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School of Economics and Management

Department of Informatics

Data-Driven Predictive Maintenance for Industries

Factors impacting the implementation of data-driven predictive maintenance

Master thesis 15 HEC, course INFM10 in Information Systems

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Data-Driven Predictive Maintenance for Industries: Factors impacting the implementation of data-driven predictive maintenance

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PUBLISHER: Department of Informatics, Lund School of Economics and Management, Lund University

PRESENTED: August, 2021

DOCUMENT TYPE: Master Thesis

FORMAL EXAMINER: Christina Keller, Professor

NUMBER OF PAGES: 119

KEY WORDS: Data-driven Predictive Maintenance, TOE Framework, Implementation, Impacting Factors

ABSTRACT (MAX. 200 WORDS): Due to the industry 4.0 paradigm shift, manufacturing and production industries are focusing on Predictive maintenance (PdM) to increase production efficiency and maintenance strategies. Also, adopting data-driven approaches to implement PdM as a result of increased data usage and exchange. However, facing technical and non-technical challenges. Previous studies majorly concentrated on technological aspects concerning the implementation of predictive maintenance, providing limited insight into organizational and environmental aspects. Considering this knowledge gap, this study focuses on examining and describing factors impacting data-driven PdM implementation in various aspects. To answer the research question, the TOE framework was adopted. We conducted qualitative research and collected data by carrying five semi-structured interviews with data-driven PdM practitioners. Research findings show that the following factors: *Data Management* and *Collaboration & Communication* are the most influential, other factors: *IT-Infrastructure*, *Organization Size & Type of Industry*, *Existing Knowledge, Awareness & Educational Efforts*, *Cost*, *Top Management Support*, *Model Selection*, and *Competitive Pressure* has certain or least influence while implementing PdM. The influence of *External Support* is considered inconclusive.

Content

1 Introduction 10
1.1 Problem 11
1.2 Research Question 11
1.3 Purpose 12
1.4 Delimitations 12
2 Theoretical Background 13
2.1 Maintenance for Industries 13
2.1.1 Maintenance Types 13
2.2 Predictive Maintenance in Industry 4.0 Context 14
2.2.1 Predictive Maintenance Approaches 15
2.2.2 Predictive Maintenance enablers in Industry 4.0 context 15
2.2.3 Research tool for Data-Driven Predictive Maintenance Implementation 16
2.3 Technology-Organization-Environmental Framework 17
2.3.1 TOE Contexts 17
2.3.2 TOE adaptation for Data-Driven Predictive Maintenance Implementation 20
3 Research Methodology 25
3.1 Research Strategy 25
3.2 Conducting Literature Review 25
3.3 Data Collection 26
3.3.1 Interviews 26
3.3.2 Interview Guide 27
3.3.3 Respondent Selection 30
3.3.4 Conducting Interview 31
3.4 Data Analysis 31
3.5 Research Quality 33
3.6 Ethics 33
3.7 Research Limitations 34
4 Research Findings 35
4.1 Predictive Maintenance Implementations 35
4.2 Technological Factors 36
4.3 Organizational Factors 39
4.4 Environmental Factors 41
4.5 Additional Factors Identified 42
4.6 Findings Overview 43

5 Discussion 46
5.1 Factors impacting Data-driven Predictive Maintenance Implementation 46
5.1.1 Technological Factors 46
5.1.2 Organizational Factors 47
5.1.3 Environmental Factors 48
6 Conclusion 50
Appendix 1: Interview Guide 51
Appendix 2: Interview 1 (R1) 54
Appendix 3: Interview 2 (R2) 69
Appendix 4: Interview 3 (R3) 81
Appendix 5: Interview 4 (R4) 96
Appendix 6: Interview 5 (R5) 107
References 115

Figures

Figure 1. Technology-Organization-Environment (TOE) Framework 17
Figure 2. Theoretical Model adopting TOE Framework 20

Tables

Table 1. Previous Studies using TOE Framework 18
Table 2. Themes / Sub Themes 23
Table 3. Interview Guide 27
Table 4. Respondent Details 31
Table 5. Codes 32
Table 6. Research Findings Overview 43

Abbreviations

PdM	Predictive Maintenance
IoT	Internet of Things
TOE	Technology-Organization-Environment
IS	Information Systems
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
RUL	Remaining Useful Life
CPS	Cyber-physical systems
MES	Manufacturing Execution System
CMMS	Computerized Maintenance Management Systems
ERP	Enterprise Resource Planning
DOI	Diffusion of Innovations
TAM	Technology Acceptance Model

1 Introduction

Recently, there has been growing interest in the advanced digitalization of factories due to Industry 4.0 revolution. In this regard, global industries focus has shifted towards the Internet of Things (IoT), advanced data analytics, cyber-physical systems (CPS) yielding effective optimization of manufacturing-related processes (Sang, Xu, Vrieze & Bai, 2020). Using these advanced technologies, Industry 4.0 focuses on creating smart factories that enable machine-to-machine, machine-to-human communication (Compare, Baraldi & Zio, 2020) by enabling enhanced data production and exchange. Also, industries implementing these technologies are empowered to deliver new services and products for their consumers with increasing quality and efficiency (Compare, Baraldi & Zio, 2020). Moreover, multiple industries are adopting data-driven tools for equipment maintenance states Golightly, Kefalidou and Sharples, (2017). Due to these changes to maintenance, equipment is getting complex and generating a large amount of data (Sai, Shcherbakov, & Tran, 2019). As a result of increased equipment complexity, numerous incidents and failures are caused resulting in potential damage to products, the environment, and people by hindering manufacturing operations and maintenance (Sai, Shcherbakov & Tran, 2019). To solve these problems and utilize the data effectively, new concepts and methodologies are introduced (Gama et al., 2020), for example, predictive maintenance.

Predictive maintenance (PdM) is one of the top priorities for manufacturing and production industries due to Industry 4.0 paradigm shift (Bousdekis, Apostolou & Mentzas, 2020). Predictive maintenance in Industry 4.0 context uses historical data and real-time data collected from equipment and IoT sensors to predict equipment future health and potential failures, and detect anomalies (Bousdekis, Apostolou & Mentzas, 2020). According to Dadashi et al. (2014), complex insights on equipment performance are drawn using data from IoT sensors and analytical tools in industrial environments. It assists maintenance teams with the data required to prevent breakdowns, reducing the risk of over-maintaining or under-maintaining machines (Dadashi et al., 2014). With this ability, PdM enables industries to perform tasks at a greater accuracy by providing the opportunity to increase production efficiency and maintenance strategies (Compare, Baraldi & Zio, 2020). As a result, industries experience maximized profit and reduced cost and loss (Pipe, 2008).

Due to the increased usage of data, industries are leaning towards data-driven decision-making to gain improved maintenance (Muller, Marquez & Iung, 2008). Meanwhile, a data-driven approach to PdM implementation is gaining more popularity and exhibiting good outcomes (Gama et al., 2020). According to Zonta, Costa, Righi, Lima, Trindade & Li (2020), there is an increase in the interest for PdM among multidisciplinary fields, suggesting the frameworks for implementation and conducting research associated with data acquisition, infrastructure, storage, distribution, security, and intelligence. However, Compare, Baraldi, and Zio, (2020) state that to encourage extensive implementation of PdM, there is a lack to inscribe multiple issues. A closer review of previous studies shows that most of the researches identified technological issues either related to specific technique/framework/machine learning models or identified constraints related to the specific industry. There is a strong need to look into the constraints that influence PdM from technological, organizational, and environmental perspectives. Hence this study will focus on exploring the technological, organizational, and environmental factors that affect data-driven predictive maintenance implementation within industries.

1.1 Problem

Industries avail improved resources usage, efficient and evidence-based equipment maintenance, and cost-effective renewals planning by implementing predictive maintenance (Golightly, Kefalidou, & Sharples, 2017). By acknowledging the potentials of PdM, multiple industries have also expanded their investment towards predictive maintenance deployments (Compare, Baraldi & Zio, 2020). As a result, there is a drastic increase in the companies employing predictive maintenance and a surge in the studies or research around this topic (Compare, Baraldi & Zio, 2020).

Implementation of predictive maintenance is complex both in terms of technical and non-technical aspects as it requires building a varied sensors network, data, and interpretation along with collaboration among teams within and across organizations (Golightly, Kefalidou, & Sharples, 2017). Also, industries encounter varied challenges to sustain new research and gain a competitive advantage while implementing new technologies (Savolainen, Magnusson & Gopalakrishnan, 2020). So, though there is an increasing trend and significant benefits associated with PdM, still its implementation in industries is one of the challenges that increased with the rise of industry 4.0, IoT, and AI capabilities (Compare, Baraldi & Zio, 2020). Golightly, Kefalidou, and Sharples (2017, p.627) state that challenges to implement predictive maintenance can occur *"due to user issues, such as interpretation of data or embedding within processes, and organisational issues, such as business change to gain value from asset analysis"*. So, there is a necessity to recognize these increased challenges and also improve knowledge toward that interest.

Several researchers identified various technological (Compare, Baraldi & Zio, 2020) and organizational (Savolainen, Magnusson & Gopalakrishnan, 2020) challenges distinctly. Also, some studies are either around the specific industry (vehicle operations (Chowdhury & Akram, 2013); manufacturing (Lee, Kao & Yang, 2014); and rail (Dadashi et al. 2014)), specific to technology/ framework (Sang, Xu, Vrieze & Bai, 2020), or specific to machine learning models (Thyago et al., 2019; Paolanti et al., 2018). However, generic studies around constraints industries face while implementing data-driven predictive maintenance from technological, organizational, and environmental perspectives are limited. Due to the relevance of this topic, there is a strong need to extend knowledge in this regard to support successful PdM implementation from all perspectives, not only from a technological perspective. Also, this study may help industries in their efforts to implement PdM or resolve existing issues. To fill this knowledge gap, this study intends to explore the factors that impact the implementation of the PdM.

1.2 Research Question

Earlier researches showed that there has been an increasing trend in the adaptation of data-driven PdM implementation in the industries. Also, previous studies mostly concentrate on the technical aspects of the implementation. Our study aims to provide a holistic view of the impacts of data-driven PdM implementation by exploring organizational, business, and stakeholder challenges. It is essential to have a holistic understanding to be prepared or to take necessary actions while facing these challenges during data-driven PdM implementation to sustain the increasing trend.

Considering the above-stated problems, this study aims to examine the following research question:

"What are the factors that affect data-driven predictive maintenance implementation in industries?"

1.3 Purpose

The purpose of this thesis is to explore the technological, organizational, and environmental factors that affect predictive maintenance implementation within industries. Earlier researches majorly focused on technological factors influencing predictive maintenance implementation. Thus, this study proposes to contribute to IS literature by identifying other factors that were overlooked (organizational and environmental), along with technological factors. Also, this study can provide information for other researchers to develop further theories and support industries in their implementation efforts.

1.4 Delimitations

This research will be delimited by focusing on identifying the factors that affect the implementation of data-driven predictive maintenance for industries in TOE contexts. So, these factors will be selected and described based on literature review by comparing them to empirical findings. Therefore, not all the factors that may impact the PdM implementation will be covered. Also, the TOE framework will be used as a research tool to understand the impacting factors of PdM implementation. Other IS theories, for example, DOI - Diffusion of Innovations (Davis, 1986), TAM -Technology Acceptance Model (Rogers, 1995) are not utilized for PdM implementation understanding. Moreover, other maintenance methods such as corrective and preventive maintenance or other approaches to predictive maintenance such as knowledge-based and model-based will be briefly described. But those are not be considered for further research.

2 Theoretical Background

2.1 Maintenance for Industries

Maintenance is a crucial part of any industry as it majorly concerns high costs and equipment failures. Usually, maintenance costs range between 15% to 60% of the total production costs in industries (Mobley, 2002). For different industries, maintenance costs may vary, yet significantly impact the productivity and profitability of the industry. According to Mobley (2002), another survey on the effectiveness of maintenance management shows that 33% of maintenance cost is wasted on inefficient or unnecessary maintenance. Due to this, every year nearly $60 billion loss is experienced says Mobley (2002). Traditionally maintenance schedule was predicated based on statistical or original equipment failure data (Mobley, 2002). As inefficient maintenance management adversely affects the industry, more and more industries are adopting various effective maintenance management methods to ensure high productivity and competitive advantage.

2.1.1 Maintenance Types

Traditionally industries have used run-to-failure and preventive maintenance approaches for effective maintenance management.

Run-to-failure Maintenance: Mobley (2002) says that this method follows simple logic that does not fix the machine until it breaks. This type of maintenance is also referred to as “reactive” or “corrective” maintenance and follows a “no maintenance” approach (Mobley, 2002). He states that plants using true run-to-failure maintenance, do not spend any money on machine or system maintenance unless it stops working. Meanwhile, other plants using run-to-failure maintenance execute few preventive actions such as lubrication, machine adjustments, and other adjustments (Mobley, 2002). Moreover, machines are not replaced or repaired till the time they fail to work. As a result, this is the most expensive maintenance type leading to high spare part inventory costs, high overtime labour costs, high machine downtime, and low production availability (Mobley, 2002). Also, he adds that plants using true run-to-failure maintenance must be able to react to equipment failures since there are no required measures are taken to predict the possible failures. Otherwise, these plants need to get failure support from external vendors. Susto et al., 2015 considers this maintenance as most unreasonable in terms of cost and efficiency due to the additional maintenance expenditures and unexpected machine downtime this method causes.

Preventive Maintenance: According to Susto et al., 2012, preventive maintenance is referred to as “time-based” or “scheduled” maintenance. They explain that this type of maintenance is performed in planned timeframes or iterations to anticipate possible equipment failures within the machine’s operational duration. Though this approach is considered as an effective approach, redundant reactive actions are taken (Susto et al., 2012), and ineffective planning or scheduling of machine maintenance may lead to an exponential rise in machine repair and operational costs (Mobley, 2002). According to Mobley (2002), the actual implementation of preventive maintenance varies depending on the specific cases. In some cases, it is restricted to lubrication and minor adjustments whereas, in other cases it involves schedule repairs,

lubrication, adjustments, and machine rebuilds for all critical equipments states Mobley (2002). This method aims to enhance the lifespan of equipment and plant productivity, and reduce maintenance costs. However, this method appends operating costs and unexploited machine lifetime, regardless of regular components replacement (Wan et al., 2017).

Due to the manual approaches, traditional maintenance types are considered less effective in reducing maintenance costs and increasing the productivity of industries. As a result, multiple other maintenance types such as conditioned-based maintenance, predictive maintenance, and prescriptive maintenance came into practice. Condition-based maintenance focus on predicting maintenance operation depending on degradation evidence and deviations from the asset expected behaviour (Merkt, 2019). In this method, equipment is monitored with multiple sensors collecting conditional data such as temperature, humidity, etc (Merkt, 2019). Moreover, predictive maintenance uses real-time data and historical data from the sensors and with the help of predictive analytics predicts equipment's remaining useful life (RUL). Here, RUL is the distance between the current time and the end of the useful life of equipment (Sang, Xu, Vrieze & Bai, 2020). However, there are contrasting views relating to conditioned-based maintenance and predictive maintenance. Some studies claim that both condition-based and predictive maintenance are one or the same (Sai, Shcherbakov & Tran, 2019) and other studies classify PdM as a sub-class of conditioned-based maintenance (Merkt, 2019). Regardless of these classifications, this study considers both conditioned-based maintenance and predictive maintenance separately. Furthermore, prescriptive maintenance is perceived as a recommendation after the execution of corrective and PdM models outcomes (Merkt, 2019).

With this initial understanding of maintenance and its types described above, we will further explore predictive maintenance in detail in the upcoming section.

2.2 Predictive Maintenance in Industry 4.0 Context

Predictive maintenance (PdM) has been practiced for decades manually. However, the effectiveness of predictive maintenance is increased in recent years due to the technological advancements taking place (Bengtsson & Lundström, 2018). According to Zhang, Yang & Wang (2019), predictive maintenance is based on the component's health assessment independent of maintenance status. PdM aims to improve productivity, product quality, and overall effectiveness of manufacturing and production industries (Mobley, 2002). Also, it helps to predict and extend the remaining useful life (RUL) of the equipment (Qiao & Lu, 2015). According to Mobley (2002), predictive maintenance is a condition-driven preventive maintenance method. He says that PdM uses direct monitoring of the mechanical condition, system efficiency, and other indicators (temperature, vibration, pressure, etc.) to determine the actual mean-time-to-failure of machines. Moreover, PdM is designed to achieve reduced failures, unexpected dangers and accidents throughout the manufacturing process (Zhou, Chen, & Xu, 2013). Moreover, it decreases unexpected downtimes and expensive operational costs, ensures safe operation and maintenance optimization (Zhang, Yang & Wang (2019). Lee et al., (2014) state that PdM provides continuous health status of equipment and achieves reduced downtime by predicting and preventing equipment failure.

Bousdekis, Apostolou and Mentzas (2020) states Industry 4.0 enables predictive maintenance capabilities and leads to efficient and optimized maintenance operations. According to them, in the industry 4.0 context significance of predictive maintenance is increased for industries. Also,

they state that organizations recognizing maintenance as a strategic business function realizing increased equipment failures concerning operational performance. Moreover, Bousdekis, Apostolou, and Mentzas (2020) describe three main predictive maintenance solution functionalities. These functions include:

Anomaly detection: According to Bousdekis, Apostolou and Mentzas (2020), this process uses historical data to detect anomalies. The authors say that anomaly detection is made whenever discrepancies measurements are noticed and an early warning is provided. These warnings activate the failure prediction process (Bousdekis, Apostolou, & Mentzas, 2020).

Failure prediction: During this process remaining useful life and its confidence levels are calculated (Bousdekis, Apostolou, & Mentzas, 2020).

Decision about maintenance actions: Followed by prediction, decisions to relieve maintenance actions taking place and time to reduce the maintenance expected loss are provided (Bousdekis, Apostolou, & Mentzas, 2020). Based on the decision, the maintenance schedule is updated accordingly (Bousdekis, Apostolou, & Mentzas, 2020).

2.2.1 Predictive Maintenance Approaches

Zhang, Yang and Wang (2019) divided PdM methods are into three categories based on the study done by Zhou, Chen, and Xu (2013):

Model-based: In this method, estimation of equipment healthy conditions and prediction of its degradation are done using the physical models (Compare, Baraldi & Zio, 2020). According to the authors, the benefits of this method can be leveraged when equipment lacks abnormal operational conditions data. They say that these physical models are not suited for IoT-enabled PdM that depend on IoT data for identifying anomaly detections and failure predictions.

Knowledge-based: This method depends on maintenance domain knowledge (Fink, 2020). Traditional maintenance methods majorly follow this approach.

Data-driven: This method is also called the machine learning method (Paolanti et al., 2018). It uses monitored operational data obtained from equipment (Compare, Baraldi & Zio, 2020) to learn a model of equipment health conditions (Paolanti et al., 2018). Also, employed when equipment is complex and interpreting its operation is not easy (Jardine, Lin & Banjevic, 2006). This method is further sub-divided into supervised (applied when machine failure data available in modelling dataset) and unsupervised (applied when logistics/ operational data available, maintenance data not available) (Paolanti et al., 2018). According to Paolanti et al (2018), maintenance data availability is based on the existing maintenance policy and supervised methods are used whenever possible.

Also, some industries use hybrid approaches acknowledging the benefits of all the above-mentioned approaches.

2.2.2 Predictive Maintenance enablers in Industry 4.0 context

Industry 4.0 revolution promotes the combination of modern industries with technological advancements such as big data and analytics, Cyber-Physical Systems, the Internet of Things, and

Predictive Maintenance (Li, Wang & He, 2016). In such environments, machines are connected through these advanced technologies to collect, exchange and analyse data systematically enabling predictive maintenance (Li, Wang & He, 2016). Below these enablers are described briefly:

Big Data and Analytics: According to Li, Chen, and Shang (2021), the manufacturing industries mainly use big data analysis to deal with a large amount of data obtained from manufacturing activities when conventional data processing systems' capabilities are exceeded. Furthermore, the authors state that collecting unstructured data from the Internet, event logs, multimedia social communication, etc. is the challenge that comes with big data. Hence, they stress the requirements for innovative and effective solutions to capture, process, and manage such data. Most manufacturing plants use the same sensors and feed alike data in the virtual workshop (Li, Chen & Shang, 2021). In such plants, the decision support system is designed according to the manufacturing setting (Li, Chen & Shang, 2021).

Internet of things (IoT): IoT is deemed the cornerstone for predictive maintenance by converting equipment physical actions into digital signals (Kwon, Hodkiewicz, Shibutani, Pecht, 2016). Also, IoT allows data from sensors (temperature, vibration, pressure, etc.) and other source systems (MES, CMMS, ERP) to flow constantly (Compare, Baraldi & Zio, 2020). The data collected from all the sources acts as source for predictive maintenance implementation (Compare, Baraldi & Zio, 2020).

Cyber-physical systems (CPS): "CPS refers to a new generation of systems with integrated computational and physical capabilities that can interact with humans through many new modalities. The key is the ability to interact with, and expand the capabilities of, the physical world through computation, communication, and control" (Baheti & Gill, 2011; Li, Wang & He, 2016, p.43).

The above sections in the "Theoretical Background" provide brief descriptions of the topics that are correlated to predictive maintenance and explain the process of data-driven implementation of predictive maintenance in the industrial settings supported by recent technological advancements. The knowledge gained from these sections will help this study further to understand the context and challenges that occur while implementing the PdM and support us to fulfil the aim of this research to investigate influencing factors.

2.2.3 Research tool for Data-Driven Predictive Maintenance Implementation

As our research is around one of the technological implementations which is data-driven PdM, we investigated how the technological implementation is studied in IS research. This investigation introduced us to two majorly used models such as the Diffusion of Innovation (DOI) theory and the Technological-Organizational-Environmental (TOE) framework highlighted by Oliveira and Martins (2011) adopt and implement organizational and technological innovations respectively. DOI highlights the importance of individual characteristics, internal characteristics of organizational structure, and external characteristics of the organization to organizational innovativeness (Rogers, 1995; Oliveira & Martins (2011)). However, the TOE framework explores the technological context, organizational context, and environmental context of an enterprise context that impacts the adaptation and implementation of technological innovation. Though both the models are majorly used for understanding technological adaptations and implementations, we believed that the TOE framework is well-suited for study, as the aim of our

research is to identify and investigate the factors in various perspectives that affect the implementation of data-driven PdM. Therefore, the TOE framework will be adopted and used as a research tool to understand the implementation of data-driven PdM exploring the factors impacting from technological, organizational, and environmental contexts.

2.3 Technology-Organization-Environmental Framework

Tornatzky and Fleischer's (1990) presented the technology–organization–environment (TOE) framework in their book "The Processes of Technological Innovation" says Baker (2012). This book explains entire process of innovations from development to adaptation and implementation of those innovations in various contexts of the organization (Baker, 2012). He further explains that TOE framework shown in Figure 1 is an organization-level theory that explains how technological, organizational and environmental contexts influence the adoption and implementation of any technological innovation in the organization. These contexts are further explained in section 2.3.1 (TOE Contexts).

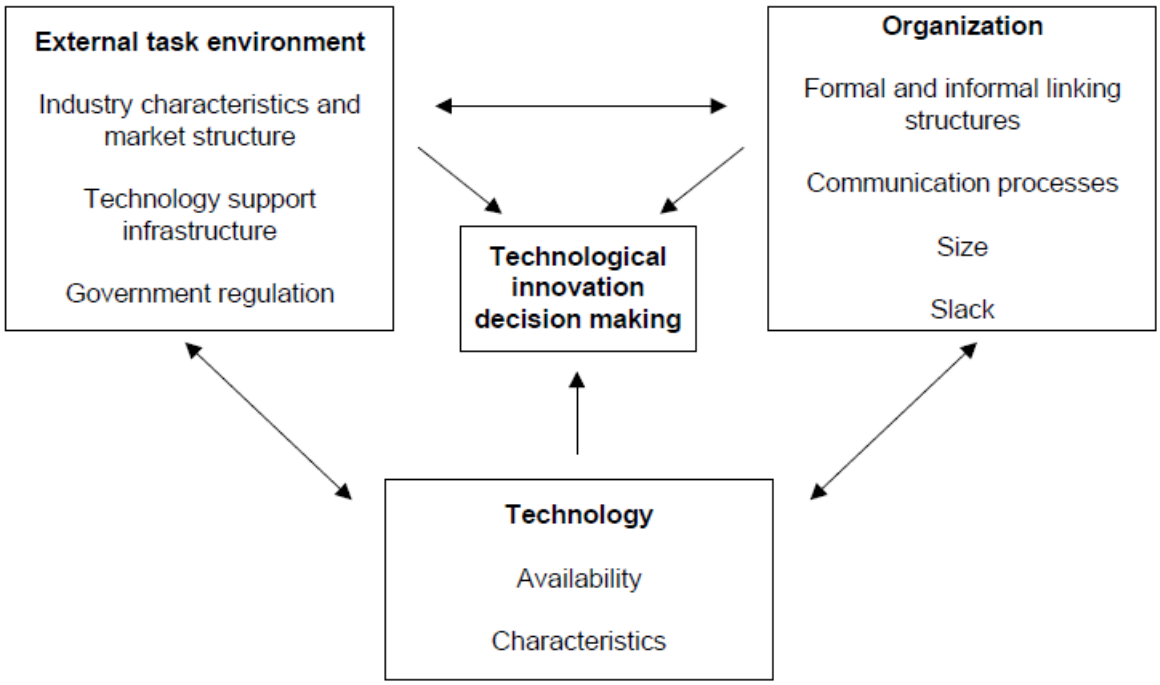

Figure 1. Technology-Organization-Environment (TOE) Framework (Tornatzky & Fleischer, 1990)

2.3.1 TOE Contexts

Technological Context:

Baker (2012) explains that the technological context in a firm includes all the existing technologies that are in use (internal) along with the external technologies that are not in use. Both internal and external technologies that are yet to be adopted by firms influence the technological change within the firm. Tushman and Nadler (1986) segregate the group of innovations that exists outside the firm into three types: incremental, synthetic, or discontinuous changes (Baker,

2012). According to Baker (2012), incremental innovations add new features or new versions to existing technologies possessing the least amount of risk and change for the adopting firm. He says synthetic innovations bring moderate changes to the firm synergizing existing technologies. In contrast, discontinuous innovations represent the removal of current technologies or processes states Baker (2012). He further explains that incremental and synthetic technological innovations allow a measured pace of adaptation or implementation in the firm. On the other hand, he says that discontinuous innovations require fast adaptation decisions.

Organizational Context:

Baker (2012) explains that organizational context describes the characteristics and resources of the firm. This context is influenced by multiple factors that include linking structures between employees, intra-firm communications, firm size and slack say Baker (2012). According to Burns and Stalker (1962); Daft and Becker (1978), organic and decentralized organizational structures affect the adaptation process of innovations (Baker, 2012). However, non-organic or mechanistic structures concern the implementation process of innovations (Baker, 2012; Zaltman, Duncan, & Holbeck, 1973). Baker (2012) further explains that the communication process also promotes or inhibits innovations. Meanwhile, top management also can encourage innovations by providing the necessary support and welcoming change in the organizational context (Tushman & Nadler, 1986; Baker, 2012). Slack and the size of the firm are remaining factors that influence the organizational context of innovation adaptation and implementation. Though there are contrasting perceptions about the impacts of slack and size of the firm, this paper considers these factors and uses them for the TOE framework development.

Environmental Context:

Baker (2012) explains that environmental context includes industry structures, the presence or absence of the technology service providers and regulatory environment. Industry structure in terms of intense competition encourages innovation adaptation (Baker, 2012; Mansfield, 1968; Mansfield et al., 1977). Also, firms innovating rapidly may influence other firms to innovate (Baker, 2012). He says that few firms use industry decline to innovate by bringing new initiatives or by expanding into new business. However, other firms may tend to avoid investment in innovations to minimize costs (Baker, 2012). According to Baker (2012), a firm's support infrastructure for technology also impacts its innovation adaptation and implementation. Firms paying high wages for skilled labour are compelled to innovate with the help of labour-saving innovations explained by Globerman (1975); Levin et al., (1987) and Baker (2012). Also, Baker (2012) states that government regulations either have beneficial or damaging impacts on the firm's innovation adaptation and implementation process.

Table 1. Previous Studies using TOE Framework

Author	Technology Studied	Context	Factors
M.G. Aboelmaged. (2014)	e-maintenance (E-M)	Technological	Technology infrastructure, Technological competence
		Organizational	Firm Size, Perceived Benefits, Perceived Challenges, Maintenance Priority

		Environmental	Competitive pressures
Mikalef et al., (2021)	AI Capabilities	Technological	Perceived Benefits
		Organizational	Perceived Financial Cost, Organizational Innovativeness
		Environmental	Perceived Government Pressure, Perceived Customer Pressure, Government Incentives, Regulatory Support
Masooda & Eggera (2019)	Augmented reality in support of Industry 4.0	Technological	System configuration, Technology hardware readiness, Technology compatibility
		Organizational	Organisational fit, User barrier
		Environmental	External support
Jia et al. (2017)	Enterprise Web 2.0	Technological	Perceived usefulness
		Organizational	Firm scope, Firm size, Subjective norms
		Environmental	Competitive pressure
Oliveira et al. (2014)	Could computing	Technological	Technology readiness
		Organizational	Top management support, Firm size
		Environmental	Competitive pressure, Regulatory support
Sun et al. (2016)	Big Data	Technological	Relative advantage, Complexity, Compatibility, Cost
		Organizational	Technology readiness, Appropriateness, Management support
		Environmental	Regulatory environment, Institutional based trust, Trading partner readiness

2.3.2 TOE adaptation for Data-Driven Predictive Maintenance Implementation

As mentioned earlier, this research adopts the TOE framework for investigating factors that influence or affect data-driven predictive maintenance implementation in any industry. Considering the relevance to the topic at hand and challenges associated with it in TOE contexts, we have chosen 11 factors that are perceived to influence data-driven predictive maintenance implementation and customised the TOE framework accordingly. These selected factors are described and presented in Figure 2. The theoretical model below.

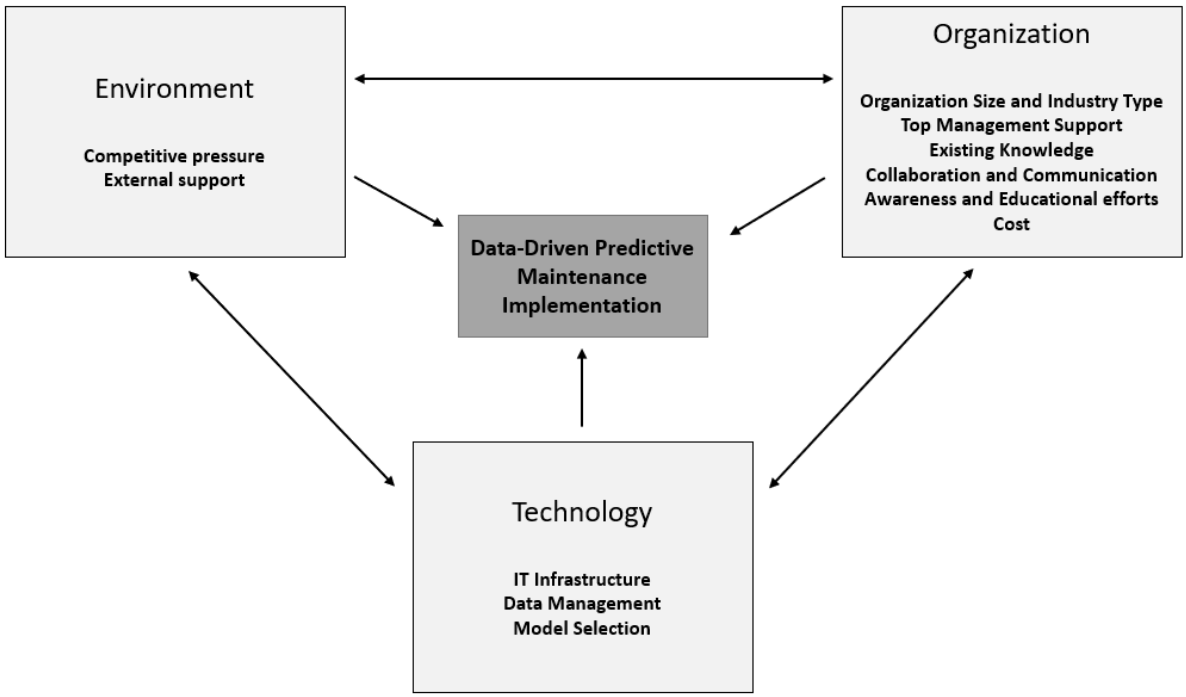

Figure 2. Theoretical Model adopting TOE Framework

Technological Factors:

IT Infrastructure: According to Golightly, Kefalidou and Sharples (2017), there is a demand for adequate IT infrastructure to enable the deployment of PdM. Here IT infrastructure refers to servers to store large volumes of data, or telecommunications networks to allow information flow from the equipment to the control centre (Golightly, Kefalidou & Sharples, 2017). Li, Wang and He (2016) states that predictive maintenance deals with industrial big data. To leverage big data, industries need to support different types of information, the IT infrastructure to store massive data sets, and the flexibility to leverage the information once it is collected and stored enabling historical analysis of critical trends to enable real-time predictive analysis (Big Data, n.d referred in (Li, Wang & He, 2016)). Therefore, this factor is considered for our studies. Due to the above-observed importance of IT Infrastructure in PdM implementation, this factor will be empirically explored further.

Data Management: Li, Wang and He (2016) explain that predictive maintenance implementation requires improved data access, data quality and data integration from multiple sources

for sharing and representing the data. As a result of multiple data sources operating in a production environment caused integration issues among the connected systems states Aljumaili et al., (2015). Moreover, Compare, Baraldi and Zio, (2020) states that acquiring larger amount of data doesn't guarantee better performance of PdM and also increases cost. So, digitalization of industries should focus on acquiring smart data instead of larger amount of data (Zio, 2016). According to Bousdekis, Apostolou and Mentzas (2020), latest technologies risks for data protection, the availability of sufficient and appropriate real-time and historical data, the integration of predictive maintenance solutions with legacy systems. Hence, impact of data management on PdM implementation will be explored further.

Model Selection: The effectiveness of predictive maintenance can be measured by the prediction accuracy obtained from the models (Li, Wang & He, 2016). In machine learning, no one model suits all problems and datasets (Sai, Shcherbakov, & Tran, 2019). Also, the authors say that selecting the best-suited model among many other competitive models is a challenge. Furthermore, models' accuracy is depending on the quality, relevance, and sufficiency of the data used (Sai, Shcherbakov, & Tran, 2019). However, if the models predict inaccurate information that may lead to unnecessary maintenance, such as early replacement of components, or production downtime due to unexpected machine failures (Li, Wang & He, 2016). According to Liu et al., (2007) the accuracy of remaining useful life prediction gives sufficient time to prepare for a maintenance operation. Therefore, model selection plays a major role to acknowledge the benefits of predictive maintenance (Li, Wang & He, 2016). Therefore, the impact of model selection on PdM implementation will be examined further.

Organizational Factors:

Organizational size & Industry type: When industries decide to implement PdM, they need to consider the long-term introduction of advanced equipment, where legacy systems are needed to be merged or replaced (Bousdekis, Apostolou & Mentzas, 2020). This can be seen as one of the challenges for large industries, due to which they may have a slow pace in adopting new technologies (Bousdekis, Apostolou & Mentzas, 2020). According to the study conducted by Aboelmaged (2014), the impact of organizational size and industry type could not be seen for e-maintenance adaptation. However, this study aspires to examine the influence of organizational size and industry type for PdM implementation.

Top Management Support: Bousdekis, Apostolou and Mentzas (2020) explain that predictive maintenance implementation in complete isolation is not possible as it involves a wide range of effects within the organization. They suggest that predictive maintenance implementation must be incorporated within the digital manufacturing strategy that is completely supported by the top management. There are multiple scenarios when top management support is required and important in significant resources and capital investments (Bousdekis, Apostolou & Mentzas, 2020) or encouraging and integrating the teams to work on the same goal of implementation. However, this factor is also significant as industries require a clear vision from company leaders who understand the power of new digital technologies and they can influence the decision-making of PdM implementation (Bousdekis, Apostolou & Mentzas, 2020). Also, Savolainen, Magnusson & Gopalakrishnan (2020) showed the impacts managerial practices on data-driven PdM implementation in their study on identify human factors affecting PdM. Therefore, this study further explores this factor.

Existing Knowledge: Success with predictive maintenance relies on skills and knowledge available in the industry (Bousdekis, Apostolou & Mentzas, 2020). The majority of manufacturing industries do not recruit necessary reliability engineers, instead they recruit data scientists (Bousdekis, Apostolou & Mentzas, 2020). Due to the advent of digitalization, industries are finding it difficult to manage competencies as there is a lack of competencies in maintenance becoming more data-driven (Pellegrino, Justiniano & Raghunathan, 2016). According to Windt, Borgman and Amrit (2019), retaining the right competencies in data analytics is seen as a common problem. Hence, the existing knowledge factor is observed to influence the PdM implementation and needs to be explored.

Collaboration & Communication: Bousdekis, Apostolou and Mentzas (2020) explain that industries need to consider structural changes by promoting cross-functional and interdisciplinary teams with multiple skills. According to Koochaki and Bouwhuis (2008), during PdM implementation, multiple technologies need to deployed and procured from various vendors. Ineffective collaboration among these teams can affect PdM implementation with limited knowledge exchange or organisational crossover (Koochaki and Bouwhuis 2008). Hence, this factor will be further examined.

Awareness & Educational Efforts: Bousdekis, Apostolou and Mentzas (2020) state the industries face some extent of resistance to change from the employees in their effort to adopt new predictive maintenance technological solutions. According to Golightly, Kefalidou and Sharples (2017, p.643), "*Staff with the knowledge of how the various aspects of a predictive maintenance solution combine to deliver useful information must be (a) supported through training on the technical aspects that they may be less familiar with (b) supported so that knowledge is retained during the long embedding phase".* Considering the relevance of this factor, it will be examined further.

Cost: Due to the lack of necessary expertise, companies tend to outsource (Bousdekis, Apostolou, & Mentzas, 2020). This involves high consulting costs as vendors are selling advanced solutions (Bousdekis, Apostolou & Mentzas, 2020). Also, it extends project duration can be another challenge that is associated with cost (Bousdekis, Apostolou & Mentzas, 2020). The authors further explain that the consulting costs can be very high even if companies decide to use open-source solutions as these projects may run very long considering their learning curves. Also, they suggest that there is the need for extensive cost-benefit analysis and feasibility studies, essentially making the business case to support predictive maintenance significant investments. Industries invest in predictive maintenance implementations if they perceive more benefits compared to other maintenance strategies (Compare, Baraldi & Zio, 2020). However, a study in this regard is limited (Wang & Pecht, 2011). Hence, this factor will be further examined.

Environmental Factors:

Competitive Pressure: Bousdekis, Apostolou, and Mentzas, (2020) state that predictive maintenance strategies and technologies by possessing enhanced equipment lifetime, reduced maintenance costs and downtimes help manufacturers gain a competitive advantage. Additionally, multiple industries such as manufacturing (Cannarile *et al.*, 2017), aviation (Pipe, 2008),

energy (Winig, 2016) etc. are implementing PdM to gain competitive advantage states Compare, Baraldi and Zio, (2020). So, this factor is considered for further examination.

External Support: Adaptation and implementation of any technology could be a challenge. Most companies do not possess the necessary skills or expertise required for implementation (Bousdekis, Apostolou, & Mentzas, 2020). The authors say that to overcome this challenge, usually, companies outsource or contract with third-party vendors, consultants, and experts. Also, earlier studies showed the need for examining external support's impact on technological changes (Jia et al., 2017). Therefore, this study will consider external support factors for further studies.

With the help of the above-observed factors (sub-themes) influencing the implementation of predictive maintenance under TOE contexts (themes), below Table 2 is developed to guide the data collection and analysis of this research.

Table 2. Themes / Sub Themes

Contexts / Themes	Factors / Sub themes	Supporting Literature
Technological context	IT-Infrastructure	• Li, Wang and He (2016) • Golightly, Kefalidou and Sharples (2017)
	Data Management	• Aljumaili et al., (2015) • Li, Wang & He, (2016) • Zio, (2016) • Compare, Baraldi and Zio, (2020)
	Model Selection	• Li, Wang & He, (2016); • Liu et al., (2007) • Sai, Shcherbakov, & Tran, (2019)
Organizational context	Organizational size & Industry Type	• Bousdekis, Apostolou, and Mentzas, (2020) • Aboelmaged (2014)
	Top Management support	• Savolainen, Magnusson & Gopalakrishnan, (2020) • Bousdekis, Apostolou, and Mentzas, (2020)
	Existing Knowledge	• Bousdekis, Apostolou, and Mentzas, (2020) • Pellegrino, Justiniano & Raghunathan, (2016) • Windt, Borgman and Amrit (2019)
	Collaboration & Communication	• Bousdekis, Apostolou, and Mentzas, (2020)
	Cost	• Compare, Baraldi and Zio, (2020) • Bousdekis, Apostolou, and Mentzas, (2020) • Wang & Pecht (2011)
	Awareness & Educational efforts	• Bousdekis, Apostolou, and Mentzas, (2020)

		• Golightly, Kefalidou and Sharples (2017)
Environmental context	Competitive pressure	• Compare, Baraldi and Zio, (2020) • Bousdekis, Apostolou, and Mentzas, (2020)
	External support	• Bousdekis, Apostolou, and Mentzas, (2020) • Jia et al., (2017)

3 Research Methodology

3.1 Research Strategy

This research seeks to explore and describe the factors that impact data-driven predictive maintenance implementation in various contexts by finding the answer to the research question "*What are the factors that affect data-driven predictive maintenance implementation in industries?"*. According to Recker (2013), research revolves or evolves around the research question. Also, the research strategy is selected based on the specific research question (Recker, 2013). Considering the type of research question, we select qualitative research methodology. Qualitative research helps to understand phenomena in context and provide explanations for the context *"why people make decisions and act the way they do"* says Recker (2013, p.88). From the previous literature, it is evident that those studies profoundly focused on identifying technological issues or factors that influence when industries implement data-driven predictive maintenance. To understand this phenomenon of data-driven predictive maintenance implementation in industries and factors that impact the implementation in various contexts through the people's experience on the topic, the qualitative method is selected. The qualitative method helps to describe *"text that captures records of what people have said, done, believed or experienced about a particular phenomenon, topic, or event"* states Recker (2013, p.88).

In Information Systems Research, "interpretivism" is one of the prominent paradigms used for qualitative research (Goldkuhl, 2012). Klein and Myers (1999) state that interpretive research helps to understand people's behaviour and action providing deeper insights into the phenomenon. Also, interpretive research assists to develop the theory of the phenomenon being studied using the data collected for the research (Bhattacherjee, 2012). Based on this understanding, we use interpretivism as a paradigm for this qualitative research. Interpretive research helps to fulfil the purpose of this research by presenting insights on the affecting factors of data-driven PdM implementation based on them based on the experiences of PdM practitioners from different industries. For this study, empirical data is collected by conducting semi-structured interviews.

3.2 Conducting Literature Review

To explore the data-driven predictive maintenance implementation and to identify the impacting factors, we conducted the literature review. Recker (2013) states that literature review helps to understand relevant theories explaining the phenomenon and it can be used to describe an investigation. Considering the topic at hand, relevant theories were examined thoroughly. Also, this study revolves around one of the technological implementations. Furthermore, we explored how technological implementations are studied previously in IS research. This search led us to one of the prominent models to study technological implementations or adaptations, i.e., TOE Framework. The factors identified from the literature review were used as a reference for the practical findings of this study. The literature review was conducted using the highly cited research papers relevant to the topic at hand. These papers were searched using combination of keywords in online search engines such as Google Scholar and LUBSearch from Lund University library. Also, following keyword combinations are made use for searching these research papers:

- “maintenance” + “industries”
- “predictive maintenance” + “Industry 4.0”
- “data-driven” + “predictive maintenance”
- “predictive maintenance” + “challenges”
- “predictive maintenance” + “impacting factors”
- “Technology Implementation” + “IS research”
- “TOE” + “predictive maintenance”

Using the findings from the literature review, we illustrated the thematic overview with themes and subthemes recognized to guide us in answering the research question.

3.3 Data Collection

3.3.1 Interviews

According to Recker (2013), interviewing is one of the most commonly used data collection techniques in qualitative research. As we mentioned earlier, empirical data for this study is collected by conducting interviews with experienced predictive maintenance practitioners. Bhattacherjee (2012) states that researchers can capture the person's opinion and explanations from respective respondents related to the research topic. Supporting this Bhattacherjee (2012)'s claims Rowley (2012) says, interviews support researchers to collect facts, obtain an understanding of respondents' experiences, processes, predictions. We believe that interviews are an effective way to collect empirical data for our research to understand and identify the factors that affect to implementation of the data-driven PdM.

According to Myers and Newman (2007), there are three types of qualitative interviews: structured, semi-structured, and group interviews. Structured interviews follow the strict script and the is no room for improvisation (Myers & Newman, 2007). The authors say that semi-structured interviews can be conducted with or without a predefined script, which also allows improvisations to the discussion. Also, group interviews are conducted with multiple respondents following structured or unstructured protocol (Myers & Newman, 2007). With this understanding, we have chosen to conduct a semi-structured interview with a predefined interview guide allowing the improvised and flexible discussion based on the answers given by the respondents. Additionally, semi-structured interviews promote two-way conversation between interviewer and respondent, also enables respondents to ask questions states Recker (2013). Moreover, these interviews allow the interviewer confirms what has been studied and gain additional knowledge (Recker, 2013). With the topic at hand, we want to understand how data-driven predictive maintenance being implemented and what are the challenges practitioners are facing or what factors are affecting the PdM implementation in industries. To attain this understanding, the semi-structured interview will assist us to confirm the factors identified from the literature review and supplement extended knowledge. We followed the below-given steps to form an interview guide for our semi-structured interview (Myers & Newman, 2007).

1. Preparing the Open
2. Preparing the Introduction
3. Preparing the key questions
4. Preparing the Close

In the first step of our interview, we (researchers) introduced ourselves to the respondent. Therefore, the opening part began with a formal introduction to the respondent (Myers & Newman, 2007). In the second step, we provided a short overview of the research topic and ethical considerations followed for the research to the respondent. Also, in the introduction part of our interview, we asked respondents for their permission to record the interview and their preference of being anonymized or not. After that, we asked generic questions to the respondent such as asking respondents to introduce themselves, provide professional background, and how their work is correlated to the PdM implementation. In the third step, key questions were asked related to the factors identified in the literature review that revolves around three main themes recognized: Technological context, Organisational context, and Environmental context to describe factors to affect PdM implementation. In the final step, we prepared to close the interview by asking respondents if they would like to add anything more to their answers and sign the consent forms or any other follow-up questions. Also, for more details about the interview guide and steps followed, refer to Table 3 or Appendix 1.

3.3.2 Interview Guide

As mentioned earlier, the interview guide for our semi-structured interview is developed following the steps suggested by Myers and Newman (2007). To identify factors that affect data-driven predictive maintenance implementation, key questions are constructed under three themes: Technological context, Organisational context, and Environmental context. For constructing these questions, we referred another master thesis (Blomberg & Moberg, 2019) from Lund University Canvas website as similar study is conducted by Blomberg and Moberg (2019). Also, the interview guide containing a set of questions asked in each step as given in Table 3. However, not all the key questions are asked in the same order. If there are any additional questions asked based on the respondents' responses, those are not given here under the Interview guide. Yet those additional questions are present in the transcripts of each interview available from Appendix 2 to Appendix 6.

Table 3. Interview Guide

Concept	Sub Concept	Question/s
Opening Questions:		• Introducing ourselves with respondent. • A short introduction about our thesis and ethical considerations of the research.
Introduction Questions:		• Do you mind if we record this interview? • Do you wish to be anonymous? • What is your background and education? • Role and responsibilities in the organization?
Key Questions:		

Data-driven Predictive Maintenance	Predictive Maintenance Implementation questions	• What type of Predictive Maintenance (PdM) have you implemented in your organization? • How is the PdM implemented in your organization? Was it built in-house? Are there any external support or third-party vendors used? • Can you explain the PdM implementation process in your organization on a high level? • In general, what are the benefits of PDM implementation? • In general, what are the challenges of PdM implementation?
Technological context	IT-Infrastructure	• Did you have the necessary IT infrastructure required for the PdM implementation? • If yes, how has it supported or influenced the implementation of PdM? • If no, do you consider this as a challenge?
	Data Management	• What is the importance of data in your organization? What type of data is used for PdM implantation? its real data or synthetic? • How is the data managed or accessed in your organization? • Did you have any data or process information missing? How do these data uncertainties affect PdM implementation?
	Model Selection	• What are the various types of Machine Learning or Deep Learning models used? • What is the importance of model selection in the implementation of PdM and how does model selection affect implementation of PdM?

Organizational context	Organizational size and Industry type	• What do you call size of your organization? • Do you believe that your size and type of industry had any influence on PdM implementation?
	Top Management Support	• Whether the organization's top management supported the decision to implement PdM? • Do you believe that the support of top management is a necessity for your organization to implement PdM?
	Existing Knowledge	• Did your organization have any existing process(domain) or technical knowledge with respect to PdM prior to the implementation? • If yes, to what extent did this influence your PdM implementation? • If no, do you consider this as a challenge?
	Collaboration and Communication	• How many teams are working on PdM implementation in your organization? • How is the knowledge transfer shared among these teams? • Do you believe collaboration and communication among teams' affects PdM implementation?
	Cost	• Do you believe whether the cost of implementation or any risks associated with it affects the PdM implementation? If yes, to what extent?
	Awareness and Educational efforts	• Are there any awareness and educational efforts taken by your organization to support PdM implementation? How does this impact PdM implementation?
Environmental context	Competitive Pressure	• Are you aware of any of your competitors that have implemented PdM?

		• Did you feel or experience any competitive pressures to implement PdM? • Did you implement PdM as a means to create a competitive advantage? • To what extent did this influence PdM implementation?
	External support	• Are there any external support used for PdM implementation? • How much of their availability (e.g., vendors or consultants) affects the implementation of PdM?
Closing Questions		• Is there anything you feel like you haven't brought up yet, or that you would like to add? • Do you have any questions for us?

3.3.3 Respondent Selection

As mentioned earlier, we wanted to conduct semi-structured interviews for this qualitative research to attain an understanding of the topic at hand and confirm the factors identified from the literature review and supplement extended knowledge. Hence, we wanted to interview respondents who are working on the predictive maintenance implementation in their organization/industry with the roles such as Data Scientist, Predictive Maintenance Engineers, Predictive Maintenance Analysts. We believed that these practitioners of predictive maintenance can provide us a more authentic understanding of PdM implementation and describe the challenges and factors that impact PdM implementation in industrial setting. So, we searched for these PdM practitioners in LinkedIn with "predictive maintenance in people" keywords and looked for their experience in PdM. Based on this criterion, we selected various experts who are working on predictive maintenance in their organization. We contacted several of them through LinkedIn by providing a brief description of our research and asked if they are willing to participate. Five of the respondents volunteered to participate in our interviews. Based on their availability further interviews were scheduled. The respondent details such as Respondent Name or ID, role, organization, duration, date, and appendix are displayed in Table 4. Some of the respondents wanted their identity to be anonymized. Considering this request, we have used IDs for all the respondents which are given as "Rx" where "x" is the Interview number. For example, R1 is a respondent from interview 1. Though some of the respondents' names are given below, to maintain uniformity across this paper we have used Respondent IDs to refer to them.

Table 4. Respondent Details

Respondent/ ID	Role	Organization / Industry Type	Duration	Date	Appendix
R1- Sergio Martin del Campo Barraza	Data scientist	Viking Analytics	60 mins	April 27 2021	Appendix 2
R2 - Shobhit Chourasiya	Data scientist	Volkswagen AG / Automobile	40 mins	May 4 2021	Appendix 3
R3 (Anonymous)	Predictive Maintenance Engineer	Anonymous / Aerospace	48 mins	May 22 2021	Appendix 4
R4 (Anonymous)	Chemical Engineer	Anonymous	32 mins	June 5 2021	Appendix 5
R5 (Anonymous)	Instrumentation engineer	Anonymous / Oil and Chemical Industry	28 mins	June 6	Appendix 6

3.3.4 Conducting Interview

Most of the semi-structured interviews are conducted face to face. Due to the Covid-19 pandemic, conducting face-to-face interviews was a challenge. Hence, we conducted the interviews through Zoom, a video conferencing platform. Through that, we could conduct interviews with respondents located globally, which supported us to collect different perspectives of various respondents for our study. We had approached the respondents through LinkedIn by providing a brief description of our study and asked if they could contribute to our research data collection through interviews. Based on the confirmations to attend an interview and their availability from the respondents, five interviews were scheduled by sending the interview invite through email. Mostly, 1-hour interview with each respondent was scheduled, to collect empirical data concerning our study. The interview guide helped us to maintain a consistent flow to the interview with the respondents. Also, it supported improvising the discussions wherever required. Since interviews were scheduled for 1 hour, we had decided to record the interviews by asking permission from respondents. During the interview, all the respondents allowed us to record the interview. Hence, all the interviews are recorded. Further, analysis of information collected during interviews is explained in the next section.

3.4 Data Analysis

Transcribing:

With the five interviews, we collected a sheer amount of data in the form of recordings. After conducting the interviews, the next step is to analyse and interpret the data collected. To start the analysis, we required information in written form or transcription. According to Kvale and Brinkmann (2009), transcriptions help to transform the oral data into written structures by supporting data analysis. We transcribed all five interviews using a web-based tool called Otter.ai,

which easily converted audio files into text format. Later, default texts produced by the Otter.ai tool were verified by us using record and play options within the tool. During this verification, we noted that some words were miss interpreted, those were corrected. While one of us worked on correcting the misinterpreted texts, the other one ensured the interview is transcribed correctly by listening to records to double-check the transcription. Also, we had some doubts about interpretations. Those texts were cross-checked with the respondents by asking them to verify the transcriptions and updated them accordingly. Transcriptions of all five interviews are available from Appendix 2 to Appendix 6.

Coding:

According to Recker (2013), coding is one of the prominent techniques that is used to produce meaningful information from the data collected. He says, coding is assigning labels to the section of data collected and it helps researchers to organize the data. Through transcribed data, we wanted to confirm the data-driven PdM implementation impacting factors identified through literature review, add other factors if any, and also categorize them according to thematic models. Hence, we coded these factors or sub-themes using abbreviations of the factors. The codes used for this study are given in Table 5. For example: If the respondent 'R1' stated that Model Selection had an impact on the implementation of data-driven PdM, then this factor would be coded as 'MS'.

Table 5. Codes

Themes	Factors/ Sub Themes	Code
Predictive Maintenance Implementation		PdMI
Other Factors		OF
Technological context	IT-Infrastructure	IT-I
	Data Management	DM
	Model Selection	MS
Organizational context	Organizational size & Industry type	OS-IT
	Top Management Support	TMS
	Existing Knowledge	EK
	Collaboration & Communication	CC
	Cost	CO
	Awareness & Educational efforts	AE
Environmental context	Competitive Pressure	CP
	External Support	ES

3.5 Research Quality

Reliability and validity are used to evaluate the research quality (Bhattacherjee, 2012). This research used both of them to ensure the research quality.

Reliability: Bhattacherjee (2012) states that the reliability of the research is secured based on the research consistency. In this research, the reliability was ensured by consistently using an interview guide to ask questions to gain answers to our research questions. Also, reliability of the study is ensured by gaining trustworthiness (Golafshani, 2003). In this study, research processes are thoroughly described to achieve trustworthiness. By following both of these both, the reliability of the study is enhanced.

Validity: Bhattacherjee (2012, p.58) describes validity as *"to the extent to which a measure adequately represents the underlying construct that it is supposed to measure"*. To ensure the validity of the empirical data collection, both of the researchers analysed and coded the interview transcriptions individually. Then discussed and corrected misinterpretation during the transcription.

External validity or generalizability: According to Bhattacherjee (2012, p.36), generalizability *"refers to whether the observed associations can be generalized from the sample to the population (population validity), or to other people, organizations, contexts, or time (ecological validity)".* Generalizability is ensured in this study, as we interviewed various practitioners of predictive maintenance implementation across the globe. Respondents were from Sweden, Germany, Iran, and India. Interviewing and collecting data from respondents from different countries helped to gain a holistic understanding of the topic. Moreover, these respondents are working in different industries. Different industrial backgrounds enabled us to collect authentic experiences from multiple industries which were required for the study.

3.6 Ethics

According to Bhattacherjee (2012, p.137), ethics is defined as *"the moral distinction between the right and wrong, what is unethical may not necessarily be illegal*". Ethics in research assists to ensure scientific conduct (Bhattacherjee, 2012). There are numerous guidelines available for the researchers to maintain research ethics (Bhattacherjee, 2012). Some of those are followed in this research. Those are as follows:

Voluntary participation and harmlessness: According to Bhattacherjee (2012), respondents participating in the research must know that their participation is voluntary, they can withdraw at any time from providing information and they will not be harmed if they participate or not. By following this guideline, we informed all respondents about their voluntary participation and can withdraw from the interview if they do not want to share any information or want to participate further. Also, harmlessness to the respondents was ensured throughout the study.

Confidentiality: According to Bhattacherjee (2012), confidentiality allows researchers to protect respondent's identity, interests, and future well-being during the research. As mentioned earlier, we ensured confidentiality by asking respondents that whether they want to be anonymized or their identity/ organization identity to be kept confidential in the study. Also, based

on respondents' decision to be anonymous or not, their identity or organization's identity is revealed or not revealed respectively in this study. Also, information from them is referred to in the report using respondent IDs.

Disclosure: During this study, disclosure was ensured. We informed all the respondents about us, the purpose of this study, how the information collected from them will be used (Bhattacherjee, 2012).

Analysis and Reporting: All the research findings are disclosed in the transcripts as well as the thesis final report (Bhattacherjee, 2012).

The above guidelines are available in the consent form provided by Lund University. We shared the consent form with the respondents and all of them have read these guidelines and signed the consent form. Also, we signed the consent form and shared it with them, assuring the ethical considerations in the written form.

3.7 Research Limitations

This research will be limited to the industries that are working on data-driven predictive maintenance implementation solutions for the empirical research data collection. Other industries who are not working on the data-driven predictive maintenance implementation are excluded from the study. Also, all the respondents whom we interviewed are mostly working for large industries. Due to this, our study could not collect insights from small or medium sized industries, that affects the research findings to draw generic conclusions.

4 Research Findings

In this section, research findings from five interviews conducted with five respondents- R1, R2, R3, R4, R5 are presented. All the interviews were conducted in English and transcripts of these interviews are available in the Appendixes (2 to 6). References mentioned in this section are referred from the specific interview with the specific respondent along with the row numbers. For example: (R1, 4) means this response is from Interview 1 with Respondent 1 (R1) available on row number 4. Initially, short descriptions of predictive maintenance implementation at the industry/organization from which respondents were interviewed followed by Technological-Organizational-Environmental (TOE) factors identified through the interviews are presented.

4.1 Predictive Maintenance Implementations

All the organizations from which respondents were interviewed are either working on the data-driven predictive maintenance implementation or helping other organizations to implement PdM or working on the PoC (proof of concept) to support their organization to implement the same. All the respondents belong to different industry types and countries. Also, they are working in the different stages of predictive maintenance implementation. Implementation is summarized as follows:

Respondent 1-R1 is working as a Data Scientist at Viking Analytics, Sweden (R1, 8). R1's organization helps other industries to understand their maintenance needs and provides solutions to implement data-driven predictive maintenance. They develop tools, methods, and analytics required to reduce machines downtime, predict and reduce unexpected equipment failures (R1, 10). In particular, R1 is responsible for developing multiple algorithms to predict and detect failures as part of their products/ solutions and also works closely with their potential customers by better understanding the needs (R1, 10). Moreover, they are creating models for different applications and mainly using supervised methods or data-driven methods (R1, 12). While facing some issues, for example, scalability, they are also exploring hybrid models (R1, 12). R1 says that the time taken to implement predictive maintenance for each industry they are working with varies and they usually follow two stages (R1, 14). In the first stage, they work on building the implementation strategy and in the second stage, they deploy the solution (R1, 14).

Respondent 2- R2 worked at Volkswagen AG, Germany, as part of R2's 3-month internship (R2, 4). R2 states that during this tenure, R2 majorly worked on building different models to achieve predictive implementation. According to R2, they used a combination of data-driven and model-based (ML models) approaches to predict the failure of the machines (R2, 6). Before R2 joins this team, R2's Ph.D. professor has been already working on the PdM implementation for about two years and one of the models was actively functional (R2, 8). R2 started with defining the existing model with new data and worked on building other models as well (R2, 8). R2 worked on predicting gluing machine failures (R2, 12). R2 says that with the initial understanding of causes of gluing machine failures, R2 tried to build different models to identify certain parameters of these machines beyond which they tend to fail (R2, 12). Also, they used Monte Carlo simulation based on current parameters of the machine along with new data that helped them to predict machine failures and schedule maintenance (R2, 12).

Respondent 3- R3 is working as a Predictive Maintenance Engineer in an Aerospace Industry, India. According to R3, applications of AI or machine learning are new to the aircraft industry, and predictive maintenance is not implemented yet in their organization or any other aircraft industry ((R3, 12); (R3, 8); (R3, 14)). R3 is part of R&D (Research and Development) in the IVHM (Integrated Vehicle Health Management) Team, building the futuristic algorithms for fault detection and prediction of the aircraft (R3, 4). Considering the aircraft failure phenomenon which is random and varies for each aircraft, R3 is using a combination of data-driven and model-based approaches for predictive maintenance (R3, 8). R3 states that they develop degradation models in the aircraft and generate data. Using this data that is collected for 5-6 months (R3, 12), models are trained to predict failures of the aircraft offline (R3, 8; R3, 12). Initially, they're detecting the machine fault occurrence using AI methods (R3, 18). Then, they're building multiple models by providing faults and identifying the fault type for one data type (R3, 18). Later, the best-performing models will be selected for identifying the fault type (R3, 18). Moreover, this process is repeated for different sets of data and models (R3, 18). Finally, based on this R3's team will provide solutions or implement PdM.

Respondent 4- R4 is working as a Chemical Engineer for a Chemical Industry in India. The organization of R4 has been building predictive maintenance activities since 2016 (R4, 10). According to R4, their organization uses the Prism tool from Aveva Schneider Electric to prepare models for all the heavy-duty rotating equipment (R4, 4). Also, predicting the remaining useful life of a catalyst, remaining useful life of falling off a heat exchanger, any other equipment failures well in advance (R4, 4). For predictive maintenance implementation R4's organization following a data-driven approach (R4, 6). Initially, they generate models and health conditions of the model using historical data from equipment (R4, 6). Then these models are deployed online and they will start predicting equipment anomalies says R4. Based on the predictions, maintenance activities are planned further.

Respondent 5- R5 is working as an Instrumentation/Maintenance Engineer at Oil Industry in Iran (R5, 4). R5 is dealing with data about machinery health conditions since 2012 (R5, 4). Also, R5's organization is mostly using a data-driven approach to implement PdM (R5, 6). Currently, R5's organization is in the first phase of data-driven PdM implementation (R5, 12). This implementation process takes about 6 months states R5 (R5, 8). According to R5, they are gathering the data and tuning some predictive models to improve the maintenance.

4.2 Technological Factors

IT-Infrastructure:

According to R1, IT-Infrastructure plays a certain role while industries are implementing predictive maintenance (R1, 20) and its importance varies for each industry at different levels. He says that industries require IT infrastructure to store and share the data required for implementing the PdM. However, he does not consider IT infrastructure as a major challenge while implementing PdM (R1, 20). Meanwhile, R2 had all the necessary IT infrastructure required (R2, 14). However, he feels IT infrastructure is important but is not aware whether R2's team faced any challenges related to it during the early phases of the implementation. So, the impact of IT infrastructure on PdM is not clear for R2 (R2, 14). Also, R3 says their team working on developing POC (proof of concept) and has not implemented actual data-driven PdM (R3, 22). Hence, they are not utilizing IT- Infrastructure to a larger extent, verification, and validation is

based on their analysis or simulation (R3, 22). Moreover, At R4's organization working on enhancing IT-Infrastructure and making it robust for the last 4 years (R4, 10). Also, R4 understands the need for IT-Infrastructure (R4, 12). However, R4 does not consider it as a challenge or affecting factor while working on PdM implementation (R4, 12). Besides, R5 considers that having necessary IT-Infrastructure is beneficial (R5, 16) and their organization got good IT-Infrastructure for gathering the data from control systems (R5, 14). R5 says *"if you want to use cloud computing, we should use IT infrastructure for implementation predictive maintenance with Cloud"* (R5, 16). Therefore, all the respondents believe that IT-Infrastructure is necessary. However, they do not consider it as a major factor concerning the data-driven PdM implementation.

Data Management:

R1 believes that data management majorly impacts data-driven predictive maintenance implementation (R1, 20). He says that in larger organizations, either single person or different teams are responsible for managing specific parts of data. Not all the teams or parts of the industry are responsible for managing the same parts of data. In some cases, when one team/part of the industry wants to access data from another part of the industry, they require permission to access the data which might be challenging (R1, 20). Hence, some industries require a clear strategy about how to manage the data effectively (R1, 20). He justifies this claim by providing the following example: Most of the industries work with vibrational data. If one part of the industry has access to a vibrational or FFT (Fast Fourier Transform) signal, another part of the industry has access to the metadata around the machine. In this case, these two parts of the industries need a permit to access each other data which is not that simple according to R1. One may get permission to access one data with the customer, but may not get permission to access another data. So, this makes it challenging to access all the parts of the data. He says that

"*So, a lot of times it is important for the company to have a clear direction about how they want to move where their data policy into data management and there is a need for management for that*" (R1, 20).

According to R1, other factors that affect predictive maintenance implementation are effective data integration, data security, and data quality (R1, 64). R1 explains that while working with data-driven PdM implementation, one must bring asset data and operational data together. However, this could be challenging to integrate these data as it may be located in different repositories and require permission to access (R1, 64). Also, he highlights the importance of formatting the data. R1 says all the extracted data might not be compatible, so they must be formatted properly. Otherwise, this increasing poor quality of data may affect the data distribution determination states R1. Moreover, R1 states that to consider data privacy while dealing with data during data integration as it may include personal data such as user IDs, or location, or preferences (R1, 64).

Meanwhile, R2 states that data is crucial for building the model (R2, 20). At R2's organization, a team is responsible for extracting and storing the data from the sensors on the machines (R2, 24). With the help of this extracted data, they worked on different models. However, he feels that retrieving the noise-free data is one of the challenges industries faces (R2, 68), (R2, 26) and that certainly has some impact on the predictive maintenance implementation. However, R3 explains that their team is building the models and managing the data generated data (R3, 28). Also, getting real-time data from aircraft they are collecting from their stakeholders in Germany and Paris (R3, 28). Moreover, the data that R3's team is dealing with has labeled data,

unlabeled data, data with missing values, and random sampling frequency data (R3, 32). R3 says that possessing these different kinds of data or missing data has affected their model predictions sometimes, as models may not predict failures correctly due to the same (R3, 32).

Furthermore, R4 states that while building data-driven models, *"better the data better the model is"* (R4, 28). The model performance will be affected if required data is unavailable (R4, 28). Also, R5 says that their organization is taking data backup regularly (R5, 32). Due to that, they do not face any data missing issues (R5, 32). However, they face unaccepted shutdowns or equipment failures and they do not have those data which is impacting PdM says R5 (R5, 32). Therefore, R1, R2, R3, R4, and R5 strongly believe that data management has a major impact on data-driven predictive maintenance implementation.

Model Selection:

R1 states that model selection varies in industries based on the problem that needs to be solved (R1, 32). Also, selecting the less complex model is better for data-driven PdM implementation (R1, 30). Usually, simple models like random forests or clustering algorithms are used (R1, 30). Deep learning or deep extensive neural networks are rarely used, when the required data might be available and depending on the problem at hand (R1, 30). Moreover, he believes in using simple ways to solve the problem without using the resources excessively. He states that model selection also depends on the data whether it is labelled or not (R1, 32). For example, supervised models are not used for unlabelled data. Hence, he believes that model selection depends on the availability of the computational resources and the availability of the data.

Meanwhile, R2 used linear models and exponential models (R2, 34). Based on the Bayesian model their team noticed the forecast on the latest information as soon as new information arrives (R2, 34). R2 believes that model selection impacts the implementation of predictive maintenance (R2, 36). R2 supplements that claim with the example that while using a linear model, signals varied linearly and it felt difficult to assess the impact on the signals. However, while using the exponential model, they noticed a rapid change in the signals and felt easier to assess the impact while using those models.

Moreover, R3's team is using machine learning models (R3, 34). R3 and R4 believe model selection is important for fault prediction and anomaly detection ((R3, 34); (R4, 32)). R3 states that some models such as k-means clustering performs better when supplied with a large set of data (R3, 38). However, the same model may not perform well when provided with a small set of data (R3, 38). But other models such as the hidden Markov model works well with a small set of data says R3. Hence, R3 and R4 believe that model selection affects anomaly detection ((R3, 38); (R4, 32)). Similarly, R5 feels that model selection is based on the data (R5, 36). However, R5 says that machine learning methods work well with a small set of data and deep learning models work well with big data (R5, 36).

Only R2 believes that model selection affects PdM implementation. However, R1, R3, R4, R5 feel that model selection depends on the availability of data or sample size of the data. In this case, the direct impact of model selection on the data-driven PdM implementation is not observed.

4.3 Organizational Factors

Organizational size & Industry type:

According to R1, organization size affects the implementation of predictive maintenance. R1 states that the implementation process for established industries takes a long time (R1, 14). He says that these industries usually decide faster to implement predictive maintenance. But they face mostly non-technological issues compared to technological issues. Due to that, R1's organization starts the implementation by developing pilot studies and pilot programs taking few months to implement. However, if these established industries have multiple plants, then predictive maintenance implementation takes longer than expected says R1 (R1, 14). Moreover, R2 believes that organization size impacts data-driven PdM (R2, 42). In the case of R2, Volkswagen being a large automotive industry, by the time teams figure out machine failures it would have reached the ramp-up stage (R2, 42). Also, this challenge increases if the organization has multiple plants (R2, 42). Furthermore, R3 and R4 say that organization size impacts data-driven PdM ((R3, 42); (R4, 38)). Because smaller organizations may have limited infrastructure required for the implementation ((R3, 42); (R4, 38)). Besides, R4 states that smaller industries find it difficult to buy expensive models (R4, 38). In contrast, R5 says that data-driven PdM implementation can be easy and fast in smaller industries (R5, 38). Also, in large industries developing machine learning knowledge and accepting new ideas could be difficult (R5, 40).

Moreover, R3 says that "*predictive maintenance implementation totally depends upon the industry*" (R3, 42). R3 states that, unlike other industries, it is difficult to implement PdM directly in the aerospace industry as it needs to consider reliability and safety factors majorly (R3, 42). Furthermore, R4 states that the predictive maintenance implementation is similar for most of the industries where generic equipment is used (R4, 40). However, R4 supports R3's claim that in other industries such as aviation or any other industry where equipment is different, then the type of industry affects data-driven PdM implementation (R4, 40).

Regarding organization size impact on PdM, all the respondents have different opinions. However, all of them believed that organization size influences implementation of data-driven PdM certainly. Meanwhile, both R3 and R4 believe that industry type also affects data-driven PdM implementation based on the problem industries are trying to solve ((R3, 42); (R4, 40)).

Top Management Support:

R1 states that top management support is certainly necessary for data-driven PdM implementation (R1, 38). He observed that top management is interested in these kinds of solutions as they understand the problem and need for the solution (R1, 36). However, he believes that along with the top management, entire industry support is required for effective implementation (R1, 38). Meanwhile, top management can help to transmit the relevance of PdM implementation within the industry (R1, 38). R2 says that top management is realizing the importance of Artificial Intelligence and it is driving multiple industries to implement PdM (R2,48). According to R4, without top management support predictive maintenance will not be implemented (R4, 48). Supporting R1's claim, R2, R3, R4, and R5 also feel the need for top management support and believes that it helps data-driven PdM implementation ((R2, 48); (R3, 50); (R4, 48); (R5, 46)).

Existing Knowledge:

R1 explains that industries usually have expertise in their products, machines, processes (R1, 40). They are aware of their processes, how to react or check machines whenever there is a problem (R1, 40). However, expertise on data science or how to implement predictive maintenance is limited as they never had an opportunity to work with that says R1. This is when R1's organization helps other industries to resolve their maintenance problem (R1, 44). However, R1 feels the existing knowledge of the industry processes and equipment is necessary for PdM implementation (R1, 44). Supporting R1's claim, R4 also feels that knowledge of data science, industry processes, and equipment is a must (R4, 16). When R4 started data-driven PdM implementation in 2016, they found it difficult to get resources well versed with predictive maintenance knowledge which may be the current situation as well (R4, 16). Also, R2, R4 and R5 believe that not having the required existing knowledge certainly impacts data-driven PdM ((R4, 16); (R5, 24); (R2, 50)). Also, R3 and R5 state that their teams are enhancing the knowledge on predictive maintenance while working it ((R3, 70); (R5, 24)). However, R3 believes that having existing knowledge is advantageous for implementing data-driven PdM as it helps them to understand the context and work on it directly without spending much time (R3, 72). All the respondents acknowledged that existing knowledge of PdM is necessary. However, they do not perceive it as a major challenge.

Collaboration & Communication:

During the interviews, all the respondents highlighted the importance of collaboration and communication on data-driven PdM implementation. R1 considers that collaboration and communication are the keys to the success of data-driven PdM implementation (R1, 46). R1 believes that good communication and collaboration with authorities or any groups/ teams is necessary. Further, he adds that each team in the industries has different goals and expectations to be fulfilled. Hence, good collaboration and communication help different teams to have the same perspective or to understand each other's goals and expectations (R1, 48). Otherwise, it can inhibit the successful implementation of predictive maintenance (R1, 48). Moreover, R2 also considers collaboration and communication are vital for any industry (R2, 52). At R2's organization, multiple teams working on data-driven PdM implementation, and they regularly shared knowledge among these teams about how to support and how the models are deployed (R2, 52). R2 explains that collaboration and communication can lead to successful implementations of PdM by sharing knowledge and exchanging ideas (R2, 56).

Also, R3 and R4 believe that collaboration among the various teams is important ((R3, 52); (R4, 54)). R3 states that sometimes the models they developed may be theoretically good, but those may not be needed in practice. In such scenarios, communication and collaboration among other maintenance teams help them to understand current problems and work better (R3, 52). So, R1, R2, R3, R4 and R5 believes that collaboration majorly impacts the implementation of data-driven PdM ((R1, 48); (R2, 52); (R3, 56); (R4, 54); (R5, 54)).

Cost:

According to R1, the cost of implementing is a huge aspect of the PdM implementation (R1, 34). Also, R1 says that it depends on how industries perceive the cost of implementing data-driven PdM, whether they consider it as an investment or a cost as such. Based on this perception, industries allocate resource which is also tied up with their company vision (R1, 34). Hence, the cost has an immense impact on PdM implementation according to R1. Generally,

industries want to increase the revenue or save the maintenance cost (R3, 44). Besides, R3 says that predictive maintenance implementation is costlier and riskier in comparison to regular maintenance. So, if predictive maintenance does not give expected result, then it will not be implemented (R3, 44). Moreover, R4's organization conducted cost benefit analysis and based on the results of this analysis they started the data-driven PdM implementation (R4, 44). Hence, R3, R4 and R5 supports R1's claim that cost of implementation has an impact on data-driven PdM ((R3, 44); (R4, 44); (R5, 44)). However, R2 is not aware or has not experienced any challenges with respect to cost at R2's organization (R2, 46).

Awareness & Educational efforts:

According to R1, most of the industries are already aware of the new capacities and the needs with respect to the organizational change that comes with the PdM implementation (R1, 52). Industries are open to these changes and no much resistance from them could be noticed (R1, 52). Also, R2 states that work itself was part of educational efforts to research and explore predictive maintenance implementation (R2, 58). Other than that, there were no addition awareness programs were held to R2's knowledge (R2, 58).

Meanwhile, R3 states that their organization provides initial training about reliability, availability, and other things to enhance knowledge on predictive maintenance (R3, 24). Also, updates the training based on the teams and their skill sets (R3, 58). R3 believes that awareness creation is important and due to that, industries are encouraging predictive maintenance adaptation (R3,60). Similarly, R5's organization takes educational efforts by providing courses or training on machine learning and PdM (R5, 56). So, R5 also feels that awareness creation and educational efforts taken by organizations are beneficial for data-driven PdM (R5, 58). Hence, the influence of awareness and educational efforts while implementing data-driven PdM is perceived to be limited.

4.4 Environmental Factors

Competitive Pressure:

When asked about the influence of competitive pressure on data-driven PdM implementation, respondents had mixed opinions. R1 believes that competitive pressure is one of the reasons why industries are implementing data-driven PdM to create a competitive advantage (R1, 54). But it is not the major reason according to R1. Also, R2 and R3 state that industries implementing PdM to gain the competitive advantage could be an indirect goal that industries perceive ((R2, 62); (R4, 62)). However, R2, R4 and R5's organizations do not feel competitive pressure ((R2, 64); (R4, 60); (R5, 64)).

Meanwhile, R3 states that their organization's competitors also working to build intelligent Aircrafts using machine learning methods (R3, 62). Predicting fault before it occurs is a major concern for every aerospace industry and implementing PdM will help them to solve it (R3, 62). Therefore, aerospace industries are researching this topic and trying to reach specific TRL (Technology Readiness Level) levels to onboard this technology (R3, 64). However, R3 feels the competitive pressure to pass these TRL levels due to the competition among aerospace industries. Upon clearing seven levels R3's organization will be allowed to implement data-

driven PdM (R3, 64). So, the impact of competitive pressure could be seen in the case of R3 specifically.

Two of the respondents felt the impact of competitive pressure and the remaining three respondents did not feel the same. Hence, the influence of competitive pressure while implementing PdM could be seen as inconclusive.

External Support:

As R1 is working in an organization that is providing external support to other industries that want to implement data-driven PdM, the influence of external support on the PdM implementation could not be explored. Industries that receive external support could shed more light on this point explaining their perspective. At R2's organization, there was no external support involved, the implementation of data-driven PdM was built within the organization (R2, 10). Similarly, R3's organization as there is no external support is used, R3's team is researching PdM implementation internally ((R3, 12); (R3, 68)). As far as R4 is concerned, their organization used the Aveva Prism application in which they build predictive maintenance models (R4, 4). Moreover, R5's and R4's organizations also did not utilize any external support ((R4, 64); (R5, 10)). Unfortunately, this study could not draw any conclusions on this factor as none of the respondents used external support or were affected by it while working on data-driven PdM.

4.5 Additional Factors Identified

Resource Capacity:

R1 highlighted that resource capacity is one of the major factors that affect data-driven predictive maintenance implementation (R1, 54). Eventually, industries are growing by increasing the number of machines, adding more machines or processes to monitor (R1, 54). However, R1 says that the number of people available to check maintenance activities is not growing at the same rate. R1 feels the strong need to increase resource capacity along with other increasing needs of industries for efficient maintenance application.

Change Management:

R4 states that change management is one of the major factors that impact the implementation of predictive maintenance or any other machine learning initiatives (R4, 12). R4 believes that people or industries are hesitant to accept these recent technological changes in the industries. Industries want to follow their traditional maintenance processes and do not adopt or implement the new solutions easily (R4, 12). R4 states that industries must start believing in data-driven PdM implementation as it helps them to predict failures well in advance.

4.6 Findings Overview

From the previous literature, 11 factors that affect data-driven predictive maintenance implementation were identified. During the interviews, we found that impact of these factors is varying. Some of them had the major influence (*Collaboration & Communication, Data Management*) or certain influence (*IT-Infrastructure, Organizational Size & Industry Type, Top Management Support, Existing Knowledge, Awareness & Educational Efforts, Cost, Model Selection, Competitive Pressure*), or influence of them was inconclusive (*External Support*). Also, we found additional factors such as *Resource Capacity, Data Integration, Security & Quality,* and *Change Management.* Overview of these factors are given in the Table.6.

Table 6. Research Findings Overview

Context	Factors	Overview
Technological context	IT-Infrastructure	This factor is certainly necessary for data-driven PdM implementation. However, all the respondents considered it as least influential concerning the implementation of data-driven PdM.
	Data Management	Data is considered crucial for building the models for data-driven predictive maintenance. There is a strong need for industries to access the data, extract, store and manage the data effectively to use it for PdM. While dealing with data, industries need to consider data integration, security and quality aspects. All the respondents confirmed the need for effective data management and believed that it impacts PdM hugely. Therefore, data management plays a major role when industries are implementing data-driven predictive maintenance.
	Model Selection	During the interviews, it is noticed that model selection depends on the availability of data and its sample size. However, it impacts PdM predictions and anomaly detection. Three respondents revealed that there is a certain impact of model selection on the data-driven PdM implementation.
Organizational context	Organizational size & Industry type	Organizational size & Industry type is observed to be influential for the implementation of data-driven predictive maintenance. Larger industries take a longer time to implement PdM and it may further increase if industries have multiple plants or factories. In the case of small industries, implementation could be faster. Also, Industry type can influence PdM implementation based on the problem that is addressing.
	Top Management Support	In all the interviews, top management was interested and supported PdM implementation. Also, all the respondents stated the need for top management support

		when industries are implementing data-driven PdM. So, this factor is deemed influential from the interviews.
	Existing Knowledge	Having the existing knowledge about PdM, maintenance process and equipment is advantageous for implementing data-driven PdM. All the respondents expressed the necessity for it. Hence, the effect of existing knowledge is observed.
	Collaboration & Communication	Most of the respondents highlighted that collaboration and communication are the keys to the success of data-driven PdM implementation. This helps various teams under industries to share knowledge, understand problems, and support each other. Hence, collaboration and communication are considered major influential factors while implementing data-driven PdM.
	Cost	The cost of implementation is considered a huge aspect of the PdM implementation. Most of the respondents believed that it depends on the industry's perception whether they see it as an investment or as a cost as such. Based on this understanding, industries allocate required resources. So, the impact of cost is noticed on the data-driven PdM.
	Awareness & Educational efforts	Through interviews, it is observed that some industries are already aware of the new capacities and open to the changes needed for PdM implementation. Yet, other industries are creating awareness or taking educational efforts to support PdM. So, the influence of awareness and educational efforts is limited on the implementation of data-driven PdM.
Environmental context	Competitive Pressure	All the respondents had contrasting opinions about the impact of competitive pressure during the implementation of data-driven PdM. While some felt the competitive pressure to implement PdM, others could not feel the same. Hence, the impact of this factor is considered least.
	External Support	This study could not draw any conclusions on external support factor. Because none of the respondents used external support or were affected by it during data-driven PdM implementation.
Other Factors	Resource Capacity	By understanding the need for PdM, industries are increasing the number of equipment and improving the processes to monitor. However, the same effort is not taken towards increasing the resource capacity.

		According to one of the respondents this is the major factor that impacts data-driven PdM implementation.
	Change Management	Industries need to accept the changes and believe in data-driven predictive maintenance implementation. Hence, one of the respondents felt that change management is needed for industries to acknowledge the benefits of PdM.

5 Discussion

Our research findings in relation to percieved factors impacting predictive maintenance implementation from previous literature are discussed in this section.

5.1 Factors impacting Data-driven Predictive Maintenance Implementation

5.1.1 Technological Factors

IT-Infrastructure:

The significance of IT-Infrastructure has been already discussed and acknowledged in the literature (Li, Wang & He, 2016). From empirical findings, it is noted that all respondents believe that IT- Infrastructure is necessary for data-driven PdM implementation. R1, R2, R4, and R5's organizations store and share the data with the help of IT- Infrastructure which is required for PdM implementation supporting the Golightly, Kefalidou and Sharples, (2017)'s claim. However, none of them facing any challenges in setting up IT- Infrastructure. Therefore, this study considers IT- Infrastructure as the least influential factor affecting data-driven PdM.

Data Management:

The empirical results of this research strongly agree with the literature on the impact of data management while implementing data-driven predictive maintenance. All the respondents consider data management as a significant factor impacting data-driven PdM implementation. Therefore, R1, R2, R3, R4, and R5 strongly believe that data management has a major impact on data-driven predictive maintenance implementation. Supporting Li, Wang and He (2016)'claim, R1 states that in industries, not all are responsible for accessing the same parts of data. Accessing data and getting a permit to access data increases the for different units or groups. Also, R1 specifies the need for effective data management strategy development for the successful implementation of PdM. Also, R1 elaboratively describes challenges of data security and data quality supporting Aljumaili et al., (2015)'s claim. If the data is having missing values or is not processed properly then it directly impacts PdM prediction models according to R1 and R3. Moreover, R2 considers extracting noise-free data as one of the challenges R2 observed. R4 feels the *"better the data better the model is"* (R4, 28) that statement is well-suited data-driven approaches. R4 and R5 express that unavailable machine data can affect PdM. Considering the various challenges associated with data management, this study considers data management as the major impacting factor when industries implement data-driven PdM.

Model Selection:

The empirical results of this research on the impact of model selection partially agree with the literature while implementing data-driven predictive maintenance. All the respondents provided varied answers to the question to find the impact of model selection. R1, R3, R4, R5 stated that model selection depends on the availability of data or sample size of the data supporting Sai, Shcherbakov and Tran (2019)'s claim that models' accuracy is depending on the quality,

relevance, and sufficiency of the data used. Some models perform well with larger datasets, some work well with smaller data sets. However, R2, R3, and R4 stated the model selection affects PdM implementation and anomaly detection partially supporting Li, Wang, and He (2016) that models predict inaccurate information that may lead to unnecessary maintenance. However, Li, Wang, and He (2016) stated that model selection impacts PdM predictions, which could not be observed through research findings. Therefore, the impact of model selection is least on data-driven PdM implementation in this study.

5.1.2 Organizational Factors

Organizational size and Type of industry:

The empirical results of this research partially agree with the literature on the impact of organization size while implementing data-driven predictive maintenance. All the respondents had different opinions on organization size. However, they believed that organization size influences implementation of data-driven PdM certainly. Supporting the Bousdekis, Apostolou & Mentzas (2020)'s claim, R1 states that larger organization takes longer time to implement PdM.

Meanwhile, R3 and R4 believe that small industries struggle to implement PdM due to the lack of necessary infrastructure or high cost to buy maintenance models. In contrast, R5 said that it is smaller industries can implement PdM easily. Though there are varying views on organization size impact, it is observed as an influential factor when industries are implementing data-driven PdM. Moreover, only two respondents felt that type of industry influences data-driven PdM implementation based on the problem industries are trying to solve.

Top Management Support:

From empirical findings, it is noted that all respondents believe that top management support is necessary for data-driven PdM implementation. Also, R1 and R2 believe that top managements are realizing the significance of AI capabilities and encouraging PdM implementation initiatives at their organizations. However, R4 believes that top management support is a must for organizations implementing PdM. Moreover, R1 states that top management can help to transmit the relevance of PdM implementation within the industry supporting Bousdekis, Apostolou and Mentzas (2020)'s claim that leaders who understand advanced technologies can influence industries decisions to implement PdM. Therefore, this study considers top management as an influential factor affecting data-driven PdM.

Existing Knowledge:

The empirical results of this research agree with the literature on the impact of existing knowledge while implementing data-driven predictive maintenance. All the respondents acknowledged the need for existing knowledge of the industry processes and equipment is necessary for data-driven PdM. Also, R4 denotes the difficulty in getting resources well-versed with predictive maintenance knowledge when their organization started the PdM implementation. R4 feels this might be the current situation as well supporting Windt, Borgman and Amrit (2019)'s claim. Meanwhile, R3 stated that having existing knowledge is advantageous for implementing data-driven PdM as it helps them to understand the problem's context and work instantly. Hence the impact of existing knowledge on data-driven PdM could be perceived in industries.

Collaboration and Communication:

The empirical results of this research strongly agree with the literature on the impact of collaboration and communication while implementing data-driven predictive maintenance. All the respondents consider collaboration and communication as key factors impacting data-driven PdM implementation. R1 and R2 stated that collaboration and communication determine the success of PdM implementation. Also, R3 believes that this factor benefits cross-functional teams to resolve problems and work effectively supporting the Bousdekis, Apostolou, and Mentzas (2020)'s claim to build effective ways of communication across disciplines and combining the know-how of the maintenance function and the IT department. Moreover, within R2 and R3's organization knowledge is shared among teams with regular meetings. Hence, the major influence of collaboration and communication is perceived while implementing data-driven PdM.

Cost:

The empirical results of this research agree with the literature on the impact of cost while implementing data-driven predictive maintenance. R1 considers cost as a huge aspect for industries implementing PdM. Supporting the Compare, Baraldi and Zio, (2020)'s claim R1 described those industries that invest in PdM initiatives based on their perception, whether they consider it as a cost or as an investment. Also, Bousdekis, Apostolou and Mentzas, (2020) expressed the need for industries to conduct an extensive cost-benefit analysis and feasibility studies, essentially making the business case to support predictive maintenance significant investments. Relevance of Bousdekis, Apostolou & Mentzas, (2020) point could be seen in R4's response as R4 stated that in their organization they conducted a cost-benefit analysis to decide on the PdM implementation. Also, R3, R5 acknowledge the importance of the Cost factor. Hence the impact of Cost on data-driven PdM could be perceived in industries.

Awareness and Educational Efforts:

The empirical results of this research agree with the literature on the impact of awareness & educational efforts while implementing data-driven predictive maintenance. R3, R4, R5's organizations are providing training and courses to upskill knowledge related to PdM supporting the Golightly, Kefalidou, and Sharples (2017)'s claim to provide training on technical aspects to get familiar with those. R3 strongly believes that the creation of awareness is necessary, as industries are leaning towards PdM implementation as a result of this. Meanwhile, R2 is believed to be the part of educational efforts taken by R2's organization to research PdM implementation. In contrast, R1 believes that industries are already aware of PdM capabilities. However, all the respondents acknowledged the need for Awareness & Educational efforts while implementing data-driven predictive maintenance. Hence the impact of Awareness & Educational efforts on data-driven PdM could be perceived in industries.

5.1.3 Environmental Factors

Competitive Pressure:

The empirical results of this research agree with the literature on the impact of competitive pressure while implementing data-driven predictive maintenance. Supporting the Compare, Baraldi and Zio, (2020) claim, all the respondents agreed that industries are implementing data-

driven PdM to gain a competitive advantage and they consider it as an indirect goal concerning these industries. Respondents agree that competitive pressure impacts PdM. However, they do not consider competitive pressure as a major challenge. Meanwhile, only R3 feels the competitive pressure to reach to specific TRL level to implement PdM in the aviation industry in real-time. Hence, we consider this factor as the least concerning factor for data-driven PdM implementation.

External Support:

The empirical results of this research on the impact of external support are inconclusive with the literature while implementing data-driven predictive maintenance. While Bousdekis, Apostolou, & Mentzas (2020) specified that industries outsource resources or skills required for PdM implementation, most of our respondents (R2, R3, R4, R5) did not experience this challenge as they have not outsourced external support for PdM implementation. Organizations of R2, R3, R4, R5 built PdM solutions in-house. However, R1's organization provided external support to other organizations, we could discuss challenges faced by other industries for whom R1's organization is providing support. However, we believe that an increased number of interviews would have helped us to gain knowledge on the impact of this factor. Therefore, the impact of external support is inconclusive on data-driven PdM implementation in this study.

6 Conclusion

In the industry 4.0 context, manufacturing and production industries are focusing on Predictive maintenance (PdM) to increase production efficiency and maintenance strategies. Also, adopting data-driven approaches to implement PdM as a result of increased data usage and exchange. Implementation of predictive maintenance is complex both in terms of technical and non-technical aspects as it requires building a varied sensors network, data, and interpretation along with collaboration among teams within and across organizations (Golightly, Kefalidou, & Sharples, 2017). Previous studies majorly concentrated on technological aspects concerning the implementation of predictive maintenance, providing limited insight into organizational and environmental aspects. Considering this knowledge gap, this study focused on examining and describing factors impacting data-driven PdM implementation in various aspects by providing an answer to the research question:

"What are the factors that affect data-driven predictive maintenance implementation in industries?"

To answer this research question, the TOE framework was adopted to explore factors impacting data-driven predictive maintenance in industries. In this regard, we identified eleven factors from previous literature. We conducted qualitative research and collected empirical data by carrying five semi-structured interviews with data-driven PdM practitioners. Research findings show that *Data Management* and *Collaboration & Communication* are considered the most influential while implementing data-driven PdM as most of the responses showed that these are the key factors for the successful implementation of data-driven PdM. Other factors such as *IT-Infrastructure*, *Organization Size & Type of Industry*, *Existing Knowledge, Awareness & Educational Efforts*, *Cost*, *Top Management Support*, *Model Selection*, and *Competitive Pressure* has certain or least influence on data-driven PdM implementation. However, the influence of *external support* is considered inconclusive as none of the respondents experienced the effect of this factor. Also, identified additional influential factors such as *Resource Capacity* and *Change Management* during the data collection.

Through this study, we have identified and described how these above-mentioned factors are impacting data-driven predictive maintenance implementation by contributing to IS Research as there was limited research in this regard. Also, study results can be beneficial for developing the initial understanding of TOE factors impacting PdM implementation. On this knowledge, further researches can be developed using expanded data collection methods.

Appendix 1: Interview Guide

The following list of questions is used as a reference for the Researcher to follow during the Interview. However exact order of these questions is not followed.

Concept	Sub Concept	Question/s
Opening Questions		• Introducing ourselves with respondent. • A short introduction about our thesis and ethical considerations of the research.
Introduction Questions		• Do you mind if we record this interview? • Do you wish to be anonymous? • What is your background and education? • Role and responsibilities in the organization?
Key Questions		
Data-driven Predictive Maintenance	Predictive Maintenance Implementation questions	• What type of Predictive Maintenance (PdM) have you implemented in your organization? • How is the PdM implemented in your organization? Was it built in-house? Are there any external support or third-party vendors used? • Can you explain the PdM implementation process in your organization on a high level? • In general, what are the benefits of PDM implementation? • In general, what are the challenges of PdM implementation?
Technological context	IT-Infrastructure	• Did you have the necessary IT infrastructure required for the PdM implementation? • If yes, how has it supported or influenced the implementation of PdM? • If no, do you consider this as a challenge?

	Data Management	• What is the importance of data in your organization? What type of data is used for PdM implantation? its real data or synthetic? • How is the data managed or accessed in your organization? • Did you have any data or process information missing? How do these data uncertainties affect PdM implementation?
	Model Selection	• What are the various types of Machine Learning or Deep Learning models used? • What is the importance of model selection in the implementation of PdM and how does model selection affect implementation of PdM?
Organizational context	Organizational size and Industry type	• What do you call size of your organization? • Do you believe that your size and type of industry had any influence on PdM implementation?
	Top Management Support	• Whether the organization's top management supported the decision to implement PdM? • Do you believe that the support of top management is a necessity for your organization to implement PdM?
	Existing Knowledge	• Did your organization have any existing process(domain) or technical knowledge with respect to PdM prior to the implementation? • If yes, to what extent did this influence your PdM implementation? • If no, do you consider this as a challenge?
	Collaboration and Communication	• How many teams are working on PdM implementation in your organization?

		• How is the knowledge transfer shared among these teams? • Do you believe collaboration and communication among teams' affects PdM implementation?
	Cost	• Do you believe whether the cost of implementation or any risks associated with it affects the PdM implementation? If yes, to what extent?
	Awareness and Educational efforts	• Are there any awareness and educational efforts taken by your organization to support PdM implementation? How does this impact PdM implementation?
Environmental context	Competitive Pressure	• Are you aware of any of your competitors that have implemented PdM? • Did you feel or experience any competitive pressures to implement PdM? • Did you implement PdM as a means to create a competitive advantage? • To what extent did this influence PdM implementation?
	External support	• Are there any external support used for PdM implementation? • How much of their availability (e.g., vendors or consultants) affects the implementation of PdM?
Closing Questions		• Is there anything you feel like you haven't brought up yet, or that you would like to add? • Do you have any questions for us?

Appendix 2: Interview 1 (R1)

Researchers: Swapna Malagi, Sathya Ruba Selvaraj
Respondent 1 (R1): Sergio Martin del Campo Barraza
Company: Viking Analytics
Country: Sweden
Date: 27-04-2021
Interview Length: 55 minutes
Language: English

Themes	Factors/ Sub Themes	Code
Predictive Maintenance Implementation	-	PdMI
Predictive Maintenance	Other Factors	OF
Technological context	IT-Infrastructure	IT-I
	Data Management	DM
	Model Selection	MS
Organizational context	Organizational size and Industry type	OS-IT
	Top Management Support	TMS
	Existing Knowledge	EK
	Collaboration and Communication	CC
	Cost	CO
	Awareness and Educational efforts	AE
Environmental context	Competitive Pressure	CP
	External Support	ES

Note: Initially, we (Researchers) introduced ourselves and gave the background of the thesis to Respondent. Upon asking the consent to record the meeting, the following meeting is recorded and transcribed as below.

Row	Person	Transcription	Code
1	Researcher	Okay, I can record this meeting.	
2	R1	Okay. Give me, Give me just one second.	
3	Researcher	Yeah, sure. Do you wish to be anonymous or your organisation name in the thesis report? Or is it okay to have your name?	
4	R1	Sure. You can, what are the implications of having my name anonymous, like, like this is part of the report like to say we	

		had interviewed this person or like in which way you want to use the information?	
5	Re-searcher	We want to use the information like we have interviewed this person who is playing this role and how his experience correlated to the implementation of predictive maintenance and likewise.	
6	R1	Okay, then sure. You can keep my name.	
7	Re-searcher	Yeah. Okay. Then, can you tell us about your background and education?	
8	R1	Yes. Okay, so well, my name is Sergio Martin del Campo Barraza. Currently, I work as a data scientist on a start-up in Gothenburg called Viking analytics. Originally, I'm from Mexico, where I studied Mechatronics, Mechatronics Engineering. After that, I worked for General Electric aviation, as an electrical systems design engineer. After working for years for General Electric, that's when I moved to Europe. First, I came to do a Master's which I did on Space Technology. Then I did, I switch from space to AI, machine learning, in did a PhD in machine learning, and well-focused towards machine learning and supervised methods for data analytics by rational acoustic mission signals. After that I did the postdoc, again, on machine learning for industrial applications, in particular, wind turbines and detection anomaly for wind turbines. And after doing that, a postdoc after two years, that's when I decided to move from academia to industry. And then I joined this start-up a year with over a year ago.	PdMI
9	Re-searcher	Interesting. Good to know that. Can you tell me about your role, which you're playing in the Viking analytics? and how is that related to predictive maintenance implementation?	
10	R1	Sure. So, Viking analytics is a company that we dedicate to support, predict. And what we want to do is to bring closer a subject matter experts into data scientists. So, what we want to do is to develop tools, methods, and certainly analytics required, in order that we reduce the machines downtime, reduce or decrease the number of unexpected stops, and predict whenever there's a force on machines in mainly focusing towards process industry. So, we thinking towards motors, bulbs for many kinds of industries, chemical industry, power plant paper industry, energy industry. So that's the overall idea. The idea is that we want to bring closer, both data scientists and subject matter experts by having these tools. So, they can, they're able to see whenever there's something that typical happening as early as possible and they have enough time to react to those circumstances. That's what the	PdMI

		company does, in general. My role within the company, like I said, I'm a data scientist. So, I'm part of the, responsible and I work with the developing of many of these algorithms that are responsible for many detections as part of our overall products. But given that it is not even a large company, and my role also includes interactions with many of our customers or potential customers, to be able to better be able to understand their needs. And given then, I already had a little bit of experience with within working in processing industry. So, I'm trying to be able to better understand techniques in translate them into actions that are able to well, in which we can create the solutions are able to predict those situations that they may be facing.	
11	Researcher	Yeah, that's good to know. Like, you're helping many industries to optimise their maintenance process. What type of predictive maintenance have you implemented? Like, is it data-driven or knowledge driven? Or model-based? how is it?	
12	R1	Mainly, we work with supervised methods. So, we're mainly dealing with data-driven methods. Unfortunately, for this kind of industry, and their may not label data is quite another system. So, it's one of the challenges. So, I guess we were going to challenge us in a moment. And that's one part. We can create models for the different kinds of different applications, but then take issue with by the study will not be as scalable as we would like to either and there is always direction for that hybrid, having hybrid models and inserting something that we would like to explore more. But right now, there has not been much or an opportunity. So mainly right now, we are dealing with data driven models are we are learning, developing, constructing based on data that we receive. Yeah, completely supervised methods.	PdMI
13	Researcher	Okay. I understand that. Like usually when you implement predictive maintenance, how long is the process? How will it take time, like, for the industry is it depending on the size or type of the industry? How is it?	
14	R1	It's quite variable thing. I will say that, a one thing, how to put, we have two different stages, which is part of the work in different stages. The part in which you develop the overall strategy, and then there is, the part in which it is deployed in. You were to put all these together, that process can be rather large, in by large, or rather long. By long, I mean, we're talking on the on the order or during years. So, it's kind of difficult, especially for established as industries, to be able to deploy this. Why because there is already a certain procedure, certainly they decide to do everything faster. But the issues a	PdMI, OS-IT

		lot of times are not technological in one part. But these more like non technological factors that can make the process even more or for it to take more time. So usually, you have to start with developing pilot studies, the pilot programmes, and that can take quite a few months, which might be good enough to develop something within even a specific plant. But then if you want to move it across multiple plants, across entire organisation, that's the part which sometimes can take more, more time.	
15	Researcher	Okay. Can you explain this implementation on a high level, how it is done on an industry? like when somebody is some companies come to you for the support or help on the implementation? Or what is the first process and how it will be initiated? How that is done?	
16	R1	But, but that's, that's the main issue, the main problem. Many companies, they don't even know what they want. Or, yes, I will separate it as, its not that they don't know what they want. Sorry. they not entirely sure about their needs. So, so the challenge here is to help them understand based on what is available, what can be done. Unfortunately, predictive maintenance machine learning in everything it is not as simple to go and put a sense of. Those are the expectations, but it is not as simple as that. It is if I were to come to you in so, I kind of like food related technologies. If I want to say to you, you know what I want to, look I had all this cacao and I want to make a chocolate cake. Why? I want to have a chocolate cake or give me a chocolate cake. And give us or the customers say, Okay I have the cacao and I want a chocolate cake. But they're not necessarily aware of everything that is required to go from the cacao to be converted into chocolate and then to be able to to generate or produce a cake. In a lot of times not all even the resources might be available. They may not have milk, they may not have eggs, they may not have an egg or they may not have an oven or they may not have all the related stuff. And, that’s the issue a lot of times with a, when dealing with many of these industries. They know they have the data. They know what they would like to have. But there is a process in between and that process is not very straightforward to go and put the same story into it. So, I will say that for each specific company, for each specific industry that they creep to go, from what I want to something that can be implemented is really really different. For some might be shorter, for other ones may be longer. It varies a lot.	PdMI
17	Researcher	Okay, yeah. Like narrowing down to maybe technological context, IT infrastructure or the IT competence of the	

		organisation. Like how important is this if the company or organisation already has any IT infrastructure? like, how it will influence the implementation or if they don't have the right infrastructure how will that be impacting on the implementation of predictive maintenance?	
18	R1	That plays such a huge role, in a lot of it depends on what we mean by infrastructure in with the IT capacities. IT part is that they have already a set of responsibilities and but (typing) sorry. So, they people already have a set of responsibilities and which are responsible for the infrastructure of the IT systems within a company.	IT-I
19	Researcher	Like what I meant was like maybe to have a server so which store large amount of data or the network's telecommunication networks which are needed for the implementation.	
20	R1	But that is… Okay. Certainly, that plays a role, Okay. Like I said, was gonna say it before. IT people which are responsible for the IT system, which is completely different field to what the data scientist do. So, they might do programming both, but is not the same kind of programming are the same kinds of capacities. Now, having said that, yes, there is a certain level of infrastructure needs. And in each company again its on a different level. Some people, some companies for an organisation they started to store all the data that they had available. But not because it is the right amount of it, not because they're storing all the data. It means that it is necessarily the right amount of data for what it is needed. And at the same time, for that it requires infrastructure to able to store that kind of data. And at the same time, you need the infrastructure to be able to share that data, which is rather different. Finally, especially in larger organisations, there is a person who is responsible for that data or a part of the organization which is responsible for that data. But unfortunately, its different parts of the company who is responsible for different parts of the data. So, not everybody is responsible for the same part of data. So, the main challenge here it is that data, as it is seen by many companies is just seen as a by-product. There is not a clear strategy, about the data, what they have, what they collecting, what how to store it. And a lot of times there's this common, or many of the times, okay, companies need the data in you make money out of the data. But the issue is that the data is like it may not be thoroughness, in a proper way. I will put up with an example. I know many companies deal with vibration data. Normally what they usually do, it is, okay, you will receive a vibration signal, create the FFT (Fast Fourier Transform) of the signal, look at the FFT and see what happened over there. If one	IT-I, DM

		wants to work with vibration data, it is far better to work with raw vibration signal than to look already with that pre-processed data, which is the FFT. Organisations that were already used to dealing with FFT, so they always discard their raw vibration signal. Instead, they were always saving the FFT. Why because that's what they always use. So, I'm not saying that one cannot do stuff, with just FFT's. Certainly, one can do a lot of stuff. But one will have done even more, you will have in access or able to have access to the raw vibration signal. So, in that part, a lot of times of the challenges with organisations data permits. Certainly, for the signal, one part of organisation has access to a vibrational or FFT signal. But then other part of the organisation that has access to the metadata around the machine from where the information is taking place. In these two elements of the organisation might not communicate with each other, or getting permit for one doesn't mean that you get a permit for the other one. Access to one data, it's not as simple as getting access to the other data. Because for one data, you have an agreement with the customer and for another data, you don't have an agreement with the customer. So, having all that part together, that's part of the challenge. So, a lot of times it is important for the company to have a clear direction about how they want to move where their data policy into data management and there is a need for management for that.	
21	Researcher	How important is the quality of data? What kind of data usually used? Is it a real time data or some synthetic data is used for implementation?	
22	R1	Well, certainly we want to have real data. We want to be able to the use data, probably it is way easier with a real data. Why because if you don't have real data, you will never be able to do a proper verification of what you're doing. It's working okay. Then operate just simulate, any simulation, but then everything will never replicate the exact conditions of what is happening out there.	
23	Researcher	Okay. If there are any uncertainties or ambiguities in the data, does it affect the predictive maintenance predictions?	
24	R1	Sorry, I didn't hear the question.	
25	Researcher	If you have any missing information in the data or some certain uncertainties in the data, does it affect the predictive maintenance implementation?	

26	R1	Certainly, certainly. Because the less data you have the less clarity that you have around it, it is way more difficult to be able to properly understand what is happening around.	
27	Re-searcher	Okay. How about data deterioration or like, from time-to-time data gets deteriorated? how is that considered while implementing?	
28	R1	At the end of the day, it depends on what you want to get. So, the idea is that whatever prediction you make, should be more or less on the time scale that are compatible with a life or the life of equipment into data that you have. You only get data once a day, certainly you cannot make a prediction in like every five minutes. Because the data is available one day. At the same time and you're getting data like every five minutes, there is not one, if I give you a prediction like 10 minutes in advance, because that is not enough time to react. So, it depends a lot of the availability of the data, when it will be able to provide a response that is compatible in the time scale, on what it is available in the capacities of the machine. Certainly, there is not one shoe fits all over here.	
29	Re-searcher	Yeah, maybe everything will not fit to the need of whatever we have it for the implementation. Yeah, I understand that. Usually, like what are the various machine learning or deep learning models used? What are the AI models used for the predictive maintenance implementation?	
30	R1	It varries. Normally, I will say that the less complex ones it can be way better. Mainly because of the availability of the computational resources and the availability of the data. So, a lot of times it can be.. a lot of times it can be as simple models as random forests, or simpler clustering algorithms, things like that. And not a lot of times it is necessarily to use deep learning or deep extensive neural networks, when even the data that might be available. Those things help to sustain, it might not make a lot of sense, for the company that having the skills for it. In fact, that's the thing. And a lot of times there's the confusion in which like the most sophisticated the model, the better. But, then a lot of times they're way simple ways to calculate some like.. to get the response without having to over use a lot of resources. It’s like if you want to kill a fly, it's like a lot of times like using a bazooka to kill a fly, yes, you might keep the fight but like you're overdoing it with bazooka when you can just simply take a newspaper and that’s it (smiles).	MS

31	Re-searcher	Yeah, model selection is important I guess in this. Are there any commonly used models or it varies depending on the industry?	
32	R1	It varies depending on the problem that you want to do, what you want to achieve and the industry. It varies in a large sense of factors. Both the problems that you have, the data that you have. And the.. yes.. and the industry that kind of stuff. Like I said a lot of times there is not even labeled data. So, when you don't even have a labeled data, well you cannot use any supervised models for example.	MS
33	Re-searcher	Okay, I understand. Coming to the organisational context of the implementation, I think we covered organisations size and type of the industries has an impact on the implementation. Right? Like...implementation of predictive maintenance varies depending on the organisation. Like...how.? Are organisations hesitant about the cost or the financial risk associated with the implementation? Does it impact their decision to adopt predictive maintenance?	
34	R1	Certainly, certainly that is a huge aspect. But for the companies to be able to determine and like how they see it. At the end of the day, the company thing needs to see if it is more like a cost or like an investment. And we don't have any control over that. That is varied from company to company. In a such, they need to be able to based on how they perceive this to be. That's how they decide to allocate the resources. Certainly, based on how they decide to perceive this problem. It is not only the amount of resources they put available. But it is the kind of vision that like the company has. Unfortunately, we as suppliers of the solutions, we don't have control over that a lot of times.	CO
35	Re-searcher	Yeah. I understand. Coming to top management support, like the top management of the organisation, do they usually support the decision to implement predictive maintenance?	
36	R1	Certainly, the management tend to be interested on these kinds of solutions. So, they tend to be interested, why because they can see a need for this problematic thing, these issues. But a lot of times, one thing is they offer interest in dealing with the people who do their work day today, in which there is large amount of interaction. So, we have two different parts of the organisation. There is the upper management which is usually interested but you never talk with. Then there is part of day today people you interact with who has the knowledge, who has expertise. And they may receive	TMS

		or another may search internally within their organisations. So that's kind of challenging.	
37	Re-searcher	Okay. Do you believe having the top management support is necessary for this implementation?	
38	R1	Certainly, certainly it is necessary. And it is important to have. Like I said, is not the only element. You need...you need the support from entire organisation, not only from the upper management. And the upper management, a lot of times also need to be able to transmit the relevance of this to their organisations.	TMS
39	Re-searcher	How often organisation have existing knowledge of predictive maintenance process? Are there any technical expertise in their organisation? If they, have it, how it impacts the implementation?	
40	R1	A lot of times for many process industries, this is not common. They have, they are experts on their products, their machine, their processes. But they don't have expertise on data science, how to do maintenance in that like predictive maintenance, that kind of stuff. They know the process processes and they need to, how to react and check the machines whenever there is something problematic. But predictive maintenance they don't have experience with because they never had a chance to interact with.	EK
41	Re-searcher	Not having the technical knowledge, do you consider it as a challenge during the implementation?	
42	R1	Here its important to define what do you mean having technical knowledge? What kind of technical knowledge are we talking about?	
43	Re-searcher	Yeah, knowing how to predict or build the models to predict the remaining usage or life of the equipment. This kind of stuff.	
44	R1	So, it's, that's our responsibility. That's the knowledge that we have. It’s not that you need to know it. But what it is important to know is that for them it is certainly know their system, to know their processes. But also, better understand what they can, like, they would like to achieve. How we can help the people to make the process more efficient. We can give recommendations. But at the end of the day, we also need to learn if the recommendations that we are doing are useful or not. And that's what we need to get from this organisation from the people who who use them. If the recommendation, the prediction of everything that we are providing it is	EK

		useful, we need to know if it is or if it is not, and in which way. So, we can start to provide and improve our solution. If what we are giving them it is not useful. In that case, well, we are certainly not helping them. So, we, the challenge here a lot of times relates to communication. To communicate what we can do in each scenario and what they can transmit. So that's a lot of times the main challenge.	
45	Re-searcher	As this involves various technologies or assets are being used, I mean many multiple teams or departments are involved in this predictive maintenance. So, how important is having the good or effective collaboration and communication important for this?	
46	R1	It is key. If you don't have it, their project most likely will not have any success. So, it is important to have good communication with authorities or any groups in teams, but also to have communication among them. Because each team has different objectives, different expectations on mind. If not, if everything is not aligning on the same page that the project, for the project to succeed becomes really really, really difficult.	CC
47	Re-searcher	So, knowledge transfer must be happening among these teams?	
48	R1	But more than knowledge transfer is good channels of communication. You don't speak the same language and by language I don’t mean in English or Python, I mean like, like, it's expectations and goals like everybody to be on the same page. It becomes rather difficult.	CC
49	Re-searcher	So, having the same perspective is important.	
50	R1	Exactly.	
51	Re-searcher	Okay. Like about awareness or educational efforts. Usually when there are any new changes in the industries, there will be like initial resistance or new cultural changes required for the any organisation to have some technological changes in the industry. How the awareness or educational efforts are taken by organisation in this perspective?	
52	R1	Here most of organisations, most of the people are aware of these new capacities and are aware of the need for them. So, in that regard, there's not much resistance. The issue here is that there's a lot of people, a lot of organizations, they tend to tend to promise too much, but they are not able to deliver. Why, because they they say that or they assume on incorrect	AE

		way that their problems will not be that complex. So, it is as simple as putting date and this date impacts it and that's it. But the issues are way more complex. A lot of times people say okay, it is way more difficult to be able to recognise a picture in there is a cow. While looking at the signals and say okay, this is the motor broken, Yes, or No? Okay, perhaps your amount options, like about a signal in a motor being like broken, what kind of on which way it broke down, it may be reduced. Why on a picture, you had a picture, you need to identify which part it is the animal and then to know which kind of animal it is. Well, there's 1000s and 1000s and 1000s responses. So, it's okay, if we can do that for pictures, we can do that for the signals or the motor. The difference is that anybody can look a picture and identify where is the cow and look at the cow. So, there is already experienced by everybody is like something that you do on a really in neat way. Like you can look at the picture and identify where is the cow if it is a cow. So, the issue because mainly at gathering enough data, which is able to be labelled properly and say like, okay, that's a cow and that's it. So basically, we have gathered a lot of data, someone like a lot of people, anybody could label that data and say like, okay, this is a cow, this is a cow and we had an issue. Now we put the model. In that we will predict it it is cow; you need to look at it here. The issue with that vibration signal from the motor is that not everybody can look at the vibration signal and say, here it is problem on a motor which is cause for this. The number of people who can do that is highly, highly, highly, highly small, that's one part. Second, the number of pictures or cows can be also millions and millions of pictures. The number of samples of signals that has a specific problem with the motor, it is really really small. So, there is not the same situation on that like what it is capable around. So, a lot of companies come or had come promising a lot of stuff and great capabilities. Because they have seen that a lot of other teams already it sees. They have not been able to deliver why because the data, the capacities, the signals those doesn't exist. So, what is happening now with the organisation is that cannot afraid to engage, why because they have tried before a lot of times and they have not delivered. So now they're becoming a bit more of acceptive about what can be done.	
53	Researcher	Yeah, I understand. Coming to the environmental context, competitive pressure. Do you have to feel that organizations implement predictive maintenance because of they experience competitive pressure, because their competitors are also implementing this? Is that the reason?	

54	R1	I will say that is a reason. But not necessarily a major one. I will say that one of the major factors as well it is because the capacities. Again, companies are growing they each day they have more machines, each day they have more machines to monitor, more process to monitor. Unfortunately, as the companies grow, the number of people that they have been available to check all this is not growing at the same rate. Why because maintenance engineer, it is not a job that attracts a lot of people. So, the amount of people that they had available to do this is decreasing, while the capacities and the needs are increasing. So, it is mainly that I will say is one of the major factors' studies describing this type of new technologies. The fact that there are not enough people who is capable to do this or to do the procedures from the typical way.	CP, OF
55	Researcher	Okay. Predictive maintenance usually affects or depending on the health of the asset it may affect production environment. While implementing whether environmental aspects also considered? like because we will be using a lot of energy consumption will be done during maintenance or taking care of the asset. Will that be considered by implementing PdM?	
56	R1	Do you mean like the energy requirements for running all the models?	
57	Researcher	Yeah, like what are the environmental impacts of it?	
58	R1	That is the thing. Many of these deep learning advanced methods are computationally expensive, which require a lot of energy. But I was mentioning earlier these methods for these kinds of problems might not necessarily that suitable. Why, because there is not the amount of data the capacities for all that kind of stuff. So, yes, you can be able to get a result with a GPU. But most of the people or most of the companies they want to be able to process everything as close as possible to the sensor itself. The greater challenge it is not where to process the information in the cloud and that's the reason a lots of companies are not satisfied with the cloud. It is to be able to win in to move all the data. When you have a sensor, especially if it is a wireless sensor, the part that consists the largest amount of energy is data transmission not data processing. In each year data processing is becoming way more efficient. But data transmission is not becoming as efficient at the same rate that data processing. That is reason there is not, there is a lot of interest or the companies would like to process everything closer to the edge, closer to the sensor. So, the constraints being able to use a lot of energy, because we are using deep	

		learning models that use a lot of GPUs, at least in this industry. It is not a major issue right now. Because there is not much, I do not want to say the capacity, but there is not a lot of resources, that is one part. Another part for many industries, process industries, they are not even capable to have data coming out of their organizations. So that is the reason you cannot put data on to the cloud, because they are not even allowed because of regulatory processes. So, I will say that atleast it concerns and the concern regarding the amount of energy use for all these models. I will say that is not a major concern right now.	
59	Researcher	Okay. In general, what are the benefits of predictive maintenance implementation for the industry?	
60	R1	Well, in general it is many. To be able to reduce the amount of downtime and to be able to schedule the maintenance actions with more times in advance in such a way that you will not have unexpected stops and in you can use the processes, whenever it is more suitable for the needs of the people in the organization. And certain factors, resourcing reduction in some case and unexpected effects. And like more, you have more fluent process and as such, well your entire production line is rather good.	
61	Researcher	Also, like major challenges, what are the major challenges you mentioned couple of them during explanation. Like what are major challenges do you see in the implementation?	
62	R1	When it goes down to that implementation of issue, it is several. First, we will say what we call class imbalance, meaning data from healthy machines is way more common that data from non-healthy machine or from anomaly data, that is one issue. Another issue will be constant, meaning both the normal state of the machine and the failure are anomalies within the machine also evolves over time. So, they are not they are not constant, they change over time. And so, they are part of the natural degradation of the machine, such you need to be able to consider that. Then when needed data collection or has the way which data was collected transmitted to create all these models can be some sort of selection bias. And so, what has been selected might not necessarily be representative for the overall situation. The entire issue regarding like, the environmental conditions are highly random, and which with a lot of variations or a lot of variability, which results in models not suitable. Then in real life, all these data are really really noisy. So, it is like, it is not like clear signals everywhere. Actually, it is really really noisy. If we have the part of the machines are like degradation is fluctuating is not like a constant degradation, but it is actually	

		fluctuating all the time. So, this not on a lot of times considered when there is this degradation in both in the operating conditions in how is the average operation known. And then, I will add like overall situations in these industries, something that is important it is, it had explained like everything that is understood it is explainable. And such like, it is not like they are not interested on black boxes in which like data input in and solution out. Like they want to know what it is happening with inside these black boxes. So, one needs to develop models that are capable or explainable and understandable for the industry.	
63	Researcher	Good to know that...We are done with questions related with the factors. Is there anything you feel like you missed out something, you want to bring it up here? Or do you want to add something along with.	
64	R1	I will say that note that or need to keep in mind when dealing with all these processes that we have two types of data. One is the asset data. And another one is the process data. So also, bringing these two data together, it is also challenging, why because it is located a lot of different repositories who have different access, who have different permits, and all the owners might be different persons. And then the formats in which the data is found or is extracted might not be being compatible. So, you need to be able to map one to each other. And for that format them as well. And then if one of the data from one part it is poor quality, well as you started transmit and pass it along, that poor quality start to get bigger and bigger and bigger, so it can increasing effect. And as such, like the data distribution determination becomes also another challenge. It is like, okay, how to do it in the right way. And finally, well, there's always data privacy, and one needs to be ensured that, well, there is not any private data, for example, especially as it relates to the process data, regarding like, user IDs, or location or preferences or that kind of stuff. So that is another factor that a lot of times need to be considered, like how to integrate the different kinds of data.	OF
65	Researcher	Yeah, data integration and data privacy. I get it. Do you have questions for us?	
66	R1	Well, mainly after this interview, so how is this information going to be used?	
67	Researcher	Yeah, As asked you about various factors in the different context. We are building the conceptual model using TOE framework, which is technological, organizational and environmental factors, which affects the predictive maintenance implementation. And your inputs are important for us to	

		understand that what influence these factors has on the organization while implementing PdM. So, we use this information for cross checking the relevance and adding the different perspective. In the last case, you have mentioned data integration and security part of it. So that is another thing we did not cover it, but we got to know from you. So likewise, we will add to our research, like that.	
68	R1	Okay, that sounds good. Well, I wish you good luck with your master thesis that hopefully everything goes rather well at the end.	
69	Researcher	Yeah, thank you. I also sent you the consent form through the mail.	
70	R1	I will sign it out in a moment, and I will send it back to you. I guess you will return it to me with one signed copy as well. or later, right?	
71	Researcher	Yeah. We will share it with you. After signing we both will sign it and share with you.	
72	R1	I will send it to you in an email with more like I had a meeting now, so I will send you an hour or something like that.	
73	Researcher	okay, then we will not consume your time. Thank you for joining us today. It was great meeting and we collected so much valuable information.	
74	R1	No, not nothing, nothing to thank for. Good luck with your master thesis.	
75	Researcher	Thank you. See you, have a nice day.	

Appendix 3: Interview 2 (R2)

Researchers: Swapna Malagi, Sathya Ruba Selvaraj
Respondent 2 (R2): Shobhit Chourasiya
Company: Volkswagen AG
Industry Type: Automotive
Country: Germany
Date: 04-05-2021
Interview Length: 35 minutes
Language: English

Themes	Factors/ Sub Themes	Code
Predictive Maintenance Implementation	-	PdMI
Predictive Maintenance	Other Factors	OF
Technological context	IT-Infrastructure	IT-I
	Data Management	DM
	Model Selection	MS
Organizational context	Organizational size and Industry type	OS-IT
	Top Management Support	TMS
	Existing Knowledge	EK
	Collaboration and Communication	CC
	Cost	CO
	Awareness and Educational efforts	AE
Environmental context	Competitive Pressure	CP
	External Support	ES

Note: Initially, we (Researchers) introduced ourselves and gave the background of the thesis to Respondent. Upon asking the consent to record the meeting, the following meeting is recorded and transcribed as below.

Row	Person	Transcription	Code
1	Researcher	Can you tell us about your background and education?	
2	R2	You so my background. I mean, I have recently finished my masters in data science and my masters are focused on basically how we implement using machine learning or artificial intelligence in the real time. While doing my masters in the university, I studied courses based on machine learning, advanced machine learning, or Bayesian networks, basically, the fundamentals of these pillars of data science. And my master's, I got a chance to do internship and master thesis,	

		two of the companies. So, I did my first internship with Robert Bosch GmbH. And then another Volkswagen AG. And then I did my master thesis in Volkswagen. And before that, I worked for around four and a half years as a software developer with Accenture. And I have my complete background in computer science because I also have a bachelor's in computer science and they also long run completely computer science background.	
3	Researcher	Can you tell us about your role? Like how your role is correlated with a predictive maintenance?	
4	R2	Yeah. So, during, in my internship with Volkswagen, I got a chance to work. During my internship I got, I mean, I worked with one of the PhD students who was doing his PhD thesis in Predictive maintenance. And during that time, for about three months, I worked with the, on a project and implementing mostly related to the technical details. But yeah, I have a little bit idea beyond what goes apart from the technical details. But mostly, I worked with the technical implementation of model how to achieve the predictive maintenance, how the model calculates in that.	PdMI
5	Researcher	Okay. What type of predictive maintenance was implemented in the organisation? Was it data-driven, or knowledge driven or model based?	
6	R2	I think it was a combination of data-driven and model based. So, we, so everything is driven by data. I mean, data has to be the core of what I mean, how you're going to achieve the how you're going to predict the failure of the machines, and as it was a data driven approach, and we tried different models to foresee how can we predict the failure of the machines. And so that’s why I would say that it's a mixture of data driven and model driven.	PdMI
7	Researcher	Do you remember like how long the process of implementation was taken? Do you know like when they decided to implement how long it was taken?	
8	R2	So, I think it took more than a year, I guess, I mean, forecasting. And I don't know the exact time because that was mostly done by my supervisor, my PhD supervisor. But I believe it was more than I guess, around two years, or maybe more than that. So, when I joined at that time, one of the models was already functional. And then I took that work and defined that model with respect to the new data that was coming in, and then try it on another model. And so, it was I	PdMI

		think, total, I can say, maybe it was more than two years or two to three years, I think.	
9	Re-searcher	Okay. Was it built in house or any external support or third-party vendors were used for the Predictive maintenance implementation?	
10	R2	No, I think it was completely in house. So, it was mostly done the implementation part or the research part that was done by my PhD supervisor, and some of it was done by me and but it was completely in house.	ES
11	Re-searcher	Okay. Can you explain the process of implementation on a high level and how it was done?	
12	R2	Yeah. So, with respect to the implementation, what we did was, so we had an idea that what causes the failure of the machines. And so, it was sort of machine was basically a glueing machine that brings the components together and we had to predict. So, if the machine fails, then it takes one, two or maybe more two more weeks, as you see, I mean, it's not easy to get hold of the maintenance person. And their schedule also difficult. So many times, it happens that the machine is failed and the production is indirectly impacted because of that. And so, what our goal was to foresee how can we predict that okay, when this machine will fail. And these these machines, the glueing machines, so we got an idea that with respect to certain parameters, we can identify that with respect to the values of these particular parameters, we can see that, okay, these machines will fail beyond these particular numerical values. And that's what we tried predicting. That was basically the implementation that with respect to different models, we tried forseeing like, we use a Monte Carlo simulation and basically simulating based on current parameter and using that data, as we keep on seeing new data to identify that foresee based on that data that what is the around usage or the usable cycles, number of cycles that the component can be used in the future. Based on that to predicting the failure of the machine and, and scheduling the maintenance.	PdMI
13	Re-searcher	Okay. That's interesting. Did you have the necessary IT infrastructure required for the implementation?	
14	R2	Yeah, that's for sure. I had all the thing most of the IT infrastructure that was already, maybe my my supervisor faced some challenges. I don't know if, but that was before me. So, I'm not aware of any challenges in that part. But yeah, I was. I had all my tools and support always provided to me.	IT-I

15	Re-searcher	Okay, and whether you had the existing competence about predictive maintenance while working on this, or you developed the necessary competence once you entered into the organization?	
16	R2	Yeah. So, I mean, honestly, I did not have much experience, not much, none of the experience with predictive maintenance. So, I started, so I had some basic idea about, about data science about how to be Bayesian methods or these basic methods work. But I did not have the idea of the application or how the application, how the forecasting works with respect to the predictive maintenance. So that I had to learn quite a lot on my own. And with respect to so we tried multiple models as well. So, one model was already developed, but some of the models that I had to explore that how can we use these models and that I had to learn on my own.	EK
17	Re-searcher	Okay. How challenging was that to not to have necessary competence already or the learning during the process? Do you think it will impact our implementation?	
18	R2	I think it is. So, it was. It's not that we had a clear path that okay, this is what we have to implement, it was more of a research-oriented work. So, when research or injury or to try and try different things, you try 10 or 20 things, and then maybe one or two works well. And that is what I think we were trying to achieve. So, it is always a process of learning and implementing going in parallel. So that was I think that was more like any other research work. This was also like that, and it was a bit challenging, because sometimes I had no clue that I mean, what, what it will at work or not, and how well and I mean, sometimes I had a lot of I was afraid as well, a lot of times because things were not working things are not going. But then yeah, I mean, that is the thing of trying and trying, again, that you keep on exploring multiple ways. And then somehow you get to that part of where things are start working better. That's what I think happened in my project as well.	EK
19	Re-searcher	Usually, the implementation requires a large amount of data to create insights and build or train any model, etc. How important was the data in your organization?	
20	R2	The data was very important. I mean, data, I believe is a critical part. It was a critical part and it remains a critical part of the most important part of matters of like foundation of any model. And luckily, we had a IoT team and they were responsible for having they had the sensors to collect the data from the machines and they installed a quite. I think the	DM

		credit goes to them for getting us the data and based on them that data then we could work and explored all those models.	
21	Re-searcher	Okay, what type of data was used? was it a real time data or any synthetic data was used?	
22	R2	So, while exploring or researching, we use the data that we already had based on the cycles. So, we had the data of cycles like how how the mean the readings of the machine from sensors, we had that data. That is the data that I used while exploring the models. So, when we deployed the model in real time, that time obviously, it was using the real time data. And because based on real data, it will assess that to what value it should get or it is getting or what values it is supposed to get. And based on that it can use the forecasting. At deployment we used real time and but to avoid exploring or while researching, we use the basically one data set specifically that so that we know that at least to ourselves that we're how other models are working irrespective of instead of using multiple data and confusing ourselves with the approach.	
23	Re-searcher	Do you know, how this data was managed or accessed in your organization?	
24	R2	So, the data so, as I said that, we had a IoT team. In our department, they were responsible for getting the data. So, I believe they manage to get the sensors on the machines and and fetch the data. Then I mean, data is always consisting of some level of noise and then we we filtered the data a bit and we try clearing out the noise a bit and then we use that.	DM
25	Re-searcher	While working on turn it, did you have any data or process information missing? If so, how the data these data uncertainties or ambiguities affect the predictive maintenance implementation?	
26	R2	So, I would not say the data was missing or something like that. Maybe that my supervisor already had some idea that how the data or what data are we receiving. So, we had limited data, and we had some information from the third party as well, I mean, the creator of the machines that suggested that this is the these are the critical parameters that you should consider. So i don't think that we may be that some more data could have improvised the forecasting process. But overall, I would not see it that we were missing something. It was I think it is it is a grey area that maybe some more data would have impacted maybe some more features would have impacted the forecasting process. But I don't think it played that much big in my project. But overall, I think predictive maintenance for in general in predictive	DM

		maintenance, you require a lot of data, I think that is the most tedious part in the predictive maintenance and getting the data and that to the noise free data.	
27	Re-searcher	Over the time, if you're using huge amount of data, there are chances that data get deteriorated. How the data deterioration is considered or addressed?	
28	R2	Data deterioration, I don't think that this was so really good not face any kind of data deterioration. So, our models were developed in such a way that it acts on the real time it acts on the latest information that we are receiving and as soon as it forecasts one, so suppose that if I have the data till today or maybe till today, and then I can say that okay, based on today's data, excuse me, I can pause for a minute. Just give me a second.	
29	Re-searcher	Yeah, okay.	
30	R2	Yeah, so once more. What was the last question? Sorry.	
31	Re-searcher	We were talking about data deterioration.	
32	R2	Yeah. So, generally, so, yeah, I was telling that the How it works is that we forecast based on the current data and as soon as the model accommodates getting the new information, that's what I was trying to say. So, I don't think we raised any kind of problem with respect to the data deterioration or something like that, at least not not in our project.	
33	Re-searcher	Okay. What types of models were used? Were they machine learning or deep learning models?	
34	R2	So, we used by Bayesian methods. Basically, we tried linear models and exponential models based on that Bayesian model that was the basic model that we use that as soon as new information arrives, it updates the forecast based on the latest information seen. And that was the core i think of in our project. And apart from that we use the Monte Carlo simulation and that thing.	MS
35	Re-searcher	Okay. So, what is the importance of model selection? How does it affect predictive maintenance implementation?	
36	R2	In my case, it was obviously the model selection impacts. Because it is the So, in case of linear model, definitely the signal will vary linearly and it is difficult to assess when there is a certain impact on the signals. That's why we tried	MS

		the exponential model and with exponential model, we saw that when there is a rapid change in the signals that is, it is easier to assess the impact in the case of those models.	
37	Re-searcher	Okay. Coming to organisational context, with respect to demographics of the organisation, do you call your organisation large or small, medium large?	
38	R2	I think Volkwagen is large.	
39	Re-searcher	And, what is the type of the industry?	
40	R2	Yeah, that is automotive.	
41	Re-searcher	Okay. Fine. Do believe whether the size or type of the industry has any impact on predictive maintenance implementation?	
42	R2	Yeah. Certainly. I mean, I would say that this is a Volkswagen is an automotive industry. And as soon as we figure out one machine that I think that product is already ramping up. And I think it will continue to do so with respect to the multiple industrial, multiple factories or all the plants.	OS-IT
43	Re-searcher	Okay. Usually, implementation of new technology involves cost of implementation or financial risks are associated with that. Do you feel like having the higher cost of implementation affects the implementation? Was there any concern due to this?	
44	R2	I do not understand the question exactly. Is it like the financial risks associated with the project?	
45	Re-searcher	Yeah. Any risk associated with the project or cost of implementation? What? Is it a factor of implementing PdM?	
46	R2	I don't know. I mean, maybe I am not the right person to answer this. So, I did not see any financial challenges. But yeah, I was just an intern. Maybe it was with respect to the managers of the department or the in between I mean, different departmental discussions. I may not be a part of it.	CO
47	Re-searcher	Yeah, fair enough. I understand that. I have another question, it's related to top management decision support for the implementation. Do you believe the having top management support is necessary for the implementation? How beneficial is it to have their support?	

48	R2	Yeah, I think it always helps. And I think it gives the confidence that okay, when the management is supporting, and I think sooner or later, the management is also understanding the impact of the artificial intelligence it is, I mean, it is driving the multiple industries, especially with respect to the predictive maintenance, that is, where it is changing the way how the maintenance, or you're saving a lot of cost as well, and improving the production efficiency as well. So, I think it's, it's overall win win, and I think they are realising and we had the support, and I think it's always good to have their support.	TMS
49	Researcher	Okay. Apart from you, in your organization, were they already had any existing domain knowledge or technical knowledge with respect to predictive maintenance implementation?	
50	R2	No, I don't think they had. But I think it was mostly done by my supervisor, my PhD supervisor, who had I think, some idea and the other was part of his PhD thesis. So, I think he was the one who was explored most of the the project.	EK
51	Researcher	Do you consider whether this will impact? like not having existing knowledge in the organisation, does it impact the implementation? Maybe your supervisor has it, but the organisation was like utilizing the knowledge of your supervisor, do you think it will have some kind of impact on the implementation?	
52	R2	I think it will. It may have a bit of impact with respect to support of the project. But I believe that knowledge transfer is always I mean, in my team, it was quite active that we the knowledge transfer person, teachers, guides about the how the support could be done, how the models are deployed, and I think that is vital in any organisation.	CC, EK
53	Researcher	Usually, the implement productive mentor maintenance implementation involves multiple teams or technologies all working together, how the knowledge transfer was shared among these teams?	
54	R2	So, it is always very important when developing the models, there is always, I think. Two or three teams which have the people in real time in the on the production line, who are having to have to deal with the machines, they also have some knowledge. And then there is our IoT team who has installed the sensors in these machines. And then there is the technical team, who is always working on exploring the models, that is when development of the model. And after development at the time of deployment, there is always	CC

		another operations team or support team, who has idea that how the models are corresponding, how the systems are working with respect to the the technical deployment of these models. And so, there is multiple teams and play and I think there may be more teams which are missing. But yeah, at least I guess, four or five teams are.	
55	Re-searcher	Okay. And do you believe whether the effectiveness of collaboration and communication among these teams affects the implementation?	
56	R2	Yeah, certainly. I mean, the more information you get, because they are it's not everyone has their own set of knowledge. It's just like that, you must have heard about the big picture of the elephant and each person is seeing their own views. And they don't know that they don't know that exactly what how what the elephant is like, but they are exploring a bit little bit area. So, it's all about bringing the knowledge together and then exchanging ideas. And then, I mean, that makes the project successful. That makes a big that is the basic for any of the project in IT.	CC
57	Re-searcher	Were there any awareness or educational programmes in the organization to support the implementation?	
58	R2	I don't think from organisational perspective there was any programme. But it was an opportunity for us to learn I mean, So, my internship, I mean, definitely, they won't expect that me I have all the knowledge. So that was itself a programme that I learned in that position. And my supervisor also was exploring and working on his PhD thesis, I would say that was itself a programme to learn and research and explore.	AE
59	Re-searcher	Are you aware of any, any of the competitors which Volkswagen have who have also implemented predictive maintenance?	
60	R2	I don't know. What I mean, I am thinking that probably it is Bosch. It is already doing maintenance to a very huge scale. I'm not sure. I mean, how? Or in what perspective, but yeah, they are. And I think most of the companies are trying because it is a I mean, with respect to the manufacturing, and it is very critical to get those details and go together to be aware of the maintenance in order to be more efficient and save more cost.	CP
61	Re-searcher	Do you believe that organisations are implementing predictive maintenance to create a means for competitive advantage?	

62	R2	Yeah, I think not specifically to our competitive advantage. I mean, that I believe that would be the indirect goal. But the goal is, obviously in saving the cost and in making more production more efficient. I think that is the most primitive goal of predictive maintenance.	CP
63	Researcher	Okay. Do you feel having the competitive pressures will have any kind of impact on the implementation in the organization?	
64	R2	No, I don't think so.	CP
65	Researcher	Okay. Overall, what are the benefits of implementing predictive maintenance in any industry?	
66	R2	Yeah, I think the foremost I think I already told that I think foremost is that there is a low downtime of the machines and efficient production and naturally saving of cost.	
67	Researcher	Okay. What are the major challenges companies face while implementing predictive maintenance?	
68	R2	I think the most important biggest challenge is the think retrieval of the data, getting the data from the machines. And I think rest of the things I think it's not that easy. But still, comparatively, once you have the data, I think it's, it's a bit easier, but yeah, retrieving the data. I think that is always the most challenging thing.	DM
69	Researcher	I think I'm done with the questions I had for you. Do you like to bring up like any other points? Are there certain factors which I may have missed? Do you like to add something?	
70	R2	Oh, no, I think it's, it's fine. I just have one question like, how is your research is oriented about the the theoretical aspects of the predictive maintenance like how is it affected in across organisations and how is it I mean, I'm not finding the right word for it, but yeah, I mean, how is it overall driven in the industry in the current time.	
71	Researcher	Usually like are these other factors which I covered, they are impacting the implementation mostly later which I covered, how the data is managed or what is the model selection and how the IT infrastructure is already existing in the organisation in terms of technical aspects. And in terms of organisational aspects, these decision support from top management to has some impact and other things like having the effective collaboration and communication and existing knowledge, like, if they have a certain domain knowledge or technical knowledge that will also have some impact in the	

		implementation and certain industries, like if you take small or medium industries, they they are more concerned about the cost and financial risk. Maybe it is not the case for large industry. But for small companies, definitely that has the impact and also the others or some industries are not knowing like what to implement the in having the competitive pressure or they want to gain competitive advantage. So, they are trying to implement predictive maintenance in most of the cases. So, that also has some kind of impact. And coming to environmental context, this, like having the external support. In your case, there was no external support, but some companies are using a third-party vendor. So, for the implementation, since they don't have the technical expertise for implementation, having the third-party vendors also has an impact like there might be delays or like financial things associated with it. So, these are the factors which are impacting. So, I wanted to I got these from the literature review. And I wanted to know, through our thesis, like how these factors are in practical scenarios when you are really working on it, to what extent these factors will influence that was the main theme of this interview. We wanted to know the difference between the relevance between theoretical and practical knowledge of this predictive maintenance implementation.	
72	R2	Interesting. So, yeah, I mean, definitely, I would be interested in will be, but I mean, is that your, would it be possible to have access to a report or dissertation once you are done?	
73	Researcher	Yeah, once we are done with the report, we will share that report. And also, this meeting, whatever I'm recording, I will transcribe them in the conversation, and I'll share it with you. If I have interpreted all the information correctly. If there are any missing things where I need to update, you can let me know so that I can modify it accordingly.	
74	R2	Yeah sure.	
75	Researcher	I also shared with you the consent form from university or for having an interview, you can sign it and send it to if you have any other questions. So, you can let me know.	
76	R2	Sure. I will. I mean, yes, certainly. Just give me a couple of days, and I will send it back to you.	
77	Researcher	Yes. Do you have any other questions for me?	
78	R2	No, I think it's, I think I don't have any more questions. I will just be interested to see I mean, the result of the thesis, like how does it because the field is interesting. And it's always I	

		mean, good to know what is exactly happening, whatever the experts have the information on, what do you think about it?	
79	Re-searcher	Yeah. It's interesting for me as well. This is the first time I'm also working on this topic. I had a background in IT earlier. So, this is new aspect for me as well, to know, the machine learning and AI part of implementation	
80	R2	Yeah, but it's fine. I mean, it's not that difficult. I'm sure that it is. me it is not that easy as well. But yeah, just do it as you can catch up with. You want to get into the that. Just that what you pursuing and be perseverance. Yeah.	
81	Re-searcher	Okay, then. Thanks for today. Thank you for sharing your knowledge. collected some valuable information. Thank you.	
82	R2	Thank you. It was pleasure talking to you. I wish you all the best.	
83	Re-searcher	Thank you so much.	

Appendix 4: Interview 3 (R3)

Researchers: Swapna Malagi, Sathya Ruba Selvaraj
Respondent 3 (R3): Anonymous
Industry Type: Aircraft
Country: India
Date: 22-05-2021
Interview Length: 48 minutes
Language: English

Themes	Factors/ Sub Themes	Code
Predictive Maintenance Implementation	-	PdMI
Predictive Maintenance	Other Factors	OF
Technological context	IT-Infrastructure	IT-I
	Data Management	DM
	Model Selection	MS
Organizational context	Organizational size and Industry type	OS-IT
	Top Management Support	TMS
	Existing Knowledge	EK
	Collaboration and Communication	CC
	Cost	CO
	Awareness and Educational efforts	AE
Environmental context	Competitive Pressure	CP
	External Support	ES

Note: Initially, we (Researchers) introduced ourselves and gave the background of the thesis to Respondent. Upon asking the consent to record the meeting, the following meeting is recorded and transcribed as below.

Row	Person	Transcription	Code
1	Researcher	Can you tell us about your background and education?	
2	R3	Yeah, sure. So, actually, I have done my masters in power electronics. Then I have done my PhD in health monitoring of IGBT (Insulated-gate bipolar transistor) semiconductors from IIT (Indian Institute of Technology) Kharagpur. Right now, I am working in an Aircraft Industry in India. The work is similar, as in my PhD, I have done health monitoring where we have developed some algorithms for continuous monitoring of health of the semiconductor device, so that before the fault, we can predict the fault kind of those work we	

		have done in PhD. In this organization, basically our team is focused on improvising the maintenance or we can say that we want a smart maintenance system where we don't have to do the scheduled maintenance. Based upon the data and based upon the forecast of our methods, we can say that whether the maintenance is required or not. Along with that, we are working on similar kind of project like predicting the fault, detecting the fault, isolation of the fault and forecasting of the fault. So, these are the kinds of work we are engaged with. And it is kind of similar domain I think what you are looking for. That's all pretty much about my education and background.	
3	Re-searcher	What role are you playing in the organization?	
4	R3	I am actually in R&D (Research and Development) in IVHM (Integrated Vehicle Health Management) Team, where we do futuristic things. So, our work will not come to market soon. Because in aerospace industry it is very difficult to get any-thing out. You do research and you cannot publish papers also, it is very confidential here. They will maintain a very much good secrecy. Because it is related to again defense and space, the technologies are everything related to the reli-ability of the aircraft. So, they don't disclose actual proper work. Basically, we are a team of five, who are doing R&D means developing the futuristic algorithms for fault detection isolation and prediction.	PdMI
5	Re-searcher	Okay. Are you helping your organization to implement the predictive maintenance or are you in the process of doing it?	
6	R3	Yeah, we are in the process. The predictive maintenance they are improving the maintenance. But the type of work we are doing, yes, we have the maintenance team with us and we know how they work and what are the problems associated with it. Because of that only we are doing something futuris-tic work.	PdMI
7	Re-searcher	Okay I understand. So, predictive maintenance, is it a data-driven or model-based or knowledge-based, how is it imple-mented?	
8	R3	So, previously it used to be like that it should be knowledge-based. Because the knowledge of the aircraft it is very im-portant. But for now, what is the problem we are facing is that for data-driven actually the market and every trend is go-ing towards the data-driven analogy and they are fast robust. The problem before it was associated is that the amount of space or memory it is taking to execute any operation. So, in	PdMI

		that case in aerospace if you want that much space, then again it is going to cost us a lot, again it is going to take another type of research level that whether we can put it there or not. So, in aircraft industry, you can see in papers also the same trend they are going to work on that is also not implemented. It is again in only analogy and only theories that they will implement onboard something and offboard something. So, what they will do with the different kinds of data, they will train the models offboard. Then they will place it in the plane. So, there is some of offline analysis as well as an online analysis, this is kind of a hybrid system. As well as this is what they're trying to do instead of totally depending on the data-driven thing, at some point which can mislead you. Because, if you see the failure phenomenon of an aircraft, it is very random. Each aircraft is different from another, each aircraft failure is different from another aircraft failure. As the aircraft is very random from that also you cannot do anything. So, they're developing some models, developing some what you call ‘degradation models’ of aircraft from that they are generating data. From that data they are training the models. Another thing we are doing is that it will be half model-based and half data-driven wherever we have data. For example, we have the actuator failures in aircraft, there we have a lot of data in that case. But for engine failure, we don't have that much enough data. So, because of that different systems and sub systems, we can approach different way based upon how much data we have. Even if we have a lot of data, whether the data is reliable or not. If every data is random, then you cannot come to a conclusion. Then you need somebody who is knowledge-based, machine learning won’t work there. So, in that way we are proceeding in the aircraft industry.	
9	Researcher	So, it is mostly a hybrid implementation then?	
10	R3	Yeah, it is mostly a hybrid kind of implementation where we have models and plane data-based or combination of both.	PdMI
11	Researcher	Yeah, okay. Whether this implementation is in built or any third-party vendors or external support is involved in the implementation?	
12	R3	See, these things are not implemented in aircraft yet. These are only in theory. Because in aircraft nothing related to AI or machine learning has been implemented yet. That is the harsh truth. This is the new generation or trend; they want to implement it. Because there are problems with the solution of memory, everything is going to solve in future. That's why this is 20 years forecasting project. So, what we do is totally	ES, PdMI

		a futuristic work. Now, they don't do it. Yes, they have developed some models, which is not related to AI for reducing the maintenance. They are doing the offline analysis, offline means after once the flight is taking off. Then they will log into that database and take all the data. Over five months to six months data they are getting and from there they can predict that which parts are degrading, which parts needs maintenance. So that type of offline side by side a kind of an analysis is going on. But actual online implementation direct AI based nothing has been done. Everything is on paper.	
13	Researcher	Is it only applicable for your organization or your entire aviation industry?	
14	R3	Yeah, it is an entire aviation industry. Nowhere artificial intelligence has been implemented yet. They are in the process or they want to implement it and they are going in that direction.	
15	Researcher	Okay, I understand that. Um, Okay. You have not implemented or you're still working on the process of implementation. Can you explain on the high level like how will be the implementation you guys are aiming to implement?	
16	R3	No, no. What you can say I mean do is you tell me that what you have done so that whether it is feasible or not, I can tell you depending upon our current situation.	
17	Researcher	Okay. We have not implemented it. But it is like mostly the companies will get data from the machines or equipment. So, they have these IoT sensors along with their machines. So, those IoT sensors will collect temperature or vibration or a specific machine data which will give the industry so, like, what is the health of the equipment. Based on using those data, they will also use the knowledge they have on the machine like when is expected to degrade or when it is expected to expire or something like that. So, based on the actual data and historical data they build this machine learning model, so, we can forecast and then predict when what is the remaining useful life of the machine. So, based on that they will plan or schedule maintenance of that particular equipment. So, it will save so much of their time. Because when the equipment is entirely like broken down without any forecasting, so, it may cause production stop. So, this will impact them. So, what is your process, how it is done in the aviation industry?	
18	R3	Yeah, it is similar kind of thing and yes, here also yes. At last, see there are three-four segments, right? First is if a fault occurs, then if already fault is there, then first step is to	PdMI

		detect the fault. So, there also you can use your AI methods and we are working on that to detect the fault occurrence. Now the thing is to identify which type of fault. In machine learning, it comes to various models that which model is able to identify which kind of fault. So, what we are doing is we don't know that which kind of fault is going to be efficiently detected by which method. Right? So, what we are doing is we are producing the methods in a bulk. We are taking the chance for every kind of methods whichever is available. And we are making a database that which is performing better in actuators, which is performing better in engine data, which is performing better in other parts of the aircraft. So, we are doing like that. Now, as the whatever data we are getting, they are dependent on various parameters like temperature, the altitude everything. Right? So, maximum in aircraft what we are extracting is the vibration data, current, voltage, pressure and temperature. So, these are the important things which changes over when you will come to land then these parameters are different and when you go up to a different altitude, these parameters are different. Right? So, taking care of those things, then what we are doing, we are passing every fault to all type of algorithms to see which algorithm is performing better in this case. So, what is the problem with the existing scenario in aircraft is that we have threshold levels means we have a binary decision whether the fault is there or not. Means if you have ever seen the cockpit, there you can find there are various colorful signals, lights are there: on, off, maybe in between one transition this type of switches are there. So, there you can see inside the aircraft, what they will do is that for example, let's say for an electrical engine to fail, let's assume it will take it 10 amperes of current. So, they were providing a threshold value, so that if it will cross the threshold value then the fault is there. And then from that, they are deciding that fault is there, so you have to do some backup plans. So, based upon that they are doing. Now we don't know whether that 10-ampere sudden increase, whether that is temporary it will go away because of some temporary short circuit or it will remain in the circuit. So, this type of situation we are taking care and what we are seeing is that machine learning algorithms are really able to do it actually. So, up to which we have seen that SVM (support-vector machine) model, the Gaussian mixture model, the hidden Markov model, these methods are able to classify the temporary faults to the continuous world which is already there. They are able to classify these faults. Now, the thing is that for one type of data set, they are able to classify. So, we have to check it with all possible type of data again whether it is short time for short circuit, then short time for any other type of fault. So, there are so many cases. So, fault	

		classification as well as taking those fault classification data with various aircraft, with various models, taking care of different temperature, different altitude, different parameters, we are generating data as well as we are seeing which methods are more applicable. And in machine learning, they are able to classify the data which is better than the threshold method. For real time application, we are using a hybrid method like using particle filters, Kalman filters, right? So, these are the hybrid filters, which are tracking the real time system. And after that the fault isolation, prediction everything can be done with the machine learning methods, that's what we have found. So, we are working on that, and it is not yet finished. It will take maybe more than one year because of the amount of data, our stakeholders and everyone wants and the number of algorithms, all the algorithms we have to do, right? And we have to check which is working best. Based on that maybe we can provide a solution that for this type of faults, we can implement this type of algorithm. So, this kind of thing we are working on.	
19	Researcher	Yeah. I understand. Did you have any necessary IT infrastructure when you started working on this? Or like you had IT infrastructure required for the predictive maintenance implementation?	
20	R3	I don't understand, IT infrastructure means?	
21	Researcher	In the sense, like necessary servers, data collection systems, services and facilities required for this implementation.	
22	R3	Okay, okay. No, no, actually, as I told you we do it in a small proof of concept type of thing. So, for that, we don't need that we only do it for validation. And as I told you, this is the R&D group. Right? So, for validation and verification, we only provide them the results from our simulation, from our analysis. This is not in implementation stage. We have not implemented to any real aircraft or we have not seen whether it is working or not.	IT-I
23	Researcher	Okay. So, regarding existing competence, did you have any existing competence about the predictive maintenance or you have developed the necessary competence while working on it?	
24	R3	Yeah, I have developed it while working on it. Also, my PhD theses are also related to similar kind of thing. After coming here, they have a short kind of a training which explain to you about reliability, availability, these things. From there you can start working. This is the normal scenario.	AE

25	Re-searcher	Then, how the data is managed? you have been collecting different types of data right? how this data is managed organization?	
26	R3	So, these data are generated by us only. So, we are managing it well.	
27	Re-searcher	Do you have a separate team who is managing data who will be like working on collecting the data and then giving it to you or your team who is working on this?	
28	R3	Yes, yes, as the modelling thing we are doing so, the model generated data we are managing. But we are getting data from our stakeholders in Germany and Paris. They are providing the real time data from the aircraft.	DM
29	Re-searcher	So, it is mostly the real time data used? or any synthetic data is involved?	
30	R3	Yeah. We are using synthetic data as well as the real time data to evaluate all our algorithms.	
31	Re-searcher	Okay. And then, if you have any missing information or any process information is missing in the data, how those affect predictive maintenance implementation?	
32	R3	Yeah, it becomes a really big headache because, you know, sometimes the data are not labelled at all. For that, we have to develop some unsupervised learning type of methods. So, where you even if you don't know anything about the data, whether which type of data, from where it is coming, still you can say that these are the problems associated with the data. Simply the unsupervised outlier detection things we can do on it. So, that is what we are doing. In our organization they are trying to actually extensively evaluate these methods. So, they are providing us unlabeled, labelled data and the data with missing values, data with sampled and random sampling frequency sample and different types of things. So, which is very challenging and on which we have to see that how the algorithms are worked. So, we have different kinds of data. It is actually affecting because, when you have a missing value in between that missing value if your features are changing. So, in that case the even if the change in that feature is missing then what the algorithm will detect is that there is no fault. But if the fault is there, then it will be a big blunder. In real time systems sometimes the bit missing concept is very normal what I have seen in real time data. So, that is very important. There are so many times that we have	DM

		failed to detect the fault but their fault is there in the data. So, that is what is happening.	
33	Re-searcher	Okay. Are you using machine learning models or any deep learning models are also used?	
34	R3	No, not yet. Only machine learning models we are using.	MS
35	Re-searcher	Okay, what are the most commonly used machine learning models?	
36	R3	Most commonly used is SVM (support-vector machine). Its performance is very good. And we are exploring Gaussian mixture model, gaussian mixture model is good. Isolation forest is very good when you don't have any idea of the data. Isolation forest actually was very good. And yeah, k-means clustering is a universal way of classifying faults. But k-means has some disadvantages, you have to provide the number of clusters. It is possible that not only anomalies are there, apart from the anomaly, the other things are there. You actually cannot classify whether it is an anomaly cluster or any other cluster. So, it is quite difficult with k-means. But as we have knowledge about the data in that case, you can do it. But for without unlabeled data and missing value data also SVM works pretty well as well as the gaussian mixture model. These two methods are working pretty much well.	MS
37	Re-searcher	How important is the model selection for the implementa-tion? Does it affect the PdM implementation?	
38	R3	Yeah, yeah it is. Because what I have seen means if you have samples of 10,000 right? some methods work really good when you provide full sample data. And some methods like k-means clustering if you to train it more or if the size is more then it will give you more better results, the anomaly detection is better. But when you cut it and provide them just for real time, you know you need very less amount of data. So, for that case, if you change it to 1000 points then it will give you not that much good data. But some methods like a hidden Markov model, even if the data size is very less it will give you very good output. So, data size is very important.	MS
39	Re-searcher	Okay. Moving on to the organization factors. How do you call the size of your organization? is it small or medium or large?	
40	R3	Our organization is a large organization. But our team in the organization is small.	

41	Re-searcher	Okay. Do you believe that having, like, the size or the type of the industry or whatever type of production they are involved, does it affect or impact predictive maintenance implementation?	
42	R3	Yes, predictive maintenance implementation totally depends upon the industry. First the 'type of industry', because if it is just a maintenance of simple motor or machines, right? then it is very easy to implement. You can go and directly implement; you can check whether it is working or not. But for aircraft, they will not directly do it because the reliability factor is very high. Here whichever technology goes on board goes through an extensive evaluation and everything. So directly implementing is very difficult in case of aerospace industry. And another thing will affect is that, yes, when the organization size is small and you have less infrastructure and everything, then it kind of limit. In our case, we don't do the direct implementation. We provide them with the R&D solution, and they implement it. So, for the implementation case directly to aircraft, even if simulating the iron bar, even that part we don't cover it. We just provide them the solution. Yeah. And so that's why the industry type is very important that in which scenario you are working and all for implementing the predictive maintenance.	OS-IT
43	Re-searcher	Okay. Also, the implementation involves a cost of implementation or the financial risks associated with it. Do you believe like, these factors are like the cost of implementation or financial risk affect predictive maintenance implementation?	
44	R3	Sure, it is. Because at the end, whatever product goes out from industry, at last it will give you some revenue, right? If it is not giving you any revenue or saving the cost of maintenance, then there is no use of it. So, the cost whether the industry is ready to invest that much of cost and that much of risk or not, that is also an important thing. And it is actually costlier and riskier than normal maintenance schedule. So, in the long run, if it is not going to give you a revenue which is more than the normal scenario then obviously it will not be implemented.	CO
45	Re-searcher	Is there any hesitancy towards adopting or implementing this one, due to these concerns?	
46	R3	Not due to the cost concerns, the risk associated with it is much more concerned. In our organization, they are much more concerned about the risk. As well as yeah, risk is the main thing that whether it will work or not. Because even if the machine learning methods are working very fine and if anything changes, it will not be able to do means it is not that	

		much mature that it will automatically do everything. So, for that mature level we have not gone up to that. So, that's why it is a risk factor obviously. So, there are some parts of the industry that they don't want it, they want a normal one. And there are some parts of the industry that they want it and they want new things, they want smarter things. This is how it works.	
47	Re-searcher	Okay, in your organization, the decision to implement predictive maintenance, is it supported by top management?	
48	R3	Yes, obviously, otherwise, they will not fund this type of R&D research.	TMS
49	Re-searcher	How important is to have the top management support in this kind of implementation?	
50	R3	It is important. See, because in industry the larger decisions everything is made by them. So, if they don't support it, there is no way to do it. So, it is obviously important, their support is very important.	TMS
51	Re-searcher	Okay. Also, like implementing predictive maintenance it involves multiple technologies or multiple teams are involved in implementing. How important is the collaboration and communication among these teams?	
52	R3	Yeah, it is very important. Because see, we are doing something which is futuristic. There are teams which are doing the normal maintenance thing and they are improving the maintenance slowly. So, we have to keep in touch to discuss about the problems associated with the normal maintenance, which is not online that scheduling, that maintenance, what are the problems associated with that. So, we have to collaborate. Otherwise, see what we will do is that we will forecast, we will come up with something which may be very good theoretically, but maybe it is not related to our industrial problem at all. So, that's why the collaboration between different groups is very important, which is related to your work. Like in our case, the maintenance group is in our collaboration, the commercial aircraft maintenance team is also in our collaboration. So, we are in connecting with them on and off to get to know that the what they are working, which kind of problem they are facing, right? So, that is very important. Without that we cannot proceed because that is the ground level, that is the biggest level from which we have to start.	CC

53	Re-searcher	Okay. How is the knowledge transferred or shared among these teams?	
54	R3	Yeah, in our organization the culture is very good actually. And whenever like I am doing in machine learning and if somebody else is doing in modelling, generating the degradation model and everything, then in that case, what we do is that on weekly basis, or monthly basis whenever we are free, we do a knowledge sharing session, where I present whatever, I have done, I make sure that they understand whatever I have developed and everything. And they make sure that I understand that whatever kind of modelling they have done. So, these knowledge sharing sessions are very important. So that whenever I am doing something that I should be capable of visualizing things which modelling people are doing, right? Even if I'm I don't have expertise in that, I should be able to know that what they are doing. So that is where knowledge transferring is very important. In our organization, even between the groups, different departments also we have seminar kind of things where they show their work, we show our work. So that type of inter collaboration and inter transmission of knowledge is there which is very helpful and which is very good also.	CC
55	Re-searcher	So, we talked about the knowledge transfer. So, do you believe collaboration and communication among the teams affects predictive maintenance implementation?	
56	R3	Sure, obviously. Indirectly, directly it will affect the predictive maintenance. Because predictive maintenance is not just a single person work, right? It is a total industrial work. So, collaboration is really very important.	CC
57	Re-searcher	Okay. Are there any awareness or educational efforts taken by your organization to support the implementation?	
58	R3	Yes. They have a set of trainings which talks about different cycles, which is important for your implementation of maintenance and everything. They have a set of trainings. Apart from that different groups have different skill sets. So, based upon that they keep on updating the trainings.	AE
59	Re-searcher	Okay. All right. Having these awareness programs, does it impact or affect any form of implementation?	
60	R3	See, because of the awareness only people are coming forward. They are really eager to do some research or develop some methodology as well as implementing that method to real system. Because of this awareness only coming. So, this is the important part. Everything starts from the awareness, right? So, the knowledge they share everything. So, from that	AE

		like even if small cases, right? that the carbon emissions should be less. So, it starts from the awareness, then industry work on that then the different team starts work on that how to reduce the carbon emission. So, this similar kind of thing that it will start from awareness only.	
61	Researcher	Okay. Are you aware of any of your organization competitors, who are also working on implementation of predictive maintenance?	
62	R3	Yeah. Boeing also working in a similar field. They are also trying to make the Aircraft more intelligent with machine learning methods. So, predictive maintenance is the one of the main concerns because predicting the fault before it occurs is the main concern to every aerospace industry, right? So, every aerospace industry is working towards that. For my knowledge, Boeing has a team in India also they are working on that.	CP
63	Researcher	Okay. Do you feel or experience any competitive pressures to implement predictive maintenance from your organization?	
64	R3	Yeah, kind of. Because everybody wants that technology to onboard as soon as possible, right? And for this research, as it is in a research and development stage, we have different TRL (Technology Readiness Level) levels to pass to get on onboard. So, for crossing each TRL level, we are facing a lot of pressure from our counterparts to overcome and pass the TRL process because of the competition. Because as soon as we will cover the up to TRL seven, then only this will be implemented in the aircraft. So that's why it is a very competitive scenario.	CP
65	Researcher	Okay. So, it is like your organization is implementing predictive maintenance to create a competitive advantage, I can take in that perspective, right?	
66	R3	Yeah. See, in aircraft industry, predictive maintenance will increase the safety of the aircraft, right? which is very much important. So, if safety is increased, then obviously they will know and they can sell it in different manners, right? that our aircraft is much safer than the other ones. So yeah, in that case, it is very important.	CP
67	Researcher	Okay. You mentioned earlier that you are working in R&D department, so there are no external vendors or external support is provided for predictive maintenance implementation, right?	

68	R3	No, there is no external support. Only the real time data is provided from the counterpart. So, that is only provided by them.	ES
69	Re-searcher	And also, we talked about your competence, you have developed it while working on the implementation, the competence to implement predictive maintenance you have learned. But did your company already had any existing competence related to domain or technical knowledge?	
70	R3	They are actually in a building process. Because this team is new and they want a competency like predictive maintenance as a competency pillar in our organization. So, for that they are working on it. But, for now, they don't have such thing. But they are working on it. There is a team working on this which is our team only and in collaboration with another maintenance team we are working on it to make a distinguished pillar in our organization as a predictive maintenance.	EK
71	Re-searcher	Okay. Now you are in the process of improving the competence. Do you believe like having existing knowledge in the team, does it have any impact on the implementation of predictive maintenance?	
72	R3	Yeah. Because, when we started, we also gone through a small set of trainings for this setting. So, it is very important because, if somebody is experienced, that's a different thing. But if somebody is new, yes, you need some person who will train you or give you the knowledge what it is required. So, it is very important. If somebody in company already is there then it is obviously an advantage that you directly can know what is going on and directly work on that.	EK
73	Re-searcher	In general, what are the benefits of predictive maintenance?	
74	R3	Yeah. So, the main reason we are heading towards the predictive maintenance because, here first as I've already said that safety is main concern. In predictive maintenance, the safety, reliability and availability: these three things are increased and which are very important for any kind of industry, right? And these three things of any machine will increase with the predictive maintenance as well as these are for scheduled maintenance, right? Apart from it, added advantage is that for any catastrophic failure: for short circuit, for sudden failures, also these tools can be used to directly detect the fault. Again, after detecting, how to isolate and how to turn on the backup thing also that can be done and can be included inside this. And after the fault occurrence	

		which kind of precautions we can do that is also included inside our work. So, in overall this predictive maintenance is giving you the forecasting and the fault detecting normal way as well as the scheduled maintenance which is increasing the reliability, safety and availability of the aircraft. Availability of the aircraft is also very important because how much available the aircraft is for flying. If the aircraft's some part is broken and you didn't know that it is broken. And suddenly it broke and then it went down and then the aircraft will not fly, right? So, in that case the availability cost of the aircraft is much more and with this predictive maintenance, the availability of the aircraft can increase by at least 10 times which will reduce the cost. So at least every industry wants to make to reduce the cost on maintenance as well as your availability in aerospace industry. So, for that the predictive maintenance is very important which is going to reduce the cost as well.	
75	Researcher	Okay. Also on a higher level, what are the challenges of implementing predictive maintenance?	
76	R3	Challenges in aircraft industry are the lack of proper or reliable data, that is the main concern. Also, the reliability of the machine learning methods is not that much that it will be directly implemented on aircraft so, that is where the problem is there. But yes, this predictive maintenance is going really in a good way. And we are maturing the algorithm, we are maturing with different kinds of data; the number of data is also coming forward. So, that's why when this memory space and everything will come together, I think it will be implemented and there will be no obstacle. But for now, we are facing this type of issue.	
77	Researcher	I think I covered pretty much all the factors which wanted to ask for during this interview. Would you like to add any other points or any other factor which I may have missed? Anything you want to add?	
78	R3	No, I think. I pretty much covered everything all the challenges with larger data sets, smaller data sets with missing values also pretty much covered, I think. So, take care of these things when you go and write your thesis.	
79	Researcher	Yeah, sure. Okay, then. I think that's it we had for today. Thank you for joining us.	
80	R3	Thank you for inviting me. It was really great to talking with you. I also explored and retrospect a lot of my work while talking with you.	

81	Re-searcher	Yeah, it was nice talking to you as well. I collected a lot of information. Thank you for sharing your experiences and knowledge.	

Appendix 5: Interview 4 (R4)

Researchers: Swapna Malagi, Sathya Ruba Selvaraj
Respondent 4 (R4): Anonymous
Country: India
Date: 05-06-2021
Interview Length: 32 minutes
Language: English

Themes	Factors/ Sub Themes	Code
Predictive Maintenance Implementation	-	PdMI
Predictive Maintenance	Other Factors	OF
Technological context	IT-Infrastructure	IT-I
	Data Management	DM
	Model Selection	MS
Organizational context	Organizational size and Industry type	OS-IT
	Top Management Support	TMS
	Existing Knowledge	EK
	Collaboration and Communication	CC
	Cost	CO
	Awareness and Educational efforts	AE
Environmental context	Competitive Pressure	CP
	External Support	ES

Note: Initially, we (Researchers) introduced ourselves and gave the background of the thesis to Respondent. Upon asking the consent to record the meeting, the following meeting is recorded and transcribed as below.

Row	Person	Transcription	Code
1	Researcher	Can you tell us about your background and education?	
2	R4	Most of the things I've already told you earlier. So, I'm a chemical engineer by profession by qualification. Most of my life I spent in refinery operations, process automation and process simulation. And for last five years, I've been doing the predictive analytics and analytics vertical data to value projects.	

3	Re-searcher	Okay. Can you tell us about your role which you are playing in the organisation? How it is correlated or how your work is correlated to predictive maintenance implementation?	
4	R4	Yeah. So, in terms of predictive maintenance, total for me and there are four verticals which I take care. So, the first is data to value where we have to extract the data and I have to take care of the plant historian servers, like Aspen ip21, and OSI pi. So, our team takes care of this portfolio right from the data generation perspective, so, that's the first thing. And thereafter, we are responsible for an application called Trendminer for the process optimization. So, process optimization, when I say there are many different methodologies to do process optimization. But here, we are mostly talking about process optimization from the data analytics perspective. So, again, the historical data is taken into consideration for optimization of the processes. So, what I mean by process is the plant chemical processes specifically. So, that is my second role. And third comes the predictive maintenance. So, in terms of predictive maintenance of we are mostly using applications called Prism. So, Prism from Aveva Schneider Electric is one of our main tools which we use for the predictive maintenance activities. And here all the heavy-duty rotating equipment, we prepare models for that heavy-duty rotating equipment. Apart from Prism, we also take care by predicting the remaining useful life of a catalyst, we also predict the remaining useful life of falling off a heat exchanger, we also try to predict any sort of equipment failure well in advance. So, yeah, these are the activities which I've been doing for a predictive maintenance. And apart from this, there is another team who is building the Power BI dashboards. So, at the end of the day, these dashboards you need to visualise because any person is not going to understand whatever models which you have built or the complicated models that you have built until unless you have the dashboards available with you. So, you need to have a dashboard and our team builds Power BI dashboards as well. So yeah, these are the mainly four applications which I've been working for.	PdMI
5	Re-searcher	Okay. What type of predictive maintenance have you been implementing in your organisation? Is it data-driven or model-based or knowledge based?	
6	R4	Yeah, so, when we talk about predictive maintenance in our organisation, it is mostly the data-driven predictive maintenance. And what I mean data-driven is that we take the past historical value of all these equipments and based on the past historical values of these equipments, we are try to generate	PdMI

		the models and we try to generate the healthy condition of the model. And once you have generated the healthy condition of the model thereafter, these models are then made online. And once these models are made online, thereafter, these models try to predict any sort of anomaly which is happening to the overall equipment. For that we take the combined signals maybe from the process, we take combined signals maybe from the vibration monitoring systems, we take bearing data, we take very various sort of temperatures of the bearing and many other parameters which you normally use for seeing the condition of the equipment in terms of condition-based maintenance. And how condition-based maintenance and predictive maintenance are different because here we are trying to detect the anomalies much before any static alarms will tell us. And these static alarms were present for many years, but here we don't rely on any static alarm, but we generate alarms based on the past historical data.	
7	Researcher	Okay. Yeah, I understand that. How is the PDM implemented in your organisation? Is it in built or any external support or third-party vendors are used?	
8	R4	Yeah, so application as I said, we are using prism application. So that application comes from Aveva prism. Aveva and Schneider Electric are the joint venture and they have got this application developed for us. As far as the model building part is concerned, I and my team are doing that. So, we build those models in the application called prism in short.	PdMI
9	Researcher	Yeah. I think you explained the implementation process. Briefly. Maybe I can take the next question. Yeah, we'll come to the technological factors, IT infrastructure. Did you have the necessary IT infrastructure required for predictive implementation when you decided to implement it?	
10	R4	No. Within our organisation, we have been building the predictive maintenance activities. So, it all started way back in 2016. And from 2016 onwards, we started building the infrastructure, especially the IT infrastructure. And still, we are developing those IT infrastructures, we are making it more robust. So, yeah, I would say that from 2016 onwards we started mostly working on industry 4.0 projects. Our organisation is aggressively working and they understand the importance of data-driven methodologies which is very necessary, how machine learning and artificial intelligence could help us in the manufacturing sector as well. Yeah, that's what I would say that we started way back in 2016.	IT-I

11	Re-searcher	Okay. How does this building the IT infrastructure over the period of time has influenced implementation? Did you consider it as a challenge, like not having the existing IT infrastructure?	
12	R4	So, once management is keen to take this any initiatives, then building the IT infrastructure is not a big challenge I would say. So, you always have the support from the vendors, you always have support from other knowledgeable persons who are in the market who can help you to build these infrastructures. So, I think the building the IT infrastructure is never a big challenge. But I would say the biggest challenge in the predictive maintenance or any sort of Machine Learning Initiative is the Change Management, where people should start believing the person who is working in plant, they should start believing this application. Because this equipment they have been monitoring for years together. But they should have faith that these technologies, yeah, they are for real, and they certainly make a difference in their day-to-day operations and it can predict failures. So yeah, that change management I would say is the biggest challenge, rather than I would say that it's the IT infrastructure. For IT infrastructure, I would say that is the easiest part that you involve any vendor like TCS, Accenture, Wipro, so they are ready to support us. And they are happy to build the infrastructure. Also, there are many start-ups who are ready to help in the IT infrastructure part. But the biggest challenge is that change management and to install the sensors. Because until and unless you know you have the sensors in the equipment you cannot do much right, you must have the sensors and then only you can build these models. Most of the time you see that the sensors are not adequate. Once you start building the model, then you realise when you do the equipment analysis and the gap analysis, you understand that the equipment is not having all the required sensors to carry out the predictive maintenance activity. And when it is a running plant, it becomes a big challenge to install the sensors. You cannot stop the overall process and install the sensors. The sensors are quite expensive as well. So, yeah, sensor installation is something very challenging, I would say. So, these are the two main challenges not IT infrastructure part.	IT-I, OF
13	Re-searcher	Okay. Regarding existing knowledge, did you have any existing competence about predictive maintenance in your organisation while implementing it?	
14	R4	Yeah. So, within Germany, our company is a German based company. So there they have got an excellent know-how and knowledge about this machine learning technologies. There	EK

		they have got experts at the global level who takes care of this machine learning initiatives. So, yeah, within Germany we are having experts available. And thereafter, we started building teams across the globe. And then we started building teams in India as well. And there are many certifications which was done by my team. Prior to joining this organization, I also did various courses on machine learning due to my interest in machine learning. And then thereafter when I joined or much before joining the organisation, I was having the required knowledge in the field of data analytics and machine learning.	
15	Researcher	Okay. How does this having the existing knowledge has influenced a predictive maintenance implementation? Do you consider not having the existing knowledge may be a challenge for implementation?	
16	R4	Yeah, so, I would say another human factor to this which is very important is to have the knowledge of predictive maintenance. When we say predictive maintenance, I would mostly say the two knowledge which you absolutely need. One is the data science knowledge, the knowledge to implement the data science machine learning models. So, specifically, we need the machine learning models here. And secondly, the person should have a sound understanding of the process and equipment as well. So, he should have a very good understanding of process equipment and machine learning. So, to get this kind of person in the market it is very rare right, you can get the best process engineer who is well versed with the chemical processes. You can have an equipment expert who is well versed with the equipment. And he has done various sort of vibration certifications and he knows in and out about this condition-based monitoring. And you have got a third person who is a data scientist, who is well versed with the data. But a person who is knowledgeable in all these three areas, it is almost impossible to find, to be very honest. At least when we started back in 2016, it was a challenge to find these kinds of persons. Yes. So, yeah, that is the gist which I was talking about in terms of getting the required knowledge from predictive maintenance perspective.	EK
17	Researcher	Yeah, I agree to that. Having the domain or process knowledge or technical knowledge would definitely help the implementation.	
18	R4	Yeah. And at the same time as I said that a person who is having knowledge in all these three areas they can only	EK

		implement and do the implementation effectively, otherwise the implementation is not effective.	
19	Re-searcher	Okay. What is the importance of data in your organisation? what type of data is used for predictive maintenance? Is it real time data or any synthetic data is used?	
20	R4	So, mostly it is real time data which comes from plant historian servers that is the place mostly we generate our data from. And secondly the data which comes from the breakdown data. So, whenever you have a failure in the plant then you have got a breakdown data which is then locked into SAP system. And yeah, these are mostly the two places where we have this data available.	
21	Re-searcher	Okay. How is the data managed or accessed in your organisation?	
22	R4	What do you mean by manage here?	
23	Re-searcher	Do you have any separate teams who are managing the data and like how effectively it is done?	
24	R4	Yeah, so, as I said, if you see the IT infrastructure and the data, there are two types of data. One is the business data which gets generated and second is the the plant data which is used for the predictive maintenance activity. So, for the plant maintenance and predictive maintenance activity mostly we are using the plant historian data which is coming from the plant historian servers. As I said that server management for the plant historian, it is mostly the responsibility of my team, who is responsible for the server management in terms of the application management. And, if we talk about the management in terms of the IT infrastructure, let's say about the server and all, we have got a central team. They manage everything from a central service in terms of the IT infrastructure management from the IT infrastructure management perspective.	IT-I
25	Re-searcher	Okay. Did you have any missing information in terms of data our process information?	
26	R4	Yeah, that is mostly the case. So, you always don't get the data properly. So, data is sometimes as I said that due to the sensor unavailability, the data is not available. But whatever sensors are present then the data is available. So, it is mostly I would say the sensor availability becomes a big challenge in terms of data availability, because you don't have the instrument to which is well instrumented.	DM

27	Re-searcher	Okay. Do you believe if there are any missing information will that affect the predictive maintenance implementation?	
28	R4	Yes, yes, certainly. So whatever model which we are trying to build here is data-driven models. So, better the data better the model is. And if you don't have a proper data available, then it is definitely going to affect the performance of the model.	DM
29	Re-searcher	Okay, what are the various machine learning models or deep learning models used in your organisation?	
30	R4	So, mostly as I said that we are using prism as an application for Machine Learning, which is a clustering-based algorithm. And it works on the clustering algorithm of machine learning, where the anomaly is getting detected. Apart from that, we also have the pattern recognition systems, which comes from the application called Trendminer. So, there they have got pattern recognition. So, they recognise the various patterns which is happening in the past. And based on that also those patterns can help you to see and check how equipment is behaving normally or not. So, mostly I would say it's pattern recognition and clustering algorithm which comes from these two applications. Apart from that, there are many other customised algorithms for catalyst remaining useful life prediction and also for the remaining useful life prediction for the falling of the heat exchangers and remaining useful life prediction for any other sort of time-driven function where it is related to time. So, there we have used ARIMA models. And those ARIMA models are also used effectively and some of the regression models as well.	
31	Re-searcher	Okay. Does model selection affect implementation of predictive maintenance?	
32	R4	Yes, it does affect. So, you need to have the right model for any sort of predictions. But if we're talking about our predictive maintenance initiative as we are working mostly with a fixed sort of model. So, we are mostly concerned about the anomaly detection at this stage.	MS
33	Re-searcher	Okay. How do you consider your organisation, is it a big organisation, small, medium or what is your organization size?	
34	R4	It is a big organisation.	
35	Re-searcher	And the type of the industry like what type of industry?	

36	R4	It’s a chemical process.	
37	Re-searcher	And do you believe that considering the organisation size and type of industry does have any influence on the implementation of predictive maintenance?	
38	R4	Yes. I do understand it because the bigger organisation as they can always get the best infrastructure available in the market. So, that is the leverage the bigger organisations get. And also, they have got more capability to buy those infrastructure and they can have a sustainable solution. Apart from that the peers who are small organisations, for them it becomes challenging to buy these expensive models. And it won't be feasible for them to implement these kinds of solutions who are small in I mean, who is small organization.	OS-IT
39	Re-searcher	Okay. What about the type of industry, does it have any impact? Like maybe industries different like aviation industry or railway industry or food or beverage industry or do you believe like different kinds of industries will have different influence or effect on predictive maintenance implementation?	
40	R4	Yeah. So, see some of the equipment are generic in nature like heat exchanger, pumps, heavy duty rotating equipments like compressors and turbines. They are same in nature or whatever they are doing or whatever these equipments are doing, these equipments are mostly generic in nature right. So, they perform in the same way as they are it is going to perform it whether it is pumping the gas or whether it is pumping ammoniam. So, it hardly changes something right. So, the fact that for the generic equipment, it is mostly I would say there is no difference as such. But at the same time, when it is not a manufacturing industry like any other industry like aviation or maybe we are trying to predict something for the banks or any other, but we are speaking from the industry perspective. So, yeah, that makes a difference, if it is not a manufacturing set up. But mostly all the manufacturing setup is more or less I would consider it same. And then not from the business perspective, but if you are doing the business predictions and business predictions is a completely different ballgame altogether.	OS-IT
41	Re-searcher	Okay. Is there any hesitancy towards implementing predictive maintenance due to cost of implementing it or any financial risk associated with it in your organisation?	
42	R4	No. So, we are fully supporting this initiative. And this initiative is well supported within our organisation. This comes as a central function from the Board of Directors that who are	CO

		giving value to digitalization. So yeah, there is no hindrance as such.	
43	Re-searcher	Okay. And do you believe whether the cost of implementation or the implementation of PdM affects the process of predictive maintenance implementation?	
44	R4	Yeah. So mostly while we do this, we always do a cost benefit analysis. And this cost benefit analysis is done pretty much in detail within our organisation. Based on the cost benefit analysis, predictive maintenance models are implemented. Once you have the past benefit models available, then only the implementation is taking place.	CO
45	Re-searcher	Yeah. Whether the organisation top management is supporting the decision to implement PdM?	
46	R4	Yeah, I just said that they are supporting.	
47	Re-searcher	Do you believe having the top management support is necessary for the implementation of PdM?	
48	R4	Yeah, definitely. So, there are these kinds of initiatives that has to come from the top management. Otherwise, if you don't have the budget and financials available, you cannot implement these sorts of solutions.	TMS
49	Re-searcher	Coming to the organisational other factors. Also, the predictive maintenance implementation involves working on or having multiple teams working together in your organisation. In your organization how many teams are working together for the PdM implementation?	
50	R4	So, in every region, we have bought a team who is working on predictive maintenance initiatives.	
51	Re-searcher	Is there any knowledge share or knowledge transfer shared among these teams?	
52	R4	Yes, yes. It is being shared.	
53	Re-searcher	Do you believe collaboration and communication among these teams affects predictive maintenance implementation?	
54	R4	Yes, this is definitely affecting it. It definitely affects the implementation, and collaboration and knowledge transfer is very important.	CC

55	Re-searcher	Okay. Are there any awareness or educational efforts taken by your organisation to support the predictive maintenance implementation?	
56	R4	Yeah, so our organisation always encourages us to have more certifications in terms of data science. So, they do support further education and they do support certifications for these activities.	AE
57	Re-searcher	Okay. Are you aware of any of your competitors also have implemented predictive maintenance?	
58	R4	Yes. So, most of the organisations nowadays they're implementing predictive maintenance. So, all the bigger organisations in the manufacturing sector they are implementing predictive maintenance.	
59	Re-searcher	Is your organisation feel any competitive pressures to implement predictive maintenance?	
60	R4	Ah, I'm not sure about that, because I'm not from the top management side. So, I'm still from middle management. So, I'm not sure about this question.	CP
61	Re-searcher	Yeah, I understand that. And do you believe the companies are implementing predictive maintenance to create a means to competitive advantage?	
62	R4	Yes, yes. So, as we all know that a predictive maintenance, we want to have a higher reliability of equipments. And this high reliability is very important know to get the maximum production out of your plants. And then that's how predictive maintenance give us an edge over others if we can predict the failures early.	CP
63	Re-searcher	You mentioned that you are using the prism tool for implementing it. Are you getting the necessary support or do you feel having the external support has some impact on the predictive maintenance?	
64	R4	No. So, we have only taken application from prism. But all the implementation is done by our team internally.	ES
65	Re-searcher	Okay, I understand. So, there is no issue of availability of the external support I would say so. Yeah. Did you consider any environmental impact while implementing predictive maintenance in your organisation?	

66	R4	Well, I don't think there is any environmental impact because this is mostly the software solution. So, there is no environmental impact as such.	
67	Researcher	Challenges I think you have explained during the explanation. Can you say the major benefits of implementing predictive maintenance?	
68	R4	Yeah. So, major benefits would be higher availability of the assets. And if your equipment is highly available, then you can get more production out of the same set of equipment because you are undoing the maintenance much more in advanced than anybody else is doing.	
69	Researcher	Okay, I think we are done with the questions we had for you today. Do you have any questions for us? Or do we consider any factors which we have missed?	
70	R4	So, once you compile this, I would like to have a look at it. If anything is misinterpreted, then I would like to have a look at it. And thereafter, maybe you can publish.	
71	Researcher	Yeah, sure. We will send you the consent form, which is a PDF form. You can sign it digitally. You so you can share it with us. We will also sign in share it with you.	
72	R4	Sure.	
73	Researcher	Okay, then. Thank you for joining today and sharing the information. Thank you.	
74	R4	Yeah, thank you. Have a nice day. Bye Bye. Take care.	

Appendix 6: Interview 5 (R5)

Researchers: Swapna Malagi, Sathya Ruba Selvaraj
Respondent 5 (R5): Anonymous
Industry Type:
Country: Iran
Date: 06-06-2021
Interview Length: 28 minutes
Language: English

Themes	Factors/ Sub Themes	Code
Predictive Maintenance Implementation	-	PdMI
Predictive Maintenance	Other Factors	OF
Technological context	IT-Infrastructure	IT-I
	Data Management	DM
	Model Selection	MS
Organizational context	Organizational size and Industry type	OS-IT
	Top Management Support	TMS
	Existing Knowledge	EK
	Collaboration and Communication	CC
	Cost	CO
	Awareness and Educational efforts	AE
Environmental context	Competitive Pressure	CP
	External Support	ES

Note: Initially, we (Researchers) introduced ourselves and gave the background of the thesis to Respondent. Upon asking the consent to record the meeting, the following meeting is recorded and transcribed as below.

Row	Person	Transcription	Code
1	Researcher	Can you tell us about your background and education?	
2	R5	Yes, I have studied electrical engineering in bachelor's degree. I have got a bachelor's degree in Electrical Engineering and master's degree in automation and instrumentation. So, I have got engineering background.	
3	Researcher	What role do you play in the organization? How is your work correlated to predictive maintenance implementation?	

4	R5	I have been working as an instrumentation engineer, especially maintenance engineer. I have been working with measurement systems, monitoring systems and distributed control systems. That's my role and I would like to talk about that I have been dealing with data about machinery health conditions since 2012.	
5	Researcher	Okay. What type of predictive maintenance have you implemented in your organization? Is it data-driven, or knowledge-based, or model-based?	
6	R5	Mostly data-driven. Because we have got monitoring systems that we can capture data from the control system. So, I work in data driven predictive maintenance.	PdMI
7	Researcher	Okay. How is this predictive maintenance implemented in your organization? Is it built in house or any external support or third-party vendors used?	
8	R5	It takes six months about implementation. But I think it takes about six months for gathering data. In fact, we are in implementation phase, and we need to tune some models and gather another data for improving or maintenance systems.	PdMI
9	Researcher	Are there any external vendors are used or any external support is used for the implementation, or it is inbuilt?	
10	R5	No, we just use control system data for implementation.	ES
11	Researcher	Okay. Can you explain the predictive maintenance implementation process on a high level?	
12	R5	We are new in predictive maintenance, I think with some consideration, as a matter of fact, machine learning is new in industry. So, we are in first phase of getting data for the implementation.	PdMI
13	Researcher	Yeah, I understand that. Did you have the necessary IT infrastructure required for the predictive maintenance implementation?	
14	R5	Because we use control systems for gathering data, we had a good IT infrastructure for gathering data and that is okay with us.	IT-I
15	Researcher	Okay. Do you feel it has been beneficial that you already had the necessary IT infrastructure for the implementation?	

16	R5	Yes, yes. Because if you want to use cloud computing, we should use IT infrastructure for implementation predictive maintenance with Cloud.	IT-I
17	Re-searcher	Okay. How about the existing knowledge or you have existing competency about predictive maintenance implementation in your organization?	
18	R5	We have good IT department that provide good IT facilities and devices, and networks for communications. So that is way more important and very useful for us.	IT-I
19	Re-searcher	Okay. Also, you had a domain knowledge or technical knowledge related to predictive maintenance implementation when you started working on this?	
20	R5	Me or the organization?	
21	Re-searcher	Organization wise.	
22	R5	No, but because that's what was one of my ideas. And I shared my idea with another department, and that was sometimes most challenging. That was my idea.	EK
23	Re-searcher	So, do you consider like not having the existing knowledge was a challenge for implementing predictive maintenance?	
24	R5	Sure. Because the department or company some of engineers or a lot of engineers don’t understand about machine learning and data science. So, at first, I just started to teach some aspects of machine learning and fortunately, because of engineering background, after some presentation, they understood the machine learning and predictive maintenance.	EK
25	Re-searcher	Okay, that's good. So, what is the importance for data in your organization? what type of data is used for the predictive maintenance implementation?	
26	R5	Because of maintenance process and high the maintenance cost of machinery, monitoring data and measurement data about facilities are very important. And another item is about providing data for supply chain and buying some machines and facilities.	DM
27	Re-searcher	Okay, how the data is managed or accessed in your organization?	

28	R5	We have a good computer network within our organization. So, we share data with Excel and some templates with sharing information. Okay.	DM
29	Researcher	Did you face any data or process information missing while working on predictive maintenance? If so, how that affected your implementation of predictive maintenance?	
30	R5	About missing monitoring data or for example, networking data which one?	
31	Researcher	Any kind of data used for implementation.	
32	R5	Yes, we backed up some important data routinely. So missing data in overall is not important, because we have got good backup data. But sometimes we encounter with a shutdown and some failures in our systems and in that we don't have data in failure system. That's most challenging problem.	DM
33	Researcher	Okay. Regarding the model selection, what are the various machine learning models used, or do you use any deep learning models for the predictive maintenance implementation?	
34	R5	As far as I know, we use support vector machine, neural network, k-nearest neighbour for classification small data. And we just started to implement predictive maintenance using convolutional neural networks. I think convolutional neural network using one dimensional data can be a good method for implementation predictive maintenance.	PdMI
35	Researcher	Okay, what is the importance of model selection in the implementation of predictive maintenance? How does it affect the implementation?	
36	R5	It depends on data. Because with small data, machine learning methods can be a good selection and unfortunately for large data, for example, big data, machine learning methods cannot be a good model. So, we should use deep learning models such as convolutional neural networks and others, for example, RNN (recurrent neural network), LSTM (Long short-term memory) for prediction.	MS
37	Researcher	Okay. How do you call your organization's size, is it small or medium or large organization?	
38	R5	Our organization is a big company in oil industry or chemical industry. But it is distributed for a chemical production. So, I can say that we are a big company. So, it can be challenging, because new idea about predictive maintenance	OS-IT

		should pass some levels for implementation. We should get some licenses for implementation. In contrast, if we work into a start-up or work over in start-up a new idea can be implemented easily and fast. That's challenge, yes.	
39	Researcher	Do you believe that size of the organization and type of the industry has some kind of influence on the implementation?	
40	R5	Yes, yes. Because understanding about machine learning and accepting new ideas in large company can be challenging.	OS-IT
41	Researcher	Okay. Is there any hesitancy in your industry towards implementing predictive maintenance due to the cost of implementation or risk associated with it? Is there any hesitancy like they consider it as a too much of a cost of implementing it?	
42	R5	No. Implementation of predictive maintenance in our company, because of good IT infrastructure and it's for computer network is not a costly object. And it doesn't have any financial risk because we have gathered data and we just use models to predict.	CO
43	Researcher	But in general, do you believe that cost of implementation or financial risk, if there are any, they can affect the predictive maintenance implementation?	
44	R5	Yes, yes because if we have poor IT infrastructure for gathering data, that can be a challenging and costly object. But if we have good infrastructure for gathering data, I think implementation can be easy and fast.	CO
45	Researcher	Okay, when you decided to implement predictive maintenance, whether your organization top management was supporting the decision to do so?	
46	R5	At first, I should introduce machine learning, data science to them. In fact, I should provide some financial motivation for them to implement PdM, that was my challenge. Because big companies can accept new ideas because of financial motivation.	TMS
47	Researcher	Yeah. Do you believe having the top management support is necessary and it has some kind of impact on the predictive maintenance implementation?	
48	R5	Yes, yes, sure. Because the implementation PDM can be taken with a team working we need some IT specialist, some maintenance technicians and other department. And handling these connections and making a team working is just	TMS

		responsible for top management roles and top management positions.	
49	Researcher	So, as you mentioned, it also involves multiple teams working together. Like you also have in your organization, multiple teams working in predictive maintenance implementation?	
50	R5	Yes, yes. Because we are working with mechanical department, and IT department. So, implementation PdM is teams working.	
51	Researcher	Okay, how is the knowledge transfer shared among these teams? Or do you guys connect to share the knowledge or how is it transferred?	
52	R5	Yes. Fortunately, team have engineering background. And the team members want to know more about machine learning and new ideas and they are new to data sciences, machine learning. They accept new ideas, and we share information with our computer network.	CC
53	Researcher	Yeah. Do you believe collaboration and communication among the teams has some influence or it affects the predictive maintenance implementation?	
54	R5	Yes, absolutely. At first, I think engineering that work in especial field have good and solid and knowledge about data. And they can interpret data, they can understand data, and that's very important. Another reason I would like to say is that they have new idea about new project, and they can bring their ideas for implementation, or introducing new projects.	CC
55	Researcher	Are there any awareness or educational efforts taken by your organization to support PdM implementation? If so, how it impacts the implementation?	
56	R5	Yes. We have educational department. They provide educational courses as long-life learning. And after implementation, we are talking to the educational department to provide new courses about machine learning predictive maintenance, and that is so supporting.	AE
57	Researcher	Yeah, is it beneficial for the implementation?	
58	R5	Yes, yes, because we can introduce machine learning and data science to other departments and field sites such as a content department and other departments. And we can introduce new	AE

		project and we can define new project in different aspects, that's so beneficial. And I think that's the most motivational reason for implementation machine learning in organization.	
59	Re-searcher	Yeah. Are you aware of any of your competitors who has also implemented predictive maintenance?	
60	R5	In our company or other company?	
61	Re-searcher	Other companies who are competitors to your organization.	
62	R5	Yes, yes. I have spoken with other mechanical engineers, that they have been working on predictive maintenance. That was so interesting. I think most of the companies that like to reduce their maintenance costs, they are working on machine learning.	
63	Re-searcher	Okay. Do you feel any competitive pressures to implement predictive maintenance because other companies are also working on that?	
64	R5	No. Because in my opinion, we share information widely in internet because we haven't solved any real and big prob-lems. So, sharing information can be a good way for improv-ing or methods.	CP
65	Re-searcher	Okay. Is your organization implementing predictive mainte-nance to create means to competitive advantage?	
66	R5	Not as a competitive advantage, because I would like to change my carrier to machine learning and data science. I have just introduced machine learning PdM.	
67	Re-searcher	So, it is not having any influence on the decision to imple-ment predictive maintenance in your case?	
68	R5	Yes, yeah.	CP
69	Re-searcher	Okay. In general, what are the major benefits you say, you will get by implementing predictive maintenance?	
70	R5	Improving life cycle of machines, another thing is about re-ducing maintenance cost, and another thing about having a good supply chain process.	PdMI
71	Re-searcher	Okay. What are the major challenges faced by your organiza-tion while implementing predictive maintenance?	

72	R5	A missing data. I think predictive maintenance industry is just data engineering.	DM
73	Re-searcher	Yeah. Okay. I think I had completed all the questions which we had for the interview, you would like to add any points or factors which we may have missed?	
74	R5	No, the questions were very good. And that's my honour to help some institutions and other engineers for implementation PdM and I just ask some question, Can I have your report about your interview with other guys and engineer?	
75	Re-searcher	Yeah, sure. We will share with you once we finalized with our master thesis report. We will share it with you.	
76	R5	Good, another question I'd like to ask you is that do you work with real data, do you work with industry or company, or you would like to work with synthesizing data?	
77	Re-searcher	We are not working on the implementation. This is more of a theoretical information which we are collecting from the people who are actually working on the implementation. But as a researcher, we are not actually working on implementation.	
78	R5	Good, Good luck.	
79	Re-searcher	Thank you for joining today. It was so grateful of you that you again joined and shared your information.	
80	R5	You are welcome, it has really made my day having a conversation with you about PdM is good. I will sign the document and I will send it to you.	
81	Re-searcher	Yeah sure. It is digitally signable, you can sign it digitally now, you need not to go to any scanning machine. It is a PDF where you can sign it digitally. So, you can make use of it. Okay, Good. Yeah.	
82	R5	Thank you and have a nice day, Bye.	

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