization of how the predictive maintenance solution could potentially help their organization was said to be important best practice by PdM solution providers and client organizations themselves. This helped to convince all the layers of the organization how this technology would support the processes of the whole company throughout different layers.

4.2.1.6 Provide a best/worst case scenario for the PdM Business Case calculation

Providing a best-case and worst-case scenario for the business case calculations helped to better quantify the effect of PdM to the clients. Furthermore, this increased the trust levels from the client-side since they understood the transparency of the solution and could rest assured that the benefits of PdM were not overpromised.

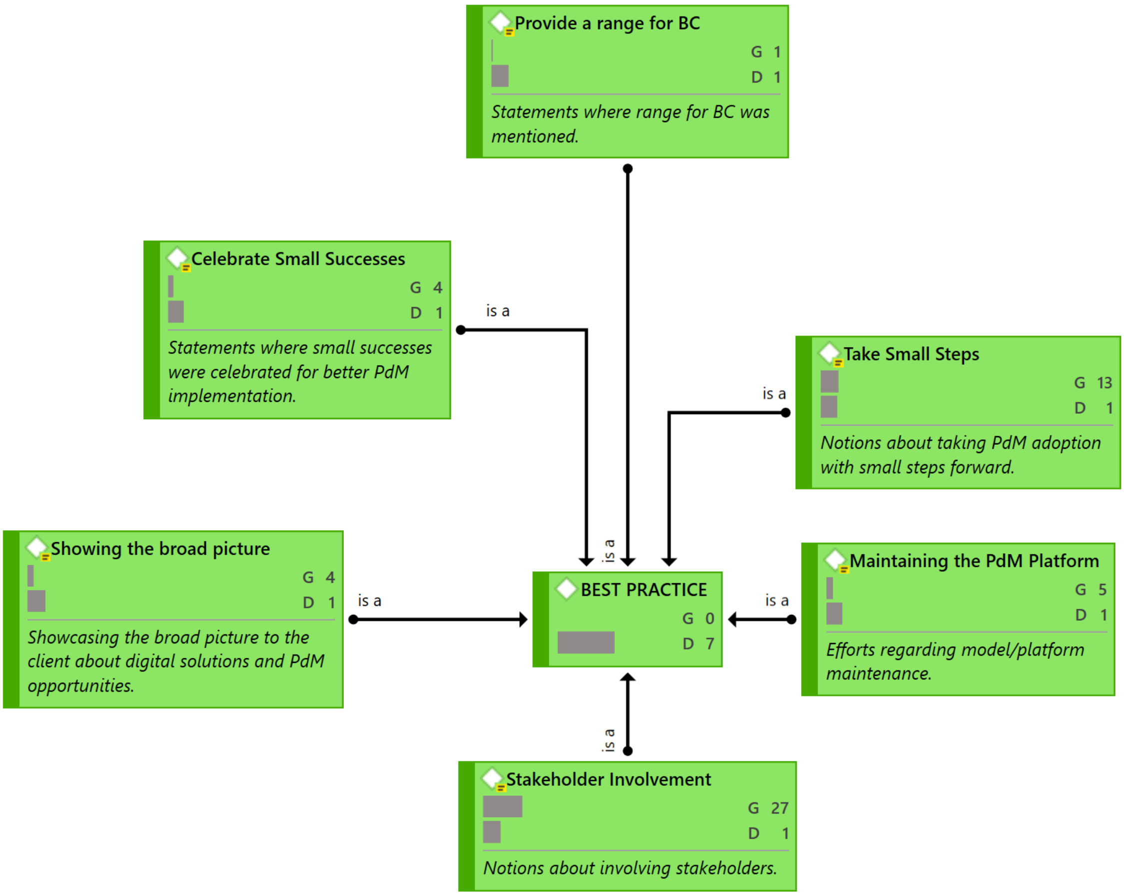

Figure 10: Overview of codes contributing to the major theme called Best Practices

4.2.2 Key factors influencing PdM adoption

4.2.2.1 PdM enablers

Interviewees highlighted enablers that make PdM implementation more seamless (Figure 11). Having a strong vision for maintenance and understanding how predictive maintenance strategy fits into existing processes and systems is an important necessity for PdM adoption. Good alignment between stakeholders helps to reach common understanding of why this new technology is brought into the company and facilitates better teamwork towards common goal throughout all layers of the organization. It is important to find organizations that are more innovative and early adaptors of new technologies since there is a higher drive to adapt to changing technological environments, decreasing the resistance inside the company. From the technical perspective, it is essential to have strong operational technologies structure where all the processes are streamlined and optimized. Furthermore, PdM relies on data to provide accurate insights, this means that data must be highly accessible, preferably from central historian as a single source of information, to make the implementation process easier. In addition, a clear and understandable data structure with correct labelling and referencing is deemed essential for predictive algorithm generation. Designing assets and solutions to be modular will enhance benefits of *plug&play* approach, making maintenance activities more efficient since integrations between different platforms are straightforward and maintaining specific modular assets in more complex processes can be done in an efficient manner.

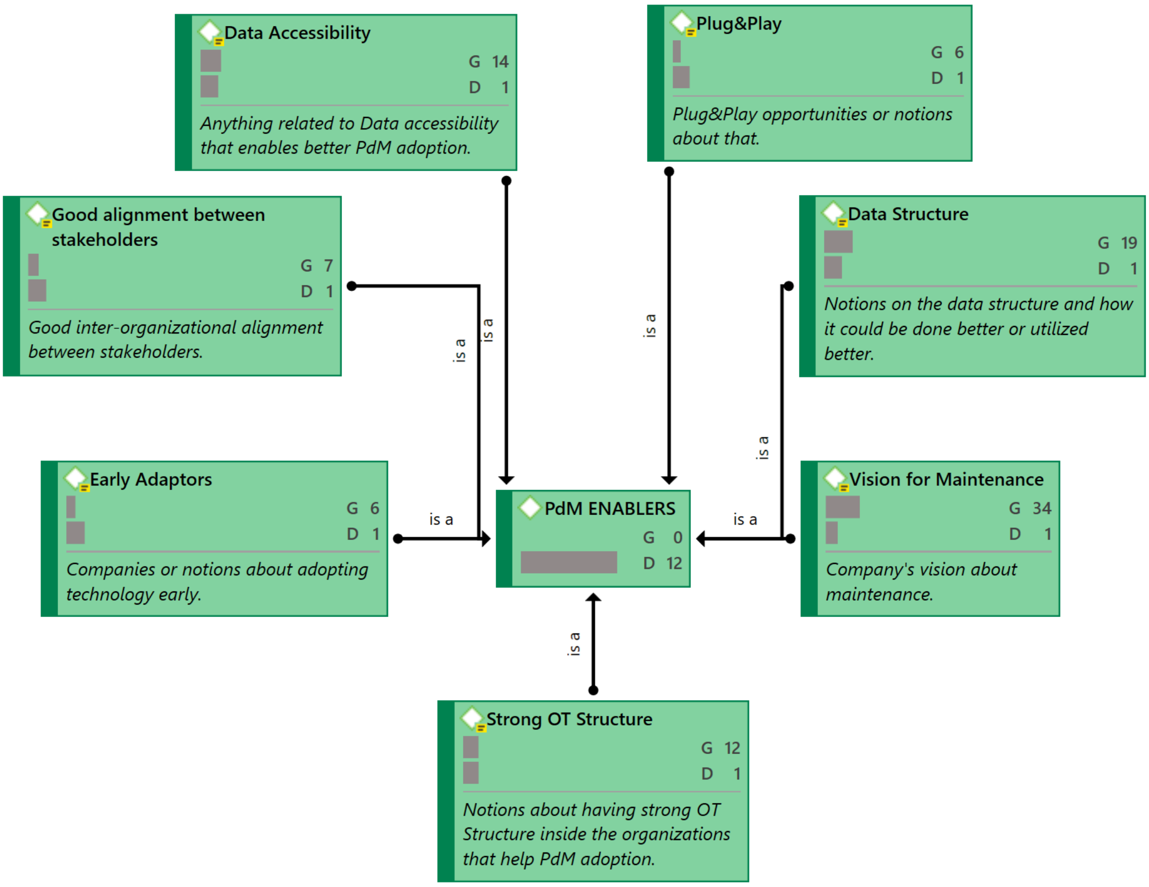

Figure 11: Overview of codes contributing to the major theme called PdM enablers

4.2.2.2 PdM barriers

Adoption of predictive maintenance technology can face many barriers along the way (Figure 12). The study found that lack of the right capabilities inside the organization proved to be a major hindrance to adoption since there is no sufficient ability to analyse the data, re-structure the maintenance processes and strategies according to PdM and algorithm development requires experienced professional. Furthermore, the sheer lack of data to build and train predictive algorithms was illustrated. In addition, if the data was present, the quality of the data was low, meaning that considerable amount of time and effort went into preparing the data for algorithm development. The suitable business case is often the foundation for PdM implementation but building a business case can be cumbersome endeavour since it is hard to quantify PdM effects. Furthermore, predictive maintenance starts showing tangible benefits after considerable time has passed, delaying the positive effects and alternating timeframe to calculate return on investment. From the organizational side, there is still scepticism present about the technology, generating resistance to adoption. Furthermore, even though some parts of the organization are confident in the new technology, they might not have sufficient decision power to push this technology to be implemented throughout the organization. Lastly, miscommunication and misunderstandings between stakeholders could lead to false expectations and failed projects along with unsuccessful partnerships.

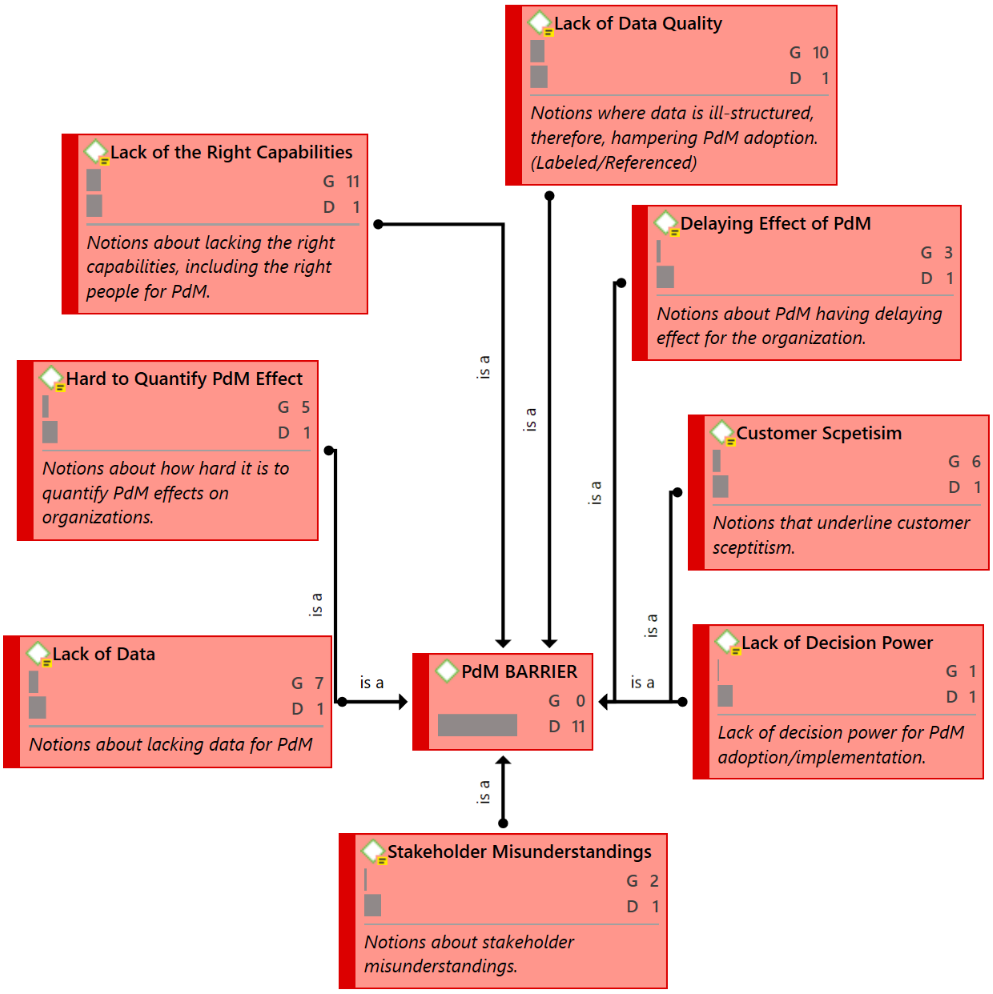

Figure 12: Overview of codes contributing to the major theme called PdM barriers

4.2.2.3 Business Case building

The consideration for PdM commonly comes from either bottom-up (from the work floor) or top-down (management push) initiatives. This affects the business case building (Figure 13) since the stakeholder dynamics making the financial decision is different in both approaches (more elaborated in the developed checklist itself). Predictive maintenance allows developing novel business models for the OEM's and suppliers, moving from strictly one-off sales-oriented to more service centred approach. This means that strong contractual agreements must be in place to make it clear for all the parties involved how the collaboration should be commenced.

Business case building for predictive maintenance can be sometimes hindered by the fact that it is hard to quantify benefits of PdM, however, it is deemed important to illustrate the benefits of PdM by using numbers on the paper. While companies make their revenue calculations and on return on investment, interviewees revealed it is important for the client organizations to understand that initial investment into necessary operational and information technology infrastructures can be costly if there is not a strong "backbone" present. The interviews disclosed that this proved to be especially critical to smaller, remote plants and facilities that were not equipped with modern IT/OT infrastructure, rendering return on investment negative in many instances.

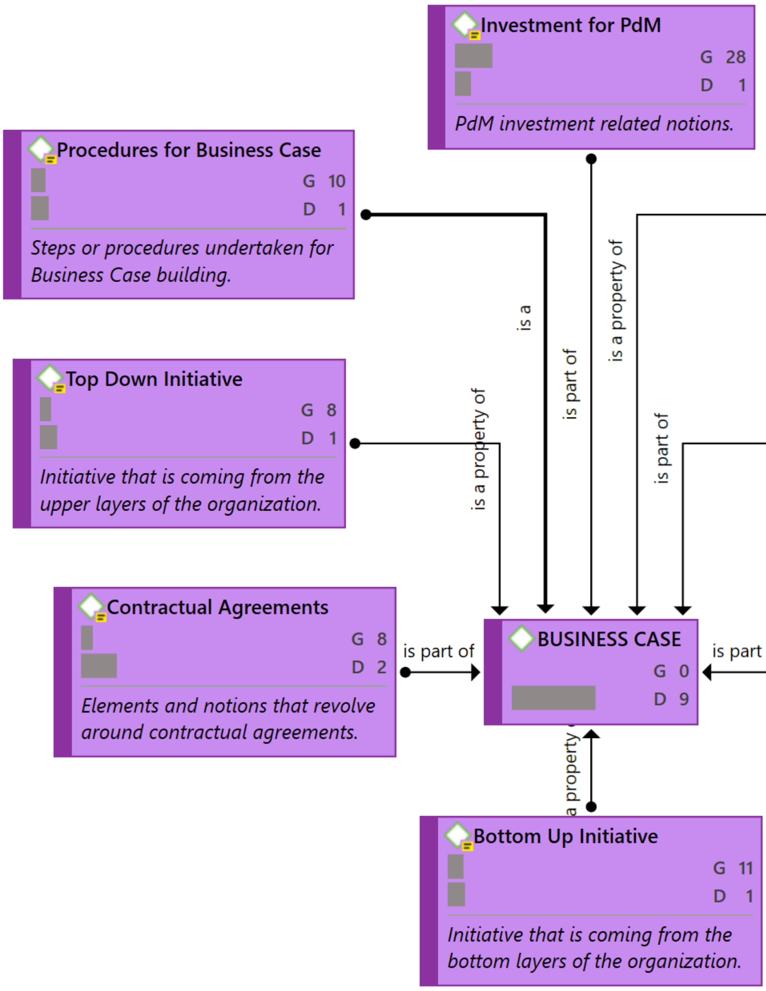

Figure 13: Overview of codes (elements) contributing to the major theme called Business Case

4.2.2.4 Concerns about PdM

Interviews revealed multiple concerns about implementing predictive maintenance technologies (Figure 14). The biggest unease was related to the cybersecurity of the PdM solutions. It was mentioned throughout the interviews that the security of the information technologies is lagging, meaning that companies are reluctant to adopt new technologies quickly since they perceive them not having the highest levels of security. This is connected to the concern of their business-critical data being leaked to other competitors that could gain an unfair advantage by having access to that information. Furthermore, PdM solution providers and clients who are implementing this technology have to share and exchange the data for processing. This creates the debate about the data ownership – who owns what portion of the data? Overcoming this concern could be supported by having clear and strong contractual agreements in place over data ownership and usage. Lastly, responsibility in implementing PdM was mentioned as a concern when safety was the main value driver for adoption. Taking full responsibility in realizing this new technology while human lives are the matter of discussion was not taken light-heartedly since if the technology fails, the person responsible for implementation would take the burden of the blame.

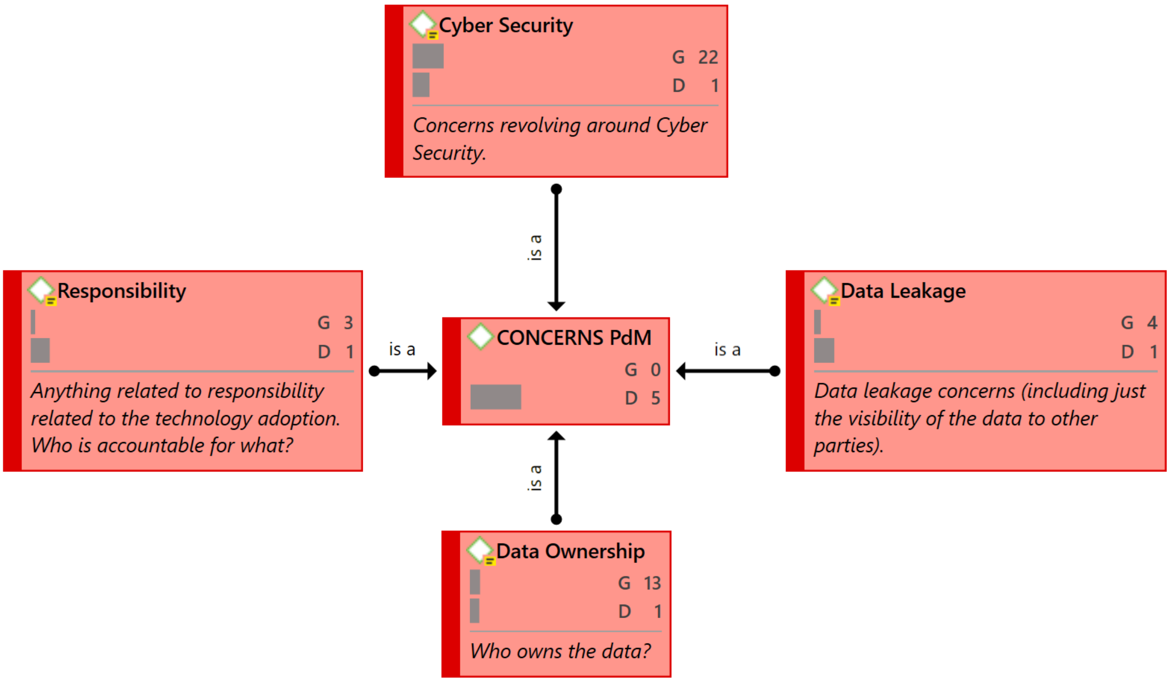

Figure 14: Overview of codes (elements) contributing to the major theme called Concerns about PdM

4.2.2.5 Convincing for PdM

It emerged from the interviews it is often necessary to convince stakeholders about the benefits of predictive maintenance (Figure 15). The most important factor in that is showcasing the reference projects from different industries where companies have successfully adopted this technology. In addition, educating the personnel in organizations and bringing awareness was deemed to be of high importance for succesful adoption. Providing the right information to the relevant stakeholders was mentioned, for example, maintenance manager wants to know the overall health of the production plant while maintenance technician would want to know information contributing to the health of a certain asset. Explanation of value drivers and delineation of positive attributes of PdM helped companies to understand how PdM could fit into their processes and existing systems. Furthermore, in-depth analysis and understanding of the implementing organization and its processes are essential to recognize how predictive maintenance could enhance the business operations. This understanding could be done by organizing workshops inside the company. Last, smooth user experience for the work floor operators using PdM solutions was highlighted to ensure higher acceptance of the technology.

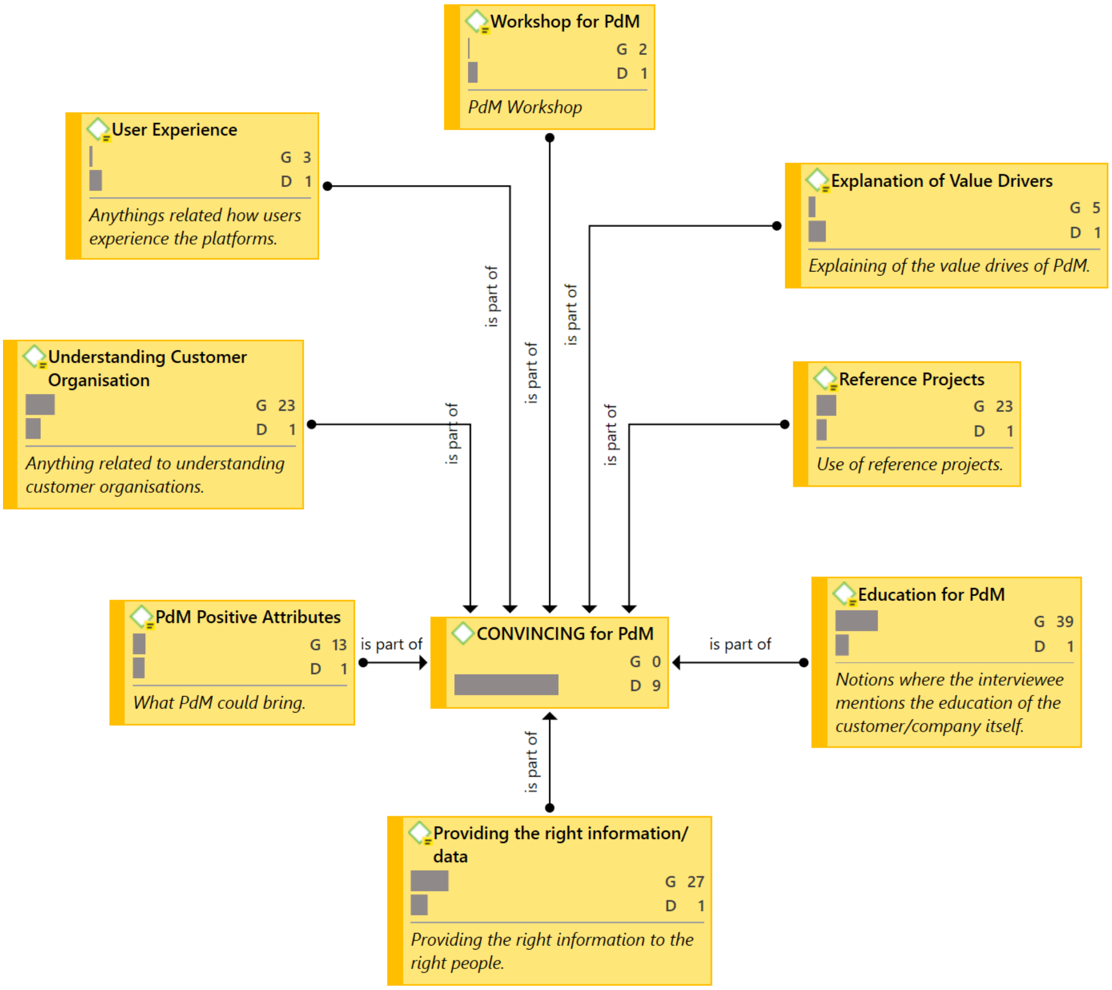

Figure 15: Overview of codes (elements) contributing to the major theme called Convincing for PdM

4.2.2.6 Integration

Ability to integrate PdM solutions with the existing process software was highlighted to contribute to the successful implementation of PdM (Figure 16). The main driver for better integration would be standardization of data structures and processes how it is handled. Furthermore, suppliers and OEM's in the industry should adopt more standardized product functionalities concerning data, its processing and integration capabilities. Some organizations are working on the standardization which would benefit the industry as a whole. Additionally, the use of open protocols from different organizations would better support integration capabilities. Usage of proprietary protocols could hindrance the implementation of PdM since the needed data in the systems would not be accessible. Black box solutions for PdM would receive some scrutiny related to the trust since maintenance personnel would want to know how these solutions come to their suggestions about commencing maintenance activities and how these can be connected to other existing systems. Last, connectivity of different sensors and assets was mentioned to be a hindrance since some assets, PdM software, sensors and other technical infrastructure do not allow connection between them, making PdM implementation harder.

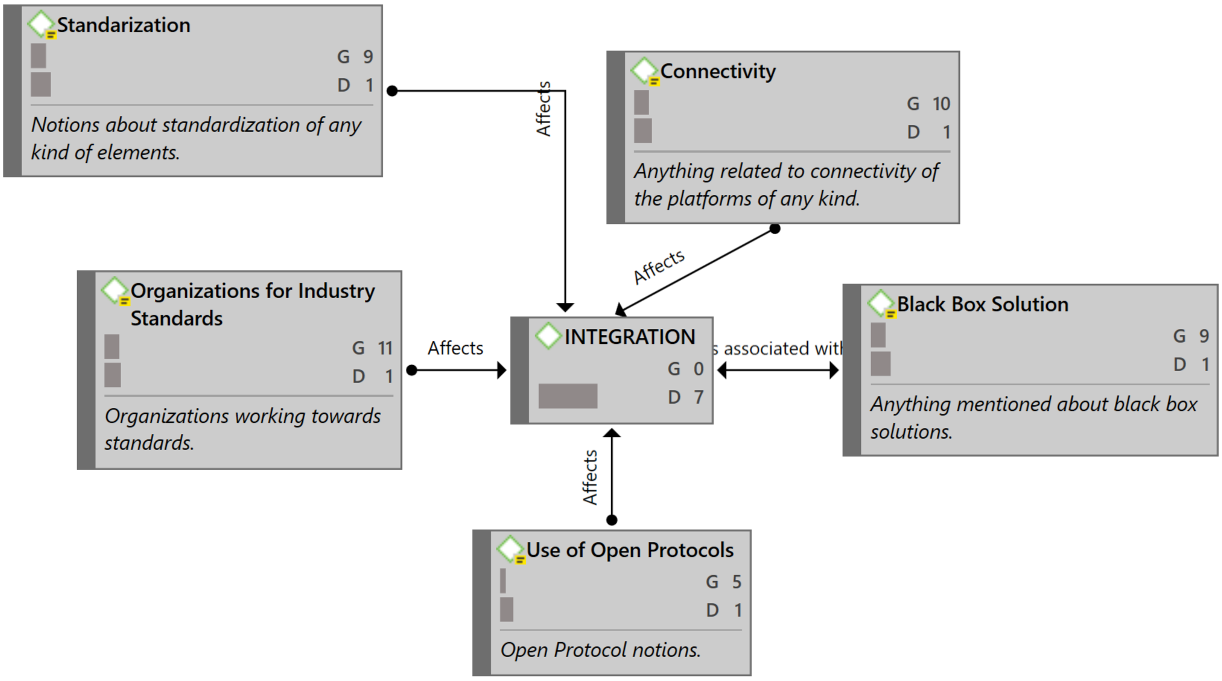

Figure 16: Overview of codes (elements) contributing to the major theme called Integration

4.2.2.7 Inter- and intra-company elements

Implementing PdM is a rather complex organization-wide project that requires a multi-disciplinary approach. This means that many factors and elements are contributing to its adoption (Figure 17). Industry in which the organization is operating in can have a considerable effect on the implementation. Process industries where continuous processes are running would receive more benefits from PdM since they aim for maximized uptime of their assets and around the clock production. The manufacturing industry, for example, can have planned cleaning and stock refill activities in which the maintenance activities can be performed, meaning that manufacturing companies could perceive slightly less value out of PdM. Furthermore, the maintenance maturity level that the company is at the present moment plays a role in implementing PdM since making progress from lower levels straight to predictive capabilities rarely happens seamlessly but is possible in theory. In addition to maintenance maturity, it is essential to have clear maintenance strategies in place to accommodate predictive maintenance into the maintenance processes. If there are no clearly defined maintenance strategies, then companies struggle to find the best suitable fit for PdM in the organization. This comes in connection with clear delineation and analysis of value drivers for predictive maintenance, meaning that explicitly laying them down will help to keep the vision for elaborated maintenance approaches.

Predictive maintenance adoption is highly collaborative between different organizations. Companies can aim to develop PdM capabilities in-house, although this is not that common since it takes a longer period and resources. Often collaborative partnerships are formed to bring in the capabilities from the outside. Some organizations are performing only first-line maintenance on their sites and plants, meaning that they are outsourcing more complex maintenance activities to external companies. This provides opportunities for those external companies to elaborate their service offering by implementing PdM into their processes which potentially increases the efficiency of their maintenance service.

The importance of suppliers and OEM’s was continuously highlighted in the interviews. Organizations have higher expectations to suppliers and OEM’s regarding their products – they would want to see condition-based monitoring and predictive capabilities embedded in the bought products. Furthermore, OEM’s and suppliers are looking for additional opportunities for enhanced service offering and alternative business models. This means that there is high interest from their side to add these capabilities to their products and service offering.

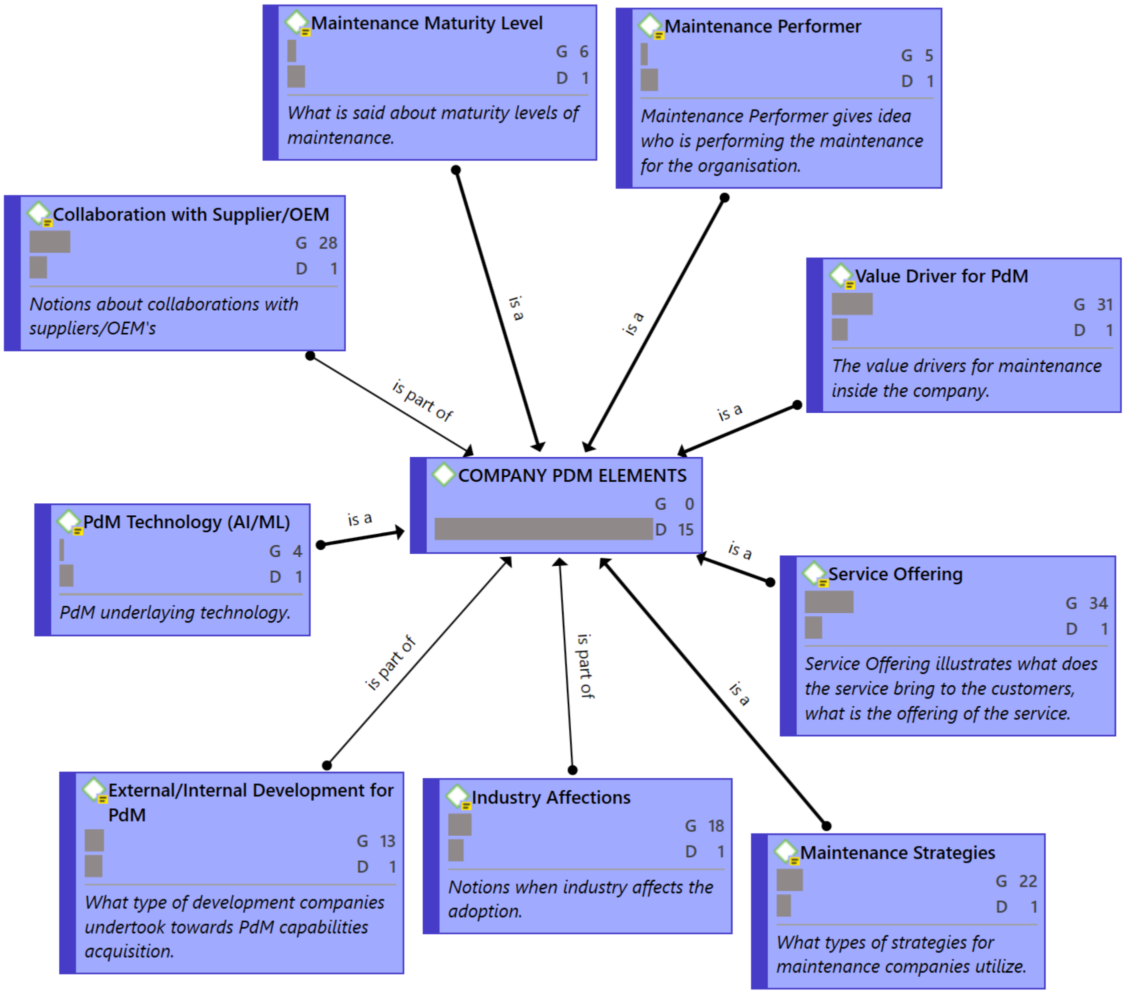

Figure 17: Overview of codes contributing to the major theme called Inter- and intra-organizational elements of PdM

4.2.2.8 Organizational changes

Organizations implementing PdM usually need to make necessary changes to accommodate this new technology into their processes efficiently (Figure 18). Mindset shift of the personnel about predictive maintenance is essential, especially the notions about changing and more flexible work roles regarding the novel ways of working. This means that maintenance personnel need to learn to work together with PdM technologies to make maintenance more effective. It was illustrated in the interviews that the importance of the human factor in the maintenance is as ever important with the coming of this new technology, meaning that their work and positions will not become obsolete since PdM is used as maintenance decision support tool, the final decision is made by the maintenance personnel themselves. Furthermore, implementing this new technology allows the perfect opportunity for organizations to re-organize their teams to adapt to the digitalized, data-driven way of working. Last, it was mentioned that companies need to design their processes in a way that enables better and more efficient maintenance activities. Organizations need to make sure they have logistic capabilities to act upon the insights provided from the predictive maintenance solutions, otherwise implementing PdM would not yield as much benefit to the operational processes of the organization.

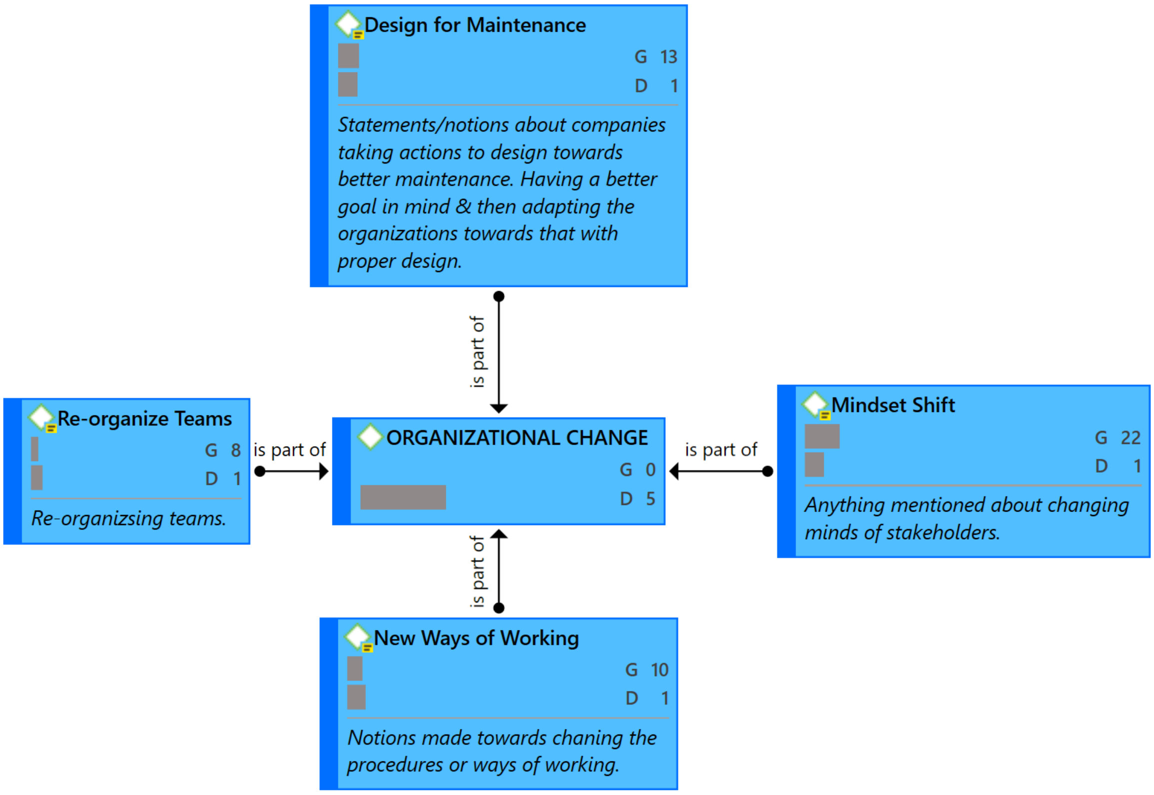

Figure 18: Overview of codes (elements) contributing to the major theme called Organizational change

4.2.2.9 PdM procedures

Predictive maintenance algorithm development usually is approached by top-down or bottom-up. The top-down approach incorporates taking all the data from the operational systems and sensors into one big data lake from which mathematical correlations and insights are drawn from. This requires powerful computing capabilities from the technological perspective and could yield some surprising insights, although together with the extensive number of trivial findings. The bottom-up approach takes another perspective – first analysis of the assets is done by identifying potential failure modes and relevant sensors that capture the required data essential for predictive algorithm generation. This means focused, analytical approach that requires more engineering experience/knowledge inside the organization but will provide concrete and direct findings.

For PdM implementation organizations need to conduct detailed maintenance process and strategy analysis (Figure 19). This means using FMEA/FMECA/Root Cause practices to reach a higher level of understanding about their maintenance-related activities. When PdM or Condition Based Monitoring capabilities are present inside the company then commonly there are teams or positions present responsible for the analytics coming from these solutions and then providing this information to the work floor to conduct maintenance activities.

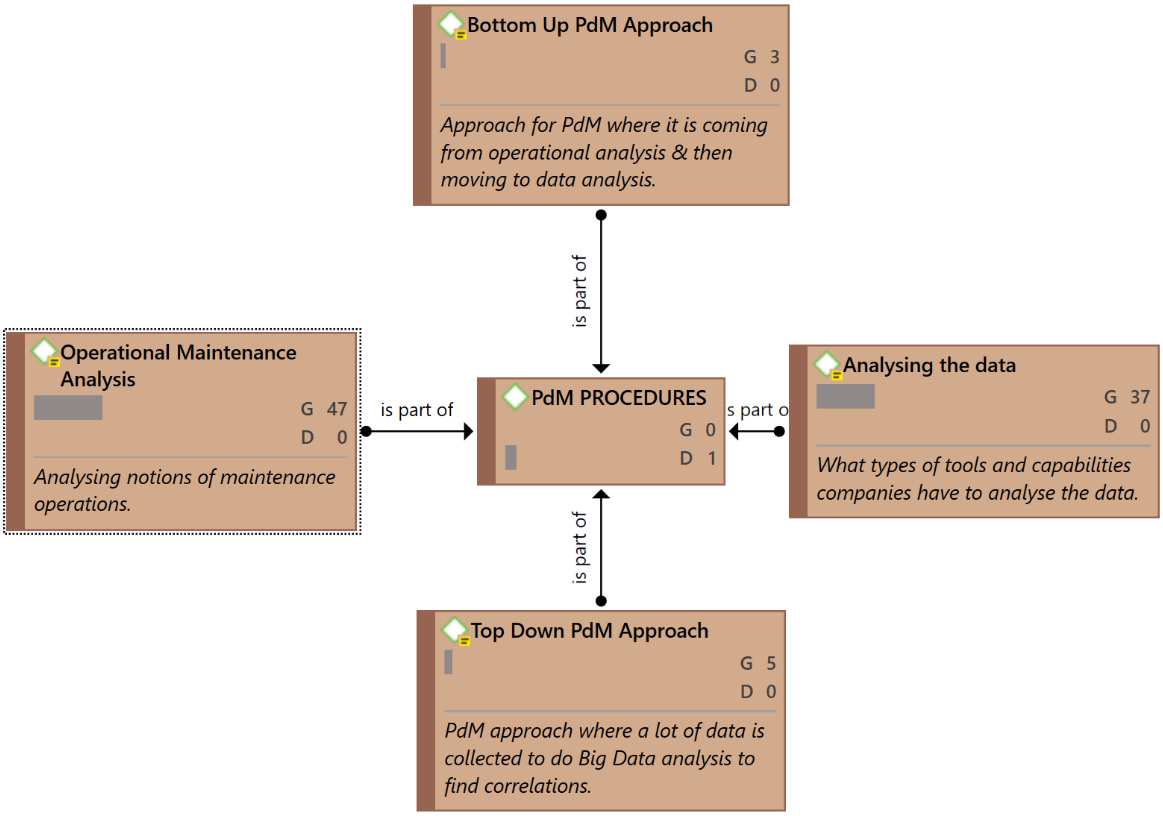

Figure 19: Overview of codes (elements) contributing to the major theme called PdM procedures

4.2.2.10 Relevant IT/OT infrastructure

Having a strong “backbone” of operational and information technologies infrastructure is essential for implementing predictive maintenance solutions (Figure 20). One of the most mentioned factors was having central historian present where it is possible to access the historical process and maintenance data from a single spot. This makes PdM implementation seamless because of the possibility to apply a *plug&play* concept where there is no need to draw data from countless different sources with alternating data structure, generating an extensive amount of extra work. Furthermore, having elaborate CMMS, MES, DCS, SCADA systems and remote process operating centres in place were highlighted to be highly beneficial for PdM adoption. Having accessibility to historical failure, process and EAMS data with coherent structure was deemed highly important for more efficient implementation.

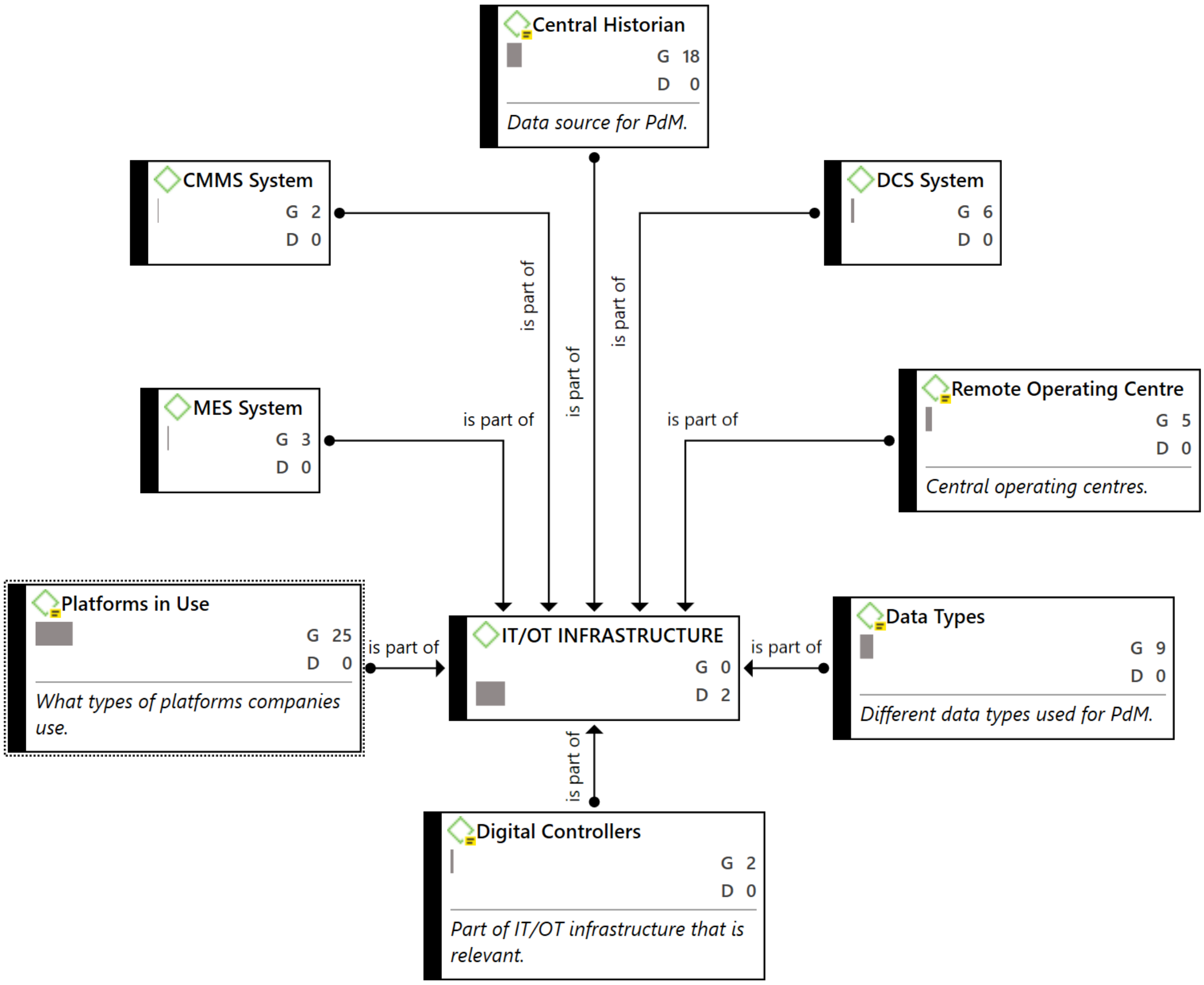

Figure 20: Overview of codes (elements) contributing to the major theme called IT/OT infrastructure

4.2.2.11 Trust towards PdM

Organizations have still scepticism about PdM to some extent since the beginning of the hype and over-promising of the technology companies were expecting quick results which were not aligned with reality. Now when the hype has passed, organizations are realizing what is needed to implement PdM effectively, being more aware of the entire process. Having more knowledge and awareness about this technology helps to improve the trust levels (Figure 21). Organizations trust predictive insights enough to base their maintenance decisions derived from the insights of the solutions. Cybersecurity is still a major concern and coming from this, organizations have higher trust levels towards on-premise solutions versus solutions running in the cloud. Also, providing the right information coupled with clear and concise dashboarding of PdM insights will elevate the trust levels of the personnel. Having transparency in how the solution comes to the maintenance suggestions, causality illustration, is highly important for technicians and engineers to trust these solutions. Black box solutions, for this reason, were mentioned to be less trusted since personnel does not understand them. It is possible to overcome this nuance by opening up these black boxes by explaining these mathematical models and how the insights were derived – this is called explainable AI. Last, organizations do not trust third party applications less because they are coming from outside the organization since there are strong contractual agreements in place and there is an understanding about the importance of having valuable collaborative partnerships.

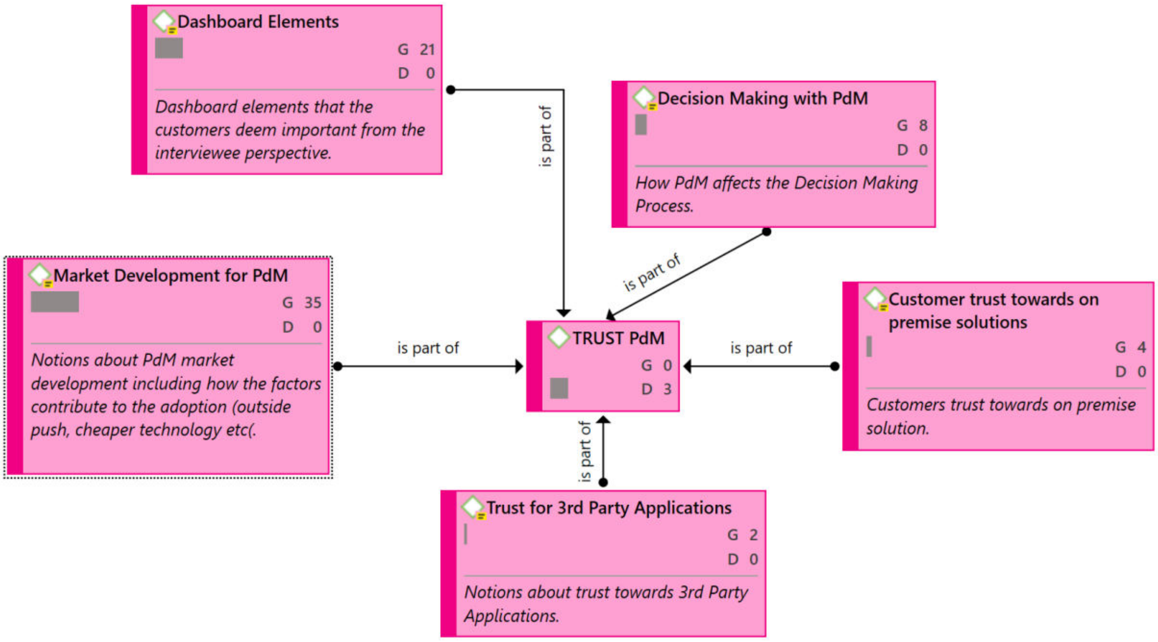

Figure 21: Overview of codes (elements) contributing to the major theme called Trust in PdM

4.2.3 What is new and surprising?

4.2.3.1 Supplier involvement importance

Throughout the interviews, it was highlighted how the importance of OEM's/suppliers in the market development for predictive maintenance is considerably growing. Asset Owners have higher expectations of the assets they buy – ideally looking for condition monitoring and predictive capabilities already embedded into the products. In addition, OEM's/suppliers are understanding the changing technological environment and are investigating alternative business models to incorporate improved services on top of just selling the product. Furthermore, collected maintenance data from predictive algorithms potentially helps the OEM's/suppliers to design better products, generating additional value and benefit.

4.2.3.2 IT and cybersecurity are lagging behind

The research revealed that information technologies and more importantly, the security levels of IT, are lagging and hampering the adoption of predictive maintenance technologies inside the industry. Organizations are concerned about the security of their business-critical data and information which falling into the wrong hands could damage the competitiveness of the company on the market. In addition, there is a clear tendency that organizations prefer on-premise solutions since their perceived security levels are higher.

4.2.3.3 Lack of awareness about PdM prerequisites

There was a continuous tendency throughout the interviews that client organizations are not fully aware of what is needed in reality to implement predictive maintenance solutions. There is usually not enough data, or its quality is not on a sufficient level, but organizations are still having high expectations about the promises of predictive maintenance. This is stemming from the lack of knowledge and experience in this domain. It could be speculated that either some companies have not done sufficient research before starting a PdM project to know what exactly is needed or there are not enough resources easily accessible that provide the right kind of information.

4.2.3.4 Trust towards 3rd party solutions and willingness to collaborate

Interviews revealed that companies do not have lower trust levels towards PdM solutions that are coming from external parties. It was mentioned that the clear and concise contractual agreements, non-disclosure agreements and other documents add an extra layer of responsibility towards cooperation, increasing trust that each stakeholder will hold up to their part as agreed. In addition, it was revealed that organizations are mostly willing and open to partnerships/ collaborations in implementing and improving this new technology.

4.2.3.5 Ambiguities with maintenance terms in use

There are some ambiguities about the vocabulary used about unplanned, planned, preventive and corrective maintenance. In some instances, the term planned maintenance has been confused with the planned inspection. When there are planned activities to investigate if assets need maintenance then it is planned inspection not planned maintenance. The inspection is planned first and then the outcome of the inspection will provide information on what maintenance activities then to commence. Furthermore, it was stressed to understand that preventive or corrective maintenance tells you something about your technical condition before or after a failure. Planned and unplanned maintenance refers to the logistic processes. There is a relation between these terms, but they have different perspectives. To a large extent, the maintenance itself is unplanned, however, it is preventive. With inspections, the goal is to do preventive maintenance. For a modern machine with many integrated technologies based on inspections - preventive becomes unplanned maintenance. This notion should be brought into the awareness of the industry and scientific domain to streamline correct usage of maintenance terms.

4.2.4 Divergent and opposing findings

4.2.4.1 Strictly mathematical versus engineering approaches

It was revealed that engineering-related approaches, where first the failure modes were investigated and the necessary data was determined for predictive algorithm development, to predictive maintenance were more efficient in providing more focused and relevant information. However, some organisations opt for strictly mathematical approaches to achieve “quick wins” and fast results. It was believed that providing the maintenance personnel just with preliminary information that something needs more in-depth inspection was enough to prove the operational benefit of this new technology. Especially this is interesting since the maintenance personnel has lower trust levels for strictly mathematical approaches because they are not informed how these solutions came to these maintenance recommendations. On the other hand, challenging maintenance personnel with these mathematical models that provide insights with sufficient accuracy levels and there is indeed something that requires maintenance, that marginally improves their trust levels towards these mathematical approaches in a step-by-step manner.

4.2.4.2 Organizational cannibalism

Organizational cannibalism happens when companies introduce new products and/or services to the market that conflict with their previous offering which results in novel products taking over market share from the old products. Maintenance service providers that offer man-hours with lower levels of maintenance strategies have internal conflicts with implementing PdM solutions since then their clients potentially would not require that many man-hours on their production plants. In addition, there were instances where OEM’s/suppliers have more elaborate and technologically advanced products that have better servicing capabilities embedded, meaning longer life-cycles and more value to the customer, but these were not sold to the client since selling more of technologically less developed products was more beneficial for the organization.

4.2.4.3 Black box solutions

The research revealed that black box solutions are generally trusted less by the organizations and especially the maintenance personnel since they do not know how these solutions came to these conclusions and recommendations for maintenance activities. However, there are organizations who want exactly to use these kind of black box solutions – they just want to know if the asset needs replacement or first-line maintenance, yes or no, nothing more. This makes it potentially interesting to investigate why some organisations do not want to use black box solutions and others are strictly looking for them.

4.3 Investigation study conclusion

This research utilized semi-structure interviews with 11 industry experts to uncover best practices used in their organizations regarding predictive maintenance and factors affecting the overall implementation process of PdM. The interviews were built up in 3 phases – introductory phase to get acquainted between the researcher and the interviewee and to additionally address questions that the interviewee has regarding the study and confidentiality; then the main part of the interview will be focusing on the questions related to the barriers chosen for the research (Business case building for PdM, Trust in PdM technologies, Data management for PdM); concluding section of the interview will go over the topics discussed and leaving some room for the interviewees to add anything they deem relevant to this research. The interviews provided insights into best practices and key factors influencing PdM adoption. There was information that could be classified as new and surprising to the researcher and additionally, interviews revealed findings that were contrasting with other pieces of information. Acquired insights were used as the main foundation for the developed best practices reference checklist for PdM project described in the following chapter.

5 Developed Best Practices Checklist on the Road to PdM

This research project regarding PdM adoption aims to support organizations in adopting this novel technology by illustrating and bringing awareness to best practices that other organizations have been following during PdM implementation. The output is developed based on the findings from the interviews and literature review analysis. Since this developed PdM project support medium does not provide an established definitive roadmap towards predictive maintenance implementation then the word usage of “method” is not completely accurate, in its place “best practices reference checklist” is used from now on. This best practice checklist based on empirical study consists of 5 phase approach where the enablers and barriers (Figure 26 on page 51) in each phase are mentioned and suggestions on how to deal with them are outlined. Furthermore, high-level steps in each phase are laid out to support organizations with PdM activities. These recommended procedural steps are constructed from the process activities that the experts delineated in the interviews, investigated scientific literature (Nemeth et al., 2018; Wagner & Hellingrath, 2019) and based on the adaptation of CRISP-DM data-based project methodology to PdM projects (Smart Vision Europe, 2020; Spendla, Kebisek, Tanuska, & Hrcka, 2017). In the concluding section of this best practices checklist, a compact core representation in Overview of Best Practice Checklist road to PdM is devised for a quick overview and it is advisable to resort back to phases in the checklist itself if the more detailed explanation is needed.

5.1 Best practices checklist

Implementing Predictive Maintenance is an organization-wide project. It is a multi-disciplinary process that requires full commitment from all layers of the company. Dividing PdM adoption into different phases would help to better comprehend and focus on directing effort into the right elements during each phase. From the scientific literature, implementing PdM was divided into four phases: concept, data, development, operationalization phase (Wagner & Hellingrath, 2019). Furthermore, coming from the experiences in the industry, a feasibility phase is added to the list to better explain the importance of *proof of concept*. This developed best practices checklist takes these phases as the foundation and then lays down the best-practices and barriers to pay attention to during the implementation. A summarized overview of what each phase entails is illustrated below:

Concept Phase – During this concept phase first the consideration for PdM is agreed, then the scope and requirements of the project are refined, dependability analysis of the equipment and its components is conducted, and cost-benefit analysis is calculated, resulting in a well-defined business case.

Feasibility Phase – Incorporates running Proof of concept (PoC); Minimum Viable Product (MVP); pilot. Targeting expected barriers early. Based on selected failures/functional degradations a full but shortened project is run from data to partial solution in order to ascertain where there are gaps and barriers.

Data Phase – Data phase targets the selection of fitting measurement techniques, the data acquisition and the preparation of data.

Predictive Algorithm Development Phase – When data is available in a suitable format, the development phase deals with the construction of algorithms for diagnostics and prognostics as well as testing and training of the algorithms.

Operation Phase – In the final operation phase, real-time data access is provided, the solution is deployed. Regular revisions are done and the solution is adjusted based on the new findings from data. Feedback from the system is taken into account, maintaining the PdM platform is planned and further roll-outs organization-wide are done.

(Wagner & Hellingrath, 2019)

This approach is developed to be a systematic best practice checklist towards PdM projects that aims to understand how organizations facilitate successful predictive maintenance implementations and then codifies this knowledge for others to draw support from. The best practice is defined as "*Best practice is a method where organisations identify their key business processes, and actively seek out and compare them with similar processes in organisations recognised for their exceptional customer service or outstanding business processes. The purpose of the comparison is to gather information and insight about better, more efficient and effective methods and approaches, with the view to identifying and implementing the 'best' practice/s.*" (Stockley, 2014).

This best practices reference checklist for realizing predictive maintenance projects is developed mainly for practitioners in the industry who are commencing with PdM projects for the first time. These project leaders can be maintenance managers, innovation managers, top-level executives et cetera. In addition, people researching PdM can gain an understanding about the best practices and barriers to PdM implementation to then further investigate them, potentially seeing how this reference checklist supports organizations in practice. The main holistic core of this best practices reference checklist is the constructed, 5-page compact Overview of Best Practice Checklist road to PdM. It covers the aforementioned 5 phases to PdM implementation projects along with the best practices and barriers in each phase. These allow for better awareness and knowledge what to potentially expect in each phase and prepare for it beforehand, possibly preventing some mistakes along the way what might have happened otherwise. In addition, reminders and recommended project steps are showcased to provide support with the project by bringing attention to the necessary activities to be considered. This acts as a reminder to practitioners in case they have overlooked or forgotten some of the procedural elements in project implementation. It is important to mention that the whole chapter of Developed Best Practices Checklist on the Road to PdM is the detailed, comprehensible explanation of that best practices PdM project reference checklist. This means that elaborate information about any of the phases and elements (steps, best practices, barriers) associated to them are provided in this chapter and should be referred to gain a deeper understanding of this research output.

This reference checklist is meant to be used before commencing and during the implementation process of PdM. This support tool provides awareness to different dynamics that affect the course of the PdM project, meaning that practitioners can understand and evaluate their organization's potential ability to start this kind of project. For example, the checklist recommends having long term vision and top-level management support for this type of maintenance projects, so personnel leading this project can ask themselves if these "boxes are ticked" before going forward with the actual implementation. Furthermore, this reference checklist should be utilized during the implementation process as a reminder to see if the recommended procedural steps are undertaken.

For clarification on how to approach this best practices reference checklist, recommendations on how to use it are described as follows:

1. **Before starting the PdM project:**
    a. Read through the chapter 5 Developed Best Practices Checklist on the Road to PdM to gain an understanding of the factors affecting the potential success of PdM projects. This includes seeing what other companies in the industry consider their best practices, having awareness about the barriers that can be expected in each implementation phase and what advised steps should be undertaken during the project.
    b. Analyse the organization's capabilities referring to the checklist to understand if the project can be undertaken and potential dynamics affecting the implementation process are considered.
    c. Examine the chapter Overview of Best Practice Checklist road to PdM for a holistic overview of the previously read chapter which supports the project during the actual implementation.

2. **During the PdM project implementation:**

   a. Refer to the Overview of Best Practice Checklist road to PdM during the project to oversee if any of the recommended procedural steps have been missed or overlooked. In addition, delineation of best practices, barriers and process steps reminds the reader to analyse if these elements are actively considered. Best practices, barriers and recommended process steps for each phase are gathered in Overview of the developed reference checklist for PdM projects.

   b. In case of the need for in-depth information about the reference checklist, refer to the specific section of the chapter Developed Best Practices Checklist on the Road to PdM for clarification.

5.2 Concept phase

In this phase consideration for PdM adoption is first made. This usually comes from the need for better maintenance coupled with different value drivers or from the market affections to being more competitive. Following, the solid business case is created to determine the initial investment and the expected pay-back period. Business goals for predictive maintenance are laid out.

Companies adopt PdM for different reasons: Uptime improvement, cost reduction, reduction of safety, health, environment & quality risks, lifetime extension of ageing assets, higher customer satisfaction and so on (Haarman et al., 2018). There are changes in the maintenance environment with recent trends emerging, which potentially facilitate competition since adopting these new technologies allow increased productivity and profits.

It is especially important to clearly define the *why* in predictive maintenance implementation, what is the goal of it? Are the goals related to the economical drivers (cost reduction) or is it related to safety (transportation for example)? Having safety as being the biggest driver changes the depth of the responsibility put on the technology since human lives are involved. This means that PdM should be coupled with another risk management strategy (human inspections for example) to minimize the risk of technology making inaccurate predictions. As a takeaway, safety-related approaches require a different perspective on predictive maintenance implementation.

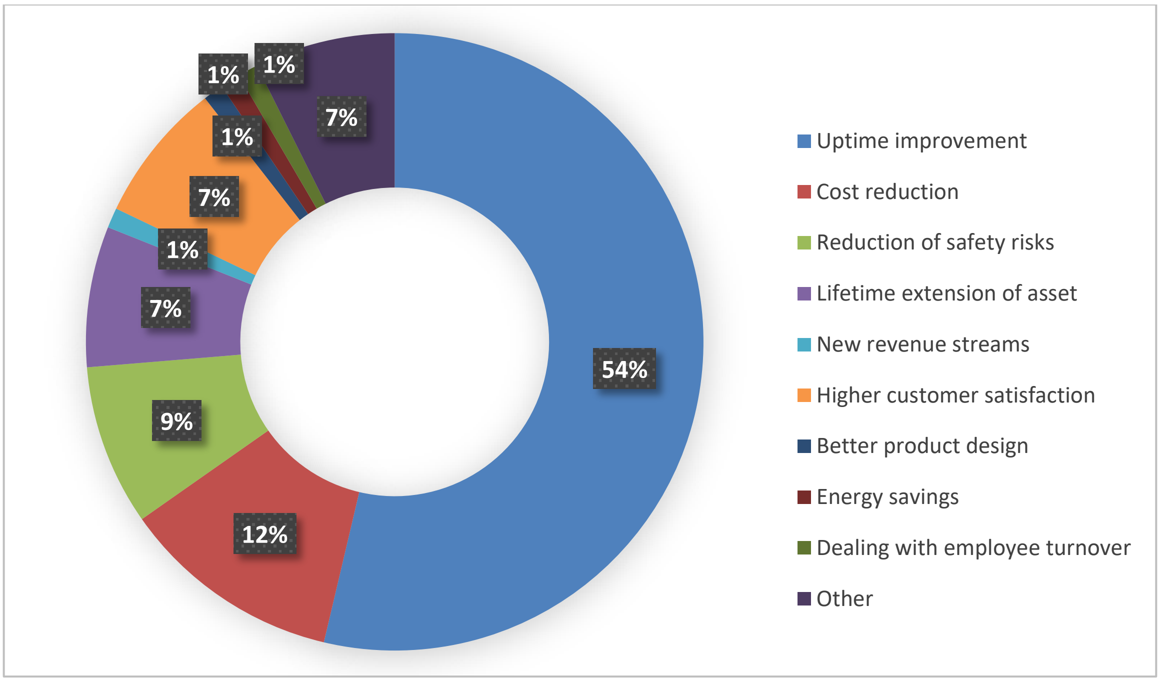

Figure 22: Primary goals for PdM adoption. Adapted from: (Haarman et al., 2018)

5.2.1 Consideration for PdM

The consideration for predictive maintenance emerges from the reasons mentioned in Figure 22. This gives an understanding why organizations are motivated to implement predictive maintenance, enabling to preliminarily probe how this technology should reach the main benchmark set by the company. The idea to adopt PdM usually comes from either of two different sides: top-down approach that is initiated by the top-level management or bottom-up initiative that is coming from the need from the work-floor and the operations (Figure 23). There are unique aspects to consider with either of the approaches and there is a possibility of hybrid initiative that captures the entire organization, but this level of commitment takes considerable effort to achieve, although being essential for successful adoption of PdM.

Top-down approaches start from more strategic levels, where upper management responds to the changing competitive environment and going along with the recent maintenance trends. The research revealed that strict top-down approaches rarely yielded successful results since the typical "push" initiations normally bring along resistance from the bottom layers of the organization. There were cases where the upper management with the IT department were pushing this new technology down the organization and the operational levels responded negatively because they deemed PdM not relevant or understandable for them.

Furthermore, often it is not clarified *why* this new technology is being implemented in this company/plant/site and this leads again to resistance because there is no clear understanding of the purpose to adopt PdM. Without clear purpose and understanding *why,* implementing predictive maintenance can become "homework" for the operational levels of the organization besides the other activities with different priorities. The idea of moving to higher maintenance maturity level, from reactive to preventive to predictive sounds great for example, but that idea has to be sold to the shop floor. If the shop-floor does not believe in this new technology, it will never fly. Hence, usually, strictly top-down approaches do not bring success.

Bottom-up approaches start from the work-floor or operational levels of the company, where the workforce sees the need to utilize this new technology because it will make their lives easier/efficient or enhance the operations of the company overall. For instance, the operational people have the problem of too many breakdowns or higher maintenance costs or the combination of these, hence these people are looking for good, predictive maintenance solution that helps to solve that problem. Having work-floor and operational level support helps to better implement this new technology since these are the people that are working with it. Having the understanding and the need for it will ensure the motivation and commitment from the end-users. Then these people can talk about proof of concept and a business case, taking the PdM idea to the upper-level management.

In some instances, operational level management had sufficient funds to run their proof of concept pilots, which became useful when convincing top-level management for wider implementation. However, the upper-level management is not always convinced with this new technology or it does not have the sufficient priority needed to be put on the action list. Hence, strictly bottom-up approaches might be more successful, but without the top-level support, the probability of efficient implementation is rather low since there is not enough decision power to fund the project and then nothing happens in the long run.

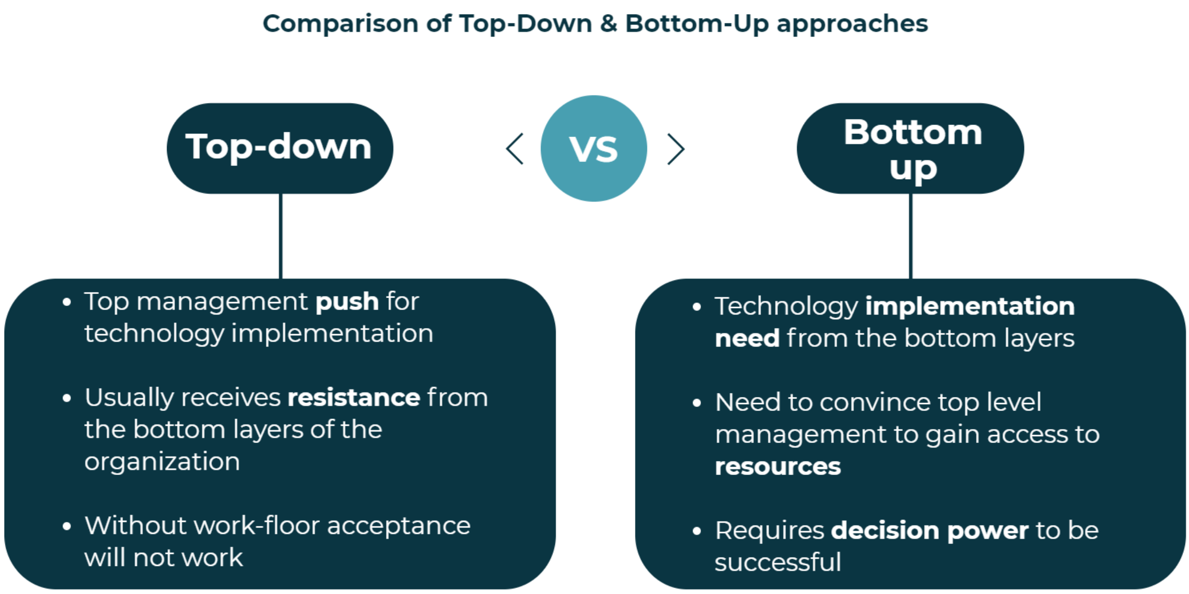

Figure 23: Comparison between top-down and bottom-up approaches

The interviews revealed that the **hybrid approach**, comprising both top-down and bottom-up initiatives where all the stakeholders were involved, proved to be the most successful. Stakeholder involvement on all organizational levels was deemed to be one of the most important factors for successful PdM implementation. The operational levels of the organization understand the need for predictive maintenance for better operations management. The top-level management understands the value of this new technology and is allocating funds for the project. The actual work and implementation then can be done on the work-floor of the organization, the end-user.

5.2.2 Success factors in the concept phase

5.2.2.1 Stakeholder involvement

As mentioned beforehand, the research revealed that stakeholder involvement is essential to ensure a higher probability of the successful PdM adoption. There are many notions of how stakeholders were involved effectively in PdM implementation, see Table 6:

Table 6: Stakeholder involvement best-practices

Stakeholder Involvement	Description
Majority understands the need/incentive towards implementing Predictive Maintenance	There can be outside facilitator like competition for example that brings the need to adopt PdM. Then everybody should align behind that notion of the need. There can also be a personal incentive to adopt PdM. “Is it less work for me? Is it more productive for me? How do I gain out of it?” There should be an incentive or a threat (from the outside), maybe a combination of both together so that people are motivated to move from one mode of working to another across all layers of the organization. The bigger the group is, the more flow the project would get.
Strong value has been showcased to the top-level management	Management cannot make the investment unless there has been strong value showcased. With strong value, it is possible to gain management support, access to resources and financials for the project.

Stakeholder Involvement	Description
Knowledge sharing between different stakeholders	Different layers of the organization are working together and sharing knowledge. Asset management consultants provide their expertise while technical sales-personnel come from the customer side understanding what the customer needs are. Different disciplines within the organisation are being involved and working together towards a common goal.
Involving all stakeholders from the beginning	It is important to involve all the stakeholders from the beginning. If only one person is convinced, then it can delay a lot if it is needed again to re-convince someone else. Reporting to everyone in the room at the very beginning – that is a big topic. So that everyone can be involved in the preparation of the business case and provide their objections and then these can be addressed together with the rest of the team.
Regular discussions and meetings between all stakeholders	Having regular discussions and meetings between all stakeholders allows to better exchange the information and make sure that everybody is on the same page.
Working together with the end-user	Working together as in asking for the input, what would the organizations want to have and brainstorming on their solution together. Different organizations have different expectations and needs, making the implementation in need of a tailored approach to each company separately. Work-floor involvement in the PdM implementation is of utmost importance since they will be the personnel using that technology. Understanding what their needs are and illustrating how it makes their work more productive is a must.
Give freedom and trust to the PdM project team	Allow the PdM project team to do their research freely by discussing experts in academia and having cross-industry cooperation. PdM project team needs their R&D time to foresee what is needed in the next upcoming years and align the organization with it. Forcing results quick rarely provides successful results in this complex domain.
Connecting people with the domain knowledge with the data scientists	Engineers provide input for the data analysts for their models. Interaction between technical people that know the systems, that have the domain knowledge and a data scientist who is good in providing useful insights with the data. But it is the interaction between the two that in the end leads to a useful result. Make sure that the data scientist is also willing to talk to technicians and is willing to try to understand what this technician is doing and what he is meaning. Because if there is a pure mathematical person who is only interested in numbers and does not want to understand what the numbers mean, then it will never lead to an elaborate and accurate result.

5.2.2.2 Sponsor for the project

Implementing predictive maintenance is affecting the entire organization and needs to be supported by top-level management. It was revealed that having a sponsor for the project is essential. A sponsor is somebody who has decision-making power, access to the resources and is genuinely sharing the vision that adopting predictive maintenance is the right way to go forward. Especially with bottom-up approaches, the sponsor plays an important role, because otherwise the project will be halted somewhere mid-way. Sponsors usually have the following characteristics:

- Makes the decision to invest;
- Has decision-making power;
- Has access to the resources;
- Supports the case in front of the board meeting with all the C-level executives;
- Pushes the project through to the higher levels in the organization;
- Aligns with operational levels and their needs.

5.2.2.3 Stakeholders

Below is the stakeholder Table 7 that indicates how each stakeholder fits in the picture for the implementation. Selecting the important stakeholders depends on the maturity of the organization and also depends on the choice of the predictive maintenance solution itself. Each organization is structured differently and has a separate set of capabilities. This means that organizations need to identify how the stakeholders would best fit within their existing processes and structure. Overview of stakeholders and their relative representative hierarchy can be seen in Figure 24.

Table 7: Relevant stakeholders for predictive maintenance implementation

Stakeholder	Key in Adoption	Role played
Project team/leader/champion	Pushing the PdM project forward inside the organization.	Needs to be invested fully & have long term vision for the project not for short term success (the change will not grow otherwise). Need to have knowledge about the technology to convince others. Need to have success factors along the way to convince the higher management.
Sponsor • **Operational manager** • **Site manager** • **Maintenance manager**	Somebody with decision-making power to allocate resources and convince the board of the executives.	Needs to believe in PdM and needs to possess knowledge about it. Trusting the PdM project team is essential, give them a green light and be patient because PdM takes some time to show value.
Board of Executives	Approves the PdM project and allocates the necessary financials.	Needs to see the value of the project by PoC's/pilots or be otherwise convinced. They want to see that business is doing well and the money invested is invested in a profitable cause.
Gatekeeper	The person who oversees interactions between operations and the maintenance people. Usually present in large organizations and allows PdM projects to be moved to higher management.	Needs to be working closely with the maintenance personnel and operational levels of the organization. Needs to have confidence in the technology.
Operational level • **Reliability engineer** • **Maintenance engineer** • **Asset engineer** • **Instrumentation personnel (sensors)**	The end-user responsible for using the technology. Responsible for analysing data, doing expertise research, and make the decision that we should do this type of maintenance because there is a specific risk	They need to believe in the solution that it helps to do their job better. Needs to work closely with a data scientist to reap the benefits of data analytics. Putting the operational teams behind the steering wheel – reliability engineer develops the models from his experience with failure modes for example.
Technicians and operators	Provide engineers with the actual information what is happening on the work-floor for the foundation of knowledge and cross-checking for results.	Need to trust the technology and understand that it will make their work more productive and is not there to replace their job. Trusts the input from the engineers.

Stakeholder	Key in Adoption	Role played
Data scientist/analyst	Turns operational knowledge of engineers into mathematical models. Can be external for the model building phase.	Needs to be consulting and working closely with the engineers. Could find all kinds of correlations but cannot interpret them without industry knowledge. Responsible for providing or cleaning the data and building the models.
Consultant	External consultant possession knowledge in the implementation of the technology.	Supports the company with the implementation.
Digital/Innovation Team	The team that would oversee pushing new technologies, and this team is generally not in charge of only predictive maintenance, but they are pushing this type of specific projects inside the organization.	Needs to possess knowledge about these new technologies to convince/educate both top and bottom layers of the organization. Change facilitators can be kind of third-person coming from outside of the company or it can be somebody from each department who is more flexible, sharper or has a possibly a better public relation.
Predictive maintenance team	The team that is strictly responsible for the PdM analysis. Rarely present in many organizations.	With more advanced organization there is already a team that is trying to analyse data and provide insights to the maintenance team or the asset management team. Responsible for monitoring of the data and running the analysis.
IT Department	Responsible for any interactions from the IT side – cybersecurity, data accessibility et cetera.	Needs to provide support to the operational department for data security, backing up and access.
Supplier	Provides necessary instrumentation and/or platform for PdM projects.	Important to fit in the business/commercial model for a good business case.

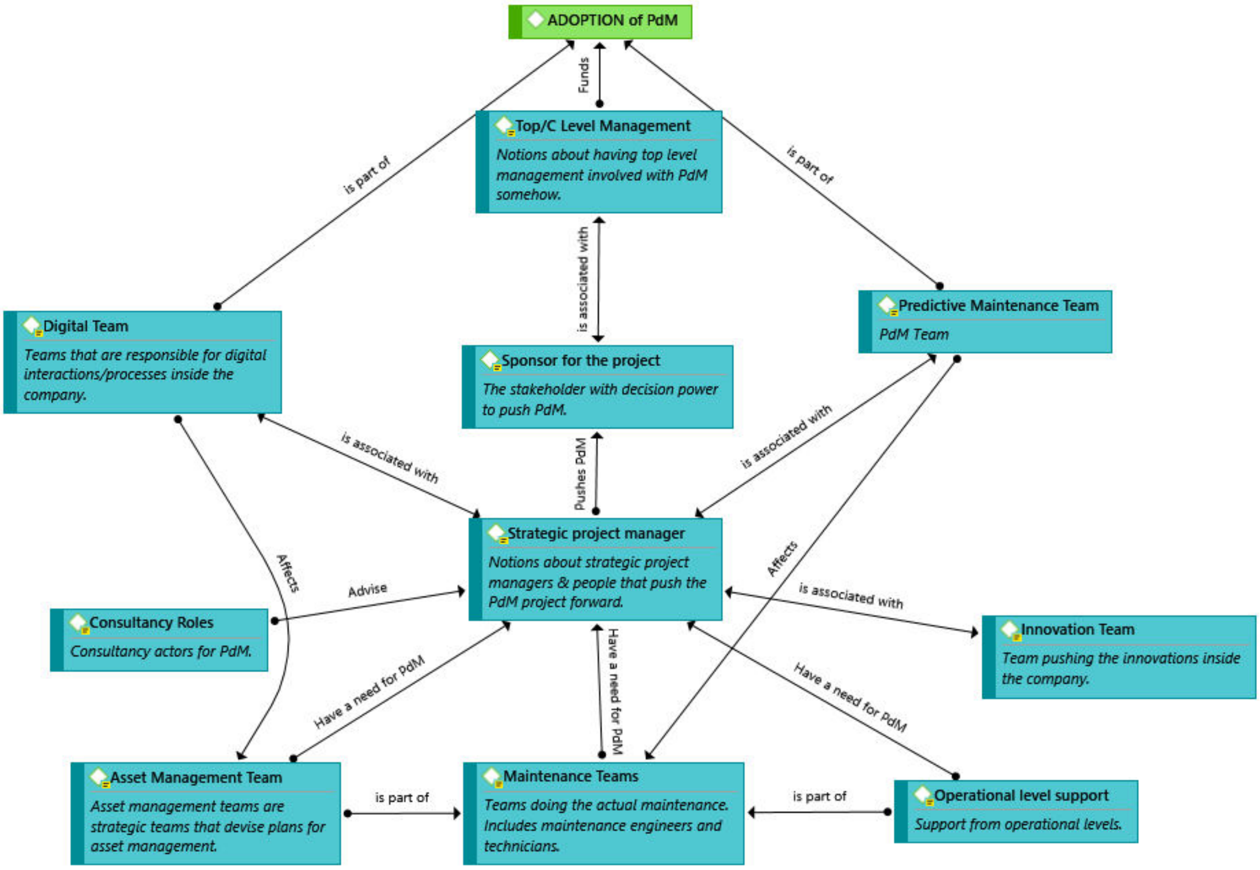

Figure 24: High-level stakeholder overview

5.2.2.4 Vision for predictive maintenance

Implementing predictive maintenance needs a strong vision from the organization about their maintenance strategies. Having a vague vision and unclear direction often leads to unsuccessful implementations of predictive maintenance. Table 8 gives elements to focus on while laying down the perspective for PdM inside the organization:

Table 8: Essential elements for having a vision towards PdM

Essential Element for Vision	Description
Giving priority to PdM	There should be a clear vision and understanding where the effort and energy will be focused on. As a company, there are always many areas to improve. Successful PdM implementation entails a high strategic level prioritization inside the company. This means that all the stakeholders are made accountable for implementation from management to the work-floor. Juggling multiple high-level projects inside the organization with a smaller team will lead to lack of focus and effort, resulting in vague outcomes.
Allocating budget, resources and making investments	Predictive maintenance requires investments to be made and these investments can be considerable. PdM projects must have enough budget allocated for them with clear investment decisions.
Having clear understandings what the organization wants to achieve – have a bigger picture in place.	It is important to understand what the desired outcome of the project is and make it known across the involved stakeholders. Not knowing the final outcome will make it hard to scope and manage the project efficiently. 1. Start with the vision, have a clear purpose in mind (What is the ideal

Essential Element for Vision	Description
	situation? Why are we doing this?) 2. Translate this into actionable strategy (How can we get there?) 3. Develop a proper design to support that strategy (What will we do?). Formulate these things explicitly. This will allow to focus on the bigger picture and have clear targets.
Learn from the market	Study what is happening on the market related to maintenance trends and study other successful implementations in different industries.
Understand what is needed for PdM	It is essential to study what is needed to implement PdM. There is always a balance of things that are needed – investment, data, internal capabilities, supporting processes, the logistic capability to act on PdM et cetera. "How much information do I have?" "What are the potential effects economically?" "What is the population of elements/machinery?" "What is the cost of the component?" "What are my critical components?" "What is the cost of failure/downtime?" Frustration from the industry can come from not identifying these types of questions. It is about managing expectations and making educated decisions.
Clear distinction of roles and KPI's	Every person or every department should know what his or her role towards that PdM objective might be for the year coming for instance and then how they can be achieved. Everybody should clearly understand how they can be integrated into the strategic objective. To support this, small action plans for roles could be developed – one or two key elements that each person can be active and focused on. And then based on that, an indicator can be changed, and all those indicators can work out together to create a KPI. And those KPIs are important for the company. Once this message is clear, and once this line of sight is clear, then the change starts to happen, step by step.
Long-term vision	There should be long term vision and focus on PdM. If the change is left unattended in the middle, it will not grow on its own – the change has to be taken care of over an extended period of time.
Have a clear ambition level	Different predictive maintenance approaches always match to certain ambition levels where distinctive levels of data and knowledge are needed. Companies should always try to see what their ambition is, what is the amount of knowledge and amount of data present. And these two should match. If there is a very high ambition, but only a limited amount of data, then it should be brought to awareness that the ambition level does not match the knowledge and data level.

5.2.2.5 Understanding the organization

Predictive maintenance involves changing processes and operations throughout the organization. It is essential to first understand either own organization or customer company where PdM will be potentially implemented. This allows to specifically identify how PdM could fit into the existing structure, making the implementation seamless and gaining more benefits out of the adoption. Table 9 illustrates best-practices and questions to ask while figuring out the fit between the company and PdM:

Table 9: Understanding the organization

Understanding the organization	Description
Determining where are the pain-points	It is essential to understand what the pain-points of the organization are and what is the value of implementing PdM to tackle these pain-points. Perhaps there might be easier options that could deal with these issues as well like condition-based maintenance et cetera. Have a clear understanding of how PdM addresses these pain-points. A clear understanding of these issues allows developing digital solutions with a better value proposition, because it is tailor more to the customer's actual needs, not what is assumed by the external company providing the service offering.
Processes of the organization	Before implementing PdM inside the organization it is necessary to have a full understanding of how the processes inside that organization work. Therefore, as mentioned beforehand, it is of utmost importance to consult all layers of the organization, especially the bottom layers who have the work-floor experience with these processes and technologies in use. Applying mathematics without understanding what these correlations mean do not yield the most optimal/accurate results.
Speak the language of the stakeholders	Each organization is different and there are major differences what each stakeholder is looking for – top-level management is looking for revenue increases, the overall health of the business et cetera. Maintenance managers and engineers talk engineering language and have a different set of value drivers for PdM. Therefore, it is important to speak the same language to understand the perspectives of different stakeholders.
Assessment of the maintenance maturity	Assessment of maintenance maturity could be undertaken to understand what maintenance processes and strategies at the moment inside the organization are. This allows to pin-point where the organization is at the moment with its maintenance maturity and what are the next steps to be undertaken to improve that.
Knowing who the end-user is	Predictive maintenance solutions should be designed with a clear understanding of who the end-user is. For example, engineers most of the times want to see the whole reasoning and causality how the digital solution came to this conclusion that XYZ needs replacement/maintenance. Maintenance manager wants to have a comprehensive overview of his fleet and its health but might not want to know the in-depth analysis of the specific pump. Therefore, try to understand what the needs of the personnel are who will use PdM technology in the end.
Predictive maintenance is not a "Holy Grail"	Predictive maintenance is not a one-off solution that will eliminate the need for all the other maintenance strategies and approaches. Therefore, it is important to understand where PdM will strategically fit in the maintenance operation of the organization. What would be the distribution of maintenance strategies?

5.2.2.6 Reference projects

Predictive maintenance would still be considered novel technology in the more conservative manufacturing industry. This brings along scepticism towards its implementation and value since companies are being cautious about being the first wave of innovators and bare the potential uncertainties of this new technology. This means that there must be some convincing factors that aid the acceptance of PdM. In this first concept phase, the most mentioned factor that builds confidence and trust towards this technology is having reference projects of successful implementations across all industries.

Uncertainty is one of the factors that might hinder the adoption of PdM (Figure 25). To overcome this uncertainty, organizations want to know that there are referrals, references and actual projects that can be showcased. Having these successful reference projects in some lagging industries can be more complicated and it would be an option to show these projects from another industry with overlapping factors. There are PwC consultancy case studies available on how Infrabel and Sitech adopted PdM (Haarman et al., 2018). In addition, IBM provides five case studies for predictive maintenance from different industries (IBM, 2020) and from the scientific literature a case study in the automotive industry can be found for example (Einabadi, Baboli, & Ebrahimi, 2019).

Having some real numbers to put on the table can provide additional support for convincing. Showing what were the KPI (for example asset uptime, production volume, unplanned downtime) and financial improvements after PdM adoption will provide more weight to the arguments in favour of PdM. Giving the timeline that during this time-period this reference company gained this much value out of it. This would at least to get that initial step towards proof of concept that will prove in the later phases of implementation that PdM could work in that specific organization as well.

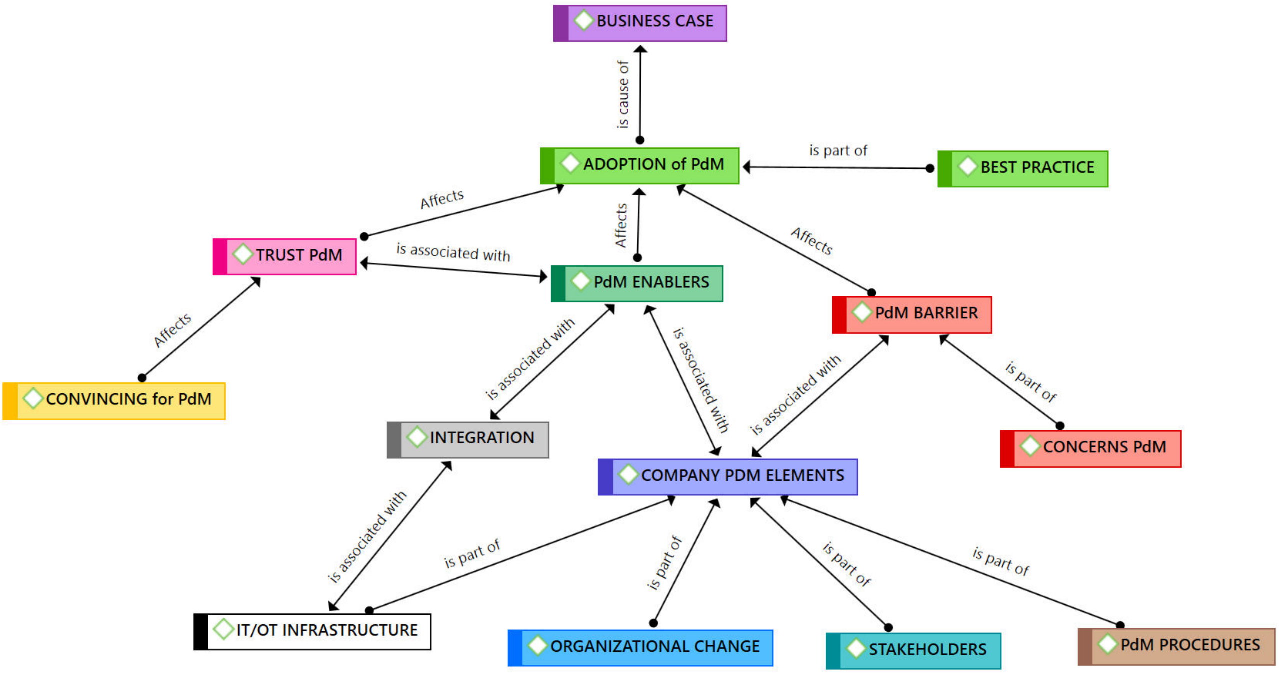

Figure 25: High-level overview of elements that affect predictive maintenance adoption (in this study)

Figure 26: Overview of enablers, best practices and barriers towards PdM implementation

5.2.3 Business Case building

5.2.3.1 Elements for Business Case

Predictive maintenance could entail considerable investments before it could be operationalized. It is essential to pay attention to the elements/factors that might play a huge part in the business case construction. Table 10 reveals factors (but not all of them since it depends on the situation of the company) that need to be considered:

Table 10: Business case investment elements

Elements for Business Case	Description
Necessary operational technologies and infrastructure • **Sensors** • **Data collection systems** • **Data re-structuring** • **Educated people**	PdM implementation is easier with strong existing OT infrastructure (OT “backbone”). This is not always the case and making the initial investment towards the necessary instrumentation and operational capabilities can be considerable. Therefore, it is important to evaluate the level of existing OT infrastructure and seriously consider further investments for the instrumentation. For instance, if there is an operational site in a rural area with limited infrastructure and personnel capabilities then it might be financially better to resolve issues with another maintenance strategy.
CAPEX/OPEX balance	That means there is a balance between CAPEX capital expenses for additional money machines that have to be bought to compensate for a non-availability and OPEX of the maintenance organization.

Education of the personnel	Relevant operational personnel must be educated about predictive maintenance and its processes for better adoption. This requires additional time, energy and resources.
Unclear ROI in many cases	It is quite well known what needs to be invested, but there are uncertainties about what benefits it will bring in the end, which makes it difficult to construct a business case. That is also due again to the fact that there are limited amount examples of successful implementation. Making it very hard to estimate ROI for the specific situation. This is one of the hurdles for convincing top-level management because the business case is not always certain with concrete numbers and timeframe. This concern might be tackled with providing a certain range for ROI, best/worst-case scenario.

5.2.3.2 Business Case procedures

Business case building and its procedures may vary between companies, but below are listed steps (Figure 27 provides visual representation of them) that should be taken into consideration:

1. **Map out the value drivers for the organization** – Understand why there is the need to implement predictive maintenance technology?
2. **Criticality analysis** – What are the biggest risks? What is the equipment that causes bottlenecks and is costing the most money when in downtime? Is that a performance killer type of asset or system? What is that critical equipment within the factories/plants, the ones that needed to be monitored, because the failure of that equipment has a high financial burden? Having those process critical systems with often enough down-time that can be prevented with PdM will already provide a good ground for positive Business Case.
3. **Revenue calculations** – Cost reduction or increase in revenues because of the need to avoid lost production by increasing the availability of critical assets. Take the financial figures of avoiding downtime of these assets with PdM. Take the preliminary historical data to estimate the baseline cost. Make some predictions/assumptions to estimate the improvement of the cost or revenues. Estimate the overall value/ROI generated to the organization.
4. **Strategy fit** – Is implementing PdM completely necessary? Perhaps we could get by only with condition-based monitoring as well? What is my capability to adapt processes to these insights from the data? It is important to understand how PdM strategically fits together with the other maintenance strategies and how it supports operational processes – the organization needs to be able to act upon these insights logistically et cetera.
5. **Check the available data** – What data is there available to retrieve from the systems for that asset group? Can we have enough historical failure data? What is the quality of the data? Is it possible to build predictive models based on that data?
6. **Go/No-go decision** – Can we build a model? If the answer is YES, then build the model and go into the PoC phase of the implementation.
   If the data is not sufficient and it is not possible to go into these predictive directions, either stay with kind of a condition monitoring type of strategy or online condition monitoring strategy. With that monitoring strategy put in some sensors already and try to enhance the data collection. And from that, we will maybe be going to build a model in the future.
7. **Rollout** – After the successful PoC, continue with further roll-out into the organization.

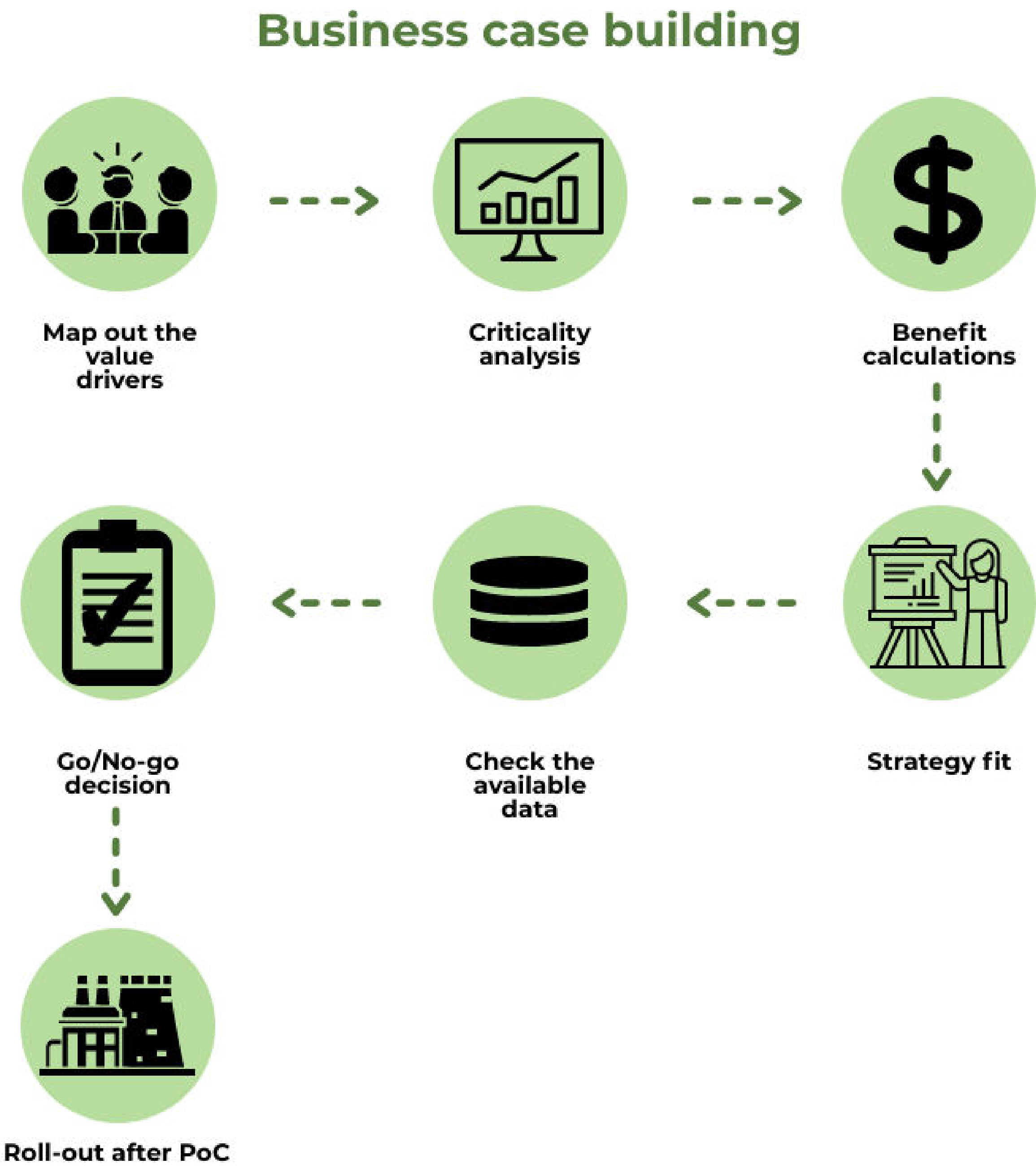

Figure 27: Business case building steps

Following these steps would allow companies to have a more structured approach towards the business case building for predictive maintenance. In addition to this step-wise approach, existing scientific literature provides a hybrid (non-) financial approach to predictive maintenance business case building for further examination (Tiddens et al., 2018). Table 11 illustrates best practices regarding business case building:

Table 11: Best practices for business case building

Best-practices for Business Case	Description
Provide the range for Business Case calculations	Provide the range for the outcomes of the calculations, worst case/best case scenario, to at least illustrate the magnitude which PdM could help with. Because not all the numbers and variables are not concrete, providing a range will show the magnitude and will generate trust as well by not overselling this new technology. It gives first an order of magnitude and second, it gives an understanding of where are the cost that are the exit mechanism to generate the value? What are the value drivers in how it works?
Simulate and model the business case	Develop a model that could predict what is the probability for different scenarios, the expected cost and benefits would be, then it is possible to more or less quantify these numbers. And then it could be said how probable are each of the scenarios and then based on that decision can be made, which is a little bit more motivated by numbers than just based on a gut feeling.

5.2.4 Barriers in the concept phase

Implementing PdM in the concept phase could be undermined by common barriers the organizations have been running into. It is important to expect encountering hardships during this novel technology's adoption since then organizations can already think about ways to mitigate these barriers listed below in Table 12:

Table 12: Common barriers encountered in the concept phase

Barriers	Description
Delay in investment versus the benefits of PdM	There is a delaying factor in seeing the benefits of PdM since it takes time lag before it provides considerable results because PdM is an improvement over time. This makes pinpointing ROI more unclear. Predictive maintenance requires a volume of projects to start showing clearly the benefits and value of the technology. Return on investment becomes more evident as the volume of these PdM projects increases throughout the organization.
Scepticism	There is still a great deal of scepticism on the market towards the predictive maintenance technologies since it is novel and there are not a plethora of success stories yet. This means that implementing PdM requires additional energy on convincing the stakeholders. This trend is slowly changing with the coming of profitable reference projects.
Frustration from unmatched expectations	Organizations do not take their time to fully understand what is needed to implement PdM in their organization and try to transition into it with haste, leading to failure in most cases. Once this happens, it is difficult to make the next step again. Furthermore, with the coming of this technology into the trending curve, there was a great amount of hype around it, which misaligned the expectations from reality.
Hard to quantify PdM effects	What is the difficulty with predictive maintenance and doing preventive maintenance, of course, service providers never get credit for things that never happened. How do the service providers get paid for solving problems that never happened? The risk levels are reduced, but the problem is that the effect of that is noticeable only when reducing the risk levels is not done properly, when the issues arise.
Lack of decision power	There might be a lot of interest from the operational side of the organization, bottom-up initiative, but they lack the decision power (support of the sponsor) and then the project does not move forward.

Lack of the right capabilities	There have been instances where the business case for predictive maintenance is clear and the models have been developed, but since the organization does not possess the right capabilities in terms of personnel, the rollout did not happen. The lack of the right people can severely affect the implementation process of PdM. This could be tackled by bringing in these capabilities by hiring needed personnel before starting the project or bringing in external consultants.
Stakeholder misalignment	The projects need to be pushed by people knowledgeable about these topics on each side of the equation - on the customer and external side. When people that are not knowledgeable about this solution talk together, it creates a lot of mess and discussion between separate stakeholders can differ a lot, generating false expectations.

Overall barrier frequency can be seen in Figure 28. This recurrence of different hindrances will give a subjective idea about their relevancy by showing their regularity in the interviews. As it can be seen, lack of the right capabilities was brought forward the most, followed by lack of data quality, lack of data itself and overall scepticism revolving around PdM technologies. This could be interpreted that organizations need better tools, personnel and knowledge resources about predictive maintenance to facilitate better adoption of this new technology. Furthermore, proper data collection and management is inadequate in the organizational processes, restricting PdM implementation effectiveness.

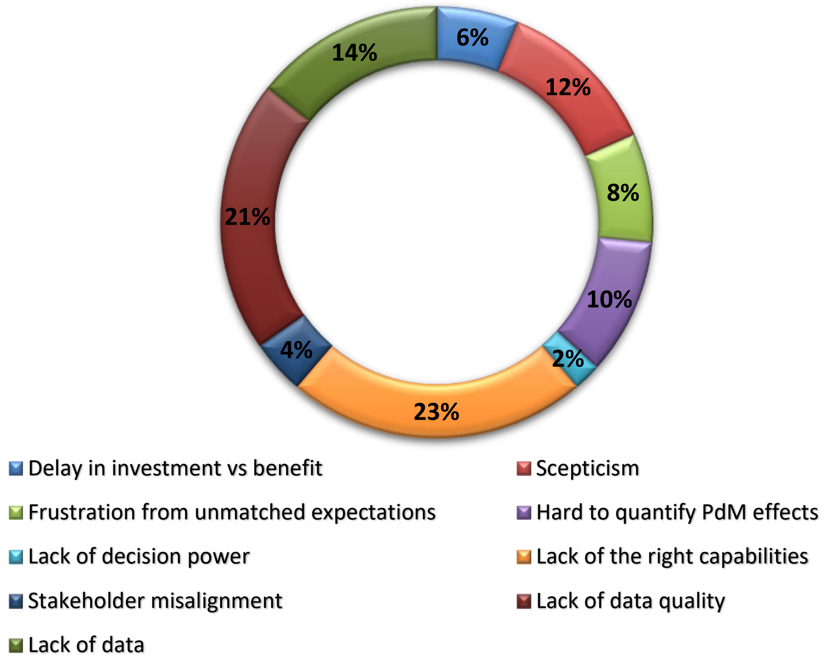

Figure 28: Overview of overall barrier frequency

5.3 Feasibility phase

Once the business case has been showcased and there is a concrete GO-decision towards predictive maintenance, feasibility phase is then commenced. Based on selected failures/functional degradations a full but shortened project (proof of concept/minimum viable product/pilot) is run from data to a partial solution to ascertain where there are gaps and barriers to target them early on before a more extensive implementation is undertaken. In short – PoC is done to verify the feasibility of the design and find out potential challenges. Commercial resources provide additional information about the importance of PoC's and how they add to the success factor of commencing with IoT projects (Embitel, 2017, 2018).

It is important to note that in this stage no real-time analysis is set-up or required, the pilot project is done all offline. The needed data can be provided by the organization on a flash drive or by any other method. The necessary technical infrastructure for the streaming data analysis is arranged during the final, operational phase (Wagner & Hellingrath, 2019).

Feasibility phase has overlapping features with the next two consecutive phases of data & development, but for focusing reasons will be treated as a separate phase because of its importance.

5.3.1 Determine the project objectives

Before the PoC project is started, it is important to lay down explicit goals and expectations for the work ahead. From here on CRISP-DM methodology will be introduced to support structuring the following implementation phases. CRISP-DM is a data-mining methodology developed to have a more structured approach to data-related projects. This way of approaching projects provides a solid backbone for the project management because of its practicality and clear guidelines. The provided methodology outline (Smart Vision Europe, 2020) is adjusted to predictive maintenance implementation by altering the step descriptions and nuances towards PdM projects. The choice to adapt CRISP-DM approach for this research came from long term industry experience of UReason implementing this methodology coupled with references in scientific literature, which adapted the same approach for its applicability (Spendla et al., 2017).

It is worth mentioning that in practice these steps can be performed following different order and it is necessary to occasionally **revise and repeat** previous steps. The adoption process of predictive maintenance is **not purely sequential** by its nature meaning that there is a need to alternate and navigate between different phases of implementation in several iterations (mostly between feasibility, data and algorithm development phase).

The first question to ask is what are the desired outcomes of the project? It is important to note that this step is iterative – when the feasibility phase is in the later phases and more comprehensive projects are being planned then it is advisable to repeat these steps. There are following steps to make these desired outcomes explicit:

1. **Set objectives** – This means describing the primary objective for this PoC/Pilot phase. This helps to keep the vision clear towards the expectations.
2. **Produce project plan** – The plan should specify the steps to be performed during the rest of the project, including the initial selection of tools and techniques.
3. **Success criteria** – Lay out the criteria used to determine whether the project has been successful regarding the expected outputs. These outputs should ideally be specific and measurable.
4. **Business success criteria –** describe the intended outputs of the project that enable the achievement of the business objectives.

5.3.2 Assess the current situation

This involves more detailed fact-finding about all of the resources, constraints, assumptions and other factors that are needed to consider when determining the project goals and planning.

1. **Inventory of resources** – List the resources available to the project including:
    - Personnel (Technicians, operational engineers, data analysts, consultants)
    - Data (Historical data, EAMS data, failure data)
    - Computing resources (hardware platforms)
    - Software (data mining tools, other relevant software)

2. **Requirements, assumptions and constraints** - List all requirements of the project including the schedule of completion, the required comprehensibility and quality of results, and any data security concerns as well as any legal issues. Make sure that stakeholders are allowed to use the data. List the assumptions made by the project. List the constraints on the project. These may be constraints on the availability of resources but may also include technological constraints such as the size of data set that it is practical to use for modelling.

3. **Risks and contingencies** – List the risks or events that might delay the project or cause it to fail. List the corresponding contingency plans - what action is taken if these risks or events take place?
4. **Terminology** – Compile a glossary of terminology relevant to the project. This will generally have two components:
   - A glossary of relevant business terminology, which forms part of the business understanding available to the project. Constructing this glossary is a useful “knowledge elicitation” and education exercise.
   - A glossary of PdM project terminology illustrated with examples relevant to the business problem in question.
5. **Costs and benefits** – Construct a cost-benefit analysis for the project which compares the costs of the project with the potential benefits to the business if it is successful. This is done for assuring the validity of the business case built beforehand.

5.3.3 Produce a project plan

Describe the intended plan for achieving the project goals and thereby achieving the business goals. The plan should specify the steps to be performed during the rest of the project, including the initial selection of tools and techniques.

1. **Project plan** – List the stages to be executed in the project, together with their duration, resources required, inputs, outputs, and dependencies. Where possible, try and make explicit the large-scale iterations in the process, for example, repetitions of the modelling and evaluation phases. As part of the project plan, it is also important to analyse dependencies between schedule and risks. Mark results of these analyses explicitly in the project plan, ideally with actions and recommendations if the risks are manifested. Decide at this point which evaluation strategy will be used in the evaluation phase. The project plan will be a dynamic document. At the end of each phase, the process is reviewed along with achievements and the project plan is updated accordingly. Specific review points for these updates should be part of the project plan.
2. **Initial assessment of tools and techniques** – At the end of the first phase the initial assessment of tools and techniques should be undertaken. It is important to assess tools and techniques early in the process since the selection of tools and techniques may influence the entire project.

5.3.4 Asset selection for the pilot

Before the criticality analysis was undertaken to pinpoint and understand which of the equipment is causing the greatest burden on the operations and revenue. There has been extensive research done in the scientific literature about choosing the assets (Tiddens et al., 2018), however, analysis of that is too deep for the scope of this study at hand. For the pilot project the asset selection is done on higher-level using the following steps:

1. **Select the assets critical to operation/risk** – Supporting the business case!
2. For selected assets **identify the functional failures** (degradation of function) and failures.
3. It is important to **choose dysfunctions for predictive maintenance by their quadrant** location (Figure 29). This diagram is a different representation of the RPM (Risk Priority Number) which is based on severity, occurrence and detectability used in the FMCEA analysis. Correct selection of the dysfunctions to focus on in a PdM program is one of the most important contributors to the success of a PdM program. Dysfunctions should be in the 4th quadrant to gain the greatest value out of PdM.
4. Using the ISO 13374 model (Figure 30) determine what is required/available for Data Acquisition, Data Manipulation, State Detection, Health Assessment and Prognostics Assessment.

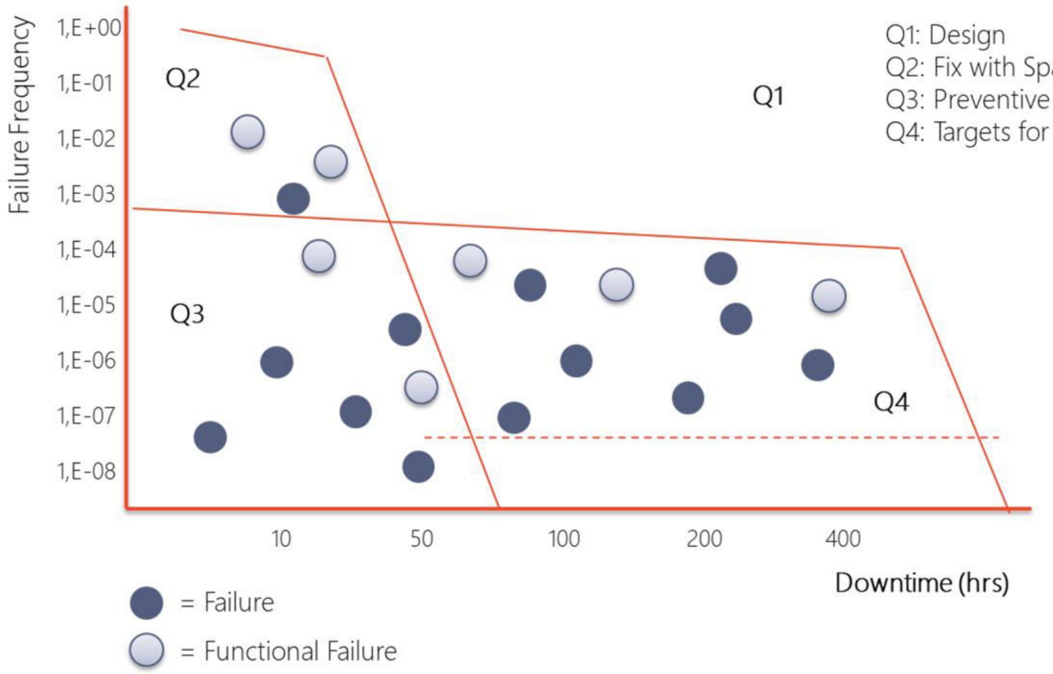

Figure 29: Diagram representing suitable dysfunctions to target for PdM **(UReason, 2020)**

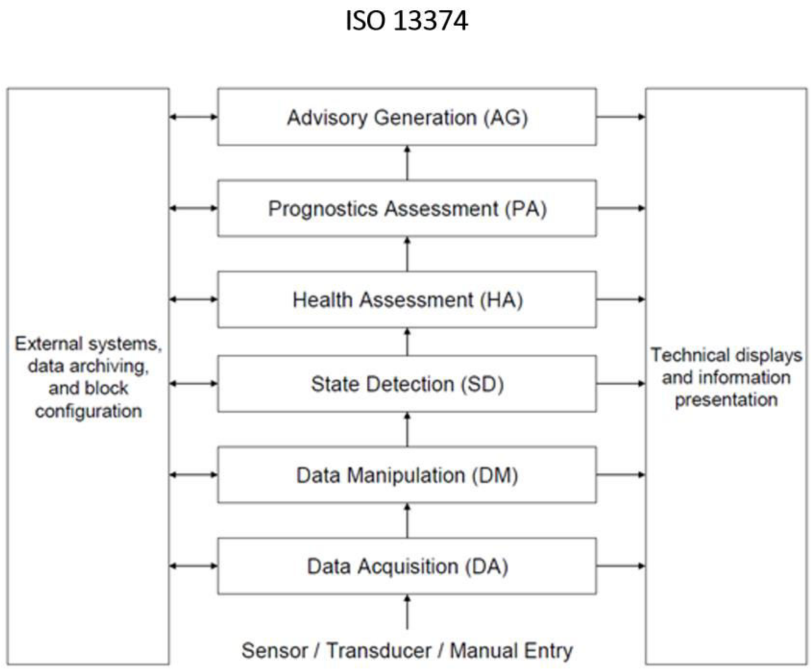

Figure 30: ISO 13374 model

Further development of the pilot project will overlap with the consecutive phases of data & development, therefore, steps regarding data collection and preparation with the model development are delineated in these phases.

Illustration of example steps for the **pilot building up towards to more comprehensive rollout** inside the organization could potentially be:

1. Showing and making a showcase with a piece of equipment (centrifugal pump for example) in lab situations – Have a data set for that equipment, develop predictive models for that and run the analysis in the software to understand the outcomes.

2. Take a piece of well-understood equipment in operation that is equipped with required sensors and run the analysis for the already known failure mode(s).
3. Have the pilot running for extended time on this one equipment in operation, gather the analysis over time and compare it with the actual situation/integrity of the equipment.
4. The decision for further implementation/rollout - If the outcome matches with the actual situation then the decision for further implementation/rollout should be made. For example, the company has a goal of having at least 80% of the success factor from the previous step, then the decision might be undertaken to move this technology towards more valuable equipment.

As mentioned, this is only an example case how the road from the pilot to the more comprehensive rollout might be. Every organization is unique and has various approaches to their maintenance strategies and steps undertaken to implement those strategies.

5.3.5 Best practices in the feasibility phase

The research revealed best practices that the companies followed during this feasibility phase. Table 13 provides overview of these positive activities employed by the interviewed organizations in this phase:

Table 13: Best practices in the feasibility phase

Best practice	Description
Take small steps • **Agile** • **Scrum** • **Step-by-step**	Taking this new technology and trying to change the entire organization in a short timeframe will usually end up with a failure. The reason to do pilots is to showcase that the technology, the methods are working and are improving the processes inside the organization. This will create more confidence and trust inside the organization, allowing them to extend these projects. It would be advisable to approach these projects with agile/scrum approach, have sprints for each development phase, evaluate and plan the next steps.
Showcase the success factors	When there are successful pilots, multiply them to have multiple cases of success. Then it is possible to approach the top-level management from the bottom up and showcase them the successes constructed together – this is what the work-floor together with middle management has been working on, these are the hours we put in, these are the sensors we added and this is the result with this % of confidence level. If these are insights that have not been present before then it will help to gain the trust of the top-level management and so the change/adoption grows in a step-by-step manner.
Celebrate the small victories	This is good for the people who have worked on it. And on the other hand, celebration gives exposure to the out-standers or bystanders which invites them to "jump on the train as well". Celebrating small successes asks for more.
Use the existing platform/tools	When running the pilots, it is important to use the existing tools that the technicians and work-floor personnel are already used to. Try to integrate the insights/analysis with the existing processes and platforms. This will soften the "shock-factor" to the end-user and allows them to get used to these new capabilities/tools. Technicians or staff members must get used to an alternative system.
Let the end-user test out the tools	During the pilot phase, it would be advisable that the end-user can "test" these tools out themselves to get accustomed to them. Furthermore, this will provide first feedback from them, so during the rollout phase, this feedback is taken into account to deal with potential resistance.

Best practice	Description
Reporting of the pilot	During this phase, it might be the case that there is still scepticism left in different layers of the organization. Providing these stakeholders with monthly reports for example with relevant KPI and performance improvements that PdM is offering to build the trust with concrete examples. This feasibility phase reporting is emphasized more with the SME's that might have tighter budgets for their maintenance operations. These types of businesses require extensive convincing in each part of the PdM implementation, they say "Show me the money!". And especially for those SME's the feasibility phase and reporting with concrete numbers is an important cornerstone for convincing.

5.3.6 Barriers in the feasibility phase

During the feasibility phase many barriers (Table 14) relating to the stakeholder and technical capabilities can hinder the proceeding of the PoC:

Table 14: Barriers in the feasibility phase

Barriers	Description
Misunderstanding between stakeholders	Stakeholder misunderstanding and miscommunication can create friction already in the early stages, leading to mistrust and determination of PoC.
The right sensors & tools are absent	The tools to commence with PoC are not capable enough or the sensors that are present do not provide information with sufficient quality. The initial investment to better tools and sensors put off the stakeholders and PoC is adjourned.
Not having enough time	The PoC needs to have an allocation of time to show results. With impatience, the PoC is ended incomplete, resulting in false conclusions about its benefits and applicability.
Lack of ownership	If the stakeholders do not own up to their part of the responsibilities and "point fingers" then mistrust will hinder the partnership and PoC will most likely fail.

5.4 Data phase

Data phase targets the selection of fitting measurement techniques, the data acquisition and the preparation of data. In this phase, data is being collected from different operational systems, analysed for deeper understanding and prepared for the model development phase.

Strong operational technology infrastructure (OT) is one of the key enablers for the implementation of predictive maintenance. Elements attributing to the solid OT infrastructure are described in Table 15. Having already the operational "backbone" from the hardware and instrumentation side will bypass the need to make considerable investments in the first place. However, if the sufficient OT is missing, but the investment decision is there, then it is advisable to commence with market reviewing, training and seminar participation to identify the high-quality sensors available on the market that provide the best capabilities for measuring the attributes that are mandatory to detect the identified fault causes (Wagner & Hellingrath, 2019).

Table 15: Important OT factors and elements

Relevant OT Infrastructure	Description
(Central) Historians	Having (central) data historians is one of the key enablers for PdM from the technological perspective. This makes PdM implementation more seamless since it is possible to connect to the historian like *plug&play* through one interface and gain access to all of the plant data.
Operational control systems • **DCS** • **SCADA** • **MES** • **CMMS** • **ERP**	These systems regularly have a history of data and its trends, making them an essential component where to collect data from.
Security of the Infrastructure	The security levels of the OT infrastructure are crucial since the instrumentation is connected with operational applications/platforms in a complex network. Meaning if one element is a liability, other elements in the network are put in danger as well. This must be avoided at all cost by having high levels of security.
Good configuration management system	This allows to understand which component is in which system at any specific time. Having this knowledge is essential for PdM model development.
Move from manual input to automatic input	Whenever possible, try to find a way to replace manual inputs from human actors with sensors or another kind of optimized data registration since manual inputs tend to be not very accurate. This will potentially reduce the number of faults and inaccuracy of the data.
Quality of the data	• Data needs to have correct labelling/linking to reference information, making it clear which equipment the data is coming from and what the data fields mean. • Clear instructions/education to the personnel how to input the data with the correct structure to avoid lower data quality.

5.4.1 Collecting the data

Data is the key element to the predictive maintenance technologies around which the models are built upon that enable to have predictive insights into the potential behaviour of the equipment under analysis. Collecting the data with sufficient quality levels for PdM might take more effort and attention that was expected in the first place. There are a couple of reminders to keep in mind while collecting the data:

- **Data collection might take considerable time** if there is not enough historical data already available. Predictive models are trained on existing historical data that describe the behaviour of the equipment. If this historical data is not present, then the equipment must be prepared with the necessary instrumentation to collect and store this data. It is a matter of bringing awareness and being clear about expectations and requirements that go into PdM, which will enable the next steps in this whole development.

- **Fleet size** is an important factor affecting data collection timeframe. The more equipment of the same type there is available in the fleet, the more data insights could be accumulated over the course of the time, shortening the data collection period since there is a greater representative set of data that represents how that type of system is used.

- **Proper registration of all the failure data (including functional degradations)** is essential to developing predictive maintenance algorithms, without that it is almost impossible to do PdM.

- **Data accessibility** is an important contributor to making the PdM implementation seamless. Having systems in place for enabling “on-demand” data will make the collection process shorter and more straightforward.

- **Have a clear measurement protocol in place** to capture the data. This will give an additional layer of information and assurance towards data quality.
- **Make sure to keep the raw data.** Typically, *time series* are the best way to store data. For the predictive model development, the collected data is usually processed and potentially reduced. If there are emerging questions along the way about the data and the original or the right data is not present anymore, going back to the complete data set with all the information would not be possible, so a lot of information is thrown away by reducing the data, which can never be retrieved in retrospective.
- **Think about the sampling rate.** Figure out which will be the sampling rate for the measurements and data collection. If the sampling frequency is lower, then it means that trends will be noticed later which will affect the response time to these trends. Sampling rate depends on how quickly an action needs to be taken to respond to the changes in trends.
- **Think about the degradation rate.** For example, if there is a compressor degrading within a couple of weeks or a couple of months, then it would be useful to sample maybe a couple of times a day or every day, if there is a large bridge, which is there for, say 15-20 or even 50 years, and it makes little sense to sample every day or every month, then maybe sampling every half a year would be sufficient. This means that the **sampling rate** should be chosen also depending on the timescale of the entire degradation process of the equipment.

5.4.2 Data understanding

To make the best use of the collected data it is of utmost importance to clearly understand what do the data mean. This is especially relevant for huge processes combining countless elements that provide millions of readings that add to the *big data lake* from which it is crucial to pick the data representing the system under analysis. Understanding the data will allow to develop more accurate and reliable predictive models. This scientific article will provide a standard of practice and further elaboration in regards to data collection and management for predictive machine learning algorithm generation (Aremu, Palau, Parlikad, Hyland-Wood, & McAree, 2018). To interpret the data, it is advisable to follow these steps:

- **Initial data collection report** – List the data sources acquired together with their locations, the methods used to acquire them, and any problems encountered. Record problems encountered, and any resolutions achieved. This will help both with future replication of this project and with the execution of similar future projects.
- **Describe data** – Examine the properties of the acquired data and report on the results. Describe the data that has been acquired including its format, its quantity (for example, the number of records and fields in each table), the identities of the fields and any other surface features which have been discovered. Evaluate whether the data acquired satisfies the set requirements.
- **Explore data** – Address data related questions using querying, data visualization and reporting techniques. Describe the results of the data exploration, including first findings or initial hypothesis and their impact on the rest of the project.
- **Verify data quality** – Examine the quality of the data, addressing questions such as: Is the data complete (does it cover all the cases required)? Is it correct, or does it contain errors and, if there are errors, how common are they? Are there missing values in the data? If so, how are they represented, where do they occur? List the results of the data quality verification. If quality problems exist, suggest feasible solutions. Solutions to data quality problems generally depend heavily on both data, operation and business knowledge.

5.4.3 Data preparation

In this phase of the project, the decision is made on which data will be used for further analysis and model development. Then this data is prepared for the developing phase by using the following steps:

- **Choose the data** – Clear criteria must be set that delineates on which basis that data is selected. The criteria might include the relevance of the data to the PdM project goals, the quality of the data, and technical constraints such as limits on data volume or data types.
- **Clean the data** – This task involves raising the data quality to the level required by the analysis techniques that have been selected. This may involve selecting clean subsets of the data, the insertion of suitable defaults, or more ambitious techniques such as the estimation of missing data by modelling. Describe what decisions and actions were taken to address data quality problems. Consider any transformations of the data made for cleaning purposes and their potential impact on the analysis results.
- **Construct required data** – This task includes constructive data preparation operations such as the production of derived attributes or entire new records or transformed values for existing attributes.
- **Integrate data** – These are methods whereby information is combined from multiple databases, tables or records to create new records or values. **Merging** data refers to joining together two or more tables that have different information about the same objects. **Aggregating** data refers to operations in which new values are computed by summarizing information from multiple records and/or tables.

These are the proposed steps to follow during the data phase on a high level. Each organization has different approaches and capabilities for doing this, so it is advisable to use this as a reference and adopt it in the way that is best suitable to the organization's needs related to the PdM implementation. Table 16 illustrates best practices in data phase:

Table 16: Best practices in the data phase

Best practices in the data phase	Description
Strong contractual agreements about data usage	Stakeholders have clear indication who owns the data and who is allowed to process it. If there are misunderstandings or disputes, then contracts will bring clarity to the situation and how data should have been handled.
Data is labelled correctly	Correct data labelling will allow quickly understand what the data means and illustrates, saving enormous amounts of time and effort between data scientists and maintenance technicians in figuring out what something means.
Data is clearly structured	The clear data structure will make the modelling process in the later phases more seamless since data does not that much of re-structuring to be fed into the algorithms.
Clear instructions for data input for the personnel	If the maintenance personnel has explicit instructions on how to input failure and maintenance data into the systems, then the data quality is considerably higher since there are no ambiguities for human input errors.

5.4.4 Negatives in the data phase

Since data, its existence, accessibility and quality are the cornerstone to PdM implementation, then there are some hurdles that companies potentially encounter in this stage of the implementation, see Table 17:

Table 17: Negatives in the data phase

Barriers	Description
Availability and quality of the data	There is an ambition to implement PdM inside the organization and the expectations are high, but these expectations and ambition levels are not matched with the available data and its quality, which seriously hampers PdM implementation. To validate the model, the actual information from practice is needed, which typically requires that it is known exactly how a certain component is used and loaded. That is something that many companies do not register. On the back end, the detailed information on when failures occurred is also needed and what type of failures occurred. And that is the other thing that is not properly organised in a lot of companies. The registration of failures is not accurate. Which means that the quality of that kind of data is very limited, which makes it very difficult to develop and to validate the models that the that are developed. Usually, companies have a lot of data of uninteresting events, the more interesting the event, the less data there is. Having limited data will have its effects on the predictive model capacity and its accuracy, steering further away from the "engineering language" that engineers trust and accept. If there is no right historical failure data, it is not possible to build a reliable model.
Poor data collection from the personnel	Human factors sometimes can have potential shortcoming when it comes to dealing and registering data. People complain that there is no data available, but it is up to them to fill the database with that. If there are clear protocols and methodologies in place for data entry that can minimize the poor availability and quality.
Poor data labelling	There can be huge data lakes where enormous amounts of data flow in but because of insufficient tagging/labelling, it is nearly impossible to tell what the data means or from which asset and parameter it is coming from.
Sensors used are not meant for maintenance or prediction	Sensors in use have drastically different output i.e. strict process control et cetera, meaning that they do not collect enough of high-quality data to develop predictive models out of them.

5.4.5 Concerns

Besides the barriers in the data phase, there are strong concerns present in the organizations relating to the data. These concerns are stemming from the conservative and risk-adverse stance of the industry. Table 18 describes these worries of organizations:

Table 18: Concerns related to the data

Concern	Description
Cybersecurity	Cybersecurity is the most mentioned concern for the organizations looking to implement PdM. Integrating existing operational systems that control and guide the whole plant with additional applications poses an enormous security risk. Furthermore, changing regulations about the cybersecurity and missing overview of safety functions from higher organizations bring along uncertainties about the potential risks and worst-case scenarios. Having better cybersecurity systems would allow faster adoption of PdM since the organizations would feel protected from liabilities, relieving the burden of doubt.
Data ownership	Organizations are worried about sharing their data to other applications since it contains business-critical information in some instances. The concerns around who can access the data and process it is especially noticed when the applications are operating in the *cloud*. Furthermore, in some industries, this data can include relevant intellectual property which intensifies the concerns. Additionally, this data ownership concern can happen inside the organization as well by different silos not wanting to share their information.
Data leakage	Worries about data leaking out from the organization were put forward. Business-critical data ending up in the hands of the competitors could undermine the position of the company.

5.5 Predictive algorithm development phase

When data is available in a suitable format, the development phase deals with the construction of algorithms for diagnostics and prognostics as well as testing and training of the algorithms. There are two ways how to approach this development phase: top-down and bottom-up.

The top-down approach towards developing PdM solution entails collecting all the data from the operational processes that is possible to get. This data is then put into one *big data lake* and trying to find correlations and information from that data lake. This is a *big data* approach which can be quite time consuming and requires complex smart technologies to gather insights from that data lake. This method could reveal some unexpected insights but on the other hand, this approach can bring along many trivial findings that provide minimal value compared to the calculation time and effort. There have not been that many instances where his approach has offered a structured way of finding solutions. Additionally, if these findings are presented to the work-floor engineers in the machine learning language without and causality explanation then the work-floor might have some struggles to accept these findings since it is not presented in the way that is understandable for them (data vs engineering language).

The bottom-up approach takes a reversed perspective on PdM development (Figure 31). It is important to understand which are the critical components, what are the mechanisms and why does the equipment fail? This way it is possible to comprehend which data and parameters are needed to predict that specific failure. This way there is no need to deal with huge data lakes, allowing more focus on specific datasets which are easier to work with. Furthermore, this approach provides more relevant information since all the unimportant trivial findings are missing from the process. The bottom-up approach is more difficult and needs more knowledge about the systems and their failures, but it is more efficient and effective in solving the problems that hurt the critical systems the most. Table 19 summarizes the advantages and disadvantages of both approaches.

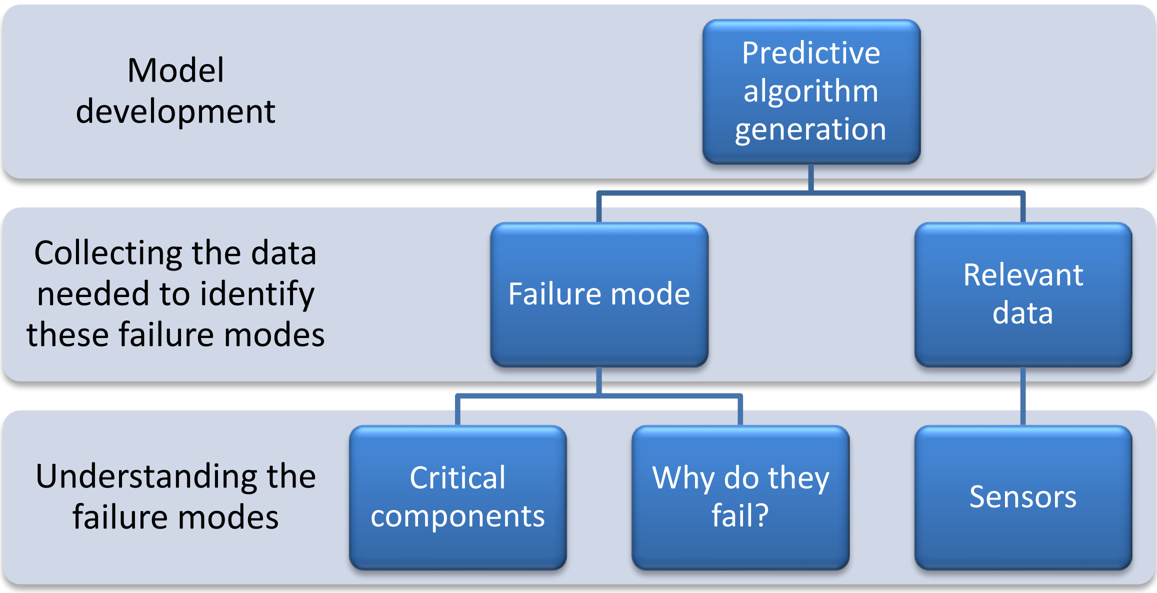

Figure 31: Bottom-up approach for model development

Table 19: Advantages and disadvantages to both approaches

Approach	Advantages	Disadvantages
Top-down	• Does not require that much knowledge about the systems and processes • Could reveal unexpected insights • Could be used to get fast results and "quick wins"	• Requires smart technologies and a lot of computing power • Can provide trivial findings that are not relevant for PdM • Engineers find it harder to trust strictly data approaches • Unstructured approach
Bottom-up	• Structured, more focused approach • Provides clearer, more useful insights for PdM • No need to work with huge data lakes • A better understanding of the critical systems	• Needs extensive knowledge about the systems and their failure modes

When the approach is determined then the development should on high-level follow these steps for understanding how predictive maintenance connects to the operational processes:

1. **Understand what is happening in the systems –** Analyse where are the bottlenecks in the processes and systems that are undermining the operations. Make a difference between critical and non-critical failures.
2. **Understand the failure mechanisms and why things fail –** Root-cause, FMEA (Failure Mode and Effects Analysis) or Pareto analysis are suitable approaches to find answers to these questions. What is the lifetime of the components? How modular the component is? How stable are the parameters? What is the P-F interval? Why is that the behaviour of the component in that condition?
3. **Identify what needs to be measured** – If the failure mechanisms are known then it is important to identify which data to measure to build the analytical models for these failure-modes.
4. **Identify how and which models can be built –** Based on the data that is accessible identify which models can be built for predicting.
5. **Understand how predictions from these models can be derived –** Understand the connections and the causality of the insights coming from the models.
6. **Iterate & improve** – After the initial feedback from the insights, find potential improvements to the processes and the developed model. Acquired data in the first phases should be a baseline for the next measurements and feedback loops. It is important to analyse the insights and tackle the root causes of problems since eliminating only the symptom will not get rid of the actual problems in the processes.

5.5.1 Model development

If the operational analysis is followed and there is a clear understanding of how the development should be undertaken, then the model could be developed following these steps:

- **Select the modelling technique –** As the first step in modelling, the modelling technique is chosen. If multiple techniques are applied, perform this task separately for each technique. Many modelling techniques make specific assumptions about the data, for example, that all attributes have uniform distributions, no missing values allowed, the class attribute must be symbolic et cetera. Record any assumptions made.

- **Generate test design** – Before an actual model is built, there is a need to generate a procedure or mechanism to test the model's quality and validity. Typically, the dataset is separated into train and test sets, the model is built on the train set, and its quality is estimated on the separate test set (70% of the data for training and 30% for validating). Following scientific article provides an example about developing PdM PoC neural network-based algorithm for machine systems (Bansal, Evans, & Jones, 2004).
- **Build model** – Run the modelling tool on the prepared dataset to create one or more models. With any modelling tool, there are often many parameters that can be adjusted. List the parameters and their chosen values, along with the rationale for the choice of parameter settings. Describe the resulting models, report on the interpretation of the models and document any difficulties encountered with their meanings.
- **Assess model** – Interpret the models according to the domain knowledge, the PdM project success criteria and the desired test design. If the model's accuracy is not what was expected then fine-tune it, revisit the parameter selection and/or acquire additional data. For fine-tuning monitor false positives, create user feedback loops (positives & false positives) and investigate if continuous learning is possible. Judge the success of the application of modelling and discovery techniques technically, then contact superiors and top-level management later in order to discuss the project results in the business context.

Development phase reaches into the more technical domain of the predictive maintenance technologies adoption which highly depends on the organization's existing tools and capabilities, meaning that there is a limited amount of high-level recommendations to follow presented. To assist the reader navigating this domain, the scientific literature is referenced to introduce resources that provide support and knowledge to have additional guidance in the development phase. Three articles delineate a comparative literature analysis and studies about machine learning algorithms that have been used for PdM in the scientific literature (Carvalho et al., 2019; Compare, Baraldi, & Zio, 2020; Silvestrin, Hoogendoorn, & Koole, 2019). In addition, the following article proposes a predictive maintenance framework using deep learning which explains data management and algorithm construction in deeper detail (Nguyen & Medjaher, 2019). Table 20 illustrates the best practices in the development phase:

Table 20: Best practices for the algorithm development phase

Best practices	Description
Cooperating with the maintenance technicians for better data understanding if needed	Strong collaboration between data scientists and maintenance teams will ensure that the model developers clearly understand the data that is the foundation for their models.
Using the right tools	The market offers a selection of tools from different vendors for modelling support for maintenance related data. Doing market research beforehand to choose the best suitable tool for the organization will ease the complexity of model development.
Asking for help	Organizations might not have the necessary capabilities to generate predictive algorithms themselves. Then it would be advisable to turn to other stakeholders and consultancies that possess this expertise and will support the proper modelling for PdM and its deployment into the organization.

5.5.2 Barriers in the algorithm development phase

The development phase is where it all comes together, and the benefits of predictive maintenance can be illustrated more clearly. Although the implementation is in the second half of the overall process of PdM, Table 21 showcases still some barriers to watch out for:

Table 21: Barriers in the development phase

Barriers in the algorithm development phase	Description
Not choosing enough data or choosing too much data	During the development, it is important to choose enough data that will represent the entire set of the fleet to build the model upon. On the other hand, if too much data is chosen for the development then the data can be overwhelming and the focus is lost, meaning that the important elements go unnoticed and unattended.
Choosing the wrong modelling technique	When the modelling technique is ill-chosen for the data type, quality and quantity, then the development process of the accurate models can be severely hindered.
Not understanding the data	If the data scientist does not understand the data which is being processed, then the model being built could draw wrong conclusions and provide inaccurate feedback to the maintenance crews.

5.6 Operation phase

In the final operation phase, real-time data access is provided, and the solution is deployed as well as regularly reviewed and adjusted with new findings from data. This PdM deployment into the company could follow these steps:

1. **Provide results from the previous phases –** Provide reporting on the PdM solution with interpretable visualizations on dashboards. These visualizations should be generated together with the end-user to have the important information provided in the right way aiming at transparency and comprehensibility.
2. **Determine PdM deployment strategy –** Investigate the optimal way to do an organization-wide rollout of predictive maintenance in a step-by-step manner. Summarise this deployment strategy including the necessary steps and how to perform them.
3. **Implement the technical infrastructure for real-time access** – Provide technical infrastructure to enable streaming data for prognostics. This means having accessibility (streaming) and storage of data in the central databases for the models. In the existing scientific literature, a big data-based ecosystem for predictive maintenance for smart manufacturing factories depicts an infrastructure connecting IoT devices to the real-time data accessibility capabilities (Yu, Dillon, Mostafa, Rahayu, & Liu, 2020). In addition, scientific articles provide insights at the architectural level how to utilize cloud platforms simultaneously with prediction algorithms for PdM (Truong, 2018; Wan et al., 2017). These resources can be used as first steps to potentially assist the reader in technical integration domain not covered by this research project.
4. **Plan monitoring and maintenance** – Monitoring and maintenance are important issues if predictive maintenance becomes part of the day-to-day business and its environment. Summarise the monitoring and maintenance strategy, including the necessary steps and how to perform them.
5. **Adjust the existing processes** – Review existing operational processes and decision-making structure to accommodate predictive maintenance into them. PdM should be used as a decision-support tool while the final decision is made by the maintenance personnel.
6. **Educate the personnel** – Sufficient education needs to be provided for the maintenance personnel on how to operate with this new technology.
7. **Continuous improvement of the solution** – Based on feedback loops from comparing the model's accuracy and the actual situation, additional model retraining is done for higher prediction accuracy if necessary. Furthermore, operational processes and the components themselves can be improved based on PdM insights.

Although predictive maintenance implementation is now nearing the finish line, it is important to stay vigilant and adopt iterative feedback loops to improve the PdM solution and processes. The best practices in the final operation phase are listed in Table 22:

Table 22: Best practices in the operation phase

Best-practices in the operation phase	Description
Adjust the existing processes to PdM	Predictive maintenance provides support (not replace) with additional information and insights to the decision-making regarding maintenance activities, planned turnarounds and logistical operations. It is important to make sure that the organization **can act** upon these new insights from the logistics perspective. This means that the logistics processes need to be adjusted to accommodate those insights from PdM leading to smart maintenance execution coupled to smart operations management.
Analysing the insights from PdM	Multi-layer analysis of the insights from predictive maintenance could be set in the organization. This means analysing the first level of insights from the platform/software and if the deeper analysis is needed then it would be advisable to have the second layer of analysis leveraged by domain experts in specific areas like hydraulics, electrical engineering et cetera. This means having sort of **expert network** that will have support in the analysis at a second level and even at the sub-level issues.
Implement quality loops for PdM	Have periodical quality loops in the process for PdM meaning when the model gives a prediction for maintenance for a specific component, have a deeper analysis of the component while it is in the maintenance to understand the accuracy of the model, could the component had been maintained earlier/later et cetera? That is a combination of machining, hardware, software and to see what was expected and what is the reality.
Reporting	Reporting on the results of PdM is of utmost importance. Having monthly reports on determined KPI's and criticality ranking of assets is essential to illustrate how PdM is affecting the organization. This will build further trust and confidence in the solution.
Re-organize teams What kind of competencies are wanted to bring into the organisation?	Implementing predictive maintenance brings changes to the processes inside the organization. To best cater to this change, it would be useful for organizations to **re-organize their teams** if needed to reap the maximum benefit out of PdM. This might mean creating additional digital/PdM teams that support the maintenance operations with the new technology. Another option would be to distribute the workload between existing stakeholders logically coming from their tasks at work, for example, putting reliability engineers in the driver seat for reliability using PdM. Having more teams and more educated people running the process requires **additional flexibility** between the teams as well, combining operations management with maintenance and reliability management. This means coming loose from their job roles and processes from the past and moving on to the new best practice standard.
Continuous improvement inside the organization	Having mental leaders inside the organization who always push the bar higher and set the tone for others to follow and be encouraged in terms of self-development and education will allow departments to move forward faster. This will help to keep the operations improving from the human perspective and effort when personnel asks: "What can I do to be better in the field or on the office?"

Organizations need to accommodate their existing systems and processes to PdM, failing to do so will lessen the benefits gained from the technology adoption. Barriers in the operation phase are listed in Table 23:

Table 23: Barriers in the operation phase

Barriers	Description
Not having proper infrastructure for real-time access	Not having real-time access to the data will obstruct using the developed PdM models in operations, limiting the application of PdM.
Personnel not having sufficient education	Maintenance personnel is the end-user that will use PdM for maintenance support. However, if the field personnel does not have sufficient education how to use these new tools, their benefit to the organization is not maximized since they are not used correctly or the full potential from the insights is not derived.
Not maintaining the PdM solution	If the environment and/or the elements, on which the PdM algorithm is running, are changed without updating and making changes to the algorithms, then the accuracy of these algorithms will decline considerably, and rates of wrongful insights will increase.
Not adjusting the processes to PdM	In some instances, an organization has built and deployed the PdM technology, but the existing operations and logistic processes are not adjusted to the use of PdM. This lowers the benefits gained from the adoption since the organization can not act on these insights with maximal efficiency.

5.7 Overview of the developed reference checklist for PdM projects

This developed best practices reference checklist for PdM projects provides high-level support in implementing predictive maintenance inside organizations. Table 24 summarizes all structured phases along with best practices, barriers and recommended procedural steps attached to them. This section gives a rundown reminder of the factors revealed in this research affecting the PdM adoption on organizational, people and technical levels. Table 24 should be used as a quick revision tool to quickly have a holistic overview of previous subsections in this chapter. Recommended process steps are illustrated after the mentioning of each consecutive phase in PdM implementation projects. Additionally, best practices and barriers are delineated in a compact manner. Presenting in this form allows to have the key information compactly in one place, enabling quicker access to the essential core parts of the best practices reference checklist.

Table 24: Overview of phases – best practices, barriers and recommended steps

CONCEPT PHASE	
Business case building for PdM 1. Map out the value drivers for the organization 2. Criticality analysis 3. Revenue calculations 4. Strategy fit 5. Check the available data 6. Go/No-go decision 7. Rollout	
Best Practices	**Obstacles**
Stakeholder Involvement - Majority understands the need/incentive towards implementing PdM - Involve all stakeholders from the beginning - Showcase strong value to the top-level management	- Scepticism - Stakeholder misalignment - Lack of decision power - Lack of the right capabilities

- Knowledge sharing between different stakeholders - Regular discussions and meetings between all stakeholders - Give freedom and trust to the PdM project team - Work together with the end-user - Connect people with the domain knowledge with the data scientists **Vision** - Have clear understandings what the organization wants to achieve – have a bigger picture in place. - Long-term vision - Have a clear ambition level - Give priority to PdM - Allocate budget, resources and making investments - Understand what is needed for PdM - Clear distinction of roles and KPI's - Learn from the market **Business Case** - Provide the range for Business Case calculations - Simulate and model the Business Case	- Delay in investment versus the benefits of PdM - Hard to quantify PdM effects - Frustration from unmatched expectations

FEASIBILITY PHASE

Determine project objectives	Assess the current situation	Produce a project plan	Select assets for the pilot
1. Set objectives 2. Produce project plan 3. Success criteria 4. Business success criteria	1. Inventory of resources 2. Requirements, assumptions, constraints 3. Risks and contingencies 4. Terminology 5. Costs and benefits	1. Project plan 2. Initial assessment of tools and techniques	1. Select the assets critical to operation/risk 2. Identify the functional failures 3. Choose dysfunctions for PdM by their quadrant 4. Determine what is required/available for DA, DM, SD, HA and PA

Best Practices	Obstacles
- Take small steps - Use the existing platform/tools - Let the end-user test out the tools - Showcase the success factors - Celebrate the small victories - Reporting of the pilot	- Misunderstanding between stakeholders - Lack of ownership - The right sensors & tools are absent - Not having enough time

DATA PHASE

Collecting the data	Understanding the data	Data preparation
1. Data collection might take considerable time 2. Fleet size 3. Proper registration of all the failure data (including functional degradations) 4. Data accessibility 5. Have a clear measurement protocol in place 6. Make sure to keep the raw data 7. Think about the sampling rate 8. Think about the degradation rate	1. Provide data collection report 2. Describe data 3. Explore data 4. Verify data quality	1. Choose the data 2. Clean the data 3. Construct required data 4. Integrate data

Best Practices	Obstacles
- Strong contractual agreements about data usage - Data is clearly structured - Data is labelled correctly - Clear instructions for data input for the personnel	- Availability and quality of the data - Poor data labelling - Poor data collection from the personnel - Sensors used are not meant for maintenance or prediction Concerns - Data ownership - Data leakage - Cybersecurity

ALGORITHM DEVELOPMENT PHASE

Understand how PdM connects to the operational processes	Model development
1. Understand what is happening in the systems 2. Understand the failure mechanisms and why things fail 3. Identify what needs to be measured 4. Identify how and which models can be built 5. Understand how predictions from these models can be derived 6. Iterate & improve	1. Select the modelling technique 2. Generate test design 3. Build model 4. Assess model

Best Practices	Obstacles
- Use the right tools - Cooperate with the maintenance technicians for better data understanding if needed - Ask for help	- Choosing the wrong modelling technique - Not choosing enough data or choosing too much data - Not understanding the data

OPERATION PHASE	
PdM deployment inside organization 1. Provide results from the previous phases 2. Determine PdM deployment strategy 3. Implement the technical infrastructure for real-time access 4. Plan monitoring and maintenance 5. Adjust the existing processes 6. Educate the personnel 7. Continuous improvement of the solution	
Best Practices	**Obstacles**
- Adjust the existing processes to PdM - Implement quality loops for PdM - Reporting - Analyse the insights from PdM - Re-organize teams - Continuous improvement inside the organization	- Not adjusting the processes to PdM - Not having proper infrastructure for real-time access - Not maintaining the PdM solution - Personnel not having sufficient education

5.8 Design for PdM

Predictive maintenance is still considered to be a novel technology. There is always room for improvement of design elements that would make PdM implementation smoother. Especially suppliers/OEM's can play an extensive role in this by being more involved with co-creation and collaboration together with the industry and their respective end-users. This research revealed insights from the interviews that would help the overall industry to collaborate better to lower the barriers to adopting PdM. Below in Table 25 are listed elements to keep in mind for future trends and designs:

Table 25: Designing for better implementation of PdM

Design element	Description
Designing assets for maintenance	The suppliers need to make parts that need maintenance as accessible as possible for example. Furthermore, improving the equipment that is used for maintenance is equally important for better efficiency. Providing assets with clear prescriptions for maintenance and having good configuration management capabilities is seen useful. Assets best suitable for PdM should be with a short lifetime, stable modules and large population.
Cyber Security	Enabling better cybersecurity capabilities for the industry is the most critical factor towards PdM implementation. Better cybersecurity could mean: • Usage of strictly **anonymized business-critical data**. • **Data encryption** • **Strong contractual agreements** about who can access and process the data. • **Track&Trace capabilities** like Estonian government uses for its citizens where they can give permission and identify who accessed and processed their data at any certain time. This same concept could be potentially implemented in the industry as well.
All-in-one platform	Large organizations in some industries are preferring comprehensive all-in-one platforms that deal with maintenance management, supply chain management, inventory management and logistics. This is due to the fact that this would remove the problematic nature of 3rd party applications and their integration between themselves. Having clearance and permission for one comprehensive platform to access and process business-critical data would reduce the effort and time for asking for permission from top-level management for each new application introduced.

Design element	Description
Knowledge sharing	Knowledge sharing towards best practices inside the industry should be encouraged more. • Having common databases and libraries within industries for failure-modes of different components • Supporting development towards industry demands in terms of cybersecurity and data for example
Supplier involvement	Not all organizations want to have more than "first-line maintenance" capabilities and turning to OEM's and suppliers for more in-depth maintenance activities. Suppliers could consider: • Providing their assets with **built-in remote condition monitoring and prognostic capabilities** that let the owners know in which condition the asset is and when exactly it needs maintenance by clear reporting. Furthermore, this would allow better supply chain planning vertically as well since the stakeholders know when their operations need to be planned. • Selling the performance of their asset over the lifetime of it rather than just the asset itself – **performance-based service**. • Providing more technical maintenance capabilities and support since they have the most knowledge about their assets. • Having these condition monitoring capabilities inside the asset will give information about the behaviour of these assets, allowing better design engineering in the future. • Having a more **standardized design** of their components and systems to enable better integration across platforms.
Modular design Plug & Play	If systems and components have a modular design then it would allow for better plug and play capabilities, which makes integration and maintenance of the processes easier.
Easy implementation	PdM implementation should be rather seamless where organizations do not have to go through the extensive education phase and re-organization of their organization. This is possible when suppliers and OEM's make sure that their additional service offering (condition monitoring for example) is well-thought-through and easy to understand/read.
Contractual agreements	Contractual agreements between different organizations and stakeholders will set clear understanding and boundaries related to the points of concern and service offering. They would allow for better development collaborations and co-creation for PdM, maintenance contracts, data ownership and service coordination between the asset owner and OEM/supplier. Moving away from transactional contracts towards more partnership contracts.
Standardization within industries	Multiple organizations work on standardization for the industries. They want to have clear standards for cybersecurity and 3rd party applications, data structure, IoT integration protocols et cetera. Better standardization across industries would allow suppliers and manufacturers to have a more efficient design of their components/systems that would allow better integration with other platforms and applications.
Use of open architecture and protocols	Organizations should try to use more open architecture and protocols to improve the integration capabilities of different solutions. Staying away from proprietary protocols would improve data accessibility and enhance the implementation of PdM.
Approval authorities	Within some industries (high safety-related like transportation) continuous improvement needs the approval of the authorities where they review all the elements from software to maintenance prescriptions for approval. This means that suppliers need to get this approval from the authorities each year or every time improvements are made. This slows down the continuous improvement and design process.

Design element	Description
Proper dashboarding and reporting	It is important to provide the right information to the right people inside the organization. This means that the end-users of the technology might want to see what the causality logic behind the platform's advice is to conduct maintenance on a certain component. Higher-level management would want to have a good overview of the most critical maintenance KPI's et cetera. Furthermore, accessing those reports should be possible from any device and at any time – smartphone, laptop et cetera. Regular reporting on what analytics are being generated and how many issues are detected will provide visibility on what is the value of predictive maintenance technology.

5.9 Trust towards PdM

Trust in these novel technologies and systems has an underlying effect towards most of the factors related to people and organization considering the adoption of the PdM technologies. Organizations implementing predictive maintenance should be aware of those factors affecting trust to cope with potential hurdles during the process. Knowing where the market stands enables to figure out the correct approaches towards the clients, allowing to potentially reach more successful projects and communication between the stakeholders. The following Table 26 illustrates these factors and how they influence the implementation process:

Table 26: Factors affecting the trust towards PdM

Factor contributing to trust	Description
Overall scepticism	There is still noticeable scepticism amongst organizations towards predictive maintenance. This is stemming from the fact that the technology is still novel and extensive successful projects are not that common yet. However, the first wave of hype is passing by and more organizations are understanding what is needed to implement PdM and are turning their sights towards that. Market developments enabling better digital solutions are supporting to reduce the scepticism.
Human factor being still important	Work-floor employees feel threatened by the coming of predictive maintenance that their work would then become obsolete. However, this is not true. Creating awareness that PdM will bring decision-support to the existing maintenance personnel. This will have some changes to the way operations are carried out, changing the way maintenance personnel works but not making their positions redundant. They have a new, adapted role to play in the entire process. Additionally, PdM does not remove other maintenance strategies and approaches, rather improves the efficiency.
On-premise vs cloud solutions	It seems that the market still trusts the on-premise PdM solutions more since they are perceived to be with higher levels of cybersecurity.
Black-box solutions	The engineers and technicians would want to understand and see the logical reasoning how PdM application comes to the conclusion/advice to conduct maintenance, therefore, black box solutions that do not provide any **causality explanation** are trusted less by the work-floor end-users. To tackle this, **explainable AI** would be the way to go by opening the black box. It shows how the algorithm is run based on what arguments and what inputs, it comes to a certain decision. The system tells the engineer how it came to this insight and it is based on these arguments, which makes it easier for the engineer to accept or to understand how the method came to that decision.
Trust towards 3rd party applications	The trust towards the platforms is not affected considerably if the PdM applications are coming from the 3rd party companies.

Factor contributing to trust	Description
Decision-making	Organizations are trusting and using predictive maintenance as a decision-support tool for maintenance operations. However, PdM is not replacing or automatizing the decision-making by the maintenance personnel, which is an indicator towards the fact that there could be improvements towards trust levels.

5.10 Best Practices Checklist to PdM implementation

Adopting predictive maintenance inside the organization is not a simple task and demands knowledge, patience, cooperation and elaborate capabilities. Successful implementation, on the other hand, can bring along increased revenue streams from better asset uptime, support in getting ahead of the competition, additional business models and higher safety for the personnel. Hopefully, these best practices and elements mentioned beforehand will be able to support organizations in adopting predictive maintenance solutions more seamlessly. Overview of Best Practice Checklist road to PdM is a compact overview of the best practices checklist for implementing predictive maintenance in the organization.

5.10.1 Comparison between different PdM implementation approaches

Implementing predictive maintenance inside the organization can take many paths since every company has their differences in processes, stakeholders and existing systems – there is no "one-way fits all" path. There are approaches in the literature that delineate the process of PdM implementation inside the organization on high-level, below is a compact overview of how this developed research output compares with them:

Table 27: Comparison between different PdM approach overviews

Content	Maintenance maturity assessment	Structured approach	Illustration of challenges	Best practices illustration	Detailed explanation of barriers and positive actions taken
PriMa-X: A reference model for realizing prescriptive maintenance (Nemeth et al., 2018)	✓	✓	✓	✗	✗
Implementing Predictive Maintenance in a Company (Wagner & Hellingrath, 2019)	✗	✓	✓	✗	✓
Beyond the hype: PdM 4.0 delivers results (Haarman et al., 2018)	✓	✓	✗	✓	✗
Predictive maintenance – From data collection to value creation (Feldmann et al., 2018)	✗	✓	✗	✗	✗
Digital Industrial Revolution with Predictive Maintenance (Milojevic & Nassah, 2018)	✗	✓	✓	✗	✗
Developed best practices checklist for this graduation project	✗	✓	✓	✓	✓

Table 27 provides an overview of the approaches examined in the literature review to PdM implementation inside organizations. Comparison criteria (columns) were chosen to match and correlate with this developed best practice approach to examine for contrast. This developed approach is missing methods to evaluate organization's maintenance maturity, however, it has an elaborate overview of challenges and best practices in an organized, understandable fashion to support organizations with the adoption of predictive maintenance. Maturity for maintenance evaluation is not covered since there has been extensive work done in the scientific literature on this topic beforehand, meaning these developed maturity models should be utilized collectively with this best practice checklist. Furthermore, this developed research output is supposed to remain high-level overview and support tool for PdM project assessment, hence analysing one nuance (maintenance maturity) in deeper detail than others does not align with the practical goals of this approach. Last, it is assumed that the organizations looking to implement PdM have an idea about their maintenance maturity levels to some extent already.

6 Evaluation

Qualitative research is prone to subjectivity since the researchers have to use their interpretations and perceptions while drawing conclusions from the presented data. It is essential to test the validity of the research findings through possible methods. For this research project, the time scope is limited to approximately six months. This means that there is not much opportunity for in-depth validation process that takes an extensive amount of time. Since predictive maintenance project implementations in the industry can take years then in-company validation for this research was not possible. Furthermore, the commonly used iterative Delphi Method for qualitative research validation was considered for a while but was neglected for the same time limitation reasons.

6.1 Expert Panel

It is explained in the scientific literature about the validity of the qualitative research: “The validity of research corresponds to the degree to which it is accepted as sound, legitimate and authoritative by people with an interest in research findings” (Yardley, Clarke, Braun, & Hayfield, 2015). Following from this ideation, the researcher turned to focus group methodology, an expert panel in more detail, to potentially validate the practical research outcome. An expert panel is a group of people specifically convened by the researcher to elicit expert knowledge and opinion about a certain issue (Bougie & Sekaran, 2016). Making up in depth what they lack in breadth, focus groups enable the moderator not only to pursue a detailed inquiry into existing opinions but also to obtain reactions to new perspectives and ideas (Newcomer et al., 2015).

To validate the best practices checklist and its potential practicality and applicability in the industry, the researcher conducted an expert panel discussion to reach consensus and common understanding of the following questions:

1. Is this method useful/helpful in supporting companies implementing PdM?
2. Is the method understandable/clear?
3. Is it generalizable to other industries?
4. Is using the expert panel the proper way to validate the method?
5. Strengths and weaknesses of the method?

These questions were chosen to reveal the expert’s opinions and expressions on how generalizable, understandable, useful and valid the developed research output is. The term *usefulness* is tightly coupled to the *purpose* of the research project that is established at the beginning of the study (Pederson, Emblemsvag, Allen, & Mistree, 2000). The purpose of this research project was to support organizations on high-level of PdM adoption. This means that this best practice checklist does not aim to dig into the deeper nuances of each element since it would be out of the scope of this project. Hence, the *usefulness* of this research output is linked to the ability of the best practices checklist to support organisations in implementing PdM. This is determined by the expert panel’s opinion built on extensive expertise in this domain. Furthermore, open-ended question about the strengths and weaknesses of this approach was asked to illustrate the strong and weak points of this developed best practices checklist.

6.2 Experience of the expert panel

The experts were chosen to the panel determined by their background and experience in the domain. In total four experts out of planned five attended the panel that was conducted online. One of the experts could not attend because of the time restriction. The experience of the panel is illustrated in Table 28 below:

Table 28: Expert panel industry and experience

Industry	Experience in years
Academia	30 years
Transport	17 years
PdM solution provider	10 years
PdM solution provider	30 years

All the experts possess extensive expertise working with predictive maintenance solutions and their implementation dynamics inside the organizations. Having people from different industries allows for better differentiation of perspectives on the research output. This makes reaching consensus having more weight since experts with different background can reach a common understanding of the questions proposed beforehand.

6.3 Build-up of the expert panel meeting

The experts received the developed best practices checklist with produced add-ons four days before the planned meeting to ensure that they would have enough time to work through them. Furthermore, the questions under the scope were provided upfront, enabling experts to already work through the documents having these in mind. During the panel meeting, the researcher took the moderator position and guided the discussion by facilitating conversation around the proposed questions and asking the experts to elaborate on certain points further if needed.

6.4 Findings from the expert panel

6.4.1 Fulfilment of purpose

For each proposed question a common ground and consensus were found. They all agreed that this developed best practice reference checklist is supporting the organizations in implementing predictive maintenance. It was said that it helps bring companies into the awareness of the obstacles and best practices regarding PdM adoption. It was agreed that this best practice checklist has thorough amounts of information while having an elaborate overview of the phases of adoption and clear delineation of barriers during the process. Knowing these hindrances and how to potentially act on them upfront helps to prevent a lot of things from happening that normally would go wrong. It was discussed that organizations sometimes begin these PdM projects without having proper awareness what capabilities and resources are actually needed to go forward with them successfully, this reference checklist shines a light on these factors by illustrating them in a structured fashion. This concludes that the developed research output is fulfilling its purpose in aiding companies with PdM implementation in the expert panel’s shared perspective.

6.4.2 Generalizability and strengths

In addition, it was agreed that this approach is generalizable to other industries since the scope of the developed best practices checklist is high-level. This means that any organization looking forward to implementing predictive maintenance for the first time would benefit from this research output. Furthermore, the structured, phase-wise approach of this best practice checklist kept it clear and understandable, making it straightforward to use. Illustrative add-ons that were designed to present the information in a compact and structured way received positive feedback. The main strengths of this developed research output are illustrated below:

- The scope and clearness;
- Structured and orderly approach;
- Collection of different barriers and best practices;
- Concise and clear overview of these insights;
- Extensive information presented in the tables.

These strengths illustrate the overall comprehensibility of this developed best practices reference checklist for PdM projects. Having clear structure, orderly approach, bringing awareness to the barriers and collection of best practices of other companies in the industry allow organizations adopting PdM for the first time to avoid some potential mistakes during the process. This would conceivably ease the implementation process of predictive maintenance to an extent.

6.4.3 Improvement recommendations

On the other hand, the experts identified a couple of improvements for this approach. First, it was agreed that the previous word usage of “method” and “roadmap” can be somewhat misleading the reader into believing that this output will have a definite approach to predictive maintenance implementation that will yield guaranteed success. Therefore, the rephrasing of the research output was advised. The process of implementing PdM highly depends on the organization adopting it; this led to the discussion if there even could be such a definitive, all-inclusive method that covers all the nuances of implementation. Second, it was illustrated that the method did not provide sufficient understanding where these insights were coming from, what was the source of them and how the researcher derived these best practices and barriers from the interviews. This was due to the fact that the researcher did not include this information in the document itself to limit the length of the material needed to be worked through by the experts, but it was illustrated in the final research report. Last, there were minor conceptual suggestions to the document and future research that will add extra value to it. All these notions from the expert panel were included in the research report, improving the coherence and understandability of it.

6.4.4 Validation

The experts discussed that the validation of the research output can depend on the desired level of detail. They advised approaching from the design process perspective – What were the objectives of this research? Are they fulfilled? The design objectives are listed below for a recap:

- Support organizations in implementing PdM more effectively;
- Clear and understandable;
- Provide a compact overview on high-level;
- Be logically structured;
- Cover the adoption from technical, organizational and people perspectives;
- Bring awareness to the important factors influencing the implementation.

They agreed that this research fulfilled its design objectives and certainly supports organisations on a high level in adopting predictive maintenance. The structure of the research output was evaluated to be logical, clear and understandable thanks to the phase-wise approach to PdM projects. Additional sections illustrating the core information of this best practices reference checklist provide a compact overview of the results and the most important information in this research. PdM adoption was approached from all three: technical, organizational and people perspectives. Although technical perspective was covered in deeper detail, this report provides scientific references for further reading and getting started with these more complex technical domains. Comprehensible illustration of best practices, barriers and recommended procedural steps towards PdM projects bring awareness for organizations about the dynamics of implementing predictive maintenance technologies.

It was said that taking into consideration the limited time scope of the research project, the expert panel is suitable for the preliminary positive validation of this research. The following complete validation should be undertaken by having this best practice checklist applied in practice by several companies and then receiving their feedback on its helpfulness and applicability in supporting them with their PdM adoption activities. This could help to investigate the correlation between applying this approach and the success factor of adopting PdM in practice.

6.5 Conclusion to evaluation

To evaluate the research output of this study, an expert panel consisting of 4 experts with extensive domain knowledge was utilized. The panel was asked to evaluate this research by reaching consensus on the following questions:

1. Is this method useful/helpful in supporting companies implementing PdM?

2. Is the method understandable/clear?
3. Is it generalizable to other industries?
4. Is using the expert panel the proper way to validate the method?
5. Strengths and weaknesses of the method?

The expert panel reached consensus on all of these questions and concluded that this research output and developed best practices reference checklist is definitely useful in supporting companies with PdM implementation. Furthermore, it was agreed that the output is clear and understandable with a well-structured approach. Coming from the high-level nature of this research, experts agreed that this research is generalizable to other industries. Also, they agreed that the expert panel provides preliminary validation to this research, but for full validation, evaluation has to be done in practice with companies inside the industry. Last, experts outlined the strengths and weaknesses of the reference checklist.

7 Discussion

This research provided a structured best practices checklist to support organizations looking to implement predictive maintenance solutions. This output will help them to assess their PdM project in an understandable and coherent way, increasing awareness of what needs to be considered before starting the project. During the implementation process, this reference checklist acts as a reminder to what practitioners can refer to, ensuring that the recommended procedural steps are considered and worked through. In this section additional aspects like triangulation of the findings with previous scientific work, limitations of the developed research output and additional notions are covered.

7.1 Generalization

This research is qualitative and explorative in its nature by relying on empirical findings from the interviews with industry experts. This means that valid generalization is not sought after with this research because of the small sample size and how the research is designed. However, the expert panel evaluating this best practice checklist agreed that this output is giving an overview of high-level generalizable to all industries and organizations that start their PdM project. This gives a preliminary indication about the generalizability which relies on the experience and knowledge of the experts.

The experts mentioned that this developed best practices reference checklist is quite holistic in its nature, meaning that it does not focus solely on one particular industry. Indeed, the interview participants were mainly consisting of experts from manufacturing and process industries, but the insights gathered from these interviews were transformed into best practices and recommended procedural steps that can be utilized universally across industries where companies are looking to implement predictive maintenance technologies.

7.2 Connection of findings with existing scientific literature

This research highlighted and brought into awareness factors and aspects contributing to the adoption of predictive maintenance technologies. New and surprising insights were mentioned in the section "What is new and surprising?", in this section a discussion about how overall findings connect to the academic context.

The findings from the interviews about the barriers to the PdM adoption reinforce findings from the previous scientific literature about barriers in embedding big data solutions in smart factories (S. Li et al., 2019). In their article, barriers were divided into three main categories: organizational, people and technical/data related barriers. In this research, the same three main categories could be identified where the barriers could be classified. Furthermore, the interviews conducted for this research illustrated that almost all the same barriers mentioned (Table 3) in their article about embedding big data solutions are also present in the implementation of predictive maintenance technologies. This means that there are strong similarities in barriers to adoption between other big data-related technologies and predictive maintenance solutions.

Prima-X, a reference model to realize the prescriptive maintenance (Nemeth et al., 2018), provides a structured approach to implementing prescriptive maintenance while illustrating hindrances in different process steps. These mentioned obstacles in the article are technical in their nature and the findings from this research align with these by having overlapping barriers illustrated regarding realizing advanced maintenance strategies. Having triangulation between different sources and common insights adds to the generalizability and validity of this research.

Article (Wagner & Hellingrath, 2019) that this research structured approach was based on, delineated challenges in the respective implementation phases which overlapped with findings from this research. These challenges were from organizational, technical and people perspectives, identifying three main challenges mentioned by their respondents: cost and benefit (concept phase), real-time access (operationalization) and reluctance and reservation (human factor). This research reinforced these findings by illustrating barriers that were connected to these same problems.

Adoption of predictive maintenance is believed to result in a boost in global competitiveness in today's dynamic business environment through better asset management, increased uptime of production systems, less downtime of processes et cetera (Compare et al., 2020; Lee, Lee, & Kim, 2019; Sezer, Romero, Guedea, MacChi, & Emmanouilidis, 2018). It is argued that predictive maintenance is a fundamental strategic approach for businesses looking to construct smart plants for the future (Lee et al., 2019). This illustrates the growing importance of predictive maintenance in the coming years. This means that organizations are in need of supporting tools and best practices that facilitate better adoption of PdM technologies. This research provides an aiding, holistic best practices reference checklist for companies looking to implement predictive maintenance, bringing awareness related to this domain and expectedly increasing the success factors of PdM projects. In addition, PdM enables industries to develop additional business models along with more reliable products and services by taking responsibility of portions of the clients' business risks and other financial burdens (Compare et al., 2020). Furthermore, implementing PdM technologies that can optimize maintenance and production processes through maximizing life cycle of assets and reducing excessive energy consumption can alleviate environmental problems (Selcuk, 2017). This research outlined in the section of Societal contribution how adopting PdM can provide societal benefits, which aligns with the shared perspectives in the scientific literature.

Industries are acknowledging the growing importance and appealing potential of predictive maintenance, this is illustrated by increased investments across countries into the development of Industry 4.0 from which extensive amount was allocated for PdM related research (Compare et al., 2020). The growing trend of making PdM related investments seems logical regards to the forecasts which predict that predictive maintenance will save 630 billion dollars in costs over the next 15 years in the manufacturing industry (Lee et al., 2019). Developments in the technical domain, especially IT/OT/ICT including sensor technologies support the development of PdM, making it more competent, applicable and affordable, hence being more appealing to all sorts of industries (Selcuk, 2017). Increased investments and intent to implement predictive maintenance inside the organization should come as a result of organizational culture, which reforms the understanding about the role of training, education and leaders, how employees can be involved with continues improvement of the company while pursuing capabilities of applying real-time big data analytics. Industry 4.0 development should also include the improvement of education and training of maintenance personnel how to deal with these new predictive algorithms and commencing cause-effect analysis with expected outcomes et cetera (Lee et al., 2019). Meaning that the multi-disciplinary nature of this research is lined up with perspectives in the scientific literature that understand that implementing predictive maintenance requires organization-wide alignment, communication, effort and support to be successful. This study illustrates the importance of involving relevant stakeholders from the beginning with PdM projects. Emphasising the significance of organizational factors in this research brings awareness to the overall academic context by showcasing how multi-disciplinary is the adoption of predictive maintenance technologies. Accepting that notion would allow organizations to take more collaborative (intra- and inter-company) approach to PdM, enhancing the probability of successful PdM project. Experts who are developing data analytic capabilities and making decisions based on these insights should be provided with more policy support (Lee et al., 2019). This research also indicated in the design section that policymakers and authorities should revise their approach to PdM acceptance to be more flexible.

Although increased investments and acknowledgement of the growing importance of predictive maintenance, PdM is still facing several challenges before adequately maturing into assured technology adopted across industries. First, industrial data analytics place high demands on data access, data quality and data merging from multiple sources where the data is originating from. Since these data sources often function in heterogeneous environments, integration between different layers of the systems proves to be problematic (Z. Li, Wang, & He, 2016). This research provides similar evidence about the need for better integration capabilities and collaboration between different stakeholders to improve the adoptability of PdM technologies.

Second, organizations need enhanced capabilities to deal with industrial big data since leveraging this massive amounts of data requires the appropriate infrastructure both from information and operational technologies perspective along with knowledge and expertise to commence the historical analysis of critical trends that allows to carry out real-time predictive analysis (Z. Li et al., 2016). This research aligns with this notion by bringing awareness to the fact that implementing predictive maintenance technologies is not as effortless as it was conceived couple years ago by the companies in the industry (Schallehn et al., 2019). Having increased knowledge about the requirements to adopt PdM and what to expect along the way during the PdM implementation project delineated by this research, organizations can manage their expectation about this technology, dissolving the perspective of unmatching ambition in contrast with the organizational capabilities and readiness to adopt PdM.

Third, security-related concerns around predictive maintenance are arising from the transactional communication protocols over the internet, lacking of structured modelling approach that quantifies the clear benefit of PdM in safety-critical contexts (nuclear, aerospace et cetera) and the fact that safety standards consider that many improvement steps are essential to make PdM technology mature enough to be implemented in safety-critical environments (Compare et al., 2020; Selcuk, 2017). This research also revealed heightened concerns surrounding the cybersecurity capabilities in relation to predictive maintenance. Interview insights gathered that industry is still cautious about the security of their critical processes and is waiting for the universal cybersecurity standards that provide extended assurance about integrating these new technologies with their critical processes. Furthermore, design improvements delineated the necessary need for the stakeholder collaboration regarding these security concerns.

Fourth, business case building around predictive maintenance is still not so seamless and in need of enhancement and further development of economic, maintenance cost models to provide sound, tangible justification for PdM investments (Compare et al., 2020). The section of 5.2.3 Business Case building focuses on the perspective of business case building around PdM, providing recommended steps on how to work towards the business case. In addition, relevant scientific literature was referenced to complement the reader with extra resources. This enables to slightly improve the uncertainty around the challenge of business case building for PdM. Furthermore, the scientific literature reveals major disbelief in Industry 4.0 that assumes that larger amounts of acquired data in IoT networks always results in better performance of PdM, which is not so since acquiring, storing, maintaining and analysing data entail a cost that increases with the amount of data (Compare et al., 2020). This research focused on the predictive maintenance algorithm development dynamics and how to approach it, top-down or bottom-up. The advantages and disadvantages of both approaches were illustrated, while the notions about the overall strength of the bottom-up approach could be observed. This means that this research sides with more cost-effective (data management related) perspective to predictive algorithm development, bringing awareness to the organizations about the benefits of the bottom-up way to deal with model construction. Last, despite the advancements regarding predictive maintenance and its dynamics, essential research work is still needed to be done regarding the trust towards PdM connecting to IoT in the Industry 4.0 environment (Compare et al., 2020). This research contributed to the scientific literature by researching into the trust that industry has regarding predictive maintenance technologies. It revealed that the industry is still cautious to adopt PdM technologies since the trust factors could be higher. Furthermore, this study outlined the trust elements and how companies should approach them to improve their capabilities in convincing their potential clients and internal organization about the benefits of implementing predictive maintenance technologies.

It is important to mention that in the existing previous literature there was not such an extensive overview present about realizing and assessing predictive maintenance projects that support organizations in adopting PdM. Consequently, coming from the amount of original content provided by this research and knowledge gap in the scientific literature, this study adds considerably to the overall academic context. This research output highlights best practices and barriers that are approached from all necessary perspectives: organizational, technical and people. This makes it a useful reference guide creating awareness about PdM for any organization starting their first project.

7.3 Limitations

This research was conducted by one researcher which decreases the validity of this research since it highly depends on the perception of the researcher who interpreted and analysed the information on which the best practices checklist was developed. Furthermore, coding and assigning themes to the qualitative information collected from the interviews was solely up to the researcher, making it vulnerable to major subjectivity. This could have been mitigated by using inter-coder agreement if the research team would have been bigger. In addition, the research output preliminary validation with the expert panel mitigates this perspective of subjectivity on this research. This developed best practices reference checklist was showcased to the expert panel for the examination which turned out to be positive. This means that the interpretations of the researcher about the qualitative content from the interviews were aligned with the experiences of the industry experts who concluded that this research output is sound and supportive for companies implementing PdM.

Since this research is qualitative in its nature then solid generalization about the research findings is hard to achieve. Additionally, having a small sample size of 11 interviews is not enough to represent the whole manufacturing industry that this best practice checklist is meant to be used by. Furthermore, this research has very limited timeframe which takes testing and validating this best practice reference checklist with the companies in the industry out of the scope for this research project since predictive maintenance implementation inside organizations can take a couple of years. This provides opportunities for future research based on this study. Correlation between this best practices reference checklist and the success factor of the PdM project should be further investigated in the practice.

This research is meant to be on high-level support tool to assess PdM projects before the organization starts the implementation and during the actual process. This means that deep analysis and elaborate practical tools/methods to overcome the illustrated barriers are not present. This is due to the fact that it is out of the scope of this research timeframe wise and adopting predictive maintenance is highly dependent on the organization doing it. This means that there is no concrete, one right way to implement predictive maintenance, making it almost impossible to develop a definite roadmap and method that tackles all the complications during the implementation process. Furthermore, this research did not focus on going into deeper detail on the predictive algorithm generation and how to connect it to the live streaming data in the operation phase. These domains are highly technical and require in-depth understanding to be elaborated more, meaning that they could be a research topic on their own. The researcher avoided going deeper into these topics since they could not be covered in sufficient depth in this research project scope, which would have resulted in fragmentary domain coverage, lowering the overall value of this research output. To mitigate these limitations, references to the relevant scientific literature were made to complement the reader going through this report by providing directions to the first sources of knowledge to get started in these technical domains.

This developed best practices reference checklist is elaborate and consists of considerable amounts of information. While this can be a clear strength, it also can be a downside in some instances. Industry practitioners can be quite overwhelmed with work and a busy schedule, meaning that reading through this extensive report fully would be out of the question since of the time limitation. This implies that important pieces of information could be overlooked and missed potentially. Interview insights are highly aggregated into tables in the main part of the research report, these make up the core of the information gained from the industry experts. Although these tables are a concentration of the gathered insights, they still can take considerable time to read through. The mentioned limitation is mitigated in this research report by providing compact overviews about the developed best practices checklist in the similar sections of Overview of the developed reference checklist for PdM projects and Overview of Best Practice Checklist road to PdM, whilst the first reference is providing the core information in a compact table, the second reference is a more illustrative overview of the developed best practices checklist. In addition, clear indications on how to approach this research output are delineated in the beginning of chapter Developed Best Practices Checklist on the Road to PdM.

This research revealed trust factors and potential design improvements that different stakeholders could make to lower the barriers to predictive maintenance adoption in the industry. Although these factors were listed and promptly introduced, further research on how to utilize them in practice should be commenced. The core of this research was developing best practices reference checklist which covered also the trust factors in the convincing section, but design improvements for PdM were treated as a complementary addition to the reference checklist. In-depth analysis and practical implications were not investigated in deeper detail due to the research scope and time constraints. On the other hand, having these design factors illustrated provides again additional opportunities for further research on how organizations and OEM's could incorporate these design improvements into their processes, improving the adoptability of predictive maintenance technologies.

7.4 Advantages

This research output consists of the development of best practices reference checklist that was based on the analysed scientific literature and 11 interviews with the industry experts in the domain of predictive maintenance. In addition, factors contributing to the trust towards PdM were examined and then delineated along with design improvements that different stakeholders can include in their processes and product to support better adoption of predictive maintenance technologies. Furthermore, the constructed reference checklist was translated into an illustrative overview for a compact presentation of the essential core information. It is important to mention that to our knowledge this kind of holistic approach to support PdM project implementation was not present in the existing literature, meaning that it fills an important gap in the scientific literature to enable better adoption of PdM technologies. Meaning this research provides a considerable amount of original content and information into the pool of scientific literature.

The developed best practices reference checklist was meant to be high-level and elaborate, meaning that it covers the process of PdM projects from the beginning to the end until the operation phase, filling the necessary steps in between. This holistic, high-level approach does not aim to go into deeper detail with more complex technical domains like predictive algorithm construction or connecting OT/IT infrastructure for real-time streaming data access. This allows to keep this research output more comprehensible for the reader to gain knowledge from. Having too much detail into complex technical domains would overwhelm the reader with information, making it hard to grasp and understand. If further knowledge is needed about these technical domains, then this report provides references to the relevant scientific literature that provides the first steps into these subject matters. Furthermore, the high-level approach allows the reader to construct an overall understanding and awareness about what to potentially expect during the process of PdM project implementation.

Industry experts agreed that this developed best practices reference checklist supports organizations who are looking to implement predictive maintenance technologies. An extensive amount of information was gathered during the conducted interviews with the industry experts and this report provides a comprehensible, systematic phase-wise presentation to these insights. Having clear scope, coherent structure and extensive overview about best practices, barriers and recommended procedural steps towards PdM project implementation brings awareness and manages expectations of organizations moving towards higher levels of maintenance maturity. Having greater knowledge about what to expect and what capabilities are required to take that step towards predictive maintenance enables companies to anticipate potential problems beforehand and prepare mitigations in advance, leading to better project preparation and potentially greater success factors. Furthermore, instructions on how to approach this best practices reference checklist along with understandable structure provide clarity for the reader how to approach this research output, gaining the most value out of it.In addition, compact overviews (Table 24 and appendix C) allow quick referencing to the core information of this best practices checklist for practitioners with constrained time schedules.

7.5 Future research

Coming from this study, future research to be done should be focused on putting this best practice checklist into practice with companies in the industry. This would allow for full validation of this developed approach in addition to positive validation from the expert panel. It would be important to understand what is the correlation between applying the stated best practices checklist and being successful in implementing predictive maintenance technologies in the practical domain? The researcher had an initial ambition to test out the developed best practices checklist in practice, but predictive maintenance projects can take multiple years, meaning that the time constraint of this research project was the main reason why this has been flagged as future research. It is important to mention that the researcher is interested to stay in contact with people and organizations who would be interested to assess and evaluate this research output in practice for feedback and improvement ideas.

This research depicts design improvements that different stakeholders could implement for better adoption possibilities of predictive maintenance technologies. Although the design improvements are illustrated, they are complementary to the main core of the research, meaning there is room for further research into bringing them into practice and how organizations would evaluate their willingness and interest to introduce them into their processes/products.

Furthermore, more elaborate tools and frameworks could be developed to overcome the delineated barriers in the checklist. This would need a prolonged timeframe to collect feedback from the industry and develop these tools from these insights. These supportive means would complement the work done in the current scientific literature (Tiddens et al., 2018), forming a better arsenal of approaches for organizations to adopt predictive maintenance technologies. In addition, contradicting findings from the interviews provide new nuances for potential further research.

8 Conclusion

This research aimed to provide organizations seeking to adopt PdM with the best practice checklist that supports on a high-level to assess and realize predictive maintenance projects. The main motivation for the research came from the knowledge gap in the scientific literature that was lacking best practices methods towards the adoption of predictive maintenance technologies. The developed support tool for PdM implementation was based on a scientific literature study and mainly on the insights gained from the semi-structured interviews with 11 industry experts with considerable domain knowledge about PdM. These insights were then analysed and transformed into the best practices reference checklist that adapted a structured, comprehensible phase-wise approach to PdM projects. Furthermore, compact overviews and illustrations about the core information presented in this research were developed to aid readers who are experiencing time constraints. In addition, design improvements that different stakeholders should incorporate in their processes/products for better PdM adoptability were outlined. Trust factors were illustrated that are important in convincing stakeholders about the benefits and usefulness of implementing PdM, enabling organizations to refine their client approaches for enhanced communication abilities. The study output was evaluated by the expert panel with extensive industry knowledge to indeed reach that goal of supporting organizations with implementing PdM. Furthermore, experts agreed that this research is generalizable to other industries and preliminary validation is done by having a positive evaluation from the expert panel.

This research highlighted important factors contributing to the adoption of predictive maintenance technologies from organizational, people and technology perspectives. This helps to create more awareness about what is needed to consider for better adoption of this technology. Furthermore, a high-level structured overview of best practices checklist is contributed to the scientific and practical domain, filling the previously outlined gap in the literature. In addition, coming from the analysed literature, this research complements the scientific literature on the topic of predictive maintenance by providing original content and additional awareness to the overall academic context regarding the dynamics of this technology's adoption.

The main research question was “How to facilitate the adoption of Artificial Intelligence-based predictive maintenance technology in the manufacturing industry?“. To find answers to this main research question, literature study and semi-structured interviews with the industry experts were commenced. These research methods provided a considerable amount of information which was utilized towards developing an understanding of how to facilitate better adoption of PdM. This research reveals that it is important to develop and increase awareness about the complex and multi-disciplinary nature of predictive maintenance and its adoption. Having greater knowledge about what is needed and what are the prerequisites to adoption will prevent a lot of complications of PdM projects along the way. Furthermore, sharing best practices between industries that have successful reference projects as a foundation is essential for better adoption rates of the technology. In addition, further development of supportive tools and frameworks would considerably help organizations on their road to implementing PdM. This research provided a best practices reference checklist to support organizations adopting PdM whilst filling the gap in the existing scientific literature.

On a principal level, the answer to this main research question lies in the ability to first understand the dynamics of predictive maintenance and how the industry perceives it. Taking the explorative approach to understanding what causes the slow adoption rates in the first place is the necessary foundation on which further activities can be planned. The industry is still cautious about this new technology since they are noticeably risk-averse, worried about the security of their business-critical processes and information, lacking the right capabilities/knowledge and want to have a tangible business case for PdM with a clear return on investment. This is illustrating that the industry needs to be further educated about this technology before adoption rates can considerably increase. Furthermore, it is evident that design improvements to lower the adoption barriers must be made to PdM related processes/products and this requires industry-wide collaboration, communication and cooperation. In parallel with educating the industry, the scientific community should develop elaborate tools and frameworks to be utilized that support companies with implementing predictive maintenance technologies when there is distinct organizational readiness, ambition and intent to do so.

Sub-question 1 about the relevant State-of-the-Art literature that supports PdM adoption method development was answered in section Predictive Maintenance in Industry 4.0 where literature review was commenced to investigate materials and information that supports the development of the best practice checklist. Literature study investigated articles about the essential concepts of predictive maintenance, trust in PdM technologies, maturity models in digitalization, maintenance implementation frameworks and Industry 4.0 technologies including how PdM fits in this new industrial revolution. Scientific literature provided sufficient information about predictive maintenance on which an understanding of the technology and its dynamics could be formed on. Furthermore, the literature study revealed potential barriers that could be focused more on during this research from which the 3 aforementioned hindrances for this research were chosen from. In addition, scientific literature provided a foundation of structured approach to PdM projects that this best practices reference checklist was constructed and developed on. On the other hand, there was a noticeable gap in the scientific State-of-the-Art literature about the overall framework to predictive maintenance implementation inside the organization that provides comprehensive information about each phase from the beginning to the end and factors to pay attention to during PdM project implementation.

Sub-question 2 about developing a method that is suitable to support the adoption of PdM technologies has been illustrated starting from section Developed Best Practices Checklist on the Road to PdM where the respective supporting best practice checklist was developed. This best practices reference checklist for PdM project implementation was mainly based on the semi-structured interviews with the industry experts. Interview participants provided insights into the best practices their organization uses regarding predictive maintenance and its adoption. Furthermore, barriers and additional notions to predictive maintenance implementation were revealed. These insights were then used to develop best practice reference checklist to facilitate better adoption of PdM by providing organizations with supportive tools. This means that again explorative approach was taken to gather information from the experts and then formulate an applicable solution to facilitate better adoption of PdM. In addition, the researcher believes that potential case studies on successful implementations could complement this approach by providing additional sources of information on which to construct this best practices reference checklist. That would increase the validity of the developed method by enabling information triangulation, positively affecting the credibility.

Sub-question 3 about validating the method applicability in practice is answered in section Evaluation where the experts provided the preliminary positive evaluation of the applicability of the best practices checklist in practice. The expert panel agreed that this developed best practices reference checklist is supporting organizations in implementing predictive maintenance technologies. Furthermore, they reached a consensus that this approach is generalizable to other industries and preliminary positive validation from the expert panel is sufficient for the scope of this research project. Although it was mentioned that for full validation of this developed best practices checklist, organizations inside the industry should utilize it in practice and provide feedback to examine the correlation between using this reference checklist and the rates of successful PdM projects.

8.1 Scientific contribution

Adoption rates of predictive maintenance are still relatively slow since the implementation of this new technology is complex, a multi-disciplinary process that requires effective collaboration between stakeholders, knowledge about the nuances of the technology and clear vision for the future of the organization. Companies can have unrealistic expectations of the technology since there is a lack of awareness what is needed to adopt predictive maintenance. This potentially comes from the scarcity of materials about PdM that help to educate the industry on a sufficient level. This research is contributing to the scientific literature by illustrating and highlighting the barriers and best practices in different phases of predictive maintenance implementation. Complex organizational, technical and people related dynamics are explained on a high-level to facilitate better comprehension of nuances about this technology. This helps to develop a deeper understanding of the reasoning why this new technology takes longer to adopt by the industry than anticipated. Furthermore, this study revealed critical technical domains (cybersecurity for example) that require improvement for better adoption of PdM.

8.2 Managerial contribution

This research provides a structured best practices checklist for organizations to assess their PdM project plan, supporting them in implementing predictive maintenance technologies. Illustrating barriers and best practices in each phase of implementation will create higher awareness about what is needed for implementation and what to potentially expect, allowing to prepare problem mitigation plans beforehand. Having a better understanding and awareness about PdM technology allows preventing a lot of complications that could wrong without the proper knowledge. Furthermore, compact and structured presentation of these insights allows easily understand and apply the presented research output in practice. In addition, for time-constrained individuals, an add-on of five-page “Checklist on a road to PdM” was developed that holds the key takeaways from the research findings. Overview of best practices and barriers is also translated into a compact format. This research also highlighted design factors that relevant stakeholders could use to develop better products that support the improved implementation of PdM. There had not been such an extensive, high-level overview present in the literature yet.

8.3 Societal contribution

This research adds to society by supporting organizations to adopt PdM more effectively. Increasing adoption rates of predictive maintenance technologies might yield multiple benefits for the overall society. First, organizations could optimize their processes based on the insights from the technology, leading to increased energy efficiency which in effect would reduce the pollution by limiting gas emissions from industrial processes. Second, since the maintenance processes are conducted more efficiently, material losses and the need to exchange assets too frequently would be eliminated, adding to the better management of resources. Third, predictive maintenance increases the safety of the employees by alerting when an asset is in critical operational condition and could inflict damage to the work floor personnel. Furthermore, sensors coupled with analytics would replace visual and instrument inspections in hazardous environments. Fourth, based on cost reduction from more optimized processes, organizations could adapt their product margins, leading to potentially better prices for the clients. Fifth, OEM’s/suppliers could improve the design of their products based on the analytical insights from PdM, providing higher quality machinery and devices.

8.4 Link between Management of Technology program and this graduation project

The Management of Technology programme aims to educate students to become professionals who can support industries to use technology as a resource that improves products, services, customer satisfaction and organization’s productivity, profitability and competitiveness. These future professionals are knowledgeable with technology-related practices and management approaches, making them an essential linkage between operational levels and top-level executives inside organizational layers. The multi-disciplinary essence of this thesis (incorporating technological, organizational and financial aspects) and comprehension of the technology-oriented occurrence (predictive maintenance adoption in the industry) perfectly showcases the type of research Management of Technology alumni should perform in practice. Analysing the factors that contribute to the adoption of a technology needed the utilization of both technical and strategic managerial perspectives to develop a structured and understandable high-level output that will help organizations to better implement predictive maintenance. This research has showcased an example that organizations will benefit from the Management of Technology students that have the ability to analyse and resolve problems of technical nature that are manifested throughout all layers of the organization.

8.5 Reflection

Industry 4.0 is becoming a more tangible reality with more and more companies adopting novel technologies that enhance their processes and enable an unprecedented increase in overall efficiency. Predictive maintenance is one of the cornerstones of Industry 4.0 revolution by its promise to decrease unplanned downtime, cut maintenance costs, improve production efficiency and develop additional business models for organizations, enabling them to provide elaborate services to their clients.

Predictive maintenance has been under the spotlight for some years now when it first appeared on the Gartner's hype cycle in 2010. Although it was 10 years ago, predictive maintenance is still a novel technology since it has not reached wide adoption inside the industry yet. This stems from unexpected hurdles and barriers in implementing PdM technologies, organizations were not expecting that they require extensive capabilities and considerable resources to successfully implement predictive maintenance technologies. These unrealistic expectations were formed by all the "hype" around this new technology that promised to "change the world" in the manufacturing and process industry regarding maintenance. By now, it seems that this excessive publicity and false expectations have subsided, and more awareness is arising about predictive maintenance and what is needed for its implementation. Therefore, it can be assumed that we are past the hype and now concrete, definite advancements can be made towards better adoption of PdM that are based on tangible experiences across industries not only speculations and assumptions. This is illustrated by increasing investments into Industry 4.0 technologies, including predictive maintenance. Organizations understand where the benefits lie but are aware that it requires effort to implement PdM which results in more strategic, calculated approach towards it. If the remaining barriers to PdM adoption are lowered or eliminated, then this technology could see extensive adoption across industries in the coming years.

Predictive maintenance along with increasing ICT, IoT capabilities revolving around artificial intelligence, big data, sensor technology et cetera provide fertile ground for Industry 4.0 which is moving toward autonomous smart factories. It seems that self-sufficient, automated production plants are the aim of this new industrial revolution. This seems like an ambitious goal, but quite frankly, I believe that this reality might be closer than we think. There have been substantial advancements in technology and autonomous processes and there is no sign of stopping to these innovations. Therefore, personally, I see the first autonomous smart factories being constructed in the timeline of 10-15 years. Issues might arise integrating these new technologies with older production plants that consist of aged assets and production systems since transforming these plants into high-tech facilities requires considerable investment and effort with combining "new" with "old". In conclusion, the coming of fully autonomous smart factories is the feasible reality and predictive maintenance has a fundamental role to play in making that happen.

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Appendices

A Research Work Plan

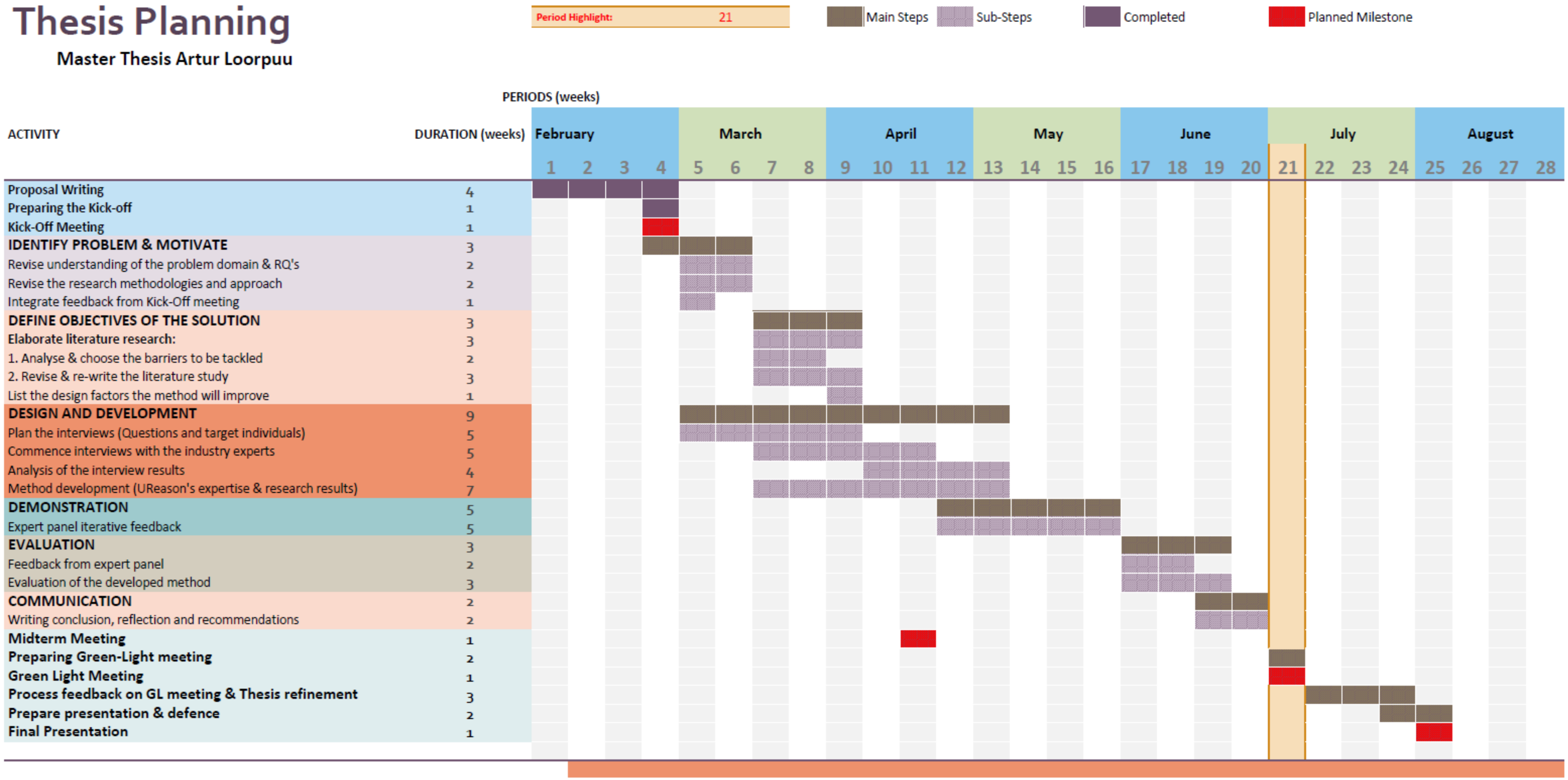


Figure 32: Master Thesis Planning

B Interview Questions

Introductory questions

- In which industry is your organization operating?
- What is your position inside the organization?
- What type of condition monitoring/predictive maintenance solutions do you have experience with? For how long?
- Do you and how would you evaluate the effect of PdM on the organization as a whole?
- What is your personal experience related to PdM?

Section of Business Case

- What was the process of building a PdM business case inside your organization?
- Who are the stakeholders involved?
- How was your experience during this process? (Open-ended, perhaps reveals something interesting)
- What are the major sticking points to business case building if there were any?
- What were the key take-aways or best practices that helped your organization during business case building?
- How could you make this business case building better in your experience?

Section of trust in predictive maintenance technologies

- How would you describe your levels of trust in the PdM technologies?
- How does it affect the trust in the PdM technology if the platform/system comes from a third party?
- How do you feel about 3rd parties having access to the data provided by your assets to run diagnostics?
- How do you ensure the proper functioning/accuracy of the PdM algorithms/platforms over time?
- What is the connection, if there is any, between coherent data visualization on dashboards and trust towards the PdM technologies? What elements do you regard essential to be illustrated?
- To what extent do you rely on PdM technologies in aiding you with process critical decisions?
- What measurements could be undertaken to increase the trust in these technologies?

Section of Data

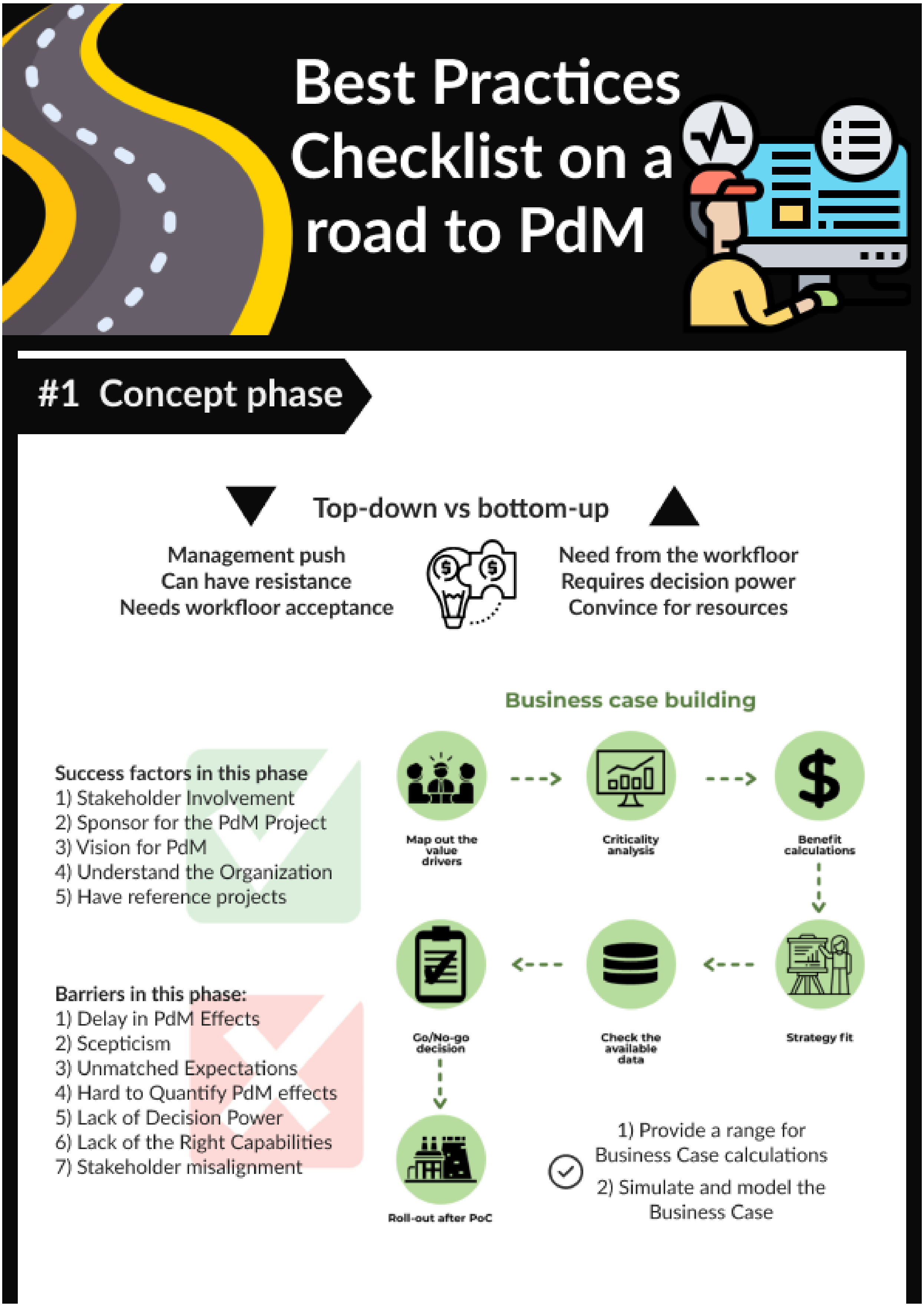
- How would you evaluate your company's relevant IT/OT infrastructure that is needed initially to start collecting PdM related data?
- What were the enablers and barriers to getting to this level of digitalization?
- How would you evaluate your organization's ability to make sense of the data collected from the assets (regarding maintenance)?
- What tools and capabilities does the organization have/use regarding working with data?
- What are the necessary steps and procedures undertaken inside your organization to utilize asset data effectively?

- What are the key points to avoid to ensure getting most out of your data and its correct utilization?
- What are the best practices inside your organization towards the efficient use of data?
- What are the measurements undertaken to ensure integration between different platforms (legacy systems, maintenance solutions from different vendors etc)?
- How could data integration between different platforms done better?
- How is the deployment of trained models (deterministic and ML) organized in your company?
- How could processes regarding dealing with data be improved in your perspective?

Final concluding questions

- What was changed/needed to be changed in the organization to adopt PdM?
- What were the key roles that played the essential part in PdM implementation and did you possess them in-house? If not, how did you resolve acquiring these capabilities?
- In your personal perspective, what were the most critical factors for successful adoption of PdM technologies?
- What are the future trends for PdM?
- Is there anything left to add to our previous discussions or anything relevant that we have not touched upon yet?

C Overview of Best Practice Checklist road to PdM



#2 Feasibility phase - PoC

Project Objectives

- Set objectives
- Produce project plan
- Success criteria
- Business success criteria

Current Situation

- Inventory of resources
- Requirements, assumtions and constraints
- Risks and contingencies
- Terminology
- Costs and benefits

Project Plan

- Project plan
- Assessment of tools and techniques

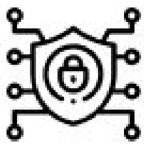
Asset Selection

- Select asset critical to operation
- Identify functional failures
- Choose dysfunctions by their quadrant
- Use ISO model - what is required / available

Success factors:
1) Take small steps
2) Showcase successes
3) Celebrate small victories
4) Use existing tools
5) "Hands on" for end-user
6) Report on the PoC

Barriers:
1) Misunderstanding between stakeholders
2) The right sensors & tools are absent
3) Not having enough time
4) Lack of ownership

#3 Data phase



Collect data

1) Data collection might take considerable time
2) Fleet size
3) Proper registration of all the failure data
4) Data accessibility
5) Have clear measurement protocol
6)Keep the raw data
7) Think about the sampling/ degredation rate

Understand data

1) Initial data collection report
2) Describe data
3) Explore data
4) Verify data quality

Prepare data

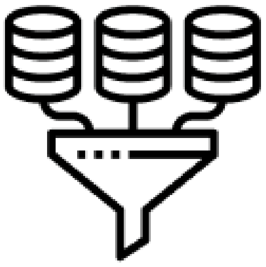
1) Choose the data
2) Clean the data
3) Construct required data
4) Integrate data

Best practices:
1) Strong contractual agreements
2) Data is labelled correctly
3) Data is clearly structured
4) Clear instructions for data input

Barriers & Concerns:
1) Data quality
2) Data accessibility
3) Data ownership
4) Data leakage
5) Cyber security

#4 Development phase

Big Data "Top-Down" VS Engineering "Bottom-Up"

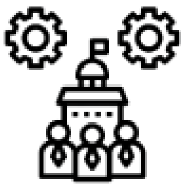


- Does not require that much knowledge about the systems and processes
- Could reveal unexpected insights
- Could be used to get fast results and "quick wins"

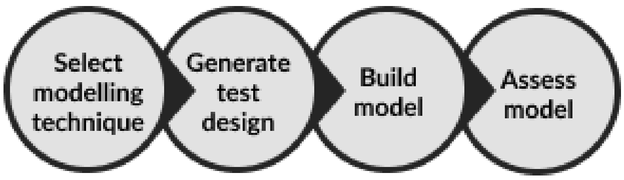
- Requires smart technologies and a lot of computing power
- Can provide trivial findings that are not relevant for PdM
- Engineers find harder to trust strictly data approaches
- Unstructured approach

- Structured, more focused approach
- Provides clearer, more useful insights for PdM
- No need to work with huge data lakes
- Better understanding of the critical systems

- Needs extensive knowledge about the systems and their failure modes



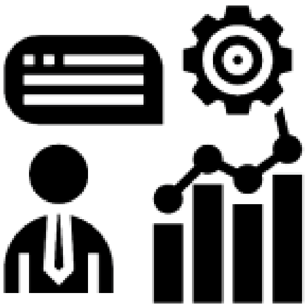
1) Understand what is happening in your systems
2) Understand the failure mechanisms and why things fail
3) Identify what needs to be measured
4) Identify how and which models can be built
5) Understand how predictions from these models can be derived
6) Iterate & improve



Barriers:
1) Not choosing enough data or choosing too much data.
2) Choosing the wrong modelling technique
3) Not understanding the data

Best practices:
1) Cooperating with the maintenance technicians
2) Using the right tools
3) Asking for help

#5 Operation phase

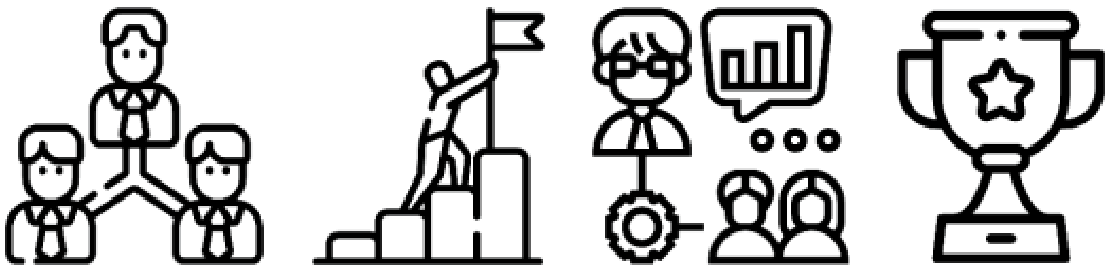


1) Provide results from the previous phases
2) Determine PdM deployment strategy
3) Implement the technical infrastructure for real-time access
4) Plan monitoring and maintenance
5) Adjust the existing processes
6) Educate the personnel
7) Continuous improvement of the solution

Barriers:
1) Not having proper infrastructure for
2) real-time access
3) Personnel not having sufficient education
4) Not maintaining the PdM solution
5) Not adjusting the processes to PdM

Best practices:
1) Adjust the existing processes to PdM
2) Analysing the insights from PdM
3) Implement quality loops for PdM
4) Reporting
5) Re-organize teams
6) Continuous improvement inside the organization

Adopting PdM requires the whole organization to work together!



All the best in implementing PdM!

@Artur Loorpuu

D Quotations and Coding

This research included 632 quotations from 11 interviews that were coded with 113 general codes together with 14 smart codes that were generated to commence co-occurrence analysis of codes. Furthermore, those 113 general codes were divided between 14 code groups that illustrate broader themes. Table 29 will give an overview of the code-groups, respective codes and the density (shows the relative importance of the code) of quotations that were linked to each code:

Table 29: Overview of used code-groups, codes and number of quotations linked to each code

Code Group	Code	Density, Number of Quotations
Best Practices	Celebrate small successes	4
	Maintaining the PdM platform	5
	Provide a range for Business Case	1
	Showing the broad picture	4
	Stakeholder involvement	27
	Take small steps	13
Business Case Building	Bottom-Up initiative	11
	Business model	8
	Contractual agreements	8
	Investment for PdM	28
	Procedures for Business Case	10
	Quantifying the value drivers	16
	Revenue calculations	9
	Top-Down initiative	8
Concerns Related to PdM	Cybersecurity	22
	Data leakage	4
	Data ownership	13
	Responsibility	3
Convincing for PdM Adoption	Education for PdM	39
	Explanation of value drivers	5
	PdM positive attributes	13
	Providing the right information	27
	Reference projects	23
	Understanding the organization	23
	User Experience	3
	Workshop for PdM	2
Integration	Black Box solution	9
	Connectivity	10
	Organizations for industry standards	11
	Standardization	9
	Use of open protocols	5
Inter/Intra-Company PdM Elements	Collaboration with supplier/OEM	28
	External/Internal development	13
	Industry affections	18
	Maintenance maturity level	6
	Maintenance performer	5
	Maintenance strategies	22

Code Group	Code	Density, Number of Quotations
	PdM Technology (AI/ML)	4
	Service offering	34
	Value driver for PdM	31
Organizational Changes	Design for maintenance	13
	Mindset shift	22
	New ways of working	10
	Re-organize the teams	8
Participant Attributes	Experience with technology	7
	Job activities of the interviewee	9
	Participant's company industry	13
	Position of the interviewee	14
PdM Barriers	Customer scepticism	6
	Delaying effect of PdM	3
	Hard to quantify PdM effect	5
	Lack of data	7
	Lack of data quality	10
	Lack of decision power	1
	Lack of the right capabilities	11
	Stakeholder misunderstandings	2
PdM Enablers	Data accessibility	14
	Data structure	19
	Early adaptors	6
	Good alignment between stakeholders	7
	Plug&Play	6
	Strong OT structure	12
	Vision for maintenance	34
PdM Procedures	Analysing the data	37
	Bottom-Up PdM approach	3
	Operational maintenance analysis	47
	Top-Down PdM approach	5
Relevant IT/OT Infrastructure	Central historian	18
	CMMS system	2
	Data types	9
	DCS system	6
	Digital controllers	2
	MES system	3
	Platforms in use	25
	Remote operating centre	5
Stakeholders involved	Asset management team	5
	Consultancy roles	8
	Cybersecurity team	1
	Digital team	10
	Financial team	2
	Innovation team	4

Code Group	Code	Density, Number of Quotations
	Maintenance manager	7
	Maintenance teams	24
	Operational level support	7
	Predictive maintenance team	7
	Reliability engineer	19
	Risk management team	1
	Rolling stock teams	3
	Site manager	5
	Sponsor for the project	24
	Strategic project manager	12
	Top/C level management	17
Trust Towards PdM	Customer trust towards on-premise solutions	4
	Dashboard elements	21
	Decision making with PdM	8
	Market development for PdM	35
	Trust for 3rd party applications	2