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**Investigation on Predictive Maintenance Implementation Cost-
Efficiency**

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This thesis is submitted in partial fulfilment of the requirements for
the degree of PhD

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Abstract

The manufacturing industry faces significant challenges in maintaining competitiveness, including the need for increased customization, reduced operational costs, improved sustainability, and the integration of advanced technologies. Predictive Maintenance (PdM) has been identified as a potential solution by optimizing equipment reliability and reducing maintenance costs. However, the adoption of PdM has been hindered by high initial costs and a lack of systematic methods to evaluate its cost-benefit.

A systematic methodology has been proposed in this research to assist manufacturing industries in evaluating the cost-benefit of PdM implementation, tailored to specific organizational needs and operational conditions. The methodology consists of two key components: the evaluation of the most suitable maintenance strategy and PdM techniques to determine tangible assets and the assessment of intangible assets such as knowledge and technology required for implementation.

The outcomes of this research provide manufacturers with a structured approach to assess PdM's suitability, enabling informed decision-making aligned with Industry 4.0 and 5.0 objectives. The developed tool can be applied at both the manufacturing system level to support specific PdM technology implementations and at the enterprise level to facilitate long-term evaluations. The foundation for future investigations into PdM's role in, digital transformation, and the broader Industry 5.0 context has also been laid.

Keywords:

Predictive Maintenance, Maintenance Strategy, Analytic Hierarchy Process, Predictive Maintenance Technique, Intangible Assets, Intangible Assets Evaluation

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Table of Contents

Academic integrity declaration.....	i
Abstract	ii
Acknowledgements	iii
List of Figures.....	ix
List of Tables	xi
List of Equations.....	xiv
List of Abbreviations	xv
CHAPTER 1 - INTRODUCTION.....	1
1.1 Motivation and background.....	2
1.1.1 Maintenance in modern manufacturing	3
1.1.2 Role of predictive maintenance in modern manufacturing.....	5
1.1.3 PdM implementation cost-efficiency	8
1.2 Problem statement and gap analyse.....	10
1.2.1 Evaluating required tangible assets for PdM implementation.....	10
1.2.2 Evaluating required intangibles assets for predictive maintenance implementation.....	12
1.2.3 Research gap analyse.....	13
1.3 Research questions and objectives and expected contribution	14
1.3.1 Research questions and objectives.....	14
1.3.2 Expected contributions to knowledge	15
1.4 Thesis structure and verification and validation strategy.....	16
Chapter Summary.....	19
CHAPTER 2 - LITERATURE REVIEW.....	21
Historical evolution of maintenance strategies.....	21
Comparative perspectives on maintenance strategies.....	23
Introduction to PdM applications.....	29
2.1 PdM implementation cost-efficiency.....	31
2.1.1 PdM implementation investment and ROI formulation	32
2.1.2 Specific PdM cases cost-efficiency calculation	33
2.1.3 PdM Implementation Cost Avoidance	33
2.1.4 Main research gaps in the thesis.....	35
2.2 AHP for maintenance strategy selection	36
2.2.1 Identified research gaps	39
2.3 PdM technique selection.....	48
2.3.1 Domain knowledge as a structural prerequisite for PdM technique selection.....	48
2.3.2 PdM techniques	50
2.3.3 Identified research gaps	53
2.4 PdM implementation intangible assets quantification.....	59
2.4.1 Intangible asset quantification methods	60

2.4.2 Identified research gaps	63
2.4.3 The need for a maturity model to evaluate intangible assets in predictive maintenance	64
2.5 Identifying research opportunities and justification	67
2.5.1 Identified research opportunities	67
Chapter Summary.....	69
CHAPTER 3 - METHODOLOGY	71
3.1 Problem statement.....	71
3.2 Maintenance strategy selection in modern manufacturing era.....	73
3.2.1 Step A Define decision-making goal, alternatives and criteria.....	75
3.2.2 Step B Decision maker judgement.....	80
3.2.3 Step C Weight relative importance of each criterion and performance measure of criteria with respect to alternative.....	82
3.2.4 Step D Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) Evaluation	84
3.3 PdM technique selection.....	87
3.3.1 Step A PdM implementation objectives, attributes, and technique capabilities investigation	88
3.3.2 Step B Framework development.....	100
3.3.3 Step C Framework Validation.....	103
3.4 Methodology – PdM implementation intangible assets evaluation.....	106
3.4.1 Step A Maintenance intangible assets type investigation.....	107
3.4.2 Step B Maintenance maturity model	109
3.4.3 Step C Maintenance intangible assets quantification equations.....	113
3.4.4 Step D Maintenance intangible assets marking scale	114
3.4.5 Step E Method Validation.....	116
Chapter Summary.....	117
CHAPTER 4 - ANALYTICAL HIERARCHICAL PROCESS FOR MAINTENANCE STRATEGY SELECTION IN MODERN MANUFACTURING ERA.....	120
4.1 Step A Maintenance strategy selection in modern manufacturing era goal, alternatives, and decision-criteria.....	121
4.1.1 Step A1 Define maintenance strategy selection goal	121
4.1.2 Step A2 Define maintenance strategy alternatives.....	121
4.1.3 Step A3 Define maintenance strategy selection criteria	122
4.1.4 Step A4 Set up of the hierarchic tree.....	132
4.2 Step B Case study – decision maker judgement	136
4.2.1 Step B1 Decision maker gathering for maintenance strategy selection.....	136
4.2.2 Step B2 Case introduction.....	137
4.2.3 Step B3 Criteria pairwise comparison	138
4.2.4 Step B4 Alternative performance marking.....	142

4.3 Step C Case study – criteria importance, alternative performance and alternative mark calculation	146
4.3.1 Step C1 Weight relative importance of criteria	146
4.3.2 Step C2 Alternative performance with respect to criteria and alternative selection	148
4.4 Step D Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) Evaluation ...	150
4.5 Discussion	152
Chapter Summary	157
CHAPTER 5 - A DECISION BASED FRAMEWORK FOR PREDICTIVE MAINTENANCE TECHNIQUE SELECTION	159
5.1 Step A Analysis of PdM technique objectives, PdM implementation capabilities, and PdM implementation attributes	160
5.1.1 Step A1 Investigate practice PdM implementation objectives	160
5.1.2 Step A2 PdM technique capabilities for achieving ALs	161
5.1.3 Step A3 Investigate PdM implementation attributes and investigate how practice PdM implementation attributes affect PdM technique selection	162
5.2 Step B Establish the decision-based framework for PdM techniques ...	164
5.2.1 Algorithm to Define PdM Implementation Ambition Levels ((Figure 5-4, Algorithm I).....	166
5.2.2 Algorithm to Check if Model-based PdM Technique is Applicable (Figure 5-5, Algorithm III)	169
5.2.3 Algorithm to Check if Physics-based PdM Technique is Applicable (Figure 5-6, Algorithm IV)	170
5.2.4 Algorithm to Check if Data-driven PdM Technique is Applicable (Figure 5-6, Algorithm V).....	171
5.3 Step C Framework validation (Figure 5-1)	172
5.3.1 Step C1 Description of the case study	172
5.3.2 Step C2 Framework application	173
5.3.3 Evaluation of Machine Learning Models for PdM Implementation..	179
5.3.4 Alternative PdM Strategies in the Context of the Case Study	183
5.3.5 Practical and Organizational Considerations for PdM Implementation.....	186
5.4 Discussion	188
Chapter Summary	194
CHAPTER 6 - INVESTIGATION ON PREDIVTIVE MAINTENANCE IMPLEMENTATION INTANGIBLE ASSETS	196
6.1 Step A PdM implementation and operation intangible assets type investigation.....	197
6.1.1 Step A1 Evaluate required intangible assets for manufacturing	197
6.1.2 Step A2 Evaluation on required intangible assets for maintenance implementation and operation	200

6.2 Step B Maintenance implementation and operation maturity model	202
6.3 Maintenance intangible assets evaluation method	209
6.3.1 Step C Maintenance intangible assets quantification equations.....	209
6.3.2 Step D Maintenance intangible assets marking scale	212
6.4 Step E Maintenance intangible assets quantification case study and implementation strategy	226
6.4.1 Case study introduction.....	227
6.4.2 Step E2 – Step E4 Intangible assets evaluation.....	227
6.4.3 Step E5 Intangible asset implementation strategy	233
6.5 Discussion	241
Chapter Summary.....	246
CHAPTER 7 - CLOSURE.....	248
7.1 Summary of thesis	248
7.1.1 Evaluating required tangible for PdM implementation	250
7.1.2 Evaluating required intangible assets for PdM implementation	251
7.2 Answering the research questions and objective achievement.....	252
7.2.1 PdM implementation tangible assets evaluation method validation	254
7.2.2 PdM implementation intangible assets evaluation method validation	258
7.3 Achievements, contributions, and limitations	260
7.3.1 PdM implementation tangible assets evaluation	261
7.3.2 PdM implementation intangible assets evaluation.....	284
References	299
Appendices.....	336

List of Figures

Figure 1-1 Maintenance modern manufacturing transformation aspects.....	5
Figure 1-2 PdM role in modern manufacturing	6
Figure 1-3 PdM enhancing maintenance aspects	8
Figure 1-4 Cost-benefit impact on successful PdM implementation practice	9
Figure 1-5 Research motivation	9
Figure 1-6 Gap in research	13
Figure 1-7 Validation Square (Pedersen, et al., 2000; Milisavljevic, 2018).....	17
Figure 1-8 Validation square	18
Figure 1-9 Organization of the thesis – presented and next chapter	20
Figure 2-1 Organization of the Thesis – Presented and Next Chapter	70
Figure 3-1 Challenges and methodology for evaluating PdM implementation cost-benefit.....	72
Figure 3-2 AHP for maintenance strategy selection in modern manufacturing era framework.....	75
Figure 3-3 Sample hierarchical tree	76
Figure 3-4 A framework for PdM technique selection – methodology	87
Figure 3-5 Method for PdM implementation and operation intangible assets evaluation – methodology.....	107
Figure 3-6 Organization of the Thesis – Presented and Next Chapter	119
Figure 4-1 AHP for maintenance strategy selection in modern manufacturing era framework.....	120
Figure 4-2 Hierarchical tree for maintenance strategy selection.....	134
Figure 4-3 Criteria (B) and sub-criteria weight (A).....	147
Figure 4-4 Alternative weight with respect to criteria	148
Figure 4-5 Alternative marks	149
Figure 4-6 Organization of the Thesis – Presented and Next Chapter	158
Figure 5-1 A framework for PdM technique selection – methodology	159
Figure 5-2 PdM technique and capability map	161
Figure 5-3 The Decision-Based Framework for Predictive Maintenance Technique Selection	165

Figure 5-4 Algorithm for defining PdM implementation ALs	167
Figure 5-5 Algorithm to Define PdM Implementation Critical Component (Algorithm II) and Algorithm to Check if Model-based PdM Technique is Applicable (Algorithm III).....	168
Figure 5-6 Algorithm to Check if Physics-based PdM Technique is Applicable (Algorithm IV) and Algorithm to Check if Data-driven PdM Technique is Applicable (Algorithm V)	171
Figure 5-7 Case study AL and suitable PdM technique define	174
Figure 5-8 Critical component and fault type define procedure	175
Figure 5-9 Data-driven PdM technique developing procedure	176
Figure 5-10 Organization of the Thesis – Presented and Next Chapter	195
Figure 6-1 Method for PdM implementation and operation intangible assets evaluation	197
Figure 6-2 Maintenance maturity levels.....	203
Figure 6-3 Case study current and target maintenance maturity level	229
Figure 6-4 Case study current and target intangible marks.....	232
Figure 6-5 Maintenance intangible assets implementation strategy map	234
Figure 6-6 Organization of the Thesis – Presented and Next Chapter	247

List of Tables

Table 2-1 Publication on AHP for maintenance strategy selection	43
Table 2-2 New decision criteria identified for maintenance strategy selection under Industry 5.0.....	44
Table 2-3 Mapping of research gaps to methodological requirements	58
Table 2-4 Connection between Research Gaps and Research Questions through Critical Literature Review.....	69
Table 3-1 Relative importance scale (Saaty and Kearns, 1985).....	81
Table 3-2 <i>RI</i> Value for N = 10 (Saaty and Kearns, 1985)	83
Table 3-3 Mapping PdM Techniques to Ambition Levels Cross Validation	93
Table 3-4 Attribute–Technique Frequency Summary Based on Real Case Studies (n = 47)	97
Table 3-5 Evaluation order, substitution logic, and feasibility rules for each technique	98
Table 4-1 Part Two, Step A3 decision criteria identified	125
Table 4-2 Part Three, Step A3 decision criteria identified	129
Table 4-3 Defined decision goal, alternatives, and criteria	132
Table 4-4 Expert participants information	136
Table 4-5 Main criteria pairwise comparison	138
Table 4-6 Cost sub-criteria pairwise comparison.....	139
Table 4-7 Productivity sub-criteria pairwise comparison	139
Table 4-8 Added-Value sub-criteria pairwise comparison	140
Table 4-9 Safety sub-criteria pairwise comparison.....	140
Table 4-10 Environmental sub-criteria pairwise comparison	141
Table 4-11 Additional Factors sub-criteria pairwise comparison	141
Table 4-12 Cost sub-criteria performance	142
Table 4-13 Productivity sub-criteria performance	142
Table 4-14 Added-value sub-criteria performance	143
Table 4-15 Safety sub-criteria performance	144
Table 4-16 Environmental sub-criteria performance.....	144

Table 4-17 Additional factor sub-criteria performance	145
Table 4-18 Distribution Condition of Statistical WRSR	150
Table 4-19 Classification Results	151
Table 5-1 Identified data-driven PdM model.....	178
Table 6-1 Identified intangible assets dimensions for manufacturing	199
Table 6-2 Intangible assets relevancy to maintenance.....	201
Table 6-3 Intangible assets for maintenance implementation and operation..	202
Table 6-4 Maturity level basic function rational.....	205
Table 6-5 Maturity level additional functions rational.....	206
Table 6-6 Interview participant information.....	212
Table 6-7 Maintenance experience/knowledge assets marking scale.....	213
Table 6-8 Maintenance Skills assets marking scale	215
Table 6-9 Maintenance training assets marking scale.....	217
Table 6-10 Maintenance attitude assets marking scale.....	219
Table 6-11 Maintenance process/routines assets marking scale	220
Table 6-12 Maintenance research expense assets marking scale	223
Table 6-13 Maintenance communication and software assets marking scale	225
Table 6-14 Case study maintenance operation function analyze	227
Table 6-15 Analysing the current state of the company's intangible assets ...	229
Table 7-1 Summary of validation of objective one.....	254
Table 7-2 Summary of Validation of Objective Two.....	257
Table 7-3 Summary of Validation of Objective Three	259
Table 7-4 Summary of contributions — AHP–WRSR method	261
Table 7-5 Limitations of the maintenance strategy selection method	264
Table 7-6 Summary of Contributions — PdM Technology selection framework	270
Table 7-7 Limitations of the PdM technique selection framework.....	275
Table 7-8 Summary of Contributions — Intangible Asset Evaluation Framework	284
Table 7-9 Limitations of the PdM intangible asset evaluation framework	291

List of Equations

(3-1)..... 83

(3-2)..... 83

(3-3)..... 83

(3-4)..... 83

(3-5)..... 83

(3-6)..... 84

(3-7)..... 84

(3-8)..... 86

(3-9)..... 86

(3-10)..... 114

(6-1)..... 210

(6-2)..... 210

(6-3)..... 210

(6-4)..... 210

(6-5)..... 210

(6-6)..... 211

(6-7)..... 211

(6-8)..... 211

(6-9)..... 211

(6-10)..... 211

(6-11)..... 212

(6-12)..... 232

(6-13)..... 232

List of Abbreviations

A	pairwise criteria comparisons matrices
λ_{max}	importance validating parameter
w	criteria vector of weights
(CR)	consistency ratio
(CI)	consistency index
(RI)	consistency index
S_{ij}	performance of each alternative
T_{ij}	score of criteria j of the alternative i
W_j	weighted score of the criteria j
R_{ij}	ranking of Sub-criteria with respect to cases
(f)	Frequency count
(Σf)	cumulative frequency
(G)	frequency range
$(G/2)$	median cumulative frequency
i_{HC1}	sub-dimension Experience of dimension Human Capital
i_{HC2}	sub-dimension Training of dimension Human Capital
i_{HC3}	sub-dimension Skills of dimension Human Capital
i_{HC4}	sub-dimension Attitude of dimension Human Capital
i_{SC1}	sub-dimension Process/Routines of dimension Structural Capital
i_{RD1}	sub-dimension Research Expenditure of dimension Research and Development
i_{IT1}	sub-dimension Communication and Software of dimension I information and technology
I	measurement of enterprises' intangibles for maintenance implementation and operation

CHAPTER 1 - INTRODUCTION

In the modern manufacturing era, industries face a range of challenges, including increasing market demands for customization, the pressure to reduce operational costs, the need for improved sustainability practices, and the integration of advanced technologies such as artificial intelligence (AI) and the Internet of Things (IoT). These challenges complicate the task of maintaining efficient and resilient production processes, making it progressively difficult for manufacturing enterprises to sustain a competitive edge. In response, Predictive Maintenance (PdM) has emerged as a potential solution, offering the promise of reduced costs, enhanced productivity, and greater sustainability, thus enabling companies to remain competitive. However, despite its growing adoption, the cost-benefit of implementing PdM remains inadequately defined in both the academic literature and industrial practice.

The principal aim of this research is to establish a systematic method to assist the manufacturing industry in assessing the cost-efficiency of PdM implementation, considering both tangible and intangible asset costs. This research addresses the complexity of evaluating PdM's cost-efficiency by providing a method that allows manufacturing industries to assess their specific requirements before initiating the implementation process. The proposed method enables manufacturing enterprises to determine whether PdM is a suitable strategy for maintaining competitiveness, especially in the face of modern production challenges.

In this chapter, the foundation of the thesis is presented. The motivation, focusing on three key topics: (1) challenges and opportunities for maintenance in the era of modern manufacturing, (2) the role, benefits, and limitations of PdM in Industry modern manufacturing, and (3) an investigation into the cost-benefit of PdM implementation are outlined in Section 1.1. Background information, covering maintenance strategy selection in Industry 4.0, PdM techniques, intangible assets for maintenance implementation and operation of PdM are provided in Section 1.2. The aim, objectives, and contributions of this thesis is detailed in

Section 1.3, while the overall structure and validation of the thesis are presented in Section 1.4.

1.1 Motivation and background

Maintenance actions are defined as the actions that retire or restore a device to its original state and ensure device functionality (British Standard Glossary of Terms, 1993). Maintenance activities are crucial for the manufacturing industry, not only because maintenance-related costs can occupy a substantial portion of the overall production expenses, ranging from 15% to 60% (Mobley, 2002). Also, maintenance actions significantly influence various key performance indicators in manufacturing, including productivity, safety, quality, etc. (Zonta et al., 2020).

Industry 4.0, often referred to as the Fourth Industrial Revolution (Lee et al., 2014), generally involves the transformation towards automation, digitalization, and the integration of different aspects of manufacturing and industrial operations. This transformation is enabled by the integration of cutting-edge technologies like the Internet of Things (IoT), artificial intelligence (AI), and the interlinking of cyber-physical systems (Pivoto et al., 2021). Building on Industry 4.0 technologies, Industry 5.0 introduces new challenges for the manufacturing sector, particularly in terms of sustainability, human-centric design, and resilience. These challenges require manufacturing enterprises to not only optimize production processes through automation and AI but also ensure that these advancements contribute to long-term environmental sustainability, prioritize human well-being, and enhance the resilience of production systems in the face of disruptions. Such advent of modern manufacturing has introduced significant challenges to the manufacturing industry, precipitating substantial changes across various aspects of business operations, production, maintenance, supply chain management, and more. This transformation is driven not only by global competition but also by the growing demand for more customized products. To enhance competitiveness, manufacturing companies must exhibit agility in responding to market shifts swiftly (Milisavljevic-Syed et al., 2020). Additionally, manufacturers are expected to foster stronger relationships with all stakeholders along the value chain and cultivate customer loyalty to maintain their competitive edge. These heightened

challenges have made maintenance operations more demanding for manufacturers. Consequently, implementing more advanced maintenance strategies, has become possible in ensuring optimal performance outcomes and effectively addressing emerging challenges.

Predictive maintenance is a strategy that is expected to overcome such challenges. PdM utilizes predictive tools to monitor device/component states, proactively identifying possible faults (Li et al., 2022). Maintenance actions are taken before faults occur, making PdM a strategy expected to both reduce maintenance costs and increase productivity (Amankwa et al., 2019). Although the advantages of PdM have been extensively studied and recognized by researchers and industry professionals, its application in practice remains limited. One main barrier is that the PdM implementation cost-benefit is still not clear. PdM requires a significant investment in technique, infrastructure, training, and consulting (Bousdekis et al., 2019). Furthermore, the costs and benefits of PdM implementations are often not clearly defined and evaluated in practice (Tiddens et al., 2018). This uncleanse leads to the primary motivation of this thesis. If the cost-benefit assessment is not conducted accurately before PdM implementation, it may lead to the project going over budget or unsatisfactory PdM capability, thus affecting the company's long-term development plan.

The overview of the motivation for this research is presented in this section. To delve deeper into the motivation, three topics are discussed in detail in the following sections: Section 1.1.1, where maintenance in modern manufacturing is covered; Section 1.1.2, where the role of PdM in modern manufacturing is explored; and Section 1.1.3, where the PdM implementation cost-benefit is examined. Background information for the thesis is provided through these sections.

1.1.1 Maintenance in modern manufacturing

Industry 4.0 and Industry 5.0

The term "Industry 4.0" was introduced at the Hannover Fair in 2011 and adopted by the German government as a strategic roadmap to digitalize and enhance

manufacturing efficiency (Potyal et al., 2021). Technologies like the IoT, Big Data, and AI are key to realizing this transformation. Industry 4.0 has gained significant attention due to its potential benefits for manufacturing organizations. According to Xu et al. (2018), the concept of Industry 4.0 has evolved over the years. It now includes the digitalization of both industrial and consumer markets, ranging from intelligent manufacturing to the entire value delivery channel (Schroeder et al., 2019). Experts from academia, government, and industry collaboratively describe Industry 4.0 as the digitalization and smartification of factories, supply chains, and all value chain members (Qu et al., 2019). In this model, people, machines, companies, and resources are interconnected across an extended value chain.

Building upon Industry 4.0 technology, Industry 5.0 represents the next step in manufacturing evolution, emphasizing human-centricity, sustainability, and resilience. Unlike the automation-driven mindset of Industry 4.0, Industry 5.0 emphasizes collaboration between humans and machines, enabling workers to leverage the power of intelligent systems while maintaining control over the creative and strategic aspects of the production process. This transformation enables the manufacturing sector to align technological advances with human values, ensuring that automation enhances rather than replaces human contributions.

Maintenance transformation in modern manufacturing

A significant focus within modern manufacturing is the collaboration between production and maintenance planning (Silvestri et al., 2020). This aims to ensure timely and efficient maintenance services, thereby enabling cost-effective production systems (Rødseth et al., 2017). McKinsey (2015) identifies maintenance as a key driver for two of the eight primary value drivers of Industry 4.0, specifically "Asset utilization" and "Services and aftersales."

Mosyurchak et al. (2017) highlight that many companies view maintenance management as foundational in the context of Industry 4.0. This transformation involves shifting from traditional corrective and periodic maintenance to predictive maintenance strategies, offering both economic and technical advantages (Silvestri et al., 2020). Research by Jazdi (2014), Alqahtani et al. (2019), Jones

et al. (2020), and Cristians and Methven (2017) underscores that the transition to Industry 4.0 maintenance requires the adoption of new technologies, resulting in significant changes in manufacturing and human resource management.



Figure 1-1 Maintenance modern manufacturing transformation aspects

Silvestri et al. (2020) conducted an analysis of the primary aspects of focus in the maintenance transformation process, which include cost, time/productivity, safety, sustainability, and social/human factors, as depicted in Figure 1-1. Numerous studies concentrate on improving one or more of these five aspects. Enhancing these aspects may present challenges for the manufacturing industry during the transformation process; however, successful implementation can enable manufacturers to maintain their competitiveness.

1.1.2 Role of predictive maintenance in modern manufacturing

In the context of Industry 4.0, PdM has gained significant attention due to its potential to improve maintenance efficiency and overall performance. Zonta et al. (2020) highlight that PdM-related publications have surged since 2014, underscoring its growing relevance in both academic research and industrial applications. PdM leverages data from multiple sensors to continuously monitor component states and performance, as well as estimate the Remaining Useful Life (Yan et al., 2017). This allows the manufacturing industry to optimize maintenance scheduling based on real-time component conditions, leading to

improved maintenance performance. As illustrated in Figure 1-2, the impact of PdM in Industry 4.0 can be seen in three main areas: cost reduction, productivity improvement, and optimization of additional performance indicators. In addition, PdM plays a pivotal role in Industry 5.0 by contributing to the broader goal of sustainability and resilience. Through improved maintenance strategies, PdM helps reduce waste, energy consumption, and environmental impact, thus supporting the sustainability objectives of Industry 5.0. Moreover, by enabling predictive capabilities, PdM aligns with the human-centric approach of Industry 5.0 by offering workers valuable insights into machinery performance and enabling them to make more informed decisions, thus enhancing their roles and contributions.

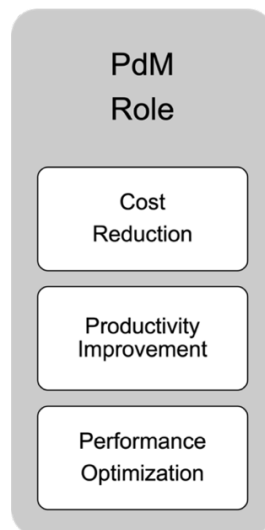


Figure 1-2 PdM role in modern manufacturing

Cost reduction

The main advantage of implementing PdM is cost reduction. PdM allows enterprises to predict the Remaining Useful Life (RUL) of components, ensuring that no components are unnecessarily replaced or maintained (Yan et al., 2017). This leads to a reduction in spare parts usage and maintenance frequency. PdM's cost model is typically based on system specifications and RUL estimation (Ran et al., 2019). Beyond maintenance costs, PdM can reduce manufacturing costs by improving efficiency, optimizing resources, and reducing energy consumption (Sarkar et al., 2014; Firdaus and Mohamad, 2019). Studies such as He et al.

(2018) and You et al. (2009) have explored cost-effective PdM strategies that optimize maintenance schedules and reduce inspection costs.

Productivity improvement

PdM also enhances productivity by maximizing equipment reliability and availability. Reliability refers to the likelihood that a system will remain functional over a specific period (Letot et al., 2017), and it is influenced by various factors, including design and maintenance quality (Narayan, 2012). PdM helps minimize unexpected breakdowns, potentially reducing downtime by 30% to 50% and extending operational lifespan by 20% to 40% (McKinsey, 2015). Moreover, PdM increases component RUL, thus reducing maintenance frequency and improving overall equipment availability (Atamuradov et al., 2017).

Other performance indicator optimization

In addition to cost reduction and productivity improvement, PdM can enhance other performance indicators like product quality, safety, customer satisfaction, and sustainability. Effective maintenance improves product quality (Maletič et al., 2012), while PdM minimizes faults, improving both operator and customer safety (Narayan, 2012; Amaechi et al., 2022). It also increases customer satisfaction by ensuring high-quality, safe, and dependable products. Furthermore, PdM contributes to sustainability by reducing material waste and minimizing failures (Abidi et al., 2022).

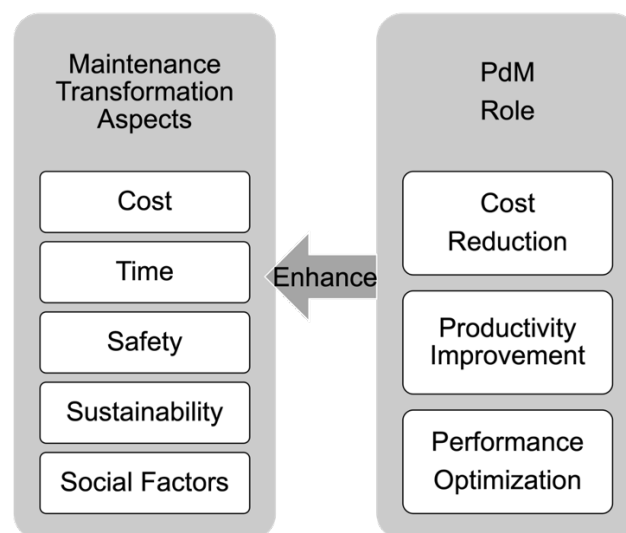


Figure 1-3 PdM enhancing maintenance aspects

As discussed in Section 1.1.2, PdM not only helps reduce maintenance and production costs while maximizing productivity, but it also addresses other challenges faced by the industry, such as fostering stronger relationships with stakeholders and enabling the production of more customized products (Figure 1-3). Therefore, PdM can be considered a viable solution for manufacturers to overcome the challenges presented by modern manufacturing including increasing market demands for customization, the pressure to reduce operational costs, the need for enhanced sustainability practices, etc.

1.1.3 PdM implementation cost-efficiency

Before adopting any technology, enterprises must conduct a thorough cost-benefit analysis. Implementing PdM demands significant investments in technology, infrastructure, training, and consulting (Bousdekis et al., 2020). However, the costs and benefits of PdM are often unclear and not fully evaluated in practice (Tiddens et al., 2015). The ambiguity arises from the variety of techniques used, which differ in principles, requirements, capabilities, and implementation costs (Ruiz et al., 2014; Zhan and Mechefske, 2007; Coble and Hines, 2011; Wöstmann et al., 2019; Grabot, 2020; Sai et al., 2019). Companies also have varying expectations, equipment conditions, and product types, making it essential to assess the cost-benefit of PdM tailored to each company's situation.

Introducing PdM without a justified cost-benefit analysis is risky, particularly for small and medium-sized enterprises (SMEs) (Amankwa et al., 2019). However, a lack of comprehensive guidance on assessing PdM's cost-efficiency exists (Alrifaey, 2020). As illustrated in Figure 1-4, understanding the cost-benefit before implementation is crucial for successful PdM adoption. This analysis clarifies the financial and non-financial requirements, identifies potential benefits, and justifies the associated costs.

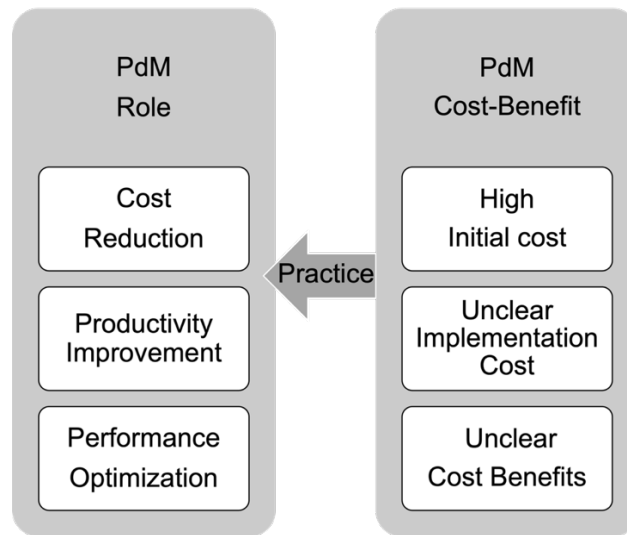


Figure 1-4 Cost-benefit impact on successful PdM implementation practice

In conclusion, justifying the cost-benefit of PdM adoption is critical for manufacturers. There is still a gap in methods to evaluate the cost-benefit of PdM before its implementation (Figure 1-5).

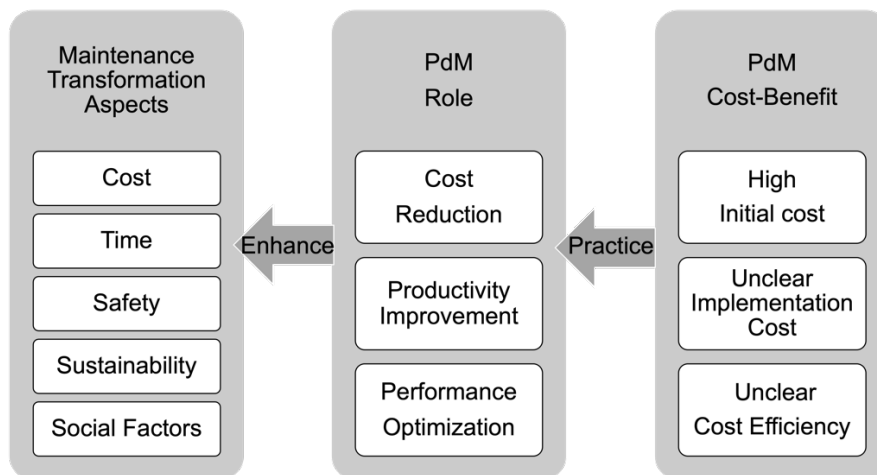


Figure 1-5 Research motivation

This research aims to address this gap by providing a systematic approach to help manufacturers assess PdM's requirements and potential benefits based on their unique circumstances. Specifically, methods to evaluate tangible and intangible assets, remain underexplored, as discussed in Section 1.2: Problem Statement and Gap Analysis.

1.2 Problem statement and gap analyse

The motivation for this thesis is introduced in Section 1.1. The problem statement, which outlines the challenges in evaluating the cost-benefit of PdM implementation, is presented in Section 1.2. Research gaps related to these challenges are discussed, including the evaluation of tangible and intangible assets for PdM implementation. These are explored in Sections 1.2.1, and 1.2.2, with the research gaps presented in Section 1.2.3.

In modern manufacturing era, manufacturers face significant challenges in transitioning their operations, with maintenance emerging as a key focus area. PdM aims to address these challenges, particularly in terms of cost, time, safety, and sustainability. However, a method for evaluating the cost-benefit of PdM before implementation remains lacking, which constitutes the central research problem of this thesis. Specifically, methods to assess the required tangible and intangible assets are needed.

1.2.1 Evaluating required tangible assets for PdM implementation

PdM requires substantial investment in tangible assets, including IoT systems, data analytics, and predictive software (Bousdekis et al., 2019). This investment may be financially burdensome for manufacturers, necessitating a clear understanding before implementation. The first step in implementing PdM is to evaluate whether it is necessary and which components or systems should be involved, aiming to optimize performance and cost (Alrifaey et al., 2020; Lee et al., 2014). Notably, around 30% of industrial equipment may not benefit from PdM (Tiddens et al., 2018). Additionally, different PdM techniques (knowledge-based, data-driven, and physics models) each have unique requirements and limitations, highlighting the need for a method to determine the most appropriate PdM technique.

Assessing suitable maintenance strategy in modern manufacturing environment

There are three types of maintenance strategies mainly applied in manufacturing practice: Corrective Maintenance (CM), Preventative Maintenance (PM) and Predictive Maintenance (PdM).

- **CM** is a strategy that allows devices to run until failure happens. Maintenance actions are taken after failure takes place.
- **PM** is a strategy in which maintenance actions are taken after devices work for a specific time or iteration.
- **PdM** is a strategy that utilizes digitized sensor data along with data analytics to continuously monitor the state of machine components or processes to determine when and where maintenance may be required.

In the modern manufacturing industry, manufacturers face technical, market, and environmental challenges in selecting the optimal strategy. Factors such as cost, productivity, and sustainability must be evaluated to ensure the best choice.

Technical challenges include the high initial cost of PdM implementation, particularly for SMEs, and the dependency of PdM performance on predictive model accuracy, labour efficiency, and cybersecurity (Compare et al., 2019; Amankwa et al., 2019). Market challenges, driven by Industry 4.0, also impact decision-making, as manufacturers must adapt to competition, customized products, and global supply chain changes (Milisavljevic-Syed et al., 2020; Li et al., 2022).

With the rise of Industry 5.0, new factors such as environmental concerns, operator well-being, and safety have become more prominent (Xu et al., 2021; Leng et al., 2022). These factors influence maintenance strategy decisions, as the industry focuses on human-centred and sustainable manufacturing practices. Additionally, regulatory pressures to reduce carbon emissions are increasing, especially for enterprises in major economies with "Net Zero" targets. Failure to meet these goals could lead to financial penalties.

In conclusion, the evolution of maintenance strategies is shaped by technical, market, and environmental challenges. As such, a robust method for selecting the appropriate strategy is essential to ensure long-term success in manufacturing.

Assessing suitable predictive maintenance technique

In addition to deciding whether PdM is necessary, selecting the most suitable PdM technique is also critical. In practice, five main types of PdM techniques are utilized: experience-based, model-based, physical-based, data-driven, and hybrid. Each technique has distinct hardware, software, and knowledge requirements, leading to implementation costs, time, and capabilities variations. The capability of PdM techniques refers to their respective tasks, such as accurate component state prediction, fault prognosis, and extension of asset service life (Schmidt and Wang, 2015; Ran et al., 2019; Sai et al., 2019; Jimenez et al., 2020; Ramesh et al., 2020). In the meantime, enterprises may have various objectives for implementing PdM. Some aim to reduce maintenance costs, some aim to improve product quality, some aim to extend device service life, and some aim to extract value from PdM (Li et al., 2022). Therefore, choosing the most suitable PdM technique for a particular setup or scenario is crucial for successful implementation in the industry. It facilitates cost and time optimization, ensures long-term financial viability, and maximizes cost-benefit.

1.2.2 Evaluating required intangibles assets for predictive maintenance implementation

Both tangible and intangible assets are essential for implementing and operating a maintenance strategy. Tangible assets in this context refer to the physical devices and tools required for maintenance, such as sensors and spare parts. On the other hand, intangible assets encompass the knowledge, experience, skills, and other non-physical elements necessary for maintenance implementation and operation (St-Pierre and Audet, 2011).

Even if all the necessary tangible assets are available, manufacturers cannot effectively implement and operate a maintenance strategy without the right type and quantity of intangible assets. In addition, manufacturers have diverse

expectations for their maintenance strategies. Some aim to reduce maintenance costs by implementing optimized maintenance planning and operations based on condition monitoring. In contrast, others focus on increasing productivity by minimizing unexpected downtime during production through condition monitoring. Additionally, some manufacturers seek to extract value from their maintenance systems, leveraging the data collected from these systems (Li et al., 2022). Each expectation requires different types and amounts of intangible assets to be effectively implemented and operated. Therefore, having the appropriate type and quantity of intangible assets is critical for successfully implementing and operating a maintenance strategy.

However, there is a lack of a systematic method to help manufacturers evaluate themselves and define the required types and quantities of intangible assets. This poses a challenge in ensuring appropriate intangible assets are in place. Developing such a method would be crucial for manufacturers to accurately assess their needs and make informed decisions about the intangible assets necessary for the successful implementation and operation of their maintenance strategies.

1.2.3 Research gap analyse

Based on the research problem discussed in Sections 1.2.1, and 1.2.2. To understand PdM implementation cost-benefit, it is necessary to evaluate the required tangible and intangible assets before implementation, as presented in Figure 1-6.

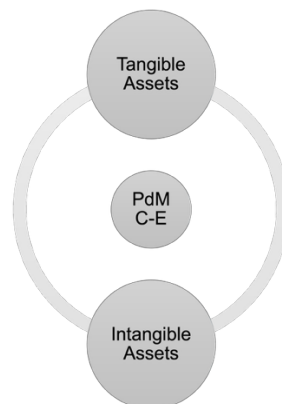


Figure 1-6 Gap in research

The detailed description of the research gaps in this thesis is presented as follows.

Gap 1: *There is a lack of methods for enterprises to evaluate the required tangible assets for PdM implementation. Specifically, there is a lack of methods for enterprises to evaluate if PdM is needed in the modern manufacturing environment. In addition, there is a lack of methods for enterprises to evaluate which PdM technique to use. In practice, five main types of PdM techniques are utilized. Each technique has distinct hardware, software, and knowledge requirements, leading to implementation costs, time, and capabilities variations.*

Gap 2: *There is a lack of a method for understanding the required intangibles for PdM implementation. Even if all the necessary tangible assets are available, manufacturers cannot effectively implement and operate a maintenance strategy without the right type and quality of intangible assets. These intangible assets are crucial for successful strategy execution. However, currently, there is a lack of a systematic method to help manufacturers evaluate themselves and define the required types and quantities of intangible assets.*

1.3 Research questions and objectives and expected contribution

In Section 1.3, the formulated research questions and research objectives presented in this thesis. The expected contribution of this research is presented in this section.

1.3.1 Research questions and objectives

Based on these research problem and gaps discussed in Section 1.2, a prime research question is formulated as follow:

Primary Research Question: *What is the method that helps evaluate the cost-benefit for predictive maintenance implementation that takes into account the investment in tangible and intangible assets of PdM?*

Furthermore, as discussed in Sections 1.2.2 and 1.2.3, there is a related set of challenges tied to assessing the necessary tangible and intangible assets before

the actual implementation. These challenges form the sub-research problems addressed in this thesis.

Predictive maintenance implementation tangible asset assessment

Research Question One: *What is the method that helps manufacturers evaluate the necessary tangible assets for PdM implementation, considering whether PdM is required and which PdM technique is needed?*

Two research objectives are achieved to answer Research Question One and validate Research Hypotheses One and Two, which are:

Objective One: *Create an AHP-based MCDM method tailored for manufacturing enterprises. This method should enable these enterprises to choose the most appropriate maintenance strategy in modern manufacturing while considering the technical, environmental, and market challenges they face.*

Objective Two: *Develop a comprehensive framework to assist enterprises in selecting the most suitable Predictive Maintenance Technique. This framework should consider the unique characteristics of each PdM technique and evaluate their alignment with the specific conditions and needs of the enterprise.*

Predictive maintenance implementation intangible asset assessment

Research Question Two: *What is the method that helps evaluate the necessary intangible assets for PdM implementation, taking into account the enterprise's specifications, before the actual implementation?*

One research objective is achieved to answer Research Question Two and validate Research Hypothesis Three, which is:

Objective Three: *Develop a method for manufacturers to accurately assess the required intangible assets necessary for successfully implementing and operating their maintenance strategies regarding their needs and situations.*

1.3.2 Expected contributions to knowledge

The expected contribution from this thesis is presented as follow:

Expected Contributions related to Objective One: Maintenance Strategy Selection Method

The identification of new decision criteria aligned with Industry 5.0 focuses on human-centricity, sustainability, and resiliency in maintenance strategies. By integrating factors like sustainability, IoT, and data-driven insights, maintenance strategy selection is enhanced for digitalized manufacturing environments. The introduction of an AHP-WRSR method offers customizable tools to prioritize criteria such as cost reduction, safety, and energy efficiency. Challenges in PdM implementation, such as fault diagnostics and data availability, are also addressed.

Expected Contributions related to Objective Two: PdM Technique Selection Method

PdM techniques are aligned with organizational ambition levels, ensuring compatibility with company goals. Key attributes, such as data availability and system complexity, are identified to aid in real-world PdM applicability. A structured framework is developed to guide manufacturers in selecting suitable PdM strategies based on their capabilities.

Expected Contributions related to Objective Three: PdM Implementation Intangible Assets

Intangible dimensions for PdM implementation are identified and linked to maturity levels, guiding resource allocation. A five-level maturity model allows for assessing and advancing PdM practices. A strategy map connects core activities with intangible assets and provides guidance on PdM adoption. Practical insights on managing intangible assets optimize PdM practices across implementation stages.

1.4 Thesis structure and verification and validation strategy

The validation and verification of a method or result is essential because method development involves numerous abstract elements, and there is no definitive answer (Milisavljevic, 2018). The Validation Squire method is adopted in this

thesis to verify the method by building confidence in the utility of methods and examples (Pedersen et al., 2000; Milisavljevic, 2018).

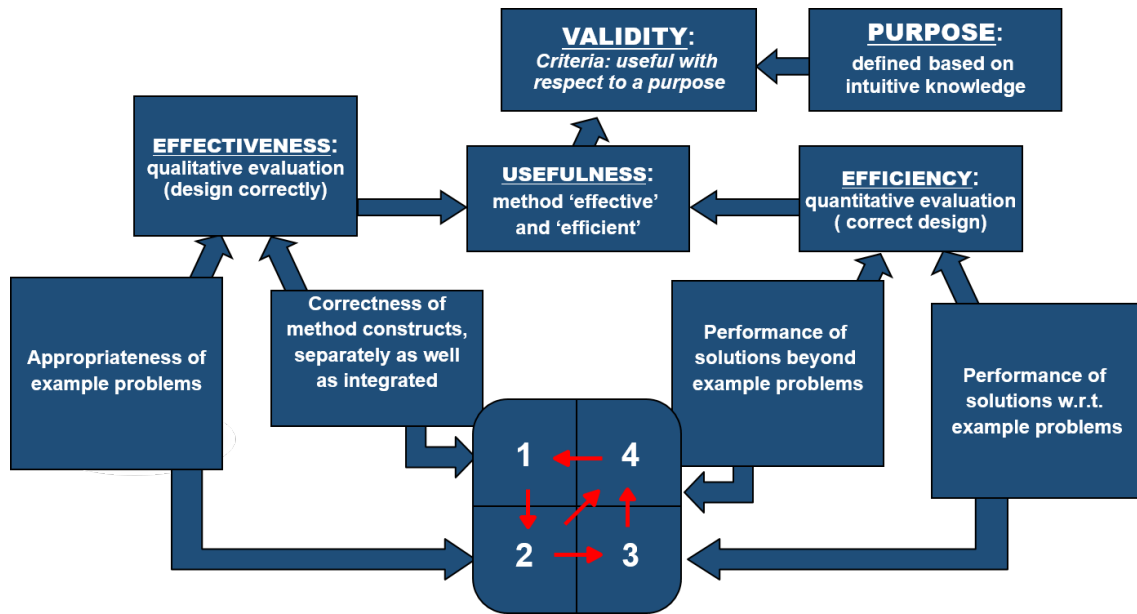


Figure 1-7 Validation Square (Pedersen, et al., 2000 ; Milisavljevic, 2018)

The validation square is employed to ascertain whether the method yields accurate design solutions in terms of both structural validity and performance validity (Choi, 2005; Milisavljevic, 2018). As presented in Figure 1-7, the validation square involves four quadrants, which are:

Quadrant 1: Theoretical Structural Validity involves evaluating the structural and logical soundness of the proposed methods, ensuring overall consistency.

Quadrant 2: Empirical Structural Validity encompasses establishing confidence in the chosen sample problems used to validate the designed methods.

Quadrant 3: Empirical Performance Validity is utilized to bolster confidence in the practical applicability of the designed methods.

Quadrant 4: Theoretical Performance Validity focuses on instilling confidence in the broader utility of the designed methods and assessing its suitability for problems extending beyond the provided examples.

The designed validation square in this thesis is presented in Figure 1-8 as follows:

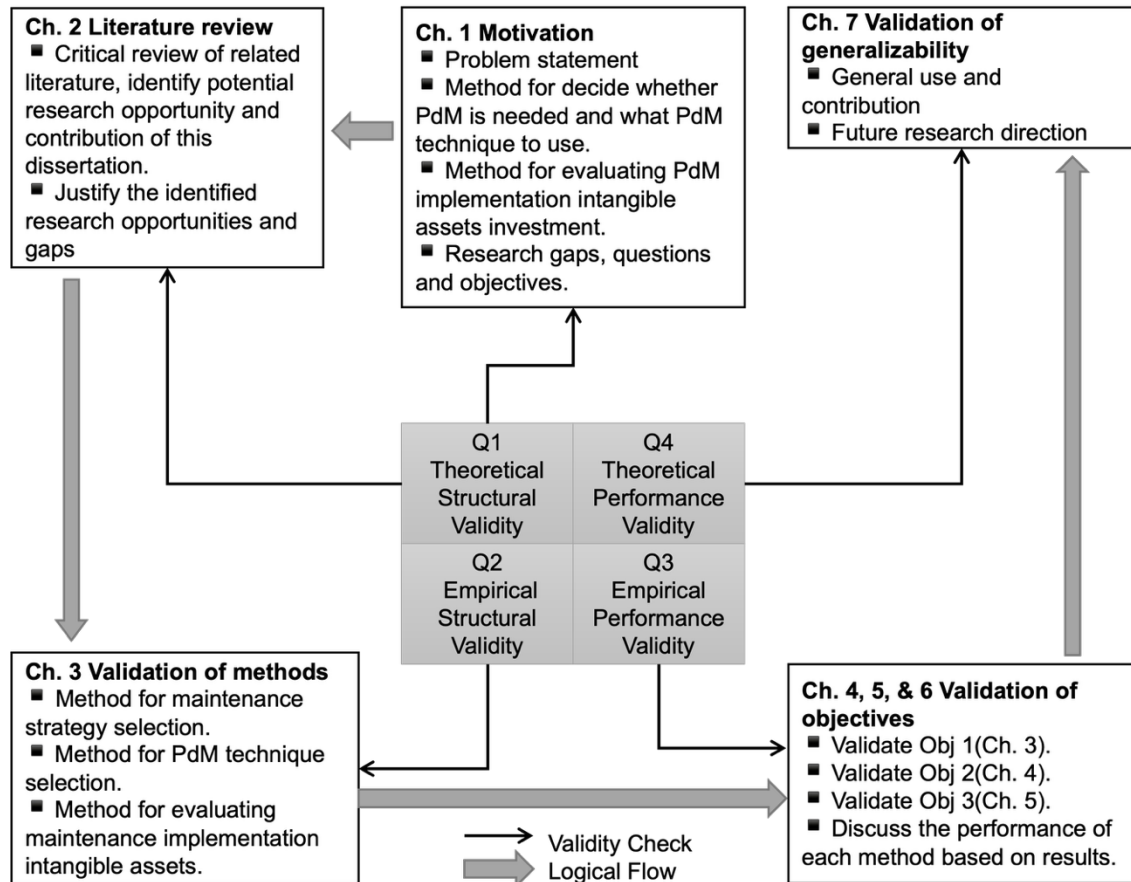


Figure 1-8 Validation square

Theoretical Structural Validation Tasks:

The research problems are identified and discussed, with the state of the art and background of the research problem examined, research gaps identified, and research questions formulated in Chapter 1. The utility, constraints, and application domains for the developed method for evaluating PdM implementation cost-benefit are identified in Chapter 1. A critical review of the relevant literature is conducted, and future research opportunities and gaps are identified and justified in Chapter 2.

Empirical Structural Validation Tasks:

The methodology for maintenance strategy selection is proposed, with a discussion of the methodology and data collection method provided in Chapter 3. The methodology for PdM technique selection is proposed, including a discussion of the methodology and data collection method, in Chapter 3. The methodology

for assessing intangible assets for maintenance is proposed, with the methodology and data collection method discussed in Chapter 3.

Empirical Performances Validation Tasks:

The result for Objective One is proposed, and the proposed method for maintenance strategy selection is tested and validated based on the test results in Chapter 4. The result for Objective Two is proposed, and the proposed method for PdM technique selection is tested and validated based on the test results in Chapter 5. The result for Objective Three is proposed, and the proposed method for assessing intangible assets for maintenance is tested and validated based on the test results in Chapter 6.

Theoretical Performances Validation Tasks:

The validity of the proposed methods is proven, and limitations are discussed in Chapter 7. Future research opportunities are identified in Chapter 7.

The overall structure of this thesis is proposed in the following Figure 1-9. The thesis is organized into eight chapters. Chapter 1 is devoted to introducing the research, with the research problem, objectives, and contributions outlined. A review of relevant literature and the theoretical foundations for evaluating the cost-benefit of PdM implementation is provided in Chapter 2. The methodology for developing methods to support PdM implementation, including asset evaluation techniques, is presented in Chapter 3. In Chapters 4 through 6, the results, testing, and validation of the three primary objectives of the research are covered, focusing on the evaluation and analysis of decision criteria, PdM techniques, and intangible assets. Chapter 7 concludes the thesis with a summary of the key findings, validation of the research questions, and suggestions for future research directions.

Chapter Summary

In this chapter, the research problem of evaluating PdM implementation cost-benefit, research gaps, and the research questions worthy of investigation are introduced.

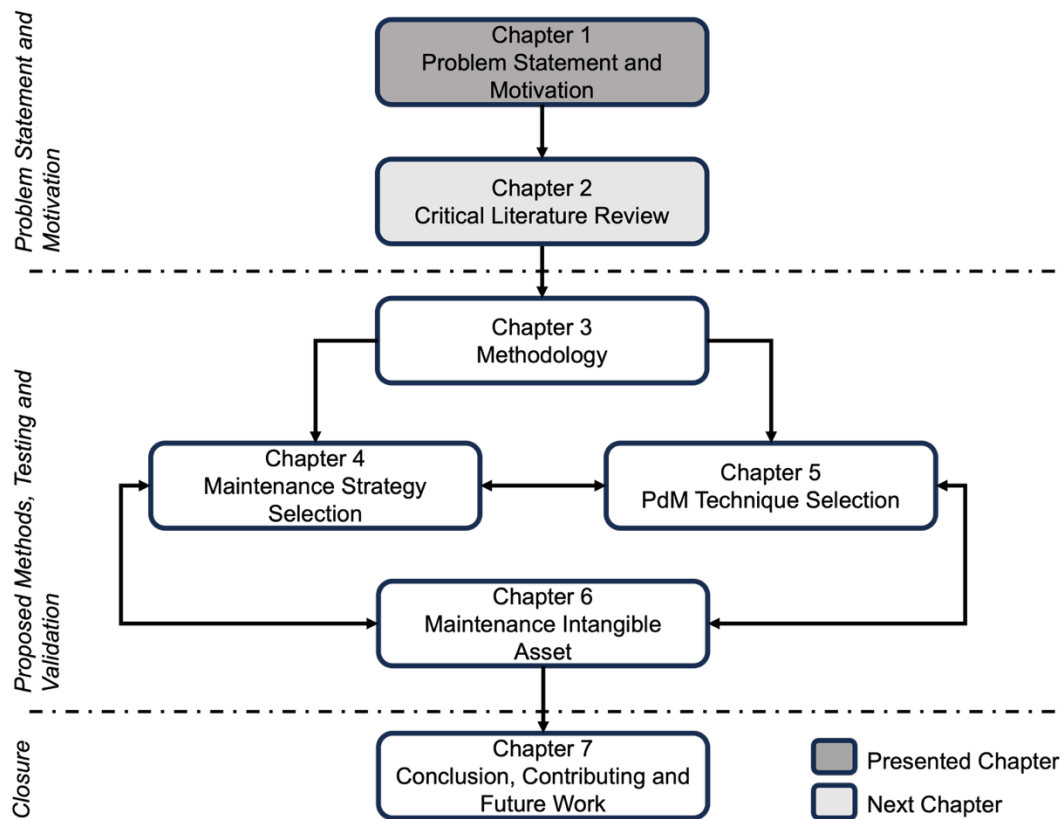


Figure 1-9 Organization of the thesis – presented and next chapter

The motivation for developing a method for evaluating PdM implementation cost-benefit is introduced through discussion on three topics: (1) the challenges and opportunities of maintenance Industry 4 transformation. (2) the role of PdM in the transformation process, and (3) the importance and problem of evaluation PdM implementation cost-benefit. The background of evaluating PdM implementation tangible and intangible assets is discussed, the research gaps, questions and objectives are presented. In the following Chapter 2, a literature review is presented to build the theoretical foundations for evaluating PdM implementation cost-benefit and provide theoretical structural validity in this thesis, see attached Figure 1-9.

CHAPTER 2 - LITERATURE REVIEW

In this chapter, the research questions outlined in Section 1.3 are justified through the identification of gaps in the existing body of knowledge, which were uncovered during a systemic literature review. The cost-benefit analysis of PdM implementation is reviewed, with a focus on required tangible and intangible assets, and these gaps are used to shape the research opportunities and future directions addressed in this thesis.

An introduction to maintenance strategies and PdM applications is presented first in this section. Next, in Section 2.1, the state of the art of PdM implementation cost-benefit is presented. In Section 2.2, publications related to the AHP method for maintenance strategy selection are reviewed. Real-world PdM implementation cases are reviewed in Section 2.3 to identify the techniques used and features of these techniques. In Section 2.4, methods for quantifying intangible assets are investigated. Research opportunities are identified from these reviews and presented in Section 2.5, which are further addressed in Chapters 4 through 6.

Historical evolution of maintenance strategies

The development of maintenance strategies is described as a gradual shift from simple failure-based actions to advanced methodologies that integrate predictive tools and organizational practices. Through this evolution, increasing emphasis is placed on reliability, cost efficiency, and production continuity in manufacturing environments.

Corrective Maintenance (CM)

Corrective Maintenance (CM), often referred to as the “run-to-failure” approach, is recognized as the earliest stage in the history of maintenance philosophy. Under CM, actions are carried out only after a failure is experienced. Minimal planning and investment are required under this approach; however, significant operational risks are faced, including unplanned downtime, loss of production capacity, and increased safety hazards (Mobley, 2002).

In the manufacturing sector, CM is still applied to non-critical assets where failures do not severely affect productivity. For production-critical assets such as CNC machines, robotic arms, and assembly lines, the unpredictability of CM is regarded as economically and operationally unsustainable. Unplanned downtime is reported to cause losses ranging between \$10,000 and \$250,000 per hour, depending on the industry (Duffuaa & Raouf, 2015). As a result, CM is mainly retained in limited contexts.

Preventive Maintenance (PM)

Preventive Maintenance (PM) is introduced as a response to the limitations of CM. In PM, maintenance activities are scheduled at predetermined intervals, based on historical data, manufacturer recommendations, or statistical averages of component lifetimes. The probability of unexpected failures is reduced when servicing or replacement is performed before end-of-life (Alsyounf, 2007).

PM is widely adopted in the mid-20th century, particularly in automotive and electronics manufacturing, where equipment uptime is regarded as critical to profitability. Despite improved predictability, inefficiencies are introduced by fixed schedules. Over-maintenance, unnecessary part replacements, and excessive labor costs are often generated (Muchiri et al., 2011). Components are sometimes replaced while still functional, leading to waste of resources.

Condition-Based Maintenance (CBM)

Condition-Based Maintenance (CBM) is marked as a more advanced stage in maintenance philosophy. Under CBM, equipment parameters such as vibration, temperature, lubrication quality, or acoustic signals are monitored in real time. Maintenance actions are initiated when a measurable threshold is exceeded, indicating the onset of potential failure (Jardine, Lin, & Banjevic, 2006).

In manufacturing, CBM is especially applied to high-value assets such as compressors, turbines, and automated production lines. Cost efficiency is improved through reduced unnecessary interventions. Nevertheless, CBM is still classified as reactive, because deterioration is only addressed after it begins. Implementation also requires significant investments in sensor technology,

monitoring systems, and skilled diagnostic expertise, which may act as barriers for small and medium-sized enterprises.

Reliability-Centred Maintenance (RCM)

Reliability-Centred Maintenance (RCM) is formalized in the aerospace industry during the 1960s by Nowlan and Heap (1978). Under RCM, failure modes, their consequences, and mitigation strategies are systematically analysed. Criticality analysis and prioritization of tasks are carried out to maintain system reliability and safety.

In manufacturing, RCM is applied particularly in high-reliability sectors such as semiconductor fabrication and aerospace component production. Nevertheless, extensive data collection, analytical expertise, and organizational resources are required, which make large-scale application difficult (Bevilacqua & Braglia, 2000). Complexity and cost are frequently cited as barriers to wider adoption.

Total Productive Maintenance (TPM)

Total Productive Maintenance (TPM), developed in Japan in the 1970s, is introduced as an approach that involves operators and frontline workers in maintenance activities. Proactive equipment care, cross-functional collaboration, and continuous improvement are emphasized (Nakajima, 1988). Alignment with lean production principles is established, with a focus on eliminating waste, reducing downtime, and improving Overall Equipment Effectiveness (OEE).

Although TPM promotes a culture of shared responsibility, its effectiveness is determined by organizational commitment, workforce training, and cultural alignment (Ahuja and Khamba, 2008). Implementation challenges are frequently observed, especially in Western manufacturing firms, and these challenges often limit scalability.

Comparative perspectives on maintenance strategies

Cost Efficiency

Corrective Maintenance (CM) is typically perceived as low-cost because no scheduled interventions are carried out. However, hidden costs are consistently

highlighted by research, including unplanned downtime, secondary equipment damage, and safety risks. In the foundational study of Nowlan and Heap (1978), it is demonstrated that corrective approaches, although inexpensive at first, usually generate the highest lifecycle expenditures. By contrast, Preventive Maintenance (PM) is shown to reduce catastrophic breakdowns, but “over-maintenance” is often created when components are replaced before the end of their useful life (Mobley, 2002). As a result, inflated labor and spare parts costs are frequently reported without proportional gains in uptime.

In the case of Total Productive Maintenance (TPM), significant reductions in equipment-related losses are reported in Japanese automotive manufacturing through direct engagement of operators (Nakajima, 1988). Nevertheless, high labor intensity and long-term cultural change are required, which limit immediate financial return (Ahuja and Khamba, 2008). Reliability-Centered Maintenance (RCM) is presented as a structured analytical framework that prioritizes maintenance tasks according to reliability and criticality. Studies from aerospace and defense industries report cost reductions of up to 30% compared with PM (Smith & Hinchcliffe, 2004). However, widespread adoption in resource-constrained environments is often deterred by RCM's complexity.

Predictive Maintenance (PdM) is regarded as superior in cost efficiency because interventions are aligned with actual equipment condition. Empirical studies report 10–40% reductions in maintenance costs, ROI ratios above 200%, and payback periods often shorter than one year (Lee et al., 2019). By minimizing both under- and over-maintenance through data-driven insights, PdM achieves a balanced management of direct and indirect costs.

Operational Reliability and Downtime Reduction

Operational reliability is consistently described as a central driver for structured maintenance strategies. Corrective Maintenance, although perceived as simple, undermines reliability because unplanned stoppages and cascading failures are introduced. In high-volume manufacturing such as automotive assembly lines, unplanned downtime linked to CM is reported to account for as much as 20% of lost productive capacity annually, with severe consequences for just-in-time

systems (Wang et al., 2017). Preventive Maintenance (PM) is reported to improve reliability through scheduled interventions, but unexpected failures are not eliminated because components sometimes fail before their scheduled replacement, particularly in harsh environments (Alsyouf, 2007).

Through the involvement of frontline operators, TPM is shown to provide reliability improvements. Nakajima's (1988) work demonstrates that Overall Equipment Effectiveness (OEE) is significantly enhanced in automotive and electronics sectors. However, reliability gains under TPM are made conditional on strong cultural commitment and active workforce participation. Where employee turnover is high or skill levels are uneven, inconsistent outcomes are frequently observed (Tsang et al., 2010).

With RCM, shortcomings are addressed by prioritizing activities according to failure criticality and system function. Documented reductions in catastrophic failures are reported in safety-critical sectors such as aerospace (Smith and Hinchcliffe, 2004). Nevertheless, heavy analytical and resource demands limit broad application in mid-sized manufacturing firms.

By contrast, PdM introduces a step change in reliability. Early detection of anomalies is enabled by real-time data and predictive models, and interventions are initiated before actual failure. Empirical studies in process manufacturing report 20–50% reductions in unplanned downtime compared with PM and TPM (Carvalho et al., 2019). Unlike RCM, PdM adapts continuously as new data are collected, producing dynamic improvements in accuracy. This adaptability establishes PdM as uniquely effective in complex manufacturing environments where reliability is essential for competitiveness.

Technological and Data Requirements

Technological and data requirements are shown to vary considerably across strategies, shaping feasibility and effectiveness. CM and PM are reported to need minimal technological support: CM is carried out without monitoring systems, and PM relies mainly on schedules supplemented by basic inspections. Although

accessible, both approaches lack integration with modern data-driven production systems (Mobley, 2002).

TPM is associated with basic tools such as visual inspection checklists, manual logs, and continuous improvement records. Improved data visibility is achieved, but dependence on human input generates variability and limits scalability (Ahuja and Khamba, 2008). RCM, while structured, is described as primarily analytical; heavy reliance is placed on expert judgment and failure mode analysis rather than on real-time monitoring.

PdM diverges from these approaches through advanced technological reliance. IoT-enabled sensors, data acquisition platforms, cloud and edge computing, and machine learning algorithms are employed to detect anomalies (Zonta et al., 2020). Although high entry barriers are introduced, PdM is positioned as the most future-proof strategy. Once infrastructure is established, scalability across diverse assets and sites is achieved, and compounding value is generated. Furthermore, PdM technologies are integrated with digital twins, allowing asset performance simulation and predictive intervention planning (Lee et al., 2014). Thus, the technological demands that restrict adoption in SMEs also constitute PdM's greatest strength in digitally advanced environments.

Organizational and Human Factors

The success of maintenance strategies is shaped strongly by organizational and human factors. CM and PM are associated with minimal cultural or skill requirements, but adaptability and long-term reliability are sacrificed as a result (Alsyouf, 2007). TPM, in contrast, requires deep organizational commitment. Routine maintenance tasks are expected from operators, supported by management systems that emphasize continuous improvement (Nakajima, 1988). While performance improvements are reported in Japanese automotive firms, resistance is often encountered in other cultural contexts where employees hesitate to take on additional responsibilities (Tsang et al., 2010).

RCM requires strong cross-functional collaboration and high-level reliability expertise. Identification of failure modes and prioritization of interventions are

carried out with contributions from engineers, operators, and managers. While knowledge sharing can be formalized, alienation of frontline workers is sometimes reported when the process is perceived as overly theoretical (Smith and Hinchcliffe, 2004).

PdM, on the other hand, necessitates hybrid competencies that combine engineering expertise with data analytics and AI knowledge (Kumar et al., 2020). Workforce upskilling and interdisciplinary collaboration are required, often challenging traditional divisions between IT, operations, and maintenance. Resistance may arise where algorithmic predictions are distrusted or perceived as opaque. Nevertheless, PdM enhances decision-making by offering actionable insights rather than rigid rules, supporting collaboration between humans and machines. This alignment with Industry 5.0's emphasis on human-centricity positions PdM as both a technological and organizational innovation.

Scalability and Applicability

Scalability is emphasized as a key dimension for sustainable maintenance strategies. CM is regarded as inherently non-scalable, because expansion of production or assets rapidly magnifies the costs of downtime. PM is moderately scalable, particularly with standardized assets, but inefficiency emerges in heterogeneous environments where asset failure rates differ widely (Mobley, 2002).

TPM demonstrates limited scalability because sustained cultural commitment is required. In labor-intensive contexts, strong benefits are achieved, but in highly automated settings reliance on human engagement restricts applicability (Ahuja and Khamba, 2008). RCM is considered partially scalable, especially where a small number of highly critical assets are managed, such as in aerospace or energy. However, application across diverse manufacturing systems is constrained by the high analytical burden (Smith and Hinchcliffe, 2004).

PdM, in contrast, is regarded as inherently scalable once digital infrastructure is established. Predictive algorithms are applied across many asset types with low incremental costs (Zonta et al., 2020). Flexibility for both discrete and process

manufacturing is provided, from high-volume automotive to small-batch production. Continuous learning from new data allows PdM to adapt under volatile demand conditions and mass customization, establishing it as the most sustainable strategy for long-term competitiveness.

Integration with Industry 4.0 and Industry 5.0

A distinguishing feature of PdM lies in its integration with Industry 4.0 (I4) and Industry 5.0 (I5). PdM is digitally embedded, employing IoT networks, cyber-physical systems, cloud and edge computing, and advanced analytics to generate predictive insights. Within I4, PdM is used to build digital twins that simulate asset behavior and anticipate failures. Real-time data analysis enables proactive scheduling, minimizing downtime and maintaining continuity. Enterprise systems are also integrated, supporting semi-autonomous decision-making and enhancing efficiency across production lines.

In the I5 paradigm, which emphasizes human-centric and sustainable manufacturing, PdM offers unique advantages. Predictive models are used to complement human expertise, enabling collaborative intelligence between operators and intelligent systems. Adaptive resilience is supported by PdM's dynamic adjustment to production requirements, reducing waste and improving sustainability. Maintenance schedules are adjusted to small-batch and customized manufacturing, consistent with I5 operations. By contrast, CM, PM, TPM, and RCM remain static and unable to utilize predictive analytics. Thus, PdM's ability to integrate with I4 and I5 is recognized as a decisive advantage, extending beyond cost savings to include agility, resilience, and competitiveness. Predictive Maintenance has emerged as a pivotal approach for anomaly detection, health state prediction, and RUL estimation in a wide range of industrial machinery. Machine Learning (ML) and Deep Learning (DL) algorithms have been extensively employed to enhance the effectiveness of PdM across various systems, including CNC machinery, pressing machines, centrifugal fans, electric motors, bearings, and even steel manufacturing processes. The research on PdM in the manufacturing sector can be classified into the following categories (Mallioris et al., 2024).

Introduction to PdM applications

PdM in CNC Machinery

In the context of CNC machinery, PdM is primarily applied for anomaly detection, tool wear prediction, and RUL estimation. Several studies have explored different ML techniques for these purposes. For anomaly detection in CNC milling machines, Züfle et al. (2021) developed an ML-based approach utilizing Decision Trees (DT), Random Forest (RF), and XGBoost. Among these, DT achieved the highest F1 score of 92.9%. Similarly, Hesser and Markert (2019) focused on tool wear prediction, comparing Artificial Neural Networks (ANN), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), with ANN delivering the best results, achieving a recall of 96.8%. For RUL prediction, Traini et al. (2021) examined tool wear and RUL prognosis using a variety of algorithms, including linear regression, Bayesian regression, decision forests, boosted decision trees, and ANN. Time and frequency domain features of vibrations, acoustic emissions, and motor currents were analyzed, with ANN yielding the most accurate results based on root mean square error (RMSE) and root relative squared error (RRSE). Additionally, Sundaram and Zeid (2021) developed a MATLAB framework integrating data preprocessing and model comparison for RUL estimation, using features such as vibration, acoustic emission, current, depth of cut, and flank wear. Meanwhile, Sang et al. (2021) implemented a Deep Learning (DL) Long Short-Term Memory (LSTM) model within the FIREWARE framework, achieving an RMSE of 21.79 and reducing maintenance costs by 4–11%.

PdM in General Machinery

PdM techniques are applied to a range of other machinery, including pressing machines, centrifugal fans, electric motors, and hydraulic systems. For pressing machines, Serradilla et al. (2021) compared algorithms like SVM, null space, 2D-CNN-AE, and autoencoders, achieving an F1 score of 99% with the 2D-CNN-AE model. In another study, Rodrigues et al. (2022) applied XGBoost to predict the behavior of industrial paper pressing machines, finding that torque was the easiest parameter to predict while pressure proved more challenging, with XGBoost outperforming ANN and LSTM. In centrifugal fans, Lis et al. (2021)

applied nearest-neighbor ML algorithms for anomaly detection, addressing imbalance and bearing deterioration, while reducing false positives compared to knowledge-based methods. Romahadi et al. (2022) used a Bayesian network for fault classification in sugar factory fans, achieving a 93.2% prediction probability, and Selvaraj et al. (2022) applied a Bayesian algorithm for fault classification in centrifugal pumps, achieving an F1 score of 98%.

For electric motor systems, studies have focused on both failure prediction and health state classification. Arellano-Espitia et al. (2020) employed ANN with hyperparameter optimization using a genetic algorithm, achieving an accuracy of 92.03%, while Li et al. (2022) used transfer learning on a rotor kit to predict motor failures efficiently without increasing computational demands. Health state classification was also explored in conveyor systems, where Kiangala and Wang (2020) applied a Convolutional Neural Network (CNN) to classify conveyor motor states, achieving a 100% failure classification accuracy. Similarly, Elahi et al. (2022) used ANN for conveyor belt health classification, optimizing tension values and achieving an accuracy of 96.8%.

PdM in Bearings and Robot Joints

In the context of bearings, PdM is widely applied for both fault detection and RUL prediction. Cakir et al. (2021) developed a system for detecting damaged motor shaft bearings using Arduino and various ML algorithms, including DT, SVM, and RF, with DT achieving an accuracy of 99.84%. In another study, Vitolo et al. (2022) combined a convolutional autoencoder for anomaly detection with CNN for failure classification of motor bearings, achieving 99.61% anomaly detection accuracy and 94.83% classification accuracy. For RUL prediction in bearings, Aye and Heyns (2018) applied Affine Mean Gaussian Process Regression using acoustic emission data, achieving accurate predictions with minimal error. Additionally, Aydemir and Paynabar (2020) employed DL models (CNN-LSTM and Autoencoder-LSTM) for RUL prognosis of thrust bearings via thermal images, showing promising results despite challenges such as sparse datasets.

For industrial robot joints, Izagirre et al. (2020) introduced a physics-based Health Assessment Program (HAP) that analysed torque signatures to detect faulty

joints. The system measured torque increases, which were correlated with load and joint orientation, revealing the importance of measuring torque in assessing robot joint health.

PdM in Steel and Metal Industry

PdM techniques is also applied in the steel and metal industry to optimize the reliability and performance of machinery. Ruiz-sarmiento et al. (2020) proposed a Bayesian filter algorithm to predict degradation in steel hot rolling mills, achieving an RMSE of 2.98. In the hot strip mill process, Gay et al. (2022) combined SVM with knowledge-based methods for RUL prediction, utilizing features like pressure, temperature, and flow rate. Data augmentation, particularly time-based augmentation, improved prediction accuracy. Similarly, in wear detection for steel manufacturing, Chen et al. (2021) focused on predicting wear in a rotating metal bush used in TATA Steel, identifying key variables such as tension and diameter as important predictors. Neves et al. (2021) applied a data mining approach for anomaly detection in a cold forming manufacturing line, achieving an F1 score of 63% for classifying healthy states using acoustic emissions.

2.1 PdM implementation cost-efficiency

This section is presented as a literature review of research on cost efficiency in PdM implementation. Publications are identified using keywords including predictive maintenance, prognostics and health management (PHM), cost efficiency, investment, cost reduction, and return on investment. Because PdM and PHM are often used interchangeably (Tiddens, 2018), both terms are included. Two main concerns motivate this review. First, inconsistent boundary conditions such as time horizon, discount rate, and scope of costs are reported, which hinders comparison. Second, technical metrics such as accuracy and recall are not always translated into economic consequences including downtime, quality losses, or safety risks, creating difficulty for assessing business value. The literature is examined from three perspectives: investment and ROI formulation, case-specific cost efficiency evaluation, and cost avoidance.

2.1.1 PdM implementation investment and ROI formulation

The economic justification of PdM is consistently regarded as decisive for implementation. Return on investment (ROI) is emphasized as a critical determinant of PHM viability (Wagner & Hellingrath, 2021), and recommendations are made that implementation should not proceed without demonstrable returns. However, traditional ROI is criticized for narrow scope and static formulation. Essential costs such as training, infrastructure, and documentation are often omitted, as argued by Feldman et al. (2009). Their extended cost breakdown improves completeness but is considered impractical in early decision stages, when reliable data are scarce.

Alternative models are also proposed. Yu and Wing Keung (2020) developed a financial framework linking technical and business aspects and demonstrated superior benefits of PdM over preventive maintenance, though generalizability is limited because findings are based on a single case study. Spiegel et al. (2018) integrated diagnostic uncertainty into cost functions, highlighting risks from false alarms and missed detections. Despite its innovation, this approach presupposes mature prognostic algorithms and well-calibrated thresholds, which are not always attainable before PdM implementation. Other contributions further illustrate heterogeneity: Adu Amankwa et al. (2019) designed an SME-focused model in the UK; Grobbelaar and Visser (2015) applied expected value of information to compare PdM with preventive maintenance for non-repairable components; and Osako et al. (2019) together with Tsao et al. (2020) embedded PdM into broader IoT-based service systems and production frameworks. While these studies expand theoretical insight, applicability across industries is uncertain.

Overall, ROI and related measures are treated as important but insufficient. Costs are often modeled as one-time investments, while recurrent expenditures such as data management, algorithm retraining, and monitoring are underestimated. Scenario and sensitivity analyses are seldom conducted, although assumptions regarding failure rates, downtime valuation, and discount rates critically shape results. Intangible enablers such as training and organizational transformation

are acknowledged but rarely monetized. These gaps reduce the value of current models for decision making before implementation.

2.1.2 Specific PdM cases cost-efficiency calculation

A second stream of studies investigates specific applications. Early contributions in aerospace and telecommunications produced tailored cost-benefit models (Goodman et al., 2005; Wood & Goodman, 2006). Later studies examined IoT-based PdM in transport assets (Houston et al., 2017), semiconductor fabrication (Koitzsch et al., 2012), and offshore wind energy (Lei, 2015). These findings confirm reductions in failures and costs, but results are fragmented and highly context-dependent.

Low-cost PdM solutions are also discussed. Kadechkar et al. (2019) and Magadán et al. (2020) designed frameworks using inexpensive hardware and open-source platforms. Broader accessibility is achieved, but integration, cybersecurity, and long-term data management costs are often underestimated. Case studies by Schmidt and Wang (2018) and Raposo et al. (2017) reported measurable savings and performance gains, yet most analyses are descriptive and retrospective, offering little predictive support for decision makers. Furthermore, counterfactual scenarios are often absent, creating a risk of overestimated benefits due to selection bias.

In summary, case-specific studies provide useful empirical insight but face three limitations. Transferability is constrained by industry-specific factors; incomplete cost categories are often presented due to missing data; and standardized benchmarks across industries are rarely provided. Consequently, predictive and generalizable value is restricted.

2.1.3 PdM Implementation Cost Avoidance

A third group of studies highlights cost avoidance, emphasizing savings gained from failure prevention and downtime reduction. Spiegel et al. (2018) addressed diagnostic uncertainty by incorporating false positives and false negatives, showing improved financial control compared with accuracy-based metrics. Reliability-oriented decision policies are introduced by Maillart and Pollock (2002)

and He et al. (2018), accounting for lifecycle trade-offs. Comparative simulations by Arnaiz et al. (2013) and Gilabert et al. (2017) reported consistent cost advantages of PdM over corrective and preventive maintenance. Florino and Melo (2011) demonstrated production cost reductions by monitoring tool wear in wood panel manufacturing.

Despite these contributions, persistent challenges are reported. First, avoided costs are sometimes double counted, inflating benefits when downtime, scrap, and warranty claims are simultaneously included. Second, overtreatment risks from false positives are underestimated. Thresholds are optimized for accuracy rather than economic cost minimization, reducing business relevance. Third, the dynamic nature of maintenance is often overlooked. Imperfect repairs modify hazard rates and future costs, but independence is often assumed. For these reasons, robustness of cost avoidance estimates under real operational conditions remains questionable.

Comparative critique across cost-efficiency perspectives

While the three identified streams ROI formulation, case-specific evaluations, and cost avoidance are each recognized as providing valuable insights, fundamentally different assumptions are reflected in how the value of PdM is measured and realized. In ROI-based approaches, emphasis is placed on ex-ante justification and investment rationalization; however, operational complexity is often oversimplified, and long-term sustainability or resilience benefits are frequently neglected. In case-specific evaluations, empirical realism is achieved, yet generalizable frameworks are seldom established, and cost savings are frequently conflated with avoided losses, thereby limiting strategic comparability. Within cost-avoidance studies, a broader perspective is adopted through the integration of uncertainty and reliability aspects, although stable system conditions are often assumed and economic gains are sometimes double-counted.

In comparative terms, PdM has generally been treated as a financial optimization problem within cost–benefit–driven research, whereas cost-efficiency has been framed as part of broader socio-technical transitions in emerging sustainability-

oriented approaches (e.g., those embedded within circular manufacturing or energy-efficient operations). The development of theory has been restricted by limited cross-dialogue between these streams: environmental or social value is rarely incorporated into financial models, and economic trade-offs are seldom operationalized within sustainability studies. A more holistic understanding of PdM implementation feasibility could be advanced through stronger integration of these perspectives, whereby short-term ROI logic is linked with long-term sustainable value creation.

2.1.4 Main research gaps in the thesis

The main research gaps are discussed in this section, as a foundation for Primary Research Question presented in *Section 1.3: What is the evaluation method for the cost-benefit analysis of predictive maintenance implementation, while accounting for the investment in tangible and intangible assets of PdM?*

Required Tangible Asset: Although a considerable body of research has been devoted to the cost–benefit of PdM, much of this work is presented retrospectively and therefore provides limited support for firms seeking to conduct meaningful pre-implementation investigations. One of the earliest comprehensive evaluations of PdM benefits in terms of reduced downtime and maintenance savings is provided by Feldman et al. (2009), while Lee et al. (2014) emphasize PdM’s potential to extend equipment lifetime. The long-term financial value of PdM is thus demonstrated once implementation is assumed, yet the prior question of whether PdM is the most appropriate strategy in a given operational context is not considered. Similarly, the importance of aligning PdM with company-specific conditions is highlighted by Tiddens et al. (2018), but their work remains conceptual rather than prescriptive, offering little concrete guidance for managers weighing PdM against alternative strategies before committing resources.

A second body of research is focused on the technical diversity of PdM techniques. Predictive algorithms and monitoring methods, each with distinctive requirements for sensors, data storage, connectivity, and computing capacity, are analyzed by Lei (2015), Osako et al. (2019), Magadán et al. (2020), Yu and Wing-

Keung (2020), and Wagner and Hellingrath (2021). These contributions are valuable for clarifying the operational mechanics of PdM, yet translation into decision-support frameworks that enable firms to assess the tangible investments associated with different techniques prior to adoption is seldom achieved. For instance, algorithmic performance in aerospace applications is evaluated by Magadán et al. (2020), but systematic consideration of how sensor and integration costs scale with technique selection is not provided. Likewise, advances in failure prediction are offered by Osako et al. (2019), but the economic implications of the required hardware remain underexplored. A pre-implementation model for SMEs is proposed by Adu-Amankwa et al. (2019), but the limited scope and small-scale orientation reduce its generalizability to larger industrial contexts. Collectively, technical progress is achieved, but managers are not equipped with structured methods to anticipate the scale of tangible asset investment including sensors, IT infrastructure, and integration platforms before implementation decisions are taken.

Required Intangible Asset: Equally significant is the widespread neglect of intangible assets in PdM evaluation. Their relevance is occasionally acknowledged but rarely treated systematically. The role of training is briefly noted by Feldman et al. (2009), and the importance of decision-support processes in human–machine interaction is discussed by Bousdekis et al. (2019). However, attempts to quantify the costs and benefits of intangible factors such as workforce training, organizational adaptation, cultural change, or operator trust in diagnostic outputs are rarely undertaken. In practice, these factors often prove decisive: without adequate skills development and organizational alignment, investments in sensors and algorithms are unable to achieve projected returns. Yet because tangible costs are predominantly modeled, intangible aspects are frequently excluded from cost–benefit analyses, producing optimistic but incomplete evaluations of PdM feasibility.

2.2 AHP for maintenance strategy selection

In Section 2.1, several overarching gaps in PdM implementation research were highlighted in relation to the methodological foundations of decision support. To

enable these gaps to be addressed systematically, the main streams of methodological approaches applied in PdM decision-making are examined in the following sections. In Section 2.2, the Analytic Hierarchy Process (AHP) is introduced as one of the most established multi-criteria decision-making (MCDM) techniques employed in maintenance strategy selection.

The Analytic Hierarchy Process (AHP) is widely employed as a multi-criteria decision-making (MCDM) method for the selection of maintenance strategies. Its appeal is attributed to its hierarchical structure, its capacity to decompose complex industrial problems into tractable sub-problems, and its reliance on tangible evaluation factors such as cost, downtime, and reliability (Aghaie & Fazli, 2012; Odeyale et al., 2013; Seiti et al., 2017). AHP is regarded as particularly suitable in industrial contexts where transparent and low-data-demanding tools are required for balancing competing strategies. Over time, refinements to AHP are proposed to address methodological limitations. The Best-Worst Method (BWM) is introduced to reduce the number of pairwise comparisons and improve consistency (Rezaei, 2015). Fuzzy-AHP is integrated with fuzzy logic to capture uncertainty in expert judgments, particularly where tangible indicators such as downtime or efficiency cannot be measured precisely (Chang, 1996; Büyüközkan et al., 2011). More recently, hybrid approaches are developed by combining AHP with machine learning (ML) methods, allowing weights to be estimated directly from operational data in order to reduce subjectivity (Zhang et al., 2019).

Despite these methodological advancements, several critical limitations are observed. First, existing approaches are almost exclusively grounded in conventional tangible criteria such as cost, reliability, and safety. As summarized in Table 2-1, emphasis is consistently placed on capital investment, downtime, and total efficiency in studies such as Aghaie and Fazli (2012), Odeyale et al. (2013), and Hemmati et al. (2019). While environmental impact or safety is occasionally incorporated (Seiti et al., 2017; Kurian et al., 2020), these aspects are treated as peripheral rather than central. This reflects the continued prioritization of efficiency-driven logic under Industry 4.0, where productivity and

automation dominate decision-making. More importantly, insufficient attention is given to the three fundamental priorities of Industry 5.0:

Sustainability: Environmental impact is occasionally included as a criterion (e.g., Seiti et al., 2017), but it is typically reduced to energy costs or emissions penalties rather than broader sustainability goals. Systematic consideration of energy efficiency, circularity, or waste prevention is absent. For instance, Zaim et al. (2012) and Ohta (2018) provide comprehensive decision criteria but omit factors such as waste minimization and resource efficiency, despite their explicit emphasis in Industry 5.0 (Zizic et al., 2022; Hein-Pensel et al., 2023). As shown in Table 2-2, more recent literature extends the decision space with sustainability-focused criteria such as energy efficiency, waste prevention, and information logistic waste.

Resilience: Optimization for steady-state performance under stable conditions is assumed in most AHP studies. Yet PdM success depends on robustness under uncertainty, including volatile supply chains, fluctuating demand, and unexpected disruptions. Reliability benefits are highlighted in works such as Kurian et al. (2020) and Darestani et al. (2022), but resilience-related aspects such as adaptability of predictive models, cross-functional integration, or fault diagnosis under variable conditions are not addressed. In contrast, emerging works (Table 2-2) introduce resilience-oriented criteria such as “people towards resilience,” “technology toward resilience,” and “maintenance–production linkage,” which emphasize robustness across organizational and technical dimensions (Gladysz et al., 2023; Wang et al., 2024).

Human-Centricity: Human-related considerations are almost entirely absent. The workforce is generally treated as a passive operator rather than an active participant in maintenance strategy adoption. While training is occasionally mentioned, intangible factors such as workforce trust in diagnostic outputs, human–machine integration, or meaningful job creation are not quantified or prioritized. For instance, Hemmati et al. (2019) evaluate strategies based solely on efficiency and safety, overlooking human-centric priorities. This omission is significant, as Industry 5.0 emphasizes meaningful human roles alongside

technological integration (Alves et al., 2023; Fatima et al., 2022). As demonstrated in Table 2-2, human-centric criteria including human needs adoption, ethical technology use, and human–machine integration remain absent from conventional AHP frameworks.

In addition to these Industry 5.0 dimensions, representation of Predictive Maintenance in existing AHP-based evaluations is often idealized. Conclusions in several studies (e.g., Kurian et al., 2020; Darestani et al., 2022) suggest that PdM is preferable due to reduced unplanned downtime and improved reliability. However, implementation barriers such as high capital requirements for sensors and IT infrastructure, issues of data availability and quality, complexity in predictive model deployment, and shortages of technical expertise are overlooked (Khan et al., 2022; Achouch et al., 2022; Hubert & Kaledio, 2024). Exclusion of these constraints leads to overly optimistic recommendations.

In summary, while AHP and its extensions contribute to structuring decisions around tangible criteria, their scope remains too narrow. Cost, efficiency, and reliability continue to dominate, whereas Industry 5.0 priorities—sustainability, resilience, and human-centricity as well as tangible feasibility constraints of PdM are insufficiently reflected. The comparison of Table 2-1 and Table 2-2 demonstrates this imbalance clearly: where the former emphasizes traditional efficiency metrics, the latter incorporates sustainability, resilience, human-centric dimensions, and PdM feasibility considerations. This gap highlights the need for an updated evaluation framework in which the clarity and accessibility of AHP are retained while the realities of modern manufacturing systems are incorporated.

2.2.1 Identified research gaps

The research gaps related to AHP maintenance strategy selection method is discussed in this section. This discussion can be used to justify the Research Question One presented in Section 1.3, which is: *What is the evaluation method that helps manufacturers evaluate the key tangible assets for PdM implementation, considering whether PdM is required and which PdM technique is needed?*

The primary research problem in selecting the most suitable maintenance strategy in modern manufacturing environments using AHP is the lack of investigation into the appropriate decision criteria that influence the maintenance strategy selection process. While various decision criteria are utilized for this purpose, there is a lack of study on which criteria should be considered essential in the maintenance strategy selection process (Lootsma, 1996). Moreover, with the emergence of Industry 4.0 and Industry 5.0, new factors such as sustainability, resilience, and human-centric considerations are increasingly important throughout the product lifecycle (Xu et al., 2021). In the context of predictive maintenance, these considerations influence not only the choice of maintenance strategies but also the design and implementation of PdM systems. Sustainability requires PdM strategies to optimize use and reduce waste, while resilience emphasizes the need for maintenance systems that can adapt to disruptions or failures. Human-centric considerations, on the other hand, focus on enhancing operator well-being and ensuring that maintenance systems are designed to be intuitive and supportive of human decision-making, ultimately leading to safer and more efficient operations. However, these factors are often overlooked in current maintenance strategy selection. Correctly defining decision criteria is crucial as it forms the basis for selecting a suitable maintenance strategy. The current lack of examination of the criteria used for maintenance strategy selection in the modern manufacturing industry underscores the need for comprehensive analysis. It is evident that existing approaches, as seen in Table 2-1, for the selection of maintenance strategies have certain limitations and unresolved difficulties. These are identified as the following research gaps:

Gap 1 Lacking consideration of the sustainability factor impact of the modern manufacturing environment

First, with respect to sustainability, most AHP applications are found to omit environmental criteria or reduce them to narrow proxies such as energy costs or emissions penalties. Even when “environmental impact” is included (Seiti et al., 2017; Hemmati et al., 2019), 15-relevant sustainability concepts such as energy efficiency, resource circularity, and waste prevention are not operationalized in

ways that link directly to PdM infrastructure decisions. Criteria and measurement constructs that would allow decision makers to evaluate how data processing, or maintenance scheduling affect energy use, material waste, or life-cycle resource intensity are missing, thereby preventing meaningful assessment of PdM's contribution to sustainability goals (cf. Table 2-2).

Gap 2 Lacking consideration of the resiliency factor impact of the modern manufacturing environment

Second, in relation to resilience, AHP studies are generally found to optimize for steady-state reliability or average performance (Aghaie & Fazli, 2012; Odeyale et al., 2013), while robustness under variability is not adequately addressed. The capacity of a maintenance strategy to perform under supply-chain shocks, demand volatility, or rapid technological change is rarely considered. Since PdM's value depends not only on expected downtime reduction but also on the adaptability of its sensing and analytics stack under disruption (Kurian et al., 2020; Darestani et al., 2022), the absence of resilience-oriented tangible criteria such as modularity of sensor networks, redundancy of data paths, or time-to-rebuild models after data loss limits ex-ante evaluation. As indicated in Table 2-2, criteria relevant to operational resilience remain underrepresented.

Gap 3 Lacking consideration of the human-centric factor impact of the modern manufacturing environment

Third, with respect to human-centricity, workforce-related considerations are typically treated as peripheral tangible costs, such as one-off training expenditures, rather than as measurable strategic outcomes. The Industry 5.0 perspective reframes human roles, emphasizing job meaningfulness, human-machine integration, and operator trust in diagnostic outputs (Zizic et al., 2022; Alves et al., 2023). Current AHP studies are not found to incorporate tangible proxies that connect PdM adoption to human outcomes, such as changes in task content, measurable operator acceptance, or human-in-the-loop redesign costs. Without these linkages, trade-offs between automation efficiency and human-centric objectives cannot be adequately evaluated.

Gap 4 Lacking consideration of PdM limitations

Beyond the three I5 dimensions, a content-specific gap is observed with respect to PdM feasibility. In many AHP analyses, PdM is identified as the superior option (Kurian et al., 2020; Darestani et al., 2022), yet concrete infrastructure and operational investments are not properly represented. Tangible elements such as sensor coverage density, edge/cloud architecture readiness, integration complexity between legacy PLCs and IIoT systems, data ingestion and labelling costs, and recurrent expenditures for sensor maintenance and model retraining are rarely modeled explicitly. Where they appear, they are subsumed under broad “capital cost” categories, preventing realistic ex-ante sensitivity or scenario analysis (Khan et al., 2022; Achouch et al., 2022). As a result, recommendations that appear robust within AHP hierarchies are often fragile when confronted with actual deployment costs and timelines.

In summary, methodological sophistication is evident in the literature (BWM, fuzzy-AHP, ML hybrids), but a content deficiency persists: the tangible criteria used to evaluate PdM remain incomplete relative to what firms must actually build and sustain. Table 2-1 demonstrates the dominance of traditional efficiency metrics, while Table 2-2 highlights the emerging I5-aligned and feasibility-related criteria that are largely absent from existing frameworks.

The research opportunities associated with the identified gaps are presented in Section 2.6.

Table 2-1 Publication on AHP for maintenance strategy selection

Paper	Decision Criteria														Maintenance Alternative				Limitation				
	Capital Investment	Annual Maintenance Cost	Training Cost	Total Efficiency	Reduced Downtime	Flexibility & Customizability	Improved Product Quality	Satisfaction and Loyalty	Safety to People	Safety to Equipment	Environment Impact & Hazard	Carbon Emission	Operator Confidence Level	Tech. Assessment	CM	PM	PdM	Other	Lacking sustainability consideration	Lacking resiliency consideration	Lacking human-centric consideration	Lacking PdM utilization consideration	Incomplete PdM limitation consideration
Abdi and Labib (2003)	✓	✓		✓	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		
Ierace and Cavaleri (2008)		✓			✓		✓		✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓		
Aghaie and Fazli (2012)	✓	✓	✓											✓	✓	✓	✓	✓	✓	✓	✓	✓	

Zaim et al. (2012)	✓	✓	✓				✓	✓	✓	✓					✓	✓	✓			✓	✓		✓
Odeyale et al. (2013)	✓				✓		✓						✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Azadeh et al. (2016)		✓		✓	✓	✓	✓	✓	✓	✓			✓		✓	✓	✓		✓		✓		
Seiti et al. (2017)		✓	✓	✓	✓		✓		✓	✓	✓		✓		✓	✓		✓	✓	✓	✓		✓
Ohta (2018)		✓					✓		✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Hemmati et al. (2019)	✓	✓	✓		✓		✓		✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Kurian et al. (2020)	✓	✓	✓		✓		✓	✓		✓	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓
Darestani et al. (2022)	✓	✓	✓		✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2-2 New decision criteria identified for maintenance strategy selection under Industry 5.0

Paper	Human needs adoption	Human-machine	Meaningful job creation	Energy efficiency	Waste prevention	Information logistic waste	Technology ethical	People towards resilience	Technology toward	Mass personalization	Resource & knowledge	Data availability	Maintenance & production	Model deployment	Fault diagnoses
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Zizic et al. (2022)	✓	✓	✓	✓		✓		✓	✓						
Alves et al. (2023)	✓	✓	✓				✓								
Hein-Pensel et al. (2023)	✓	✓	✓												
Gladysz et al. (2023)	✓	✓	✓												
Wang et al. (2024)	✓	✓	✓												
Kasinathan et al. (2022)	✓	✓	✓												
Destouet et al. (2023)	✓	✓	✓	✓	✓			✓	✓						
Madzik et al. (2024)	✓	✓	✓												
Paschek et al. (2022)		✓			✓					✓					
Fatima et al. (2022)		✓	✓												
Vyhmeister & Gabriel (2024)		✓	✓	✓	✓										
Taj & Zaman (2022)		✓								✓					
Zafar et al. (2024)		✓													

Gomathi et al. (2023)		✓			✓										
Tavares et al. (2022)		✓			✓										
Panagou et al. (2024)		✓													
Baig & Yadegaridehkordi (2024)				✓	✓										
Dhayal et al. (2023)				✓	✓										
Khan et al. (2022)											✓	✓			
Achouch et al. (2022)											✓	✓		✓	
Sivanuja & Sandanayake (2022)											✓	✓	✓	✓	✓
Hassankhani et al. (2021)											✓				✓
Cheng et al. (2022)											✓				
Hubert & Kaledio (2024)											✓	✓		✓	✓
Ucar et al. (2024)												✓	✓		✓

Çınar et al. (2020)												✓			
Mallioris et al. (2024)												✓			
Zonta et al. (2020)													✓		
Nunes et al. (2023)															✓

2.3 PdM technique selection

2.3.1 Domain knowledge as a structural prerequisite for PdM technique selection

In industrial predictive maintenance research and practice, domain knowledge is consistently identified as a structural prerequisite for the selection and development of techniques rather than as an auxiliary factor. Numerous studies (e.g., Tinga et al., 2019; Aivaliotis et al., 2021; Bonci et al., 2021; Ciano et al., 2024; Tejani, 2024) demonstrate that the definition of problems, the prioritization of analytical targets, and the parameterization and validation of algorithms are guided by expert understanding. Without such expertise, even advanced data-driven approaches are prone to misapplication and limited operational value is produced. The identification of critical components, the interpretation of sensor signals, and the comprehension of physical degradation processes are required to be carried out with both theoretical understanding and practical experience. This requirement is made particularly evident when objectives extend beyond anomaly detection toward prognostics and lifecycle optimization.

Domain knowledge is not obtained from a single source but is assembled through three primary channels: internal expertise, external consultancy or vendor support, and secondary data such as published failure models and open datasets. Each channel is associated with distinct advantages and limitations. Internal experts are shown to contribute contextual familiarity and tacit knowledge, though their insights are often fragmented or undocumented. External consultants are observed to provide advanced modelling and machine learning expertise, though this can create dependency and misalignment with plant constraints. Secondary data is frequently employed to provide initial modelling baselines, but transferability issues often arise due to domain shifts. As reported by Ciano et al. (2024) and Znaidi et al. (2025), successful PdM implementations are typically achieved through combinations of these channels to close gaps. Nevertheless, existing frameworks rarely evaluate the sufficiency and sourcing of knowledge as an explicit part of technique selection.

Alongside knowledge, data is identified as another foundational resource for PdM. While domain knowledge constrains and validates modelling, data enables training, calibration, and scaling. The literature demonstrates that the availability, quality, and representativeness of historical data frequently determine which methods are feasible. Data-driven approaches are found to require large volumes of labelled failure data, whereas physics-informed or hybrid approaches are typically adopted when data are sparse but expert input is strong. Even where abundant data are available, challenges such as sensor unreliability, noisy labels, and distribution shifts are shown to limit performance unless expert insight is incorporated (Sang et al., 2021; Fordal et al., 2023). The relationship between data and domain knowledge is not characterized by substitution but by synergy: empirical evidence is provided by data, while interpretability and constraints are imposed by expertise. Iterative feedback loops, in which expert validation refines data-driven outputs and empirical results reshape fault taxonomies, are frequently reported (e.g., Natanael & Sutanto, 2022). This interplay is highlighted as a key success factor, yet the literature reveals a persistent bias, as many studies adopt either a technique-first or a data-first orientation, with insufficient consideration of how organizational knowledge resources condition feasibility. Taken together, these observations indicate that PdM feasibility is not evaluated in isolation from the resources of knowledge and data. To clarify how these resources condition implementation, the technical alternatives available to practitioners are examined in the following section.

While the benefits of PdM are well acknowledged, practical implementation often faces numerous obstacles. A primary obstacle lies in the absence of systematic methodologies to aid enterprises in selecting the optimal PdM technique tailored to their unique requirements (Li et al., 2022). The PdM technique applied in practice can be classified into five groups, which are: experience-based, model-based, physical-based; data-driven; and hybrid. PdM technique selection is a critical step for implementation process, it is necessary to develop a selection scheme that compares the suitability of each technique by considering not only the attributes of the application but also the proficiency and unique requirements of the user (Lee et al., 2014). The lack of a systematic approach appears as a

major barrier to the widespread implementation of predictive maintenance systems in real-scale industrial applications (Jimenez et al., 2020). Each PdM technique comes with its specific requirements in terms of hardware, software, and information, among other factors. Consequently, the implementation cost and time for each technique vary, as does their capability spectrum. PdM technique capability encompasses tasks such as accurate component state prediction, fault prognosis, and asset service life extension. Selecting the most suitable PdM technique for a given setup or scenario is crucial for successful implementation in the industry. This selection is essential for optimizing costs and time, as well as ensuring overall financial viability and return on investment in the long run (Li et al., 2022). To address this research challenge and aid enterprises in selecting PdM techniques in practice, a review of PdM techniques presented in publications is conducted. This review aims to identify research issues and gaps pertaining to PdM technique selection.

2.3.2 PdM techniques

Experience-based PdM techniques are derived from accumulated practical experience (Majstorović and Milačić, 1990; Freyermuth, 1992; Hao et al., 2009; Ruiz et al., 2014; Grabot, 2020). Knowledge is built up by human experts through years of maintenance practice, and tacit knowledge is employed to identify faults, describe component wear, and predict failure (Hao et al., 2009; Jimenez et al., 2020). In computer-aided systems, experience-based techniques are implemented to facilitate automated diagnostics and prognostics, often at moderate costs and varying levels of complexity. Their explicability is highlighted as a notable strength (Vogl et al., 2014), but their prognostic capability is consistently reported to be limited (Jimenez et al., 2020).

Data-driven PdM techniques are positioned at the opposite end of the spectrum. In Industry 4.0 contexts, manufacturing systems are equipped with sensors through which operational data streams (e.g., vibration, humidity, noise, temperature, pressure, rotation speed) are continuously recorded. These data streams are analyzed to monitor wear and provide prognostics regarding Remaining Useful Life (RUL) (Jimenez et al., 2020). Artificial Neural Networks

(ANN), Support-Vector Machines (SVM), and Decision Trees (DT) are widely applied and high accuracy in fault prediction and RUL estimation is reported (Wöstmann et al., 2019; Sai et al., 2019; Ramesh et al., 2020; Shamayleh et al., 2020). Nevertheless, these techniques are found to require abundant labelled data and are subject to limitations caused by noisy signals and distribution shifts.

Model-based PdM techniques rely on mathematical models to describe or capture the state of degradation of systems or components (Zhan and Mechefske, 2007; Coble and Hines, 2011; Cheng et al., 2012; Du et al., 2014; Aye and Heyns, 2017). These techniques use models for fault diagnosis and prognosis, utilizing residuals as features. Residuals compare measured results with the expected behavior of the process, as defined by the analytical model (Ran et al., 2019). Commonly used models include Markov chains, Gaussian models, linear systems, and Wiener models. These models are well-suited for estimating the RUL of components, as they are regression models. Model-based techniques offer high prediction accuracy and the significant advantage of reusability (Ran et al., 2019). However, they are computationally expensive and require advanced mathematical understanding for development. Additionally, a drawback of model-based techniques is that mathematical models can only describe a limited number of wear and tear types, such as abrasion, corrosion, fatigue, cavitation, erosion, and friction-induced wear.

Physics-based PdM techniques utilize the principles of physics to assess the degradation of components. These techniques employ physics behavior models to generate highly accurate simulations of component wear and tear (Jimenez et al., 2020). While both physics-based and model-based techniques can be described by mathematical equations, model-based techniques are not necessarily related to physical laws or phenomena, and they can involve statistical or stochastic equations. Physics-based models enable the monitoring and assessment of part wear and tear through computational simulations (Jennions et al., 2016; Climente-Alarcon et al., 2017; Li et al., 2019; Qiao and Brian, 2018). However, they can accurately describe and simulate only limited wear and tear phenomena, such as fatigue and crack formation in mechanical

components, or rotor cage damage and degradation in industrial robots. Additionally, factors like external environmental conditions, such as temperature and pressure, may influence prediction accuracy (Schmidt et al., 2015). Developing physics-based techniques also requires advanced knowledge of physics.

Hybrid-approach In the context of Industry 4.0, manufacturing systems are becoming increasingly complex, often including multiple manufacturing stations or facilities to meet growing demands for high-quality, customizable products with reduced lead times and costs. The complexity of such systems means that not all components can be effectively assessed with a single model, requiring the use of multiple PdM techniques in combination (Jimenez et al., 2020; Alaswad et al., 2019). For example, Al-Dulaimi et al. (2019) present multiple data-driven systems for a simulated jet engine, while Grabot (2020) combines experience-based techniques with data-driven techniques for complex systems. However, the main drawback of the hybrid approach is its higher implementation cost compared to single-technique PdM systems.

This review demonstrates that distinct requirements in terms of data availability, expert knowledge, computational resources, and implementation costs are exhibited by each PdM technique. For instance, experience-based approaches are shown to rely heavily on tacit expert knowledge while offering limited prognostic capability (Jimenez et al., 2020). Data-driven methods are reported to achieve high prediction accuracy, but abundant, high-quality labelled datasets and strong computational infrastructure are required (Wöstmann et al., 2019; Sai et al., 2019). Model-based and physics-based techniques are found to capture degradation mechanisms effectively, but sophisticated modelling skills, in-depth domain knowledge, and significant computational resources are demanded (Zhan and Mechefske, 2007; Coble and Hines, 2011; Li et al., 2019). Hybrid techniques are described as combining strengths, but higher complexity, integration challenges, and resource intensity are also incurred (Jimenez et al., 2020; Grabot, 2020).

What becomes evident across these categories is that the requirements of each technique are often implicit but not systematically articulated in the literature. While the technical performance of algorithms or models is typically described, explicit preconditions for successful implementation such as sufficiency of domain knowledge, origin and quality of data, enterprise objectives, or trade-offs among cost, interpretability, and accuracy are seldom examined. As a result, enterprises are frequently confronted with a paradox: although a broad technical catalogue of PdM methods is available, guidance on which method aligns with their existing resources and objectives remains underdeveloped.

This gap is considered particularly critical from the perspective of industrial practitioners. Enterprises are rarely observed to begin with an unconstrained choice of techniques; rather, they operate under bounded conditions defined by available knowledge, data readiness, and organizational priorities. Yet the literature predominantly adopts a “technique-first” perspective, whereby resources are assumed to be mobilized to fit the method, instead of beginning from the reality of what resources are available. The absence of frameworks in which requirements such as knowledge sourcing or attribute–objective alignment are operationalized is found to directly limit the identification of suitable PdM techniques for specific contexts. This shortcoming is consistently linked to the persistent difficulty of scaling PdM beyond isolated pilot projects into consistent industrial practice.

2.3.3 Identified research gaps

The research gaps related to PdM technique selection method are discussed in this section, this discussion can be used to justify the Research Question One presented in Section 1.3, which is: *What is the evaluation method that helps manufacturers evaluate the key tangible assets for PdM implementation, considering whether PdM is required and which PdM technique is needed?*

Based on the above critical synthesis, it is evident that although substantial progress has been achieved in developing and categorizing PdM techniques, several fundamental gaps remain in the way these techniques are analyzed,

contextualized, and aligned with industrial needs and resources. These gaps are outlined as follows.

Gap 1 Lacking PdM technique capability analysis

Numerous predictive models and algorithms have been developed for each PdM technique, with varying capabilities in terms of fault prediction accuracy, Remaining Useful Life (RUL) estimation, and practical usability (Ruiz et al., 2014; Zhan and Mechefske, 2007; Coble and Hines, 2011; Wöstmann et al., 2019; Grabot, 2020; Sai et al., 2019). However, systematic comparisons or structured frameworks for understanding these capabilities are rarely provided. A clear understanding of what each technique can and cannot achieve is critical for rational selection, yet this analytical perspective is largely absent.

Gap 2 Lacking PdM implementation objective analysis

Existing literature related to PdM implementation fail to offer a consistent explanation of the objectives of the implementation process. These objectives should accurately represent the needs of enterprises for PdM implementation. It is observed from the literature that researchers and enterprises have different objectives for PdM implementation. Some aim to predict the fuzzy state of components, while others aim to predict the accurate state of components. Additionally, some aim to extend device service life, while others aim to optimize multiple key performance indicators (Hao et al., 2009; Vogl et al., 2014; Du et al., 2014; Li et al., 2019). Furthermore, the choice of which PdM technique to use depends on the needs of enterprises for implementation (Jimenez et al., 2020). However, existing literature often starts PdM with the data acquisition process but neglects the needs/objective analysis. Therefore, it is necessary to develop a method that allows enterprises to analyze their objectives before deciding which PdM technique to select. This approach will ensure that the selected PdM technique aligns with the specific objectives and needs of the enterprise, leading to more effective implementation and utilization of PdM systems.

Gap 3 Lacking PdM implementation attributes analysis

Different PdM implementation attributes are observed from the literature review, including cost, data availability, expert knowledge, etc. (Jimenez et al., 2020). However, in the existing literature describing the PdM implementation process, it can be observed that certain attributes are mentioned, but there is no systematic explanation of which attributes have been considered, nor any discussion of how these attributes impact the overall implementation process. These attributes can be used to describe the unique situation of each PdM user. Moreover, these attributes have a significant impact on determining which PdM technique is suitable for an enterprise, as well as the possibility for enterprises to develop a PdM technique.

Gap 4 Lacking linkage among PdM implementation attributes and objectives with PdM techniques

A holistic investigation is required on the attributes considered in the PdM implementation process and to link these attributes and objectives with PdM techniques. This comprehensive analysis will provide valuable insights into the factors influencing the selection and implementation of PdM techniques, enabling enterprises to make informed decisions that align with their specific needs and circumstances.

Gap 5: Lack of operationalization of domain knowledge sourcing

Although domain knowledge and data are consistently recognized as co-determinants of PdM feasibility (Tinga et al., 2019; Aivaliotis et al., 2021; Bonci et al., 2021; Ciancio et al., 2024; Tejani, 2024; Sang et al., 2021; Fordal et al., 2023), most frameworks stop at acknowledging their importance. Very few studies specify how knowledge should be sourced (internal, external, or secondary), how sufficiency should be evaluated, or how gaps should be compensated. Furthermore, the interaction between data availability and expert knowledge often identified as decisive for successful implementations (Natanael & Sutanto, 2022; Ciancio et al., 2024; Znaidi et al., 2025) remains under-theorized. The absence of such operationalization severely restricts the ability of enterprises to select appropriate PdM techniques based on their existing resources and constraints.

The requirement for PdM technique decision support

The review of existing literature has highlighted several gaps in the selection of PdM techniques. While PdM methods have been comprehensively categorized, the decision-making process in practice remains fragmented and under-theorized. Specifically, studies tend to emphasize either algorithmic performance or isolated case demonstrations, while paying insufficient attention to the contextual resources that condition feasibility. As identified in the previous sections, enterprises frequently face constraints in terms of internal expertise, access to external support, and availability of high-quality data. Yet, current approaches offer no systematic way of linking these constraints with the requirements and capabilities of different PdM techniques. This lack of operationalized decision guidance increases the risk of selecting techniques that do not align with enterprise objectives or resource realities.

These gaps motivate the need for a structured framework that systematically supports PdM technique selection. The rationale for such a framework is twofold: first, to overcome the descriptive tendencies of existing studies by offering a resource-driven perspective; and second, to provide enterprises with a practical tool that ensures alignment between methodological capabilities and industrial objectives under real-world constraints.

The review of the literature makes it clear that what is needed is not another technique-centered comparison, but a decision framework that is explicitly resource-driven. Such a framework must be designed to overcome the shortcomings observed in current studies, particularly the lack of systematic attention to resource constraints, the weak alignment between technique capabilities and enterprise objectives, and the fragmented treatment of implementation attributes. In order to be useful for both researchers and practitioners, the framework must therefore rest on three interrelated principles.

First, it must be resource-aware. The literature shows that domain knowledge and data availability are co-determinants of PdM feasibility, yet current studies rarely evaluate them in a structured way. A resource-driven framework should begin by explicitly assessing the sufficiency and sourcing of these resources,

ensuring that enterprise-specific limitations such as fragmented expertise or noisy data are recognized and incorporated into the selection process.

Second, the framework must ensure capability-objective alignment. Different PdM techniques have distinct capabilities, such as fault detection accuracy, life-cycle prognostics, or multi-objective optimization. Yet the review revealed that enterprise objectives are often under-specified, leading to misalignment between chosen techniques and expected outcomes. A systematic linkage between technique capabilities and enterprise objectives is therefore required to make the selection process evidence-based rather than ad hoc.

Third, the framework must integrate critical implementation attributes. Cost, data requirements, and expert knowledge are frequently mentioned but inconsistently considered in the literature, often treated in isolation. A comprehensive framework must consolidate these attributes into a structured assessment, allowing enterprises to evaluate trade-offs holistically and avoid overlooking constraints that directly affect feasibility.

To make such a framework practically viable, it should also be supported by clear design mechanisms. One is the Knowledge Source Triad, which distinguishes between internal expertise, external consultancy, and secondary data as complementary channels of domain knowledge. As the literature shows, successful PdM implementations often combine these sources to close knowledge gaps (Ciancio et al., 2024; Znaidi et al., 2025). Another is a rule-based feasibility matrix that operationalizes the interaction of data readiness and knowledge sufficiency, offering actionable guidance on feasible technique choices. For example, limited labelled data but strong internal expertise points toward physics-informed or hybrid methods, while abundant high-quality data but limited expertise suggests data-driven methods supplemented by external validation (Sang et al., 2021; Fordal et al., 2023; Natanael & Sutanto, 2022).

In short, what the field requires is a framework that is resource-driven, objective-sensitive, and attribute-integrated. By operationalizing these principles and mechanisms, such a framework would move beyond descriptive comparisons

and algorithmic preferences, providing enterprises with a rigorous yet practical tool for PdM technique selection.

To ensure that the methodological design is directly aligned with the deficiencies identified in the literature, the specific research gaps and the corresponding requirements for methodological development are summarized in Table 2-3. Through this mapping, a clear linkage is established between the critical findings of the review and the subsequent framework development in Chapter 3, by which the derivation of each methodological component from an identified gap in PdM decision-support research is demonstrated.

Table 2-3 Mapping of research gaps to methodological requirements

Identified Gap (from Chapter 2)	Research Methodological Requirement (What Needed to Address the Gap)	Implementation (What is Chapter 3)
Fragmented treatment of PdM implementation objectives, attributes, and technique capabilities	Develop an integrated analytical framework that systematically links objectives, attributes, and technique capabilities	Step A (3.3.1) – Systematic Literature Review (SLR) synthesizing objectives, attributes, and capabilities
Lack of explicit classification of PdM implementation objectives	Define a structured typology of PdM objectives representing different ambition and maturity levels	Step A1 (3.3.1.1) – Development of Ambition Levels (AL1–AL4)
Limited understanding of how PdM technique capabilities align with objectives	Map and validate PdM techniques according to their analytical suitability and ambition levels	Step A2 (3.3.1.2) – Mapping PdM Techniques to Ambition Levels and Cross-Verification (Table 3-3)

Identified Gap (from Chapter 2)	Research Methodological Requirement (What is Needed to Address the Gap)	Implementation (What is Chapter 3)
Inadequate identification of key attributes influencing PdM technique selection	Conduct systematic identification and categorization of implementation attributes affecting technique feasibility	Step A3 (3.3.1.3) – Comprehensive Attribute Identification
Absence of structured decision logic connecting attributes and technique feasibility	Establish a rule-based evaluation mechanism linking attributes to technique feasibility	Step A4 (3.3.1.4) – Frequency Mapping and Rule Logic Construction (Table 3-5)
Limited empirical validation of technique–objective–attribute linkage	Introduce quantitative validation through case studies and contribution probability data	Step A2 (3.3.1.2) – Cross-Validation of Technique Mapping (Table 3-3)

2.4 PdM implementation intangible assets quantification

Intangible assets encompass the knowledge, experience, skills, and other non-physical elements necessary for production and business operation (St-Pierre and Audet, 2011). Intangible assets are proved that is able to assist manufacturing sector in productivity and profitability improvement (Horvat et al., 2019; Turovets, 2019; Cette et al., 2021).

In terms of Predictive Maintenance implementation, it is important for businesses to consider these intangible costs as part of their overall risk assessment and mitigation strategy when evaluating the cost and the benefits of implementing

PdM (Franceschini and Midali, 2019). Scholars also consider different types of intangible assets in the PdM implementation and operation process. Specifically, expert or organizational knowledge has been applied for PdM model development and implementation (Vogl et al., 2014; Jimenez et al., 2020; Wang et al., 2023). Training is considered a critical process required for PdM operation (Bousdekis et al., 2019) and cost-efficiency evaluation (Feldman et al., 2009). However, it is observed that there is currently a gap in knowledge regarding the holistic understanding of the required intangible assets for PdM implementation and operation, as well as measuring the required intangible assets before PdM implementation. Although it is challenging to measure the intangible assets required, having a thorough understanding of their potential long-term impact on future sales and customer retention can help entrepreneurs and managers gain a clear view of the real cost of maintenance (Franceschini and Midali, 2019). To address this research challenge, the existing methods for measuring intangible assets are reviewed to identify the research issues and gaps in evaluating PdM implementation and operation intangible assets.

2.4.1 Intangible asset quantification methods

Despite the growing recognition of intangible assets as critical drivers of economic growth and innovation, standardized and comprehensive methods specifically tailored to the manufacturing sector are still lacking. The existing research reflects a fragmented landscape, with methodologies emerging from diverse academic and professional domains. Insights have been synthesized from multiple fields, including macroeconomic expenditure-based approaches, survey-based quantification, firm-level financial data analysis, occupation/task-based methodologies, and scaling techniques. While collectively these approaches have expanded understanding of intangibles, they are primarily retrospective, heavily data-dependent, and insufficiently adapted for anticipatory evaluation of intangible resources required for predictive maintenance.

CHS expenditures-based approach

The expenditures-based tradition is attributed to Corrado, Hulten, and Sichel (CHS), where the argument is made that any expenditure designed to generate

future benefits should be capitalized as investment (Corrado et al., 2005; Criekingen et al., 2022). Within this framework, intangibles are categorized into economic competencies, innovative property, and computerized information, and subsequent studies incorporate these into growth accounting (Corrado et al., 2005, 2009; Criekingen et al., 2022). The perspective revealed that intangible investments had been systematically underrepresented in GDP and provided new explanations for productivity dynamics (Corrado et al., 2009). The Innodrive project extended the method to the EU27 (Jona-Lasinio et al., 2011; Roth & Thum, 2013; Criekingen et al., 2022). Despite its macro-level power, reliance on aggregated expenditure data renders the approach unsuitable for assessing specific intangible needs at the enterprise level, particularly prior to PdM implementation. The method identifies “how much” is spent but not “what kind” of intangible resources are necessary, thereby limiting its applicability for transition planning in manufacturing contexts.

Survey based quantification of expenditures

A parallel stream of measurement is carried out through survey instruments designed to capture firm-level intangible expenditures. Innovation surveys, such as the Oslo Manual framework (OECD & Eurostat, 2005), record activities including R&D, IPR, training, and design (Criekingen et al., 2022). Measures across innovative, human, and branding capital were constructed using the German Mannheim Innovation Panel (Crass & Peters, 2014), while the UK’s Investments in Intangible Assets (IIA) survey covered six categories including training, software, and design (Awano et al., 2010; Criekingen et al., 2022). Dedicated surveys were also conducted in Albania, Italy, and through Eurobarometer (Prasnikar et al., 2012; Moultrie & Livesey, 2014; Angotti, 2017; Criekingen et al., 2022). Although these methods provide greater granularity than macroeconomic data, their scope remains limited: computerized information is often excluded (Crass & Peters, 2014), and organizational capital is only captured through proxies such as process adoption dummies. In the PdM context, survey-based measures offer insights into the distribution of intangible investments but fail to evaluate project-specific needs (e.g., diagnostic skills or cultural readiness) prior to implementation, which are essential for roadmap design.

Measurement based on firm balance sheet data

Firm-level accounting data are also employed to quantify intangible assets. For example, Peters and Taylor (2017) combine reported intangibles with R&D and SG&A to capture knowledge and organizational capital in U.S. firms, while Marrocu et al. (2012) analyse European companies using BVD-Amadeus data. Broader definitions enabled by Italian accounting standards allowed Bontempi and Mairesse (2015) to include intellectual and customer capital, while Belo et al. (2014) assessed brand capital through financial reports. Although these approaches leverage standardized financial datasets, they remain inherently conservative due to accounting rules and exhibit high variability across jurisdictions (Criekingen et al., 2022). More importantly, only “realized” intangible investments are captured retrospectively. For PdM, this ex-post orientation is problematic, since anticipation of intangible resources for transition is required rather than reporting those already capitalized.

Occupation or task-based approach

Micro-level studies estimate intangible assets by identifying employees engaged in intangible-producing activities. Within the Inno drive project, organizational, ICT, and R&D capital were estimated using linked employer–employee data (Görzig et al., 2010b). The approach was extended to U.S. firms by Squicciarini and Le Mouel (2012), who identified occupations generating organizational capital, while later applications classified roles into branding, design, and networks (Martin, 2019; Blanco-Alcantara et al., 2019; Criekingen et al., 2022). These methods provide fine-grained insights into workforce contributions and are particularly relevant for PdM, where human expertise and data interpretation form critical resources. Nevertheless, the reliance on detailed microdata restricts practical applicability, and sufficiency of intangible resources relative to a PdM transition pathway is not directly quantified.

Scaling method

Scaling approaches construct descriptive metrics for intangible assets by developing rating systems. Multidimensional scaling was applied to intellectual capital in the public sector (Cinca et al., 2003), spirituality at work was quantified

by Kinjerski and Skrypnek (2006), and cognitive values in cultural heritage were assessed by Su et al. (2020). These methods rely on rating scales derived from expert or survey input, making them the only approaches that allow evaluation of intangible resources prior to financial investment (Criekingen et al., 2022). The flexibility of scaling offers strong potential for PdM, where readiness in domains such as cultural openness, trust, and knowledge-sharing must be assessed before the introduction of new technologies. However, heavy reliance on expert judgment and the need for robust design of scoring frameworks raise concerns regarding consistency, transferability across firms, and industrial applicability.

2.4.2 Identified research gaps

The research gaps related to PdM implementation required intangible assets quantification method are discussed in this section, as a foundation for the Research Question Two presented in Section 1.3, which is: *What is the evaluation method for evaluating the key intangible assets for PdM implementation, while accounting the enterprise's specifications, before the actual implementation?*

Gap 1 Lack of comprehensive analysis of intangible asset types

Intangible assets are frequently treated either as a single aggregated category or examined only in restricted subsets (Jona-Lasinio et al., 2011; Prasnikar et al., 2012; Belo et al., 2014; Martin, 2019; Redek et al., 2019). Consequently, limited guidance is provided on the composition and role of different intangible assets. Within the context of PdM, this constitutes a significant limitation, since specific intangibles such as diagnostic expertise, trust in algorithms, or cross-departmental collaboration play distinct roles in enabling technical progression and cannot be adequately represented by aggregate measures.

Gap 2 Limitations in evaluating intangible assets in advance

The majority of the reviewed methods focus on quantifying the amount of intangible assets for specific companies, relying on financial data at either the company or national level for asset quantification. However, when a company aims to evaluate the necessary intangibles or cost-benefit before implementing a

project or technology, these methods may not yield appropriate results. For such applications, the methodology must possess the capability to assist in evaluating the required intangibles for a given project outcome in advance.

Gap 3 Limitations in data availability

With the exception of scaling methods, the methodologies reviewed are highly dependent on data availability, such as expenditure, cost, and investment data. If the necessary data for these studies is unavailable, the methodologies cannot be applied effectively (Jona-Lasinio et al., 2011; Prasnikar et al., 2012; Belo et al., 2014; Martin, 2019; Redek et al., 2019). In other words, these methods only allow for the quantification of intangible assets after the investment action has been completed. Scaling methods, however, are the only approach that does not rely on cost-related data for quantifying intangible assets, making them capable of assessing intangible assets before investment actions are taken.

2.4.3 The need for a maturity model to evaluate intangible assets in predictive maintenance

Maturity models are widely recognized as tools that not only benchmark organizational capabilities but also enable the evaluation of resource progression across stages of development. In the context of predictive maintenance, such staged structures provide opportunities to capture not only technological readiness but also the evolution of intangible assets including knowledge, cultural readiness, and decision-making practices that are otherwise difficult to quantify. By positioning intangible assets within maturity levels, the co-evolution of non-physical resources and technical capabilities can, in principle, be evaluated, and the additional intangible resources required to progress from one level to the next can be identified. However, existing maturity models in maintenance and digital transformation do not provide sufficient mechanisms for such evaluation, thereby limiting their applicability for organizations seeking to manage both tangible and intangible aspects of PdM adoption.

Frameworks such as the Capability Maturity Model Integration (CMMI; Paulk et al., 1993) and the Asset Management Maturity Model (AMMM; ISO 55000)

exemplify this staged approach, in which organizations are depicted as progressing from basic to advanced practices. Although these models establish useful benchmarks, their orientations towards software processes (CMMI) or physical asset management (AMMM) restrict their relevance for PdM, where technological adoption must be matched by organizational knowledge and cultural readiness. More recent digital-domain models attempt to address technological transformation. Digital Maintenance Maturity Models (Ferreira et al., 2019) position condition monitoring and analytics as milestones in maturity progression, and Industry 4.0 readiness models (Schumacher et al., 2016; Bibby & Dehe, 2018) incorporate PdM as one element of broader digitalization. While these frameworks advance the discussion by emphasizing data infrastructure and system integration, they remain technology-centric, offering limited guidance on the human and organizational capabilities that underpin PdM implementation. As several authors note, intangible factors such as experiential knowledge, communication flows, and data interpretation skills are critical to PdM success but are consistently overlooked in mainstream maturity assessments (Franceschini & Midali, 2019; Bousdekis et al., 2019).

Another limitation is observed in the definition of maturity levels and their transitions. Stages are often described in broad terms (e.g., “basic,” “intermediate,” “advanced”) without clear specification of the distinguishing features or the resources required to progress. For example, AMMM outlines operational, tactical, and strategic capabilities but does not articulate the pathways between these layers. Similarly, digital readiness models emphasize end goals such as system-wide integration while providing little explanation of the intermediate capabilities necessary to achieve them. This vagueness constrains their practical utility: organizations may be able to identify their current stage but receive no concrete direction for capability development. Beyond this, most maturity models function primarily as diagnostic rather than developmental tools, describing “what is” but not “how to move forward.” For PdM, where technical adoption and intangible asset growth must evolve in tandem for instance, sensor investments must be matched by diagnostic expertise and cross-departmental data interpretation this limitation is particularly critical.

Taken together, these models reveal three critical insights. First, a structural convergence around staged maturity frameworks confirms the value of levels in capturing the evolution of maintenance capabilities. Second, despite occasional recognition of culture or leadership, intangible assets are rarely treated as explicit drivers of maturity; instead, they are marginalized as implicit or secondary to technical and procedural dimensions. Third, no existing maturity model systematically connects the technical trajectory of PdM from reactive practices to prescriptive intelligence with the progressive accumulation of intangible assets such as workforce skills, organizational trust in algorithms, cross-departmental collaboration, and cultural readiness for innovation. These shortcomings render existing models inadequate as methodological foundations for assessing PdM adoption.

Nonetheless, literature review demonstrates that structural inspiration can still be drawn from these frameworks. Across diverse domains software engineering (CMMI), asset management (AMMM), digital transformation (Industry 4.0 readiness), and predictive analytics (digital maintenance models) a recurring five-stage trajectory can be discerned. At the lowest stage, early maintenance studies (Löfsten, 2000; Parida et al., 2009) and AMMM depict organizations as reactive, responding to failures in an ad hoc manner. A second stage emphasizes preventive maintenance, focused on scheduled routines but overlooking intangible enablers such as workforce discipline and procedural knowledge (Gouiaa-Mtibaa et al., 2018). A third stage, observed in frameworks emphasizing condition monitoring and diagnostics (Schumacher et al., 2016; Ferreira et al., 2019), highlights sensors and monitoring systems but neglects diagnostic expertise and cross-functional data flows. The fourth stage, predictive automation, appears in digital transformation models (Gill & VanBoskirk, 2016; Saez et al., 2018), which emphasize real-time analytics while disregarding organizational enablers such as trust in algorithms and coordination with production planning. Finally, strategic integration is articulated in ISO 55000 and Industry 4.0 strategic frameworks (Bibby & Dehe, 2018), where maintenance is positioned as inseparable from enterprise objectives, but intangible resources such as collaboration culture or innovation readiness remain unspecified.

This trajectory is not adopted wholesale from any single model but synthesized through a critical comparison of the literature. The staged logic is consistently validated, but the substantive foundations of each level particularly the intangible dimensions remain underdeveloped. Consequently, the five-level maturity framework proposed in this research is reconstructed rather than replicated: staged progression is retained as structural logic, while intangible assets are explicitly embedded as both indicators and enablers of advancement. In this way, the framework provides a methodological scaffold for empirical investigation, enabling the specification of intangible requirements at each level through expert input and supporting the design of a roadmap that links technical adoption with the staged development of intangible resources an integration that existing models have not achieved.

2.5 Identifying research opportunities and justification

In this chapter, methods, and approaches related to evaluating PdM implementation cost-benefit are considered. State of the art in the capabilities of methods and approaches in investigating PdM implementation cost-benefit are critically evaluated with respect to the needs of evaluating required tangible and intangible assets, introduced in Chapter 1, as a part of theoretical structural validation. Research opportunities are identified from these reviews, and research questions are justified based on Section 1.3.

2.5.1 Identified research opportunities

In this section, research opportunities identified through a critical literature review are presented, establishing a connection between these opportunities and the research questions outlined in Chapter 1, Section 1.3, as shown in Table 2-4.

Evaluating PdM implementation required tangible assets

The first step is selecting the most suitable maintenance strategy for a defined setup or a piece of device is a critical process for product lifecycle management. It substantially impacts manufacturing key performance indicators, including cost, productivity, product quality, safety, etc. Additionally, in the PdM implementation cost-benefit evaluation process, selecting the most suitable maintenance strategy

should be considered the starting point, as not every system or device can benefit from PdM implementation.

In this research, AHP is observed as a powerful tool for assisting in maintenance strategy selection. However, existing practices have ignored the impact of Industry 4.0 and Industry 5.0, which have resulted in changes in manufacturing design, production, logistics, service, etc. Moreover, the maintenance selection process should not only consider the impact on maintenance practice but also the potential impact on the whole product lifecycle. Lastly, the potential drawbacks of PdM are not fully considered in existing practices, which may lead to a wrong result in maintenance strategy selection.

The second step is selecting most suitable PdM technique. There are five PdM techniques, including variable models, developed for enabling component/device state monitoring. Each technique requires different costs and effort for implementation and operation, and each also has different capabilities and capability levels. Such diversity in PdM techniques and models leads to the challenge of selecting the most suitable PdM technique for enterprises, as an unsuitable PdM technique for a defined setup may result in wasted capital and time, as well as unsatisfactory functionality.

In this research, it is observed that there is a lack of methods for assisting in selecting the most suitable PdM technique. Such a method needs to help enterprises understand the capability of each technique and evaluate their objectives for PdM implementation and establish links between attributes for PdM implementation and PdM techniques.

Evaluating PdM implementation required intangible assets

Intangible assets are recognized as a part of the capital of enterprises and are widely considered as elements for optimizing company financial performance. In terms of digitalized systems, intangible assets are required for both the implementation and operation processes and have a critical impact on digitalized system performance. Researchers have only considered investment in some types of intangible assets for PdM implementation and operation. Lacking

consideration of intangible asset requirements will lead to misjudgment on PdM implementation cost-benefit.

It is observed in this research that there is a lack of method for evaluating required intangible assets before PdM implementation. Such a method needs to take into consideration all types of intangible assets required for PdM implementation and operation, allowing intangible asset evaluation before implementation.

Table 2-4 Connection between research gaps and research questions through critical literature review

Research Opportunity	Critical Literature Review	Research Question
PdM implementation cost-benefit	Section 2.1	Prime Research Question Chapter 1, Section 1.3
Tangible assets	Section 2.2	Research Question 1
	Section 2.3	Chapter 1, Section 1.3
Intangible assets	Section 2.4	Research Question 1 Chapter 1, Section 1.3

Chapter Summary

In this chapter, the state-of-the-art publications related to PdM implementation cost-benefit are reviewed. It is identified in Section 2.1 that there are three main research issues for PdM implementation cost-benefit evaluation, which are: (1) tangible assets evaluation, and (2) intangible assets evaluation. In Section 2.2, it is established that the main issues in maintenance strategy selection are: (1) existing work ignored the impact of modern industry environment on maintenance strategy selection and (2) existing work ignored part of the drawbacks of PdM. In Section 2.3, it is identified that the main issue for PdM technique selection includes: (1) lacking PdM technique capability analysis method, (2) lacking PdM implementation objective analyse method and (3) lacking PdM implementation attributes analyse. In Section 2.4, it is identified that the main issue for required

PdM implementation intangible assets includes: (1) lack of comprehensive analysis of intangible asset types, (2) limitations in evaluating intangible assets in advance, and (3) limitations in data availability.

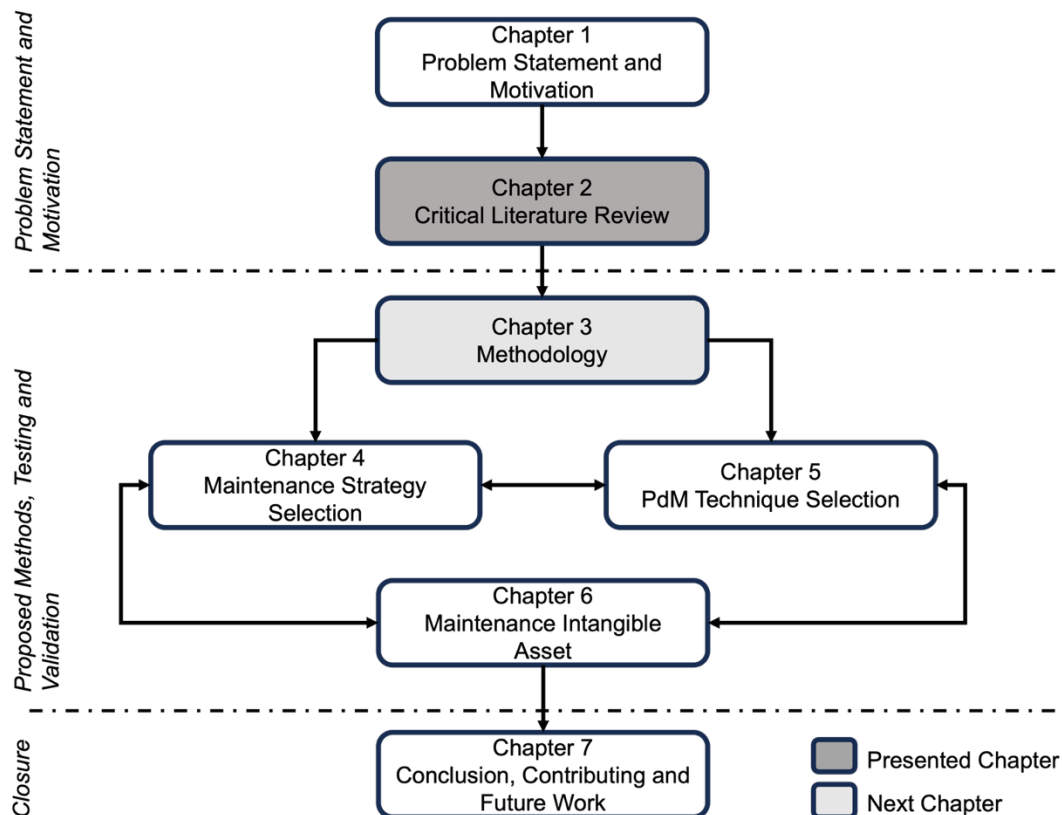


Figure 2-1 Organization of the Thesis – Presented and Next Chapter

In Chapter 3, the problem statement, research approach, and methods are outlined, followed by theoretical structural validity of maintenance strategy selection (Section 3.2), PdM technique selection (Section 3.3), PdM implementation and operation intangible assets evaluation (Section 3.4), as presented in Figure 2-1.

CHAPTER 3 - METHODOLOGY

In previous chapters, the research gaps are introduced, and research questions are formulated in Chapter 1, and further justified through the literature review in Chapter 2. Identified gaps lead to the Primary Research question that is worthy of investigation “What is the method that helps evaluate the cost-benefit for predictive maintenance implementation that takes into account the investment in tangible and intangible assets for PdM implementation?” In this chapter, the research methodology for developing the methods to evaluate PdM implementation cost-benefit is presented.

The research problems in this research are presented in Section 3.1. The methodology for achieving and validating each research objectives are presented Sections 3.2 - 3.5, covering: (1) the maintenance strategy selection method, (2) the PdM technique selection method, and (3) the PdM implementation intangible asset evaluation.

3.1 Problem statement

Maintenance activities play a pivotal role in the manufacturing industry, impacting various key performance indicators such as productivity, safety, and quality. Industry 4.0, known as the Fourth Industrial Revolution, involves the integration of cutting-edge technologies like the IoT and AI, revolutionizing manufacturing operations (Potyal et al., 2021). This transformation, driven by global competition and the demand for customized products, presents challenges for manufacturers in maintaining competitiveness. PdM emerges as a strategy to address these challenges, utilizing predictive tools to proactively identify faults and optimize performance. Despite its recognized benefits, the widespread adoption of PdM faces obstacles, notably the unclear cost-benefit of its implementation. In order to justify the high initial cost, understand the total cost required, and assess the cost efficiency of PdM implementation, it is necessary to evaluate the cost-benefit before PdM implementation. This involves considering the required tangible and intangible assets of PdM implementation, as presented in Fig 3-1 (A).

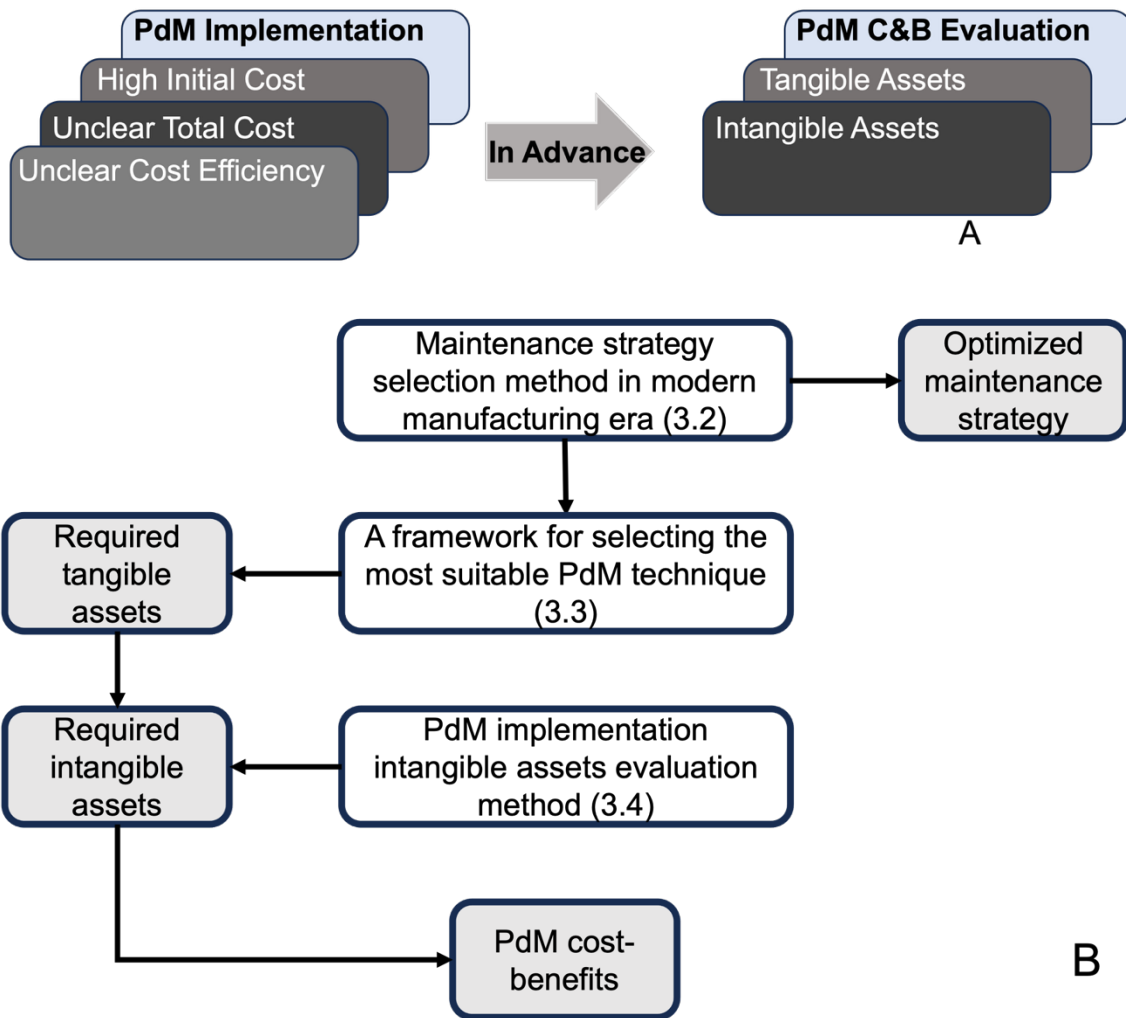


Figure 3-1 Challenges and methodology for evaluating PdM implementation cost-benefit

Specifically, as presented in Figure 3-1 (B), in Section 3.2, a method for selecting a maintenance strategy in the modern manufacturing era is presented. Using this method, manufacturing companies can determine whether Predictive Maintenance is a suitable strategy for their operations, based on current manufacturing requirements. Building on this, the decision-based framework for PdM technique selection presented in Section 3.3 helps companies choose the most appropriate PdM technique, depending on their specific situation and goals, once PdM is identified as the right strategy. This framework also guides companies in determining the necessary investments in tangible assets, such as sensors, computers, data storage, and processing infrastructure. Furthermore, the method for evaluating intangible assets for maintenance implementation, as

discussed in Section 3.4, enables companies to assess the required investments in experience, knowledge, and skills needed for successful PdM implementation. By integrating these three proposed methods, a more comprehensive evaluation of PdM implementation can be conducted, providing valuable insights into its feasibility and long-term benefits.

3.2 Maintenance strategy selection in modern manufacturing era

In this section, the methodology for developing and validating the first objective in this research, which is *'Create an AHP-based MCDM method tailored for manufacturing enterprises. The presented method enables the selection of the most appropriate maintenance strategy for modern manufacturing, addressing the technical, environmental, and market challenges encountered by enterprises.'*

AHP is applied in this chapter for developing the maintenance strategy selection method in modern manufacturing era. It is a type of decision analyse technique. Decision analyses techniques were initially intended for individual decision-makers to make critical decisions considering all dimensions in the decision-making process (Reichert et al., 2007). These techniques can also be used to organize problems, define outcomes, and communicate decisions in group decision-making settings. Over the past few decades, the process of decision-making has become more advanced, utilizing methods such as expert judgment, cost-benefit analysis, and risk analysis to model complicated socio-technical systems in uncertain circumstances. As a result, Multi-Criteria Decision Analysis tools have been developed to provide a dependable framework for group decision-making (Asuquo et al., 2019).

As intricate machineries become more complex in manufacturing, decision makers face greater difficulties in determining suitable alternatives. Therefore, it is necessary to have analytical tools that are both strong and adaptable, capable of considering multiple criteria and decision outcomes despite these challenges (John et al., 2014). To overcome, several methods have been developed over years including Multiple Attribute Decision Making (MADM), Multiple Objective Decision Making (MODM), Multi-Attribute Utility Theory (MAUT), AHP, Simple

Multi-Attribute Rating Technique (SMART), Goal Programming (GP), TOPSIS, etc. The method applied in this research is AHP, which is introduced in detail in the following Section 3.2.1.

Saaty (1980) developed a tool for decision-making called AHP, which is helpful for managing qualitative and quantitative elements. The model has a hierarchical structure and offers multiple options for decision-making while also allowing for sensitivity analysis of criteria and benchmarks. The model has a hierarchical structure and offers multiple options for decision-making while also allowing for sensitivity analysis of criteria and benchmarks. AHP is an extensive system that can be used to make decisions with multiple criteria, as it involves creating a hierarchical problem structure that incorporates both quantitative and qualitative criteria. Moreover, by applying AHP, the opinion of different stakeholders can be considered together to make one decision simultaneously.

AHP is extensively used in the maintenance strategy selection application. It has the capacity to effectively overcome the difficulties caused by the complex nature of the maintenance strategy selection process. Firstly, people from different sectors need to work together in the maintenance strategy selection process. These decision-makers may include experts from the management team, production, maintenance, supply chain, and other relevant areas. By applying AHP, the judgments of these decision makers can be brought together to make a single decision (Kaczmarek et al., 2021). Secondly, decision makers may have different backgrounds or varying levels of education, so the decision-making method need to be applicable to every decision maker. AHP does not require a lot of academic knowledge or technical expertise to apply; decision makers only need to make judgments on the criteria based on tacit knowledge. Finally, various decision-making criteria need to be considered simultaneously in the maintenance strategy selection process, and applying AHP can ensure that all decision criteria are evaluated (Hemmati et al., 2020).

A: Define maintenance strategy selection goal, alternatives, and criteria	A1: Define maintenance strategy selection goal
	A2: Define maintenance strategy selection alternative
	A3: Define maintenance strategy selection criteria
	A4: Set up hierarchical tree
B: Decision maker judgement	B1: Decision-maker gathering
	B2: Case introduction
	B3: Criteria pairwise comparison
	B4: Alternative performance marking
C: Weight relative importance of each criterion and performance measure of criteria with respect to alternative	C1: Weight relative importance of each criterion
	C2: Performance measure of criteria with respect to alternative
	C3: Select optimized alternative
D: Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) Evaluation	D1: Determine the ranking of Sub-criteria with respect to cases
	D2: Calculate the weighted rank sum ratio of each case
	D3: Evaluation objects sort and classification

Figure 3-2 AHP for maintenance strategy selection in modern manufacturing era framework

As presented in Fig 3-2, in this research, the methodology for developing the AHP for maintenance strategy selection in modern manufacturing era followed the steps for developing AHP methods, which including four steps, Step A: Define maintenance strategy selection goal, alternatives, and criteria, Step B: Decision maker judgement, Step C: Weight relative importance of each criterion and performance measure of criteria with respect to alternative, and Step D: Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) Evaluation. Where Step B, C, and D serve as the validation process for the developed method.

3.2.1 Step A Define decision-making goal, alternatives and criteria

In the initial stage, the goal of decision-making was brought into the picture hierarchically with respect to the relevant decision-making elements, these elements encompass decision criteria and alternative.

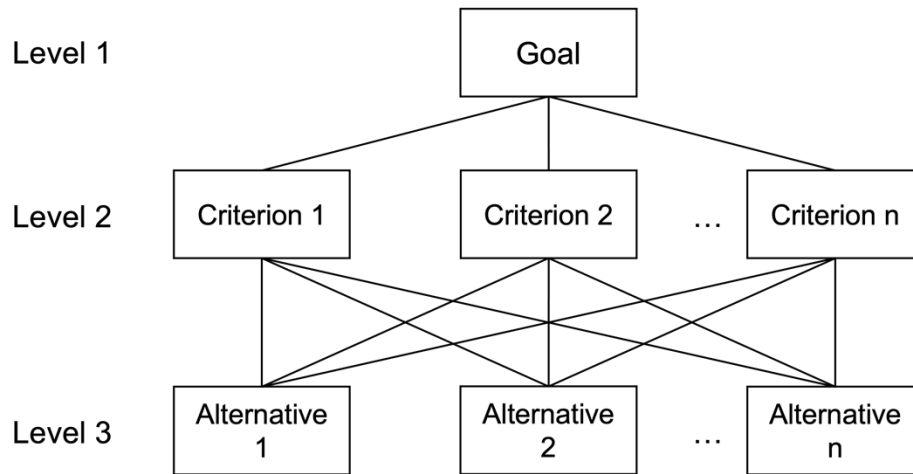


Figure 3-3 Sample hierarchical tree

Next, the decision- making individual or team need to establish a hierarchical tree based on Fig 3-3 to reflect the issue at hand.

Step A1 Define decision-making goal

Specifically, for Step A1, the goal for maintenance strategy selection is centered, which is Objective One in this research: ***'Developing the AHP method for maintenance strategy selection in the modern manufacturing era.'*** This objective serves as the foundation for the entire methodology, directing the selection and evaluation of criteria for maintenance strategies.

Step A2 Define decision-making alternatives

In Step A2, the focus is to identify and define the three primary maintenance strategies most commonly used in industry: **corrective maintenance, preventative maintenance, and predictive maintenance**. These strategies are selected based on their applicability and prevalence in manufacturing contexts, allowing for a targeted analysis of factors impacting each strategy's selection and implementation.

Step A3 Define decision-making criteria

Step A3 serves as the core of this study's methodology, addressing the research gaps identified in Chapter 2—namely, the lack of consideration for sustainability, resilience, and human-centric factors in modern manufacturing, as well as the limitations of PdM. These considerations form the foundation of the AHP-based

maintenance strategy selection model, serving as key decision-making criteria. To ensure that these criteria are comprehensive, methodologically rigorous, and well-defined, a Systematic Literature Review (SLR) is conducted.

The use of an SLR is justified for two primary reasons. First, SLR is widely recognized as a rigorous and reliable method for identifying decision-making criteria in MCDM studies, particularly those involving complex industrial processes. By systematically reviewing existing research, the study extracts well-grounded criteria from prior studies, ensuring a robust basis for maintenance strategy evaluation. Second, existing studies have not systematically compiled the criteria required for maintenance strategy selection in the context of modern manufacturing. Traditional frameworks have primarily focused on cost, reliability, and downtime, while Industry 5.0 demands a more forward-looking approach incorporating sustainability, resilience, and human-centric design. Given the absence of a comprehensive and structured analysis of these criteria, an SLR-based methodology is required to ensure objectivity and completeness.

The SLR process is guided by three Research Questions (RQs), each addressing a key aspect of maintenance strategy selection. The review is conducted across IEEE Xplore, ScienceDirect, and Springer, using predefined keywords and inclusion criteria to ensure methodological robustness.

Research Questions and Methodological Approach

RQ1: What decision criteria have been used in AHP-based maintenance strategy selection within the manufacturing sector?

This question aims to compile and analyse decision criteria from previous AHP-based maintenance strategy selection studies in the manufacturing sector.

Keywords: "Maintenance strategy," "AHP," "manufacturing," "production"

Inclusion Criteria:

1. Studies must focus on maintenance strategy selection in manufacturing.
2. Papers must provide a detailed explanation of decision criteria used in AHP-based frameworks.

3. Only peer-reviewed journal articles and conference papers published in the last 25 years are included.

Outcome: A comprehensive list of established decision criteria, forming the foundation for further refinement and integration.

RQ2: What decision criteria should be considered in maintenance strategy selection to align with Industry 5.0 priorities?

This question explores how sustainability, resilience, and human-centric design should be integrated into maintenance strategy selection to align with Industry 5.0.

Keywords: "Industry 5.0," "Industry 5," "I 5.0," "sustainability," "resilience," "human-centric"

Inclusion Criteria:

1. Only literature review papers that explicitly discuss sustainability, resilience, or human-centric factors in maintenance decision-making are included.
2. Studies focusing exclusively on individual Industry 5.0 technologies (e.g., AI, IoT) without broader strategic implications are excluded.
3. Only peer-reviewed journal articles and conference papers published in the last 10 years are included to ensure relevance to modern advancements.

Outcome: A refined set of decision criteria that align with Industry 5.0 priorities, ensuring a more forward-looking and sustainable approach to maintenance strategy selection.

RQ3: What are the limitations of PdM that affect its implementation and operational feasibility?

This question identifies the practical challenges and barriers of PdM, ensuring that the proposed decision criteria reflect real-world constraints.

Keywords: "PdM," "Predictive Maintenance," "limitation," "challenge," "barrier," "scalability," "data availability," "integration"

Inclusion Criteria:

1. Only literature review papers that discuss general PdM limitations are included.
2. Studies focusing solely on specific PdM technologies (e.g., Digital Twin, Reinforcement Learning) are excluded unless they address broader PdM challenges.
3. Papers must explicitly describe PdM limitations related to implementation, scalability, data requirements, or integration issues.

Outcome: A set of decision criteria accounting for PdM's practical constraints, ensuring a realistic and applicable maintenance strategy framework.

Expert Validation of the AHP Structure

Three domain experts are invited to review the proposed AHP structure, with purposeful selection ensuring diverse yet complementary perspectives across academic and industrial domains. The first expert is a senior maintenance engineer with more than 15 years of experience in discrete manufacturing sectors such as automotive and electronics, specializing in transitions from preventive to predictive maintenance and failure analysis in high-speed production environments. The second expert is a professor of industrial and systems engineering, whose research addresses maintenance strategy optimization, and Industry 4.0/5.0 integration. The third expert is a digital transformation consultant with extensive experience in deploying AI- and IoT-based predictive maintenance platforms for multinational corporations, with specific expertise in system integration and data governance.

Each expert is provided with the complete AHP hierarchy including the goal, alternatives, main criteria, sub-criteria, and their explanations and structured forms are used to collect feedback. Selection is based not only on domain knowledge and expertise in maintenance strategies but also on contextual alignment with the industrial cases analysed in this chapter. All three experts possess professional familiarity with the technologies, operational conditions, and decision-making challenges typical of the manufacturing sectors under examination.

The senior maintenance engineer contributes operational insight through extensive experience in discrete manufacturing environments comparable to the case studies, particularly within automotive and electronics sectors where production continuity, equipment reliability, and rapid changeover are critical. The academic expert provides a conceptual and methodological perspective, having engaged in research and consultancy projects involving digital transformation in maintenance; this dual orientation supports assessment of the theoretical soundness and practical robustness of the AHP framework. The consultant adds system-level and implementation-focused expertise, grounded in hands-on deployment of PdM systems in factory contexts characterized by limited data maturity, resource constraints, and integration challenges conditions shared by several case study firms.

To mitigate potential bias, experts are drawn from distinct domains academic and operational ensuring a balanced review that combines theoretical rigor, practical experience, and system level insight. Structured feedback forms and semi-structured interviews are used to reduce interpretation ambiguity and to provide a consistent basis for comparison. Responses are reviewed independently before being synthesized into refinements to the model, thereby minimizing dominance bias and preserving diversity of evaluation.

Through this process, expert validation is ensured to be both theoretically grounded and practically relevant, while measures are incorporated to safeguard objectivity and reduce personal bias.

3.2.2 Step B Decision maker judgement

As presented in Figure 3-2, the decision makers are gathered to make judgement on the defined alternatives and decision-criteria in Step B.

Step B 1 and B 2 Decision maker gathering and case introduction

In the subsequent step, a questionnaire was prepared and distributed among decision makers who is involved in the decision-making process (such as managers, experts, users, etc.) to gather their opinions for pairwise comparison. What should be noted is that the selected experts in this research must meet the

following standards: work in the manufacturing sector for at least 5 years, and each group must include experts working in management, production, and maintenance sectors. The details of the maintenance strategy selection case are introduced after the experts are gathered.

Step B3 and B4 Criteria pairwise comparison and alliterative performance marking

Each decision-maker assigned a preferred value to each member, and the individual judgments of each respondent were converted into group judgments for each pairwise comparison using the geometrical average method. The scale used in the questionnaire ranges from one to nine, with one that the two elements are equivalent or equally important, while nine implies that one element is significantly more crucial than the other in a pairwise matrix. The Table 3-1 illustrates the pairwise scale and importance value attributed to each number recommended in Saaty and Kearns (1985).

Table 3-1 Relative importance scale (Saaty and Kearns, 1985)

Intensity of Relative Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to Objective 1.
3	Moderate importance of one over another	Experience and judgment slightly Favor one activity over another.
5	Essential or strong importance	Experience and judgment strongly Favor one activity over another.
7	Demonstrated importance	An activity is strongly favoured, and its dominance is demonstrated in practice.

9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation.
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When a compromise is needed.

In the pairwise comparison process, a comparison matrix needs to be created for each level of the hierarchy, starting from the second level, and moving downward. The criteria in each level are compared in pairs to determine their level of importance, as well as the importance of each criterion with respect to the criterion in the next higher level. The comparison process in the AHP involves comparing elements in each level in pairs to determine their relative importance to an element in the next higher level. This pairwise comparison process is initiated from the top of the hierarchy and proceeds downwards. At each level, the pairwise comparisons can be represented by square matrices $A = [a_{ij}]_{n \times n}$.

3.2.3 Step C Weight relative importance of each criterion and performance measure of criteria with respect to alternative

As presented in Figure 3-2, the relative importance of each criterion and performance of criteria with respect to alternatives is calculated in Step C.

Step C1 Weight relative importance of each criterion

After data collection process is finished, the next step is to weight of experts or relative importance of each criterion and performance measure of alternatives with respect to criteria.

The process of calculating weights in the pairwise comparison method involves two main steps after creating all pairwise comparison matrices. First, the matrix $A = [a_{ij}]_{n \times n}$ is normalized using Equation (3-1) and then the vector of weights, $w = [w_1, w_2, \dots, w_n]$, is computed using Equation (3-2) based on Saaty's eigenvector procedure.

$$a_{ij}^* = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}} \quad (3-1)$$

for all $j = 1, 2, \dots, n$.

$$w_i = \frac{\sum_{j=1}^n a_{ij}^*}{n} \quad (3-2)$$

for all $i = 1, 2, \dots, n$.

Equation (3-3) demonstrates the relationship between the pairwise comparison matrix, A , and the vector of weights, w , where:

$$A_w = \lambda_{max} w \quad (3-3)$$

Saaty (1980) established the importance of λ_{max} as a validating parameter in AHP, which serves as a reference index to screen information by computing the consistency ratio (CR) of the estimated vector. To determine the CR , the consistency index (CI) of each n -order matrix can be obtained using equation (3-4), where:

$$CI = \frac{\lambda_{max} - n}{(n - 1)} \quad (3-4)$$

Equation (3-5) can be utilized to calculate CR , wherein the random consistency index (RI) from a randomly generated pairwise comparison matrix is used.

$$CR = \frac{CI}{RI} \quad (3-5)$$

Saaty (1980) proposed a table (Table 3-2) that presents the values of RI for matrices with orders ranging from 1 to 10. A CR value below 0.1 indicates acceptable comparisons. In contrast, CR values exceeding 0.1 suggest inconsistent judgments. In such cases, it is necessary to re-evaluate and modify the initial values in the pairwise comparison matrix A .

Table 3-2 RI Value for $N = 10$ (Saaty and Kearns, 1985)

N	1	2	3	4	5	6	7	8	9	10
<i>RI</i>	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.46	1.49

Step C2 Performance of each alternative calculation

Please note that the performance of each alternative, denoted as S_{ij} , also needs to be calculated at this step. The procedures for calculating S_{ij} are exactly the same as the procedures for calculating the weight of each criterion. The only difference is that the values used in the pairwise comparison matrix A are the pairwise comparisons of each criterion with respect to the alternatives.

After the weight of each criterion is calculated, it is possible to calculate the score of each alternative. The score of each criterion of the individual alternative is calculated using the following Equation (3-6):

$$T_{ij} = S_{ij} * W_j \quad (3-6)$$

Where T_{ij} is the score of criteria j of the alternative i , T_i is the total score of the alternative i , W_j is the weighted score of the criteria j , and S_{ij} is the performance of the criteria number j with respect to alternative i that is derived using Equations (3-1) and (3-2) and evaluated using Equations (3-3) to (3-5) in step three.

Step C3 Alternative performance marking

Finally, the total score of each alternative is calculated with the aid of the Equation (3-7) below:

$$T_i = \sum_{j=1}^n S_{ij} * W_j \quad (3-7)$$

3.2.4 Step D Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) Evaluation

As presented in Figure 3-2, the Sub-Criteria Weighted-Rank-Sum Ratio of criteria are calculated and ranked in Step D. The WRSR method has been developed as a statistical analysis technique that integrates classical parametric and modern nonparametric statistics, providing a versatile tool for data evaluation in decision-

making processes. In this approach, ranks are transformed into a dimensionless statistic, allowing parametric statistical techniques to be applied in analysing the distribution of WRSR values. Through this transformation, a structured mechanism is established for comparing criteria based on their relative advantages and disadvantages.

The WRSR value, derived through this method, is utilized for direct ranking of evaluation objects. Each criterion is classified into different grades according to its rank, enabling a comprehensive assessment of performance relative to predefined alternatives. This structured evaluation process enhances the clarity of decision outcomes while ensuring a systematic comparison among criteria.

In this research, the WRSR method is applied to validate the decision criteria identified through the SLR. Although SLR serves as a fundamental step in identifying relevant criteria, its inherent limitation lies in the lack of empirical validation of the criteria's importance. While a comprehensive set of decision criteria can be established through SLR, insights into their relative significance in maintenance strategy selection remain unaddressed. This gap is bridged by WRSR, which quantifies the relative importance of each criterion, enabling a ranked prioritization based on expert evaluations.

Through the application of WRSR, the theoretical relevance of SLR-defined criteria is substantiated with empirical validation. Weights are assigned to each criterion based on expert judgments obtained through pairwise comparisons, ensuring that the identified criteria reflect real-world decision-making priorities.

A key limitation of SLR-defined criteria is their reliance on existing literature and expert opinion, which may not fully capture the specific needs of individual enterprises. Since operational environments, strategic priorities, and challenges vary across organizations, the relevance of certain criteria may differ. For instance, enterprises emphasizing sustainability may prioritize environmental factors in maintenance strategy selection, whereas those experiencing frequent equipment failures may assign greater importance to reliability and downtime reduction.

The WRSR method addresses this limitation by offering a customizable and adaptable approach. Through pairwise comparisons, decision-makers can adjust the relative weights of criteria to align with their specific operational context. This flexibility ensures that the methodology remains applicable across diverse organizational settings, enhancing its practical utility.

By employing WRSR, enterprises can systematically determine the most relevant criteria for their decision-making processes. When selecting a maintenance strategy, multiple factors—such as cost, reliability, sustainability, and ease of implementation—must be considered. Although all these factors hold significance, WRSR enables decision-makers to prioritize them according to their unique strategic objectives.

Furthermore, data-driven decision-making is facilitated through WRSR, allowing organizations to base their maintenance strategy selection on empirical evidence rather than theoretical assumptions. By evaluating and ranking criteria according to their practical relevance, enterprises can ensure that selected maintenance strategies effectively address their specific challenges while maintaining methodological rigor.

Step D1 Determine the ranking of sub-criteria with respect to alternative

Specifically, the first step of WRSR is to determine the ranking of Sub-criteria with respect to cases, where:

$$R_{ij}(i = 1, 2, \dots, N; j = 1, 2, \dots, K) \quad (3-8)$$

Step D2 Calculate the weighted rank sum ratio of each case

The next step is to calculate the weighted rank sum ratio of each case according to equation (3-9), where: $WRSR_i$ is the weighted rank sum ratio of the i-th case, W_j is the weight of the j-th criteria.

$$WRSR_i = \frac{\sum_{j=1}^k W_j R_{ij}}{N \sum_{j=1}^k W_j} \quad (3-9)$$

Step D3 Evaluation objects sort and classification

The subsequent steps in the analysis process involve grouping the data based on the weighted rank sum ratio and creating a frequency distribution column. Frequency count (f), cumulative frequency ($\sum f$), frequency range (G), median cumulative frequency ($G/2$) and the percentile 100% (G/N) are determined.

Subsequently, a linear regression equation is constructed using the weighted rank sum ratio (WRSR) as the dependent variable and the probability unit Probit as the independent variable. The least square method is employed here. Finally, the evaluation objects are sorted and classified based on their weighted rank sum ratio values. The results of each step are presented in Chapter 4.

3.3 PdM technique selection

In this section, the methodology for developing and validating the second objective in this research, which is *'Develop a comprehensive framework to assist enterprises in selecting the most suitable Predictive Maintenance technique'*. This framework should consider the unique characteristics of each PdM technique and evaluate their alignment with the specific conditions and needs of the enterprise' is presented. The steps for the methodology are included in the following Figure 3-4.

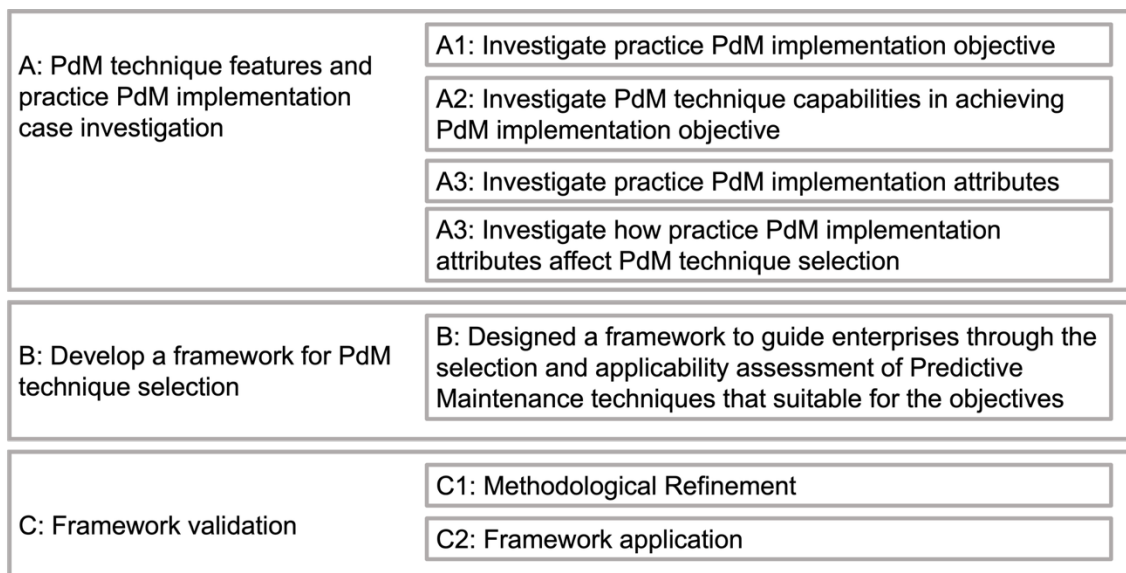


Figure 3-4 A framework for PdM technique selection – methodology

The purpose of Step A is to address gaps in the literature regarding the lack of detailed analysis of PdM implementation objectives, attributes, and technique capabilities, as well as the lack of established linkages among these elements (Chapter 2, Section 2.3.2). The attributes that influence PdM technique selection and how each technique aligns with specific implementation objectives are clarified through the exploration of these factors.

The methodology in this section for PdM technique selection is driven by insights and gaps that are identified in the literature as presented in Chapter 2, Table 2-4. It is recognized that the success of PdM implementation is not determined by algorithmic sophistication alone but is shaped by the interplay of available domain knowledge, data readiness, and organizational constraints. Existing PdM implementation studies are often limited because a linear progression from data to algorithm is assumed, without consideration of whether the necessary knowledge is sourced internally, externally, or from secondary data. It is consistently reported in the literature that many projects are made successful not through the isolated selection of the “best” technique but through the alignment of techniques with ambition levels and the compensation of missing attributes by alternative knowledge sources.

3.3.1 Step A PdM implementation objectives, attributes, and technique capabilities investigation

As presented in Figure 3-4, Step A addresses critical gaps in the literature regarding the integration of PdM implementation objectives, attributes, and technique capabilities, as well as the lack of established linkages among them (Chapter 2, Section 2.3.2). While these elements have been discussed in prior studies, no systematic synthesis or classification has been conducted to clarify their roles in PdM technique selection. Although attributes influencing PdM selection, expected implementation objectives, and technique capabilities are frequently mentioned in the literature, they have often been analysed in isolation without a comprehensive framework to illustrate their interrelationships.

To bridge this gap, a SLR is conducted. This method provides a structured approach for identifying and categorizing relevant attributes, objectives, and

capabilities, ensuring that scattered insights from various studies are synthesized into a cohesive framework. The SLR focuses on identifying key objectives, attributes, and capacities associated with PdM techniques in practical applications (Steps A1 – A4). Real-world case studies from the past ten years are analysed, while simulated or experimental studies are excluded. Reputable databases, including IEEE Xplore, ScienceDirect, and Springer, are used to ensure a comprehensive foundation for the analysis.

Through the SLR, previously identified but unstructured criteria are systematically classified, enabling a clearer understanding of how PdM techniques align with organizational objectives, required attributes, and technical capabilities. This structured categorization clarifies how objectives such as reducing downtime, lowering costs, and improving reliability correlate with specific PdM techniques.

The SLR methodology not only addresses the lack of integrative analysis but also establishes a foundation for systematically linking attributes, objectives, and capabilities. This framework ensures that PdM technique selection aligns with enterprise needs, operational goals, and technological capabilities, thereby facilitating an informed and practical selection process.

Research Questions

RQ1: What are the key attributes affecting PdM technique selection and implementation in industry, and how do these attributes influence technique suitability?

RQ2: What are the primary objectives of PdM implementation, and how does each PdM technique fulfill these objectives?

Scope and Inclusion Criteria

The SLR targeted studies addressing both the preparation phase and the data acquisition phase of PdM implementation. The preparation phase included defining PdM goals, identifying critical components, and specifying parameters for detecting deterioration. The data acquisition phase focused on describing the hardware infrastructure and data availability essential for PdM deployment.

Specific search terms, such as “Predictive Maintenance”, “PdM,” “technique selection,” and “implementation case studies,” guided the selection process to ensure the inclusion of relevant studies.

3.3.1.1 Investigation on PdM implementation objective and Definition of PdM Ambition Levels

To ground the framework in the objectives pursued by industrial stakeholders through Predictive Maintenance, a typology of implementation goals is constructed and referred to as Ambition Levels (ALs). These levels are defined as representing increasing maturity and complexity in PdM deployment, reflecting a progression from basic failure detection to advanced asset-level optimization.

A total of 78 peer-reviewed case studies is retrieved, and in the end, 47 studies are selected, as they explicitly document organizational objectives and are considered suitable for thematic analysis. By doing so, the gap identified in Section 2.3.3 which is *Lacking PdM implementation objective analysis* can be addressed.

The 47 case studies are systematically reviewed through qualitative coding methods, and recurring objectives behind PdM adoption are identified. These objectives are classified along three primary dimensions. The first dimension, precision of output, is defined as differentiating between binary anomaly detection, numerical Remaining Useful Life (RUL), and prescriptive guidance as the output of PdM. The second dimension, component coverage, is categorized by whether the PdM approach is applied to a single machine component or spans multiple systems. Finally, the third dimension, decision scope, is distinguished by whether PdM supports local maintenance scheduling or broader asset lifecycle strategies, from which recurring objectives behind PdM adoption are identified and subsequently defined as ambition levels in this thesis; these ambition levels are classified along three primary dimensions precision of output, component coverage, and decision scope and are further detailed and visualized in Chapter 5, Section 5.1.1, and Figure 5-2.

3.3.1.2 Evaluation on PdM technique capabilities and Mapping PdM Techniques to Ambition Levels

This phase is designed to determine the suitability of different PdM techniques for the predefined Ambition Levels (ALs), ensuring that the selected techniques are aligned with the complexity and objectives of PdM implementation. In this stage, empirical findings from the literature and case studies are utilized to construct a mapping between PdM techniques and the corresponding ambition levels. By doing so, the gap identified in Section 2.3.3 which is *Lacking PdM technique capability analysis* can be addressed.

Mapping Analytical Capabilities to Ambition Levels

The analytical capabilities required for each Ambition Level (AL) are assessed, and the most appropriate PdM techniques are identified for each level based on the availability of data and domain knowledge.

AL1: Basic Anomaly Detection (Single Asset)

At AL1, the objective is defined as the detection of early signs of failure in a single asset using simple methods, as the RUL remains vague at this stage.

Experience-based techniques are regarded as highly suitable, since they rely on operator intuition and simple thresholds for fault detection. These techniques are considered effective with minimal data and are well understood in operational contexts. Model-based techniques can be applied for quantitative analysis but are generally not required, given the simplicity of the task and the absence of complex data. Data-driven techniques are considered unsuitable, as they require large amounts of historical and labelled failure data, which are often unavailable at this stage. Physics-based techniques are also assessed as inappropriate, as they demand extensive domain knowledge and detailed datasets, which are rarely accessible for single-asset detection.

AL2: RUL Prediction for Well-Monitored Components

At AL2, the objective is shifted to the prediction of RUL for well-monitored components. Greater precision is achieved because systems are sufficiently monitored, and historical sensor data are available.

Data-driven techniques are considered highly suitable, as labeled historical data enable machine learning models to provide accurate RUL estimates, a finding confirmed in the studies of Mohan et al. (2023) and Mourtzis et al. (2021). Model-based techniques are regarded as viable, particularly when simple regression-based models are sufficient. Experience-based techniques are considered conditionally useful but are often limited in accuracy for complex components, though they may remain relevant in data-scarce contexts. Physics-based techniques are applicable when the degradation mechanisms of the component are well understood and governed by established physical laws.

AL3: Prognostics Across Interconnected Systems

At AL3, the focus is placed on multi-component prognostics, where interdependencies between components are significant and failures can propagate across systems.

Data-driven techniques are regarded as highly suitable, since they can process multi-sensor data and predict failures across interconnected systems. Advanced approaches such as ensemble learning and federated learning are frequently applied. Model-based techniques are also used, but they must be highly sophisticated to capture the complexity and interdependencies of multi-component systems. Physics-based techniques are considered particularly effective when degradation models are available for multiple components, enabling precise prognostics. Hybrid techniques, which integrate data-driven and physics-based methods, are identified as especially suitable, as they combine complementary strengths to provide robust multi-system predictions.

AL4: Full-System or Lifecycle Optimization

At AL4, the objective is defined as system-wide optimization or lifecycle management, with the goal of minimizing costs and maximizing asset availability throughout the lifecycle.

Hybrid techniques are identified as the most suitable, as they combine data-driven approaches with physics-based degradation models, thus enabling a holistic optimization strategy. Data-driven techniques continue to play an important role, particularly for performance prediction and optimization at the system level. Model-based and physics-based techniques remain relevant at this stage, especially for specific component-level modeling and lifecycle-oriented analysis.

Cross-Verification of PdM technique capability mapping and Insights

Beyond the theoretical mapping and case studies, contribution probability data presented in the case investigation table (Table 3-3) is employed as an additional layer of empirical validation. This data is used to quantify the prevalence and effectiveness of each PdM technique across different Ambition Levels (ALs). The evidence thereby provided is regarded as corroborating the findings derived from both the analytical mapping and the case studies.

Table 3-3 Mapping PdM Techniques to Ambition Levels Cross Validation

AL	Technique	Contribution Probability (%)	Paper
1	Experience-Based	100%	Roda et al., 2019; Majstorovic and Milacic, 1990
2	Data-Driven	50%	Abdelmajid et al., 2024; Mohan et al., 2023; Prawatya et al., 2025; Sang et al., 2021
	Model-Based	50%	Ciancio et al., 2020; Magadan et al., 2018; Mourtzis et al., 2022
3	Data-Driven	60%	Tejani, 2024; Ciancio et al., 2024; Nainwal et al., 2023; Chen et al., 2021
	Model-Based	30%	Natanael and Sutanto, 2022; Farahani et al., 2022; Znaidi et al., 2025
	Physics	20%	Izagirre et al., 2022; Belim et al., 2024
	Hybrid	20%	Taşcı et al., 2023; Dereci and Tuzkaya
4	Hybrid	70%	Bahador et al., 2021; Larrinaga et al., 2018
	Data-Driven	30%	Abdelmajid et al., 2024

Experience-based techniques are reported to have a 100% contribution probability for AL1, confirming that these methods are regarded as central to PdM implementations at this stage. This high contribution probability is considered consistent with the conclusion that experience-based techniques are most effective when data is sparse, and failure detection is simple.

Data-driven techniques are identified with a 50% contribution probability at AL2, confirming their suitability when historical data is available for precise RUL prediction. Specifically, studies such as Mohan et al. (2023) and Mourtzis et al. (2021) are cited as emphasizing the predictive accuracy of these models in real-world scenarios, thereby supporting the analytical mapping for AL2.

Hybrid techniques are reported to demonstrate a 70% contribution probability at AL4, indicating their dominant role in lifecycle optimization. Studies such as Bahador et al. (2021) and Larrinaga et al. (2018) are highlighted as supporting the need for a combined approach that integrates both data-driven and physics-based techniques for system-wide optimization. This finding is regarded as consistent with the analytical mapping for AL4, where hybrid methods are identified as most suitable.

Data-driven techniques are observed with a 30% contribution probability at AL4, confirming their utility in lifecycle management and component-level optimization. This observation is supported by the work of Abdelmajid et al. (2024), which aligns with the analytical mapping that positions physics-based techniques as particularly useful for component-level modelling in AL4.

By cross-referencing the analytical mapping of PdM techniques with the case investigation table, robust validation of the findings is achieved. The experience-based, data-driven, model-based, hybrid, and physics-based techniques are shown to align with the Ambition Levels, and these findings are consistently confirmed by both the case studies and contribution probability data. This cross-validation is considered to enhance the credibility of the study by providing a clear empirical foundation for selecting the most appropriate PdM techniques according to the complexity of the implementation goals. The mapping result is further discussed virilized in Chapter 5 Section 5.2.1 and Figure 5-2.

3.3.1.3 Comprehensive attribute identification

This step is focused on identifying the critical attributes that are regarded as influencing the selection and implementation of PdM techniques. Six universal attributes are identified as essential for the effective deployment of PdM techniques. These attributes are considered not only as applicable to specific PdM methods but also as guiding principles for organizations in choosing the most suitable PdM solutions. By doing so, the gap identified in Section 2.3.3 which is *Lacking PdM implementation attributes analysis* can be addressed. The identified attributes are as follows:

Component Clarity

The organization's understanding of critical components, their failure modes, performance characteristics, and operational limits is identified as a decisive factor. In PdM, clarity regarding components is considered essential because it determines which parts of the system are monitored and which failure modes 'require prediction. This attribute is particularly significant for experience-based and model-based methods, in which accurate thresholds and reliable models are dependent on in-depth component knowledge.

Historical Data Availability

The availability of historical data, including sensor logs, maintenance records, and failure histories, is recognised as a crucial factor for data-driven and model-based PdM techniques. The accuracy of predictive models is regarded as directly dependent on the volume, quality, and labelling of this data. Essential PdM tasks such as anomaly detection, trend analysis, and Remaining Useful Life (RUL) prediction are therefore enabled by historical data.

Domain Knowledge

Domain knowledge is defined as the organization's understanding of degradation mechanisms, the physical interpretation of sensor data, and the relevance of specific features. It is considered vital for guiding the design, selection, and application of PdM methods. In data-driven techniques, domain knowledge is

required for sensor selection and data interpretation; in model-based approaches, it informs model structures and parameters; in experience-based methods, it shapes threshold settings and fault logic. Moreover, domain knowledge is regarded as crucial for interpreting system behaviour and inter-component interactions.

Internal Expertise

Internal expertise refers to the organization's capability to develop, validate, and interpret PdM models. Skills in data science, physics-based modelling, and rule-based system design are recognised as essential for advanced PdM applications. A strong internal knowledge base is considered to facilitate the adoption of complex PdM methods, whereas insufficient expertise may force reliance on external or secondary knowledge sources.

External and Secondary Knowledge Sources

External knowledge, such as vendor-provided models, consultants, academic literature, or open datasets, is considered essential when internal expertise is lacking. These resources are recognised as filling technical gaps in predictive modelling, degradation analysis, or failure mode assessment. Secondary data is also employed to compensate for limited or poorly labelled internal datasets.

Computational Infrastructure and Cost

The availability of computational resources and the associated costs are identified as significant constraints in PdM deployment. Advanced PdM approaches, particularly data-driven methods such as deep learning, are recognised as requiring substantial hardware, software, and budget. Computational capability and financial feasibility are therefore considered critical determinants in selecting appropriate PdM solutions.

3.3.1.4 Aline PdM technique with identified attribute

The purpose of this section is to establish a systematic connection between various PdM techniques and the attributes that influence their applicability. This

connection is derived through two complementary steps: Frequency Mapping and Rule Logic Construction.

Frequency Mapping provides an evidence-based understanding of which attributes appear most consistently across real-world PdM applications, thereby highlighting potential enablers of successful implementation. Building on these insights, Rule Logic Construction translates the attribute–technique relationships into a structured decision-making framework. Together, these steps form the methodological foundation for selecting PdM techniques that are both technically feasible and strategically aligned with organizational objectives.

Frequency Mapping

In the first step, the frequency of attributes associated with PdM techniques is analysed based on 47 case studies. Attributes that recur consistently are interpreted as practical enablers. The results are summarized in Table 3-4, where it is shown, for instance, that data-driven techniques are heavily reliant on historical data (92%) and domain knowledge (100%), while model-based techniques are consistently dependent on both historical data (100%) and internal expertise (100%). Frequencies derived from small sample sizes (e.g., hybrid, experience-based) are treated as indicative rather than conclusive.

Table 3-4 Attribute–Technique Frequency Summary Based on Real Case Studies (n = 47)

Technique	n	Historical Data	Internal Expertise	Cost Sensitivity	External Support	Component Clarity	Secondary Data	Domain Knowledge
Data-driven	24	22 (92%)	17 (71%)	18 (75%)	11 (46%)	21 (88%)	16 (67%)	24 (100%)
Physics-based	5	4 (80%)	5 (100%)	4 (80%)	2 (40%)	5 (100%)	4 (80%)	5 (100%)
Model-based	10	10 (100%)	10 (100%)	7 (70%)	2 (20%)	10 (100%)	8 (80%)	10 (100%)
Hybrid	3	3 (100%)	3 (100%)	3 (100%)	1 (33%)	3 (100%)	3 (100%)	3 (100%)

Technique	n	Historical Data	Internal Expertise	Cost Sensitivity	External Support	Component Clarity	Secondary Data	Domain Knowledge
Experience- based	1	1 (100%)	1 (100%)	1 (100%)	0 (0%)	1 (100%)	0 (0%)	1 (100%)

Rule Logic Construction

In the second step, a rule-based logic system is constructed to evaluate the feasibility of PdM techniques under varying organizational conditions. This logic is defined according to the following principles:

Component clarity as prerequisite – If component clarity is absent, feasibility is excluded.

Data sufficiency as determinant – Data-driven and model-based techniques are regarded as requiring extensive historical data, while physics-based methods are observed to operate with more limited but specific datasets.

Domain knowledge as universal enabler – Implementation is considered successful only if expertise is available. Internal knowledge is preferred, but external consultants or secondary sources are allowed to act as substitutes.

Infrastructure and cost feasibility – Techniques are treated as viable only if computational and financial resources are sufficient.

Conditional feasibility – Certain methods are considered feasible only if organizational gaps (e.g., lack of ML expertise) are addressed through outsourcing or external data sources.

The evaluation order, substitution logic, and feasibility rules for each technique are presented in Table 3-5.

Table 3-5 Evaluation order, substitution logic, and feasibility rules for each technique

Technique	Attribute Evaluation Order	Substitution Logic	Rule Highlights
Experience-based	Component clarity → Domain knowledge (internal/external/secondary) → Cost	External support (operators/consultants) can partly replace missing internal knowledge	IF component clarity = no → infeasible. IF no domain knowledge (none of 3 sources) → infeasible.
Model-based	Component clarity → Historical data → Domain knowledge (internal/external/secondary) → Cost → Infrastructure	External consultants or literature models can replace missing modelling expertise	IF no data AND no external/literature → infeasible.
Physics-based	Component clarity → Domain knowledge (physics expertise) → Historical data → Cost → Infrastructure	External expertise (physics consultants) or literature wear models can substitute partially	IF no physics expertise and no substitutes → infeasible.
Data-driven	Component clarity → Historical data → Domain knowledge (ML expertise) → External/secondary → Infrastructure → Cost	ML expertise can be external; secondary datasets can bootstrap models	IF no historical data → infeasible. IF no expertise and no external → infeasible.
Hybrid	Component clarity → Historical data → Domain knowledge (covering multiple approaches) → Cost → Infrastructure	External and secondary sources may supplement technique but not replace all required knowledge	IF any sub-technique fails feasibility → hybrid fails.

Multi-step Evaluation Process

The rule logic is applied hierarchically:

Component clarity is assessed first; if absent, feasibility is excluded.

Data sufficiency is evaluated against the required volumes and quality thresholds.

Domain knowledge availability is examined; if internal expertise is missing, the possibility of external or secondary substitutes is checked. If none are available, infeasibility is concluded.

Infrastructure and cost feasibility is assessed to confirm whether computational resources and budget are adequate.

Conditional feasibility states are defined to capture cases where techniques can be implemented only if external support or supplementary datasets are introduced.

By integrating frequency mapping with rule-based evaluation, a systematic framework for PdM technique selection is developed. In this framework, techniques are ensured to be consistent with organizational objectives, supported by available resources, and adapted to conditional constraints. In this way, empirical insights are bridged with practical deployment.

Outcome

The review yielded a categorized list of PdM attributes, implementation objectives, and technique capacities. These findings established a foundation for the selection criteria and decision-making framework developed in Step B, as illustrated in Figure 3-4. By integrating these insights, the methodology contributes directly to advancing the understanding and practical application of PdM in modern manufacturing environments. The results on the different PdM technique selection rule logics are discussed in detail and visualized in Chapter 5, Section 5.2.1 and Figure 5-4 to 6-6.

3.3.2 Step B Framework development

As presented in Figure 3-4, the aim of Step B is to create a systematic framework for guiding companies in selecting suitable PdM techniques based on the relationships identified in Step A between PdM objectives, attributes, and technique capabilities. This step addresses the need for a structured decision-making tool that aligns PdM implementation with the company's organizational goals and operational context. By doing so, the gap identified in Section 2.2.3,

which is *Lacking linkage among PdM implementation attributes and objectives with PdM techniques* can be addressed.

A hierarchical decision-making model is employed to evaluate and prioritize key factors influencing PdM technique selection. This model is designed to address complex decision-making scenarios, where multiple criteria must be simultaneously considered. The decision criteria are organized into levels, with each level representing a different aspect of the decision. At the top level, the overall goal of PdM implementation (e.g., reducing downtime, improving asset reliability) is defined. Beneath this, specific objectives (e.g., cost reduction, energy savings) and influencing attributes (e.g., resource availability, data requirements) are placed. At the bottom level, PdM techniques and their capabilities are evaluated. This model allows complex decisions to be broken down into manageable parts, ensuring alignment with broader organizational goals. The relationships between objectives, attributes, and techniques are clarified, enhancing the transparency of the decision-making process.

Framework Development Method

The methodology for this research begins with the development of a framework to guide the selection and implementation of PdM techniques. The first step in the framework development is *aligning the company-specific objectives* with the goals of PdM. These goals could include *reducing downtime, lowering maintenance costs, or improving asset health monitoring*. By clearly defining and prioritizing these objectives, organizations can ensure that the PdM techniques selected will effectively support their operational strategy.

The next step involves constructing a hierarchical decision-making model that helps companies evaluate key factors influencing PdM technique suitability. This model considers essential attributes such as *resource availability, internal expertise, external support, and data requirements*. These factors are critical in selecting the most appropriate PdM techniques for the company's specific context.

The framework organizes these key attributes into a *hierarchical structure*, providing a step-by-step process for evaluating PdM techniques. This structured approach ensures that important considerations like *resource availability* and *data requirements* are accounted for, allowing for a systematic selection process.

Methodology Structure

A three-layer hierarchical decision support framework is constructed, with each layer being assigned a specific function that progressively narrows the set of viable predictive maintenance (PdM) techniques. Through this hierarchical structure, each stage is ensured to address distinct and critical elements of the decision-making process, ranging from high-level objectives to detailed feasibility assessments.

The adoption of this framework is motivated by the necessity to integrate the relatively independent components of PdM—ambition levels, PdM attributes, and technique capabilities—into a coherent and structured process. Clarity is enhanced by systematically organizing these elements into discrete yet interconnected steps, ensuring that each layer builds upon the preceding one.

Objective Filtering (Layer 1)

In this layer, a direct alignment between organizational goals and ambition levels is established, and PdM techniques are filtered according to their ability to fulfill strategic objectives (Section 3.3.1.1).

Capability Filtering (Layer 2)

In this layer, practical implementation factors such as data availability, technical expertise, and resource capacity are considered. Techniques that lack feasibility to meet the identified ambition levels are excluded, so that unnecessarily complex solutions for less demanding goals are avoided (Section 3.3.1.2).

Feasibility Evaluation (Layer 3)

In the final layer, the availability of resources and domain-specific knowledge is evaluated, since these elements are recognized as essential enablers for PdM techniques. Only techniques considered feasible within the organization's operational constraints are retained (Section 3.3.1.3 and Section 3.3.1.4).

Outcome

The outcome of this methodology is a structured decision-making framework that enables organizations to systematically evaluate and select PdM techniques tailored to their operational needs, available resources, and implementation goals. By following this framework, companies can optimize their PdM implementation process and maximize the potential benefits of these techniques.

3.3.3 Step C Framework Validation

As presented in Figure 3-4, the validation methodology for the framework is designed as a structured, multi-step process aimed at ensuring the practical applicability and effectiveness of the proposed framework in real-world settings as introduced in Figure 3-4. The methodology consists of theoretical assessments and empirical validations, which allow for a thorough evaluation of the framework's ability to meet organizational objectives and address challenges associated with PdM implementation. The validation process is critical in confirming the framework's feasibility, relevance, and potential for successful deployment.

The framework evolved through iterative versions, Version 1 being derived from literature synthesis (Chapter 2, Table 2-4), Version 2 being refined through expert consultation, and Version 3 being finalized following peer review so that transparent development from theoretical foundation to validated application was ensured.

Step C1 Methodological Refinement

The methodology is refined through a multi-stage process that integrates expert consultation, terminology clarification, and peer-reviewed validation.

Expert Consultation

To ensure practical feasibility and conceptual robustness, two domain experts are engaged. The first expert, selected from the manufacturing industry, evaluates the sequencing of attributes such as component clarity and cost sensitivity against operational realities. The second expert, drawn from academia and specializing in predictive maintenance and industrial AI, assesses the conceptual soundness of ambition-level classification and rule logic. Based on their feedback, several refinements are introduced. Component clarity is placed at the earliest stage of rule evaluation to serve as a baseline feasibility requirement. Domain knowledge is reconceptualized as a composite resource that may be sourced internally, externally, or from secondary data, with substitution rules incorporated into the logic. Hybrid techniques are reframed as emergent outcomes of implementation rather than initial choices, and conditional paths are adjusted accordingly.

Terminology and Structural Clarification

Following expert consultation, terminology is clarified to align with both industrial practice and academic literature. Attributes such as external expertise and secondary data are explicitly defined as potential substitutes for internal expertise. The rule logic is restructured into a sequential evaluation chain consisting of component clarity, data sufficiency, domain knowledge, and infrastructure and cost. This restructuring ensures that the framework is expressed in a consistent and transparent manner.

Peer-Reviewed Validation

The revised framework is submitted to a peer-reviewed journal in the field of manufacturing systems and predictive maintenance. The submission includes ambition levels, attribute–technique mappings, rule matrices, and validation tables. During the review process, reviewers request a more detailed explanation of how domain knowledge substitution operates, a concrete case study to illustrate framework application, and a simplified visualization of the decision framework. These revisions are incorporated, and the article is subsequently published in the CIRP CMS proceedings, providing academic validation and

enabling broader dissemination within the predictive maintenance research community

To test the practical useability of the designed framework, a real-world case study that is representative of the target context for implementing the PdM framework. The case study serves as the foundation for the application of the framework, providing the necessary context for testing its relevance.

Step C2 Framework Implementation

After the objectives of case study company have been defined, the PdM framework is applied to the case study setting. The decision-making algorithms are used to assess the alignment between the organization's needs and the PdM techniques proposed. This application ensures that PdM strategies are tailored to the organization's specific operational context.

The Ambition Level (AL) for PdM implementation is determined first. The AL provides a structured means of determining whether a data-driven, hybrid, or fully automated PdM approach should be employed, depending on the company's technological capabilities and infrastructure.

Next, the critical components of the equipment and the fault types that need to be addressed by the PdM strategy are identified. This identification is based on the analysis of historical maintenance data and expert input. Historical failure patterns, mean time to failure (MTTF), and maintenance costs are examined to determine which components most significantly impact system performance and downtime.

Once the critical components and fault types have been identified, the feasibility of implementing a PdM technique is assessed. The assessment evaluates whether the organization possesses the necessary data and infrastructure to support the development of a predictive maintenance model.

The availability of operational data, such as machine parameters (temperature, vibration, pressure), is examined to determine if sufficient data exists to build the model. The required internal expertise for developing and deploying predictive

models, such as proficiency in machine learning and data analytics, is also assessed. If necessary, external resources, such as open-source models or external consultants, are considered. This assessment ensures that the PdM framework can be realistically implemented, given the available resources and expertise within the organization.

The financial feasibility of implementing the PdM strategy is assessed in the final step. The evaluation includes an analysis of both the initial and ongoing costs associated with the implementation of the PdM system. Initial infrastructure costs, including sensor installation, software, and computing resources, are calculated. Ongoing operational costs, such as data storage, cloud computing, and software licensing fees, are also considered.

Outcome

Validation of the framework's usability and effectiveness in a real-world scenario, demonstrating its ability to guide PdM technique selection and support successful PdM implementation. The case study findings also provide insights into refining the framework for broader applicability.

3.4 Methodology – PdM implementation intangible assets evaluation

The methodology is aimed at addressing key gaps identified in Chapter 2, Section 2.4 by developing a structured approach to '*analysing and quantifying intangible assets for predictive maintenance implementation*'. This approach is organized into five main steps (A–E), each serving a unique purpose and contributing to the research goals. These steps include a literature review, expert surveys, the development of a maturity model, intangible asset quantification, and validation through a case study. Below is an outline of each step's purpose, method, and expected outcome.

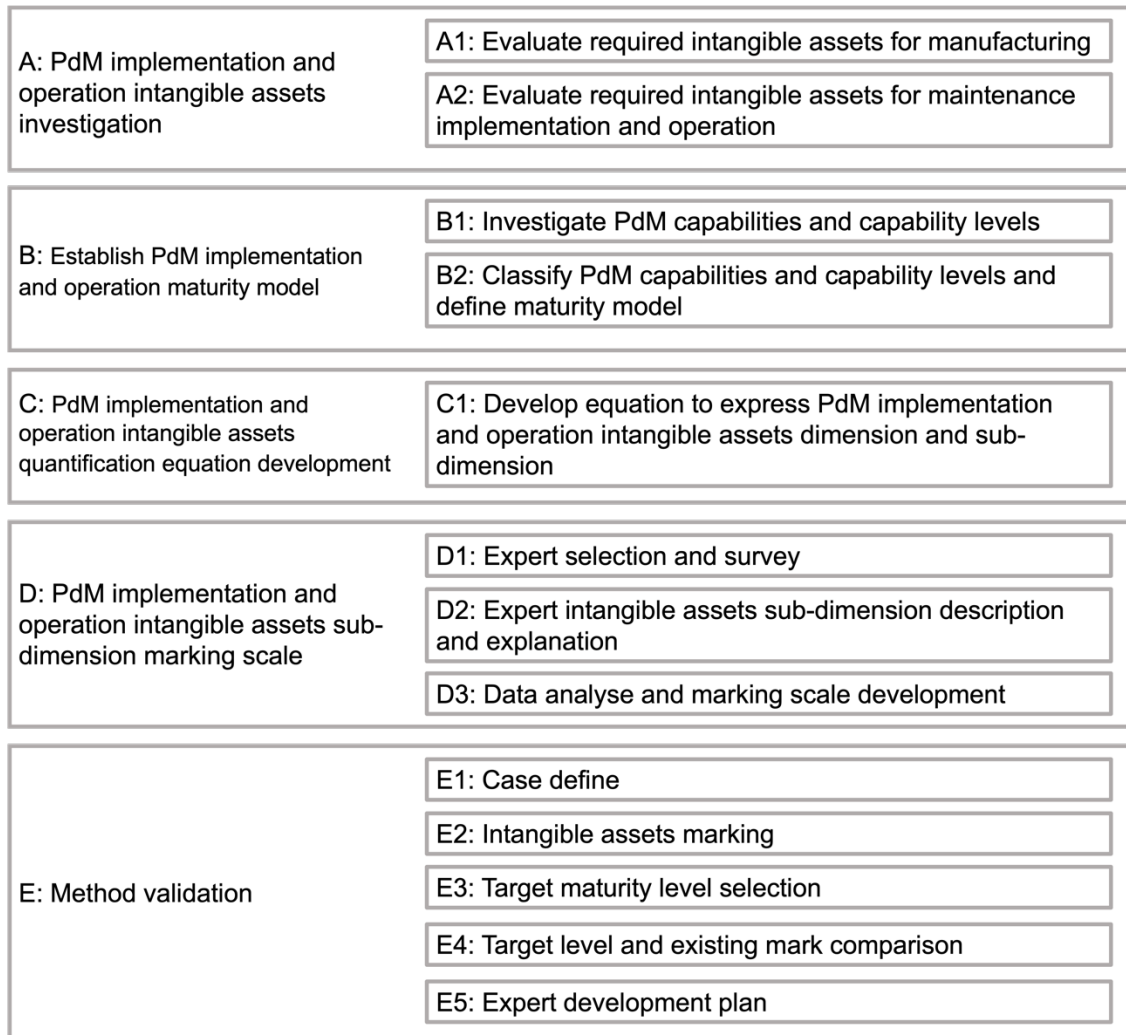


Figure 3-5 Method for PdM implementation and operation intangible assets evaluation – methodology

3.4.1 Step A Maintenance intangible assets type investigation

The purpose of Step A (Figure 3-5) is to address the gap identified in Section 2.4.2, where a comprehensive analysis of intangible asset types specific to the manufacturing industry is lacking. In this step, intangible assets are dissected to determine which are essential for the successful implementation and operation of PdM. The objective is to identify and categorize the key intangible assets that critical for PdM adoption and support the effective implementation of maintenance strategies.

Previous research has often treated intangible assets as a unified concept, without distinguishing between the various types that influence PdM

implementation. While intangible assets such as organizational culture, employee expertise, leadership capabilities, and knowledge management are acknowledged, their specific functions to PdM strategies remain unexplored. This lack of clarity presents a challenge for organizations that are uncertain about which intangible assets should be prioritized to ensure the success of PdM initiatives.

To bridge this gap, Step A1 utilizes a SLR to systematically identify the intangible assets necessary for PdM in manufacturing contexts. The SLR method provides a comprehensive review of existing literature, capturing relevant intangible assets from multiple high-quality sources. This approach minimizes researcher bias and ensures that the assets identified are rooted in evidence from a broad range of studies. A structured framework for categorizing intangible assets is also provided, facilitating the identification of those with the most significance for PdM implementation.

Once the SLR has identified the intangible assets, an Expert Survey is conducted in Step A2 to validate and refine these findings. The Expert Survey allows for the prioritization of intangible assets based on real-world experience. Experts with direct experience in PdM implementation evaluate the relevance and importance of the identified assets, ensuring that they are contextually aligned with the specific challenges and operational goals of manufacturing organizations.

By combining SLR and the Expert Survey methods, intangible assets are identified in a comprehensive, systematic, and contextually grounded manner. The SLR serves as the foundation, providing a broad, evidence-based list of assets, while the Expert Survey refines this list, ensuring that the assets identified are practical and relevant to PdM success. This combined methodology enhances the reliability of the findings and addresses the limitations of previous studies that failed to clearly distinguish and prioritize intangible assets critical for PdM implementation.

Step A1 Evaluate required intangible assets for manufacturing method - Systematic literature review

The first step involves conducting a **Systematic Literature Review** to identify the types of intangible assets required in the manufacturing sector. This review uses databases such as *IEEE Xplore Digital Library*, *ScienceDirect*, and *Springer*, focusing on articles from the past 10 years that specifically discuss intangible assets in relation to manufacturing. Articles that treat intangible assets as a single category or lack clear definitions of these assets are excluded. The search includes terms such as "Manufacturing," "intangible assets," and "intangibles." A thematic analysis will be conducted to categorize the types of intangible assets based on their relevance to the manufacturing process and operations.

Step A2 Evaluate required intangible assets for maintenance implementation and operation method - Expert survey

Following the systematic literature review, an **Expert Survey** is conducted to validate and refine the intangible asset types identified in the literature. The goal of this survey is to confirm the necessary intangible assets for maintenance strategy implementation and operation. Experts with at least five years of experience in manufacturing—particularly in maintenance, production, or management—will participate. The survey asks participants to select and rank the intangible asset types they consider critical for PdM operations. The outcome of this survey is a validated list of intangible asset types, organized by their relevance to different maintenance strategies.

3.4.2 Step B Maintenance maturity model

The purpose of Step B (Figure 3-5) is to establish a maturity model that categorizes PdM capabilities into progressive levels. The model is designed to allow organizations to evaluate their current capabilities and identify target levels for PdM, thereby addressing the gap in intangible asset evaluation prior to PdM implementation, 'limitations in evaluating intangible assets in advance', presented in Chapter 2, Section 2.4.2. In addition, combined with the maintenance intangibles implementation strategy map that is presented in Step

E (Figure 3-5), it allows for the evaluation of the types and quantities of intangible assets needed before starting the PdM implementation process.

Step B1 Investigation PdM capability and capability level method - Systematic literature review

Foundational Review and Theoretical Basis

The proposed predictive maintenance maturity model is grounded in the tradition of staged frameworks that are used to assess organizational capabilities, such as CMMI in software engineering (Paulk et al., 1993), PMI standards in project management (PMI, 2013), and digital transformation models (Gill & VanBoskirk, 2016). In the field of maintenance and asset management, frameworks such as the Asset Management Maturity Model (AMMM), the Digital Maintenance Maturity Model (Ferreira et al., 2019), and Industry 4.0 readiness models (Schumacher et al., 2016; Bibby & Dehe, 2018) are frequently referenced.

Although relevant, these models are considered limited when they are applied to PdM as discussed in Chapter 2, Section 2.4.3. Technological infrastructure is usually emphasized, while organizational enablers such as training, leadership, and cultural readiness are underrepresented. Intangible assets, including experiential knowledge, communication flows, and data interpretation, are rarely considered, even though their importance is recognized (Franceschini & Midali, 2019; Bousdekis et al., 2019). Transitions between maturity levels are often defined vaguely, and their rationale or performance implications are seldom explained. In addition, integration with operational decisions such as planning, scheduling, logistics, and safety is treated weakly.

To address these limitations, a PdM-specific model is developed. Intangible assets are explicitly incorporated, and a capability-based approach is adopted to focus on what organizations are actually able to perform at each level. A two-dimensional structure is introduced, in which operational functions (e.g., safety, productivity, quality) are distinguished from strategic functions (e.g., optimization, sustainability, transparency). Matrices that link capabilities to outcomes and intangible resources are also employed.

Data Collection: Systematic Literature Review

A systematic literature review (SLR) is conducted to collect evidence on PdM capabilities and implementation practices. The review covers IEEE Xplore, ScienceDirect, and SpringerLink databases. Search keywords include “Predictive Maintenance,” “Maintenance Strategy,” “Maturity Model,” “PdM Capabilities,” and “Industrial Maintenance Development.”

Inclusion criteria require that: (1) studies report PdM capabilities or implementation practices, (2) studies are peer-reviewed, and (3) studies are related to industrial or manufacturing contexts. Exclusion criteria remove purely algorithmic papers without applied context. To ensure contemporary relevance, the review focuses on publications from 2013 to 2023.

Thematic Analysis and Capability Extraction

The selected studies are analyzed through a structured thematic coding process. Relevant text is first coded into functional roles such as data collection, diagnostics, or scheduling. Capabilities are then grouped into broader categories according to technical complexity, integration level, and reported outcomes. Definitions and attributes are consolidated into capability statements, and traceability to the original sources is preserved.

This process ensures that both technical and organizational aspects of PdM are captured and prepared for classification into maturity levels.

Capability Classification and Level Definition

The extracted capabilities are organized into a five-level maturity structure, which follows established maturity modeling principles. Each capability is evaluated according to five criteria:

Technical complexity (manual, sensor-based, automated, real-time)

Predictive intelligence (reactive, condition monitoring, predictive, prescriptive)

Organizational integration (limited to maintenance vs. cross-departmental use)

Automation and data usage (manual, semi-automated, system-driven)

Strategic alignment (focused on equipment uptime vs. broader goals such as sustainability or transparency)

Capabilities that are reactive or manual (e.g., fixed-interval scheduling) are placed at Levels 1–2. Data-driven diagnosis and semi-automation are placed at Level 3. Real-time analytics and automated decision-making are associated with Level 4, while cross-functional optimization and strategic integration are placed at Level 5. When a capability appears across multiple levels, it is assigned to the lowest level at which it becomes operational, so that internal consistency is maintained.

Capabilities are divided into basic operational functions and strategic functions, reflecting the progression from equipment uptime and safety toward optimization and sustainability. The classification logic is refined iteratively and validated through expert consultation.

Initial Model Structure

The resulting five-level model is shaped by both the precedent of established frameworks (e.g., CMMI, ISO) and the specific needs of PdM. A structured pathway is provided for organizations to progress from operational efficiency toward broader strategic value creation as discussed and explained in Chapter 2, Section 2.4.3.

Step B2 Maturity model define method - Expert validation

To refine the proposed maturity model and to evaluate the intangible assets and intangible asset capabilities required at each maturity level, expert consultation is conducted. Seven experts are invited representing a balanced mix of academic researchers and industry professionals. Their expertise spans mechanical engineering, industrial design, manufacturing engineering, production management, and maintenance engineering, with qualifications ranging from postgraduate to doctoral levels.

The academic participants ensure theoretical rigor, methodological soundness, and alignment with the state-of-the-art knowledge of predictive maintenance and

related technologies. Their backgrounds in engineering research and education support the structured formulation of maturity levels, the classification of capabilities, and the integration of intangible assets into the model.

The industrial participants contribute extensive practical experience in production and maintenance management. Their expertise provides critical insights into organizational realities, operational feasibility, and managerial concerns, ensuring that the model captures decision-making processes, workflow integration, and the value of experiential knowledge.

The combination of academic and industrial perspectives secures both conceptual validity and practical applicability. In addition, the diversity of age, career stage, and industrial sector represented in the panel introduces a range of viewpoints, reducing the risk of bias and enhancing the generalizability of the findings.

Therefore, the selection of these experts is considered appropriate and necessary. Their complementary knowledge enables the maturity model to be refined in a balanced way, while also ensuring that the evaluation of intangible assets and related capabilities reflects both theoretical foundations and industrial practice. This step is conducted to refine the model and confirm its applicability in practical settings (Step D and E).

In addition, the refined model is also presented at a peer-reviewed conference (AMEST), but no further comments on the maturity model are received during or after the event.

Outcome

As an outcome, a PdM maturity model with clearly defined capability levels is developed. This model is intended to guide organizations in assessing their current PdM capabilities and planning for future development

3.4.3 Step C Maintenance intangible assets quantification equations

Step C is designed to quantify intangible assets using a scaling method adapted from Cinca et al. (2003), addressing the research gap in accurately measuring

intangible assets for PdM implementation with limited data, as discussed in Chapter 2, Section 2.4.1.

Scaling Method Application:

The **scaling method is applied** to quantify intangible assets, representing their values in a matrix format composed of sub-dimensions. Each sub-dimension is assigned a quantitative value to reflect its contribution. The model is expressed as follows:

$$I = \{i_{11}, i_{12}, i_{13}, i_{21}, i_{22}, i_{23}, i_{31}, i_{32}, i_{33}, i_{41}, i_{42}, \dots i_{nn}, \} \quad (3-10)$$

Where I represents the required value of intangible assets for maintenance implementation and operation, and i_{11} to i_{nn} are the values assigned to each intangible sub-dimension. The values for these sub-dimensions **are derived** from the **marking scale** developed in Step D (Figure 3-5).

Outcome

As an outcome, a quantified measure of intangible assets is produced in the form of a matrix, enabling a detailed evaluation and effective planning for predictive maintenance implementation.

3.4.4 Step D Maintenance intangible assets marking scale

The objective of Step D, as presented in Figure 3-5, is to create a marking scale that quantifies the intangible asset dimensions identified in Step A. This scale is designed to provide a standardized method for measuring intangible assets and to serve as a validation tool for the PdM maturity model developed in Step B. Key intangible assets necessary for PdM implementation are identified, and their relevance and effectiveness at different maturity levels of PdM practices are quantified.

The expert survey method is employed to capture specialized knowledge from professionals with direct experience in PdM implementation. Insights into intangible assets, such as organizational culture, employee skills, and leadership effectiveness, are gathered. This method ensures that the intangible asset dimensions are relevant, applicable, and aligned with real-world challenges,

providing depth that general surveys or secondary data cannot offer. The expert survey method allows for the refinement and prioritization of the intangible asset dimensions identified in Step A.

The expert survey method also serves to validate the PdM maturity model developed in Step B. Feedback from experts is used to assess how intangible assets influence each stage of the PdM maturity model, ensuring its real-world applicability. This validation process confirms that the model is aligned with industry standards and can be practically applied across various organizational contexts.

The reliability of the marking scale is ensured through the expert survey method by grounding intangible asset dimensions in real-world experience. Defined scales are used by experts to mark intangible asset dimensions, allowing for consistent, quantifiable data to be obtained. This consistency ensures that the intangible asset framework is applicable across different industries and organizations.

Step D1 and D2 Expert survey and expert intangible assets explanation method - Expert survey for marking scale development

The survey is designed to collect expert input on the performance of intangible asset sub-dimensions across different PdM maturity levels. Experts are asked to provide qualitative descriptions, which are converted into a quantifiable marking scale for consistent measurement. Validation criteria are established to ensure the reliability of the results. Experts are required to represent companies operating at various PdM maturity levels and must have at least three years of PdM-related experience.

Step D3 Data analyse and marking scale development

A validated marking scale is developed to quantify intangible asset sub-dimensions. This scale supports the application of the PdM maturity model and enhances its reliability and practical utility.

3.4.5 Step E Method Validation

The objective of Step E is to ensure that the previously developed quantitative methods for intangible assets are theoretically reliable and can operate effectively in practical applications. To achieve this goal, the method is applied to a real-word case study. Finally, based on the insights of industry experts, the PdM implementation strategy is further refined. This research method is divided into a series of carefully structured steps, aiming to verify the effectiveness of the intangible asset quantitative methods, assess the implementation readiness of PdM, and create a strategic roadmap for the successful implementation of PdM.

For this case study, a manufacturing company was selected based on its established maintenance processes and demonstrated interest in adopting PdM. Data collection was carried out through interviews, document analysis, and observations to assess the company's current intangible asset values. These values were then compared with the target levels defined in Step C and Step D (Figure 3-5), which helped to identify gaps and inform the planning for PdM implementation.

After collecting the data, the research team compared the current value of the company's intangible assets with the target levels set in Step C and Step D (see Figure 3-5) to assess the gap and identify the areas for improvement. In addition to validating the quantitative methods for intangible assets, the research also aimed to support the implementation of maintenance-related intangible assets. In Step E5 (Figure 3-5), a Maintenance Intangible Asset Implementation Strategy Map was created based on insights gathered from industry interviews. This strategy map focuses on guiding the acquisition and development of intangible assets required during the PdM implementation process, particularly for maturity levels 3 to 5. Through this strategy map, the research provided detailed guidance for PdM implementation, supporting companies plan and develop intangible assets in a targeted manner.

Ultimately, the research not only verified the effectiveness of the quantitative method for intangible assets but also provided a strategic roadmap for the company, assisting it in effectively implementing PdM at different maturity levels.

This process ensures that the company can rationally allocate intangible assets when implementing PdM, thereby providing strong support for the successful execution of PdM. It should be noted that this case study is more focused on demonstrating the applicability of the proposed method in practice rather than serving as a full validation of the entire method.

Step E 1 – E5 Case study design method and application

The first step is defined by the need to select the case study used to validate the intangible asset quantification method. A manufacturing company is chosen based on its established maintenance processes and demonstrated interest in PdM adoption. The specific objectives of PdM implementation in the case study company are outlined. These objectives are used as the basis for testing the intangible asset quantification method and measuring PdM effectiveness.

A detailed scenario description is provided, covering the company's current maintenance strategy, systems in place, and challenges faced. Expected outcomes from PdM implementation, such as reduced downtime and lower maintenance costs, are identified.

In this step, the intangible assets currently possessed by the company are assessed and compared with the target levels identified in earlier steps (Steps C and D). Interviews with key stakeholders, document analysis, and observations are employed to gather qualitative data on the company's intangible assets, such as employee skills, organizational culture, and leadership commitment.

The current intangible asset values are compared with the target levels established in previous steps. Gaps in intangible assets are identified as areas for improvement.

Chapter Summary

In this chapter, the methodology applied in this research is presented to address the gap identified in Chapter 1 and justified in Chapter 2. Specifically, the methodology for developing the maintenance strategy selection method for the modern manufacturing era is outlined in Section 3.2. The approach for selecting

predictive maintenance techniques is described in Section 3.3. The methodology for evaluating the intangible assets involved in predictive maintenance implementation is detailed in Section 3.4.

In the methodology design, extensive expert consultations and validation activities are undertaken to ensure both theoretical rigor and practical applicability of the developed artefacts. A comprehensive summary table is included in Appendix E, where all expert participants, their areas of expertise, validated artefact components, and key contributions across the research stages are consolidated. To manage instances in which expert opinions diverge, a structured consensus approach is applied. All feedback is thematically coded and cross-compared among experts; where discrepancies arise—particularly in the sequencing of decision attributes or the interpretation of ambition levels—reconciliation is achieved through follow-up correspondence, and resolution is reached by majority agreement, with minority viewpoints preserved in annotation notes. The synthesis is conducted independently so that dominance bias is minimised and methodological transparency is maintained. Through this process, refinements to the framework are ensured to be grounded in balanced expert perspectives and supported by a transparent and systematic validation procedure.

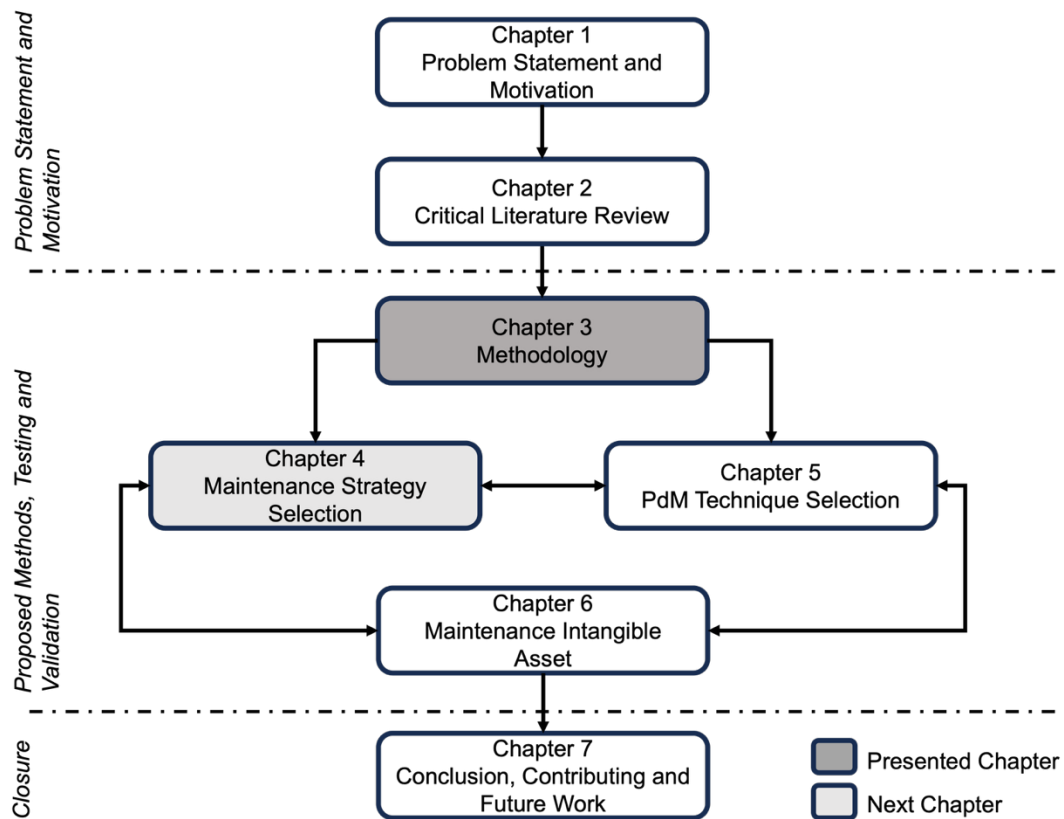


Figure 3-6 Organization of the Thesis – Presented and Next Chapter

In Chapter 4, as presented in Figure 3-8 the results, validation, and discussion of the maintenance strategy selection method for the modern manufacturing era will be presented, following the steps outlined in Section 3.2 of this chapter.

CHAPTER 4 - ANALYTICAL HIERARCHICAL PROCESS FOR MAINTENANCE STRATEGY SELECTION IN MODERN MANUFACTURING ERA

In this chapter, a method, analytical hierarchical process for maintenance strategy selection in modern manufacturing era is presented to answer Research Question One *What is the method that helps manufacturers evaluate the necessary tangible assets for PdM implementation, considering whether PdM is required and which PdM technique is needed?* introduced in Chapter 1, Section 1.3, and justified through critical literature review in Chapter 2, Section 2.2 The analytical hierarchical process for maintenance strategy selection in modern manufacturing era is the first objective for investigating PdM implementation tangible assets.

A: Define maintenance strategy selection goal, alternatives, and criteria	A1: Define maintenance strategy selection goal
	A2: Define maintenance strategy selection alternative
	A3: Define maintenance strategy selection criteria
	A4: Set up hierarchical tree
B: Decision maker judgement	B1: Decision-maker gathering
	B2: Case introduction
	B3: Criteria pairwise comparison
	B4: Alternative performance marking
C: Weight relative importance of each criterion and performance measure of criteria with respect to alternative	C1: Weight relative importance of each criterion
	C2: Performance measure of criteria with respect to alternative
	C3: Select optimized alternative
D: Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) Evaluation	D1: Determine the ranking of Sub-criteria with respect to cases
	D2: Calculate the weighted rank sum ratio of each case
	D3: Evaluation objects sort and classification

Figure 4-1 AHP for maintenance strategy selection in modern manufacturing era framework

Following the methodology for designing the Analytical Hierarchy Process for maintenance strategy selection in the modern manufacturing era introduced in Section 3.2 and presented in Figure 4-1, the first section in this chapter (Section 4.1) includes the defined maintenance strategy selection goals, alternatives, and decision criteria. Section 4.2 is dedicated to the expert judgment process, and the marking and ranking of maintenance alternatives are presented in Section 4.3. In Section 4.4, the identified decision criteria are calculated and ranked based on their importance. Lastly, a discussion of the results is presented in Section 4.5.

4.1 Step A Maintenance strategy selection in modern manufacturing era goal, alternatives, and decision-criteria

To ensure a structured approach, this chapter follows the AHP framework, as outlined in Figure 4-1. Each step (A1–A4) corresponds to a specific phase in the decision-making process, as depicted in the framework. Steps A1–A3 represent the initial phase of problem definition, where the goal, alternatives, and decision criteria are identified. Step A4 corresponds to the process of structuring the decision problem, which involves organizing the decision criteria and alternatives into a hierarchical structure.

4.1.1 Step A1 Define maintenance strategy selection goal

As discussed in Section 3.2.2, the goal of maintenance strategy selection is centred on Objective One of this research: 'Developing the AHP for maintenance strategy selection in the modern manufacturing era.'

4.1.2 Step A2 Define maintenance strategy alternatives

This step has been conducted during the critical literature review process in Chapter 2.2. The identified alternatives are:

- **Alternative One Corrective Maintenance (CM):** CM is a strategy that allows devices to run until failure happen. Maintenance actions are taken after failure take place.
- **Alternative Two Preventive Maintenance (PM):** PM is a strategy in which maintenance actions are taken after devices work for a specific time or iteration.
- **Alternative Three Predictive Maintenance (PdM):** PdM is a strategy that utilizes digitized sensor data along with data analytics to continuously monitor

the state of machine components or processes to determine when and where maintenance may be required.

The reason why tacked CM into consideration is because firstly, it is still extensively applied in practice. According to Plant Engineering maintenance survey 2018, CM is still a viable option for some assets, fell from 61% in 2017 to 57% in 2018 in the US. Secondly, according to Deighton (2016), CM is cost-effective alternative when having limited access to resources and maintenance infrastructure, including tools, technologies and expertise.

4.1.3 Step A3 Define maintenance strategy selection criteria

Identifying the decision criteria used in previous studies

This step is divided into three parts. The first part involves identifying the decision criteria used in previous studies related to AHP manufacturing maintenance strategy selection. This part was also conducted during the critical literature review process in Chapter 2.2. The identified criteria are:

- **C_1 Cost:** It refers to the amount of cost required for maintenance implementation and operation.
 - **C_{11} Capital Investment:** Capital investment in terms of maintenance refers to the investment required to implement a maintenance strategy, including investment in hardware and software. These investment actions usually take place before maintenance strategy implementation.
 - **C_{12} Annual Maintenance Cost:** It refers to the annual maintenance and operation cost of specific devices or manufacturing systems, including the cost of repair, part replacement, cost of spare parts and cost of acquiring tool.
 - **C_{13} Training Cost:** Training is required to implement any kind of maintenance strategy. Operators need to understand when and how to take maintenance actions.
- **C_2 Productivity:** It refers to the capability of machine/production line to produce products.

- C_{21} *Total Efficiency*: It refers to the time required to finish a specific production job.
- C_{22} *Reduced Downtime*: When any unexpected machine fault happens, operators may need to shut down the machine and take maintenance actions. In addition, devices are also needed to be shut down to take preventative maintenance actions.
- C_{23} *Flexibility and Customizability*: In the context of global competition and modern manufacturing, companies are no longer confined to producing a limited range of products for higher profit margins. The receipt of more diverse orders creates new profitability opportunities. To capitalize on this, manufacturing companies require production flexibility to quickly adjust production lines. Similarly, within Industry 4.0, the increasing demand for customized products necessitates the ability to rapidly adapt production lines, thereby enhancing competitiveness.
- **C_3 Added Value**: It refers to the value conducted by machine or production line beyond products themselves.
 - C_{31} *Improved Product Quality*:
Correct, efficient and timely maintenance operations can largely avoid difficult-to-find quality defects in the final product, such as stress problems on metal parts.
 - C_{32} *Increased Satisfaction and Loyalty*: In the context of Industry 4.0, companies are looking for more customers repurchase rates. Correct, efficient and timely maintenance operations can improve product quality while ensuring that there will be no unexpected downtime during the production of orders to be delivered on time. In this way, user satisfaction can be improved, and loyalty can be cultivated.
- **C_4 Safety**: It refers to the potential risk to operators or equipment
 - C_{41} *Safety to People*: Machine damage can lead to risks to operator safety. For example, operators may be injured when unexpected machine

damage happens. Operators may also be injured when taking maintenance actions on damaged machines.

- *C₄₂ Safety to Equipment:* Some machine faults can lead to severe machine damage.
- **C₅ Environmental:** It refers to the impacts to environment caused by maintenance operations.
 - *C₅₁ Environment Impact & Hazard:*

In some industries like chemistry, machine damage or belated maintenance actions can lead to risks to the surrounding environment.
 - *C₅₂ Carbon Emission:* Countries are increasingly focusing on reducing greenhouse gas emissions. In China, for example, the government has set goals for carbon peaking and carbon neutrality. Additionally, a carbon emission tax has been introduced on an experimental basis, limiting the amount of carbon emissions allowed for companies. Those exceeding emission limits will face additional tax burdens.
- **C₆ Additional Factors:** It refers to the factors that affect maintenance performance but hard to product and control.
 - *C₆₁ Operator Confidence Level:* It refers to the maintenance operator's confidence level in predictive maintenance tools when applying predictive maintenance. Studies have shown that in some enterprises that apply predictive maintenance, some operators have insufficient confidence in predictive tools or do not know enough about operating specifications, so they do not perform maintenance according to the predictions but still perform preventive maintenance.
 - *C₆₂ Tech-Assessment:* Tech-Assessment involves assessing the feasibility of implementing a technology into a system or setup in terms of technology, management, and skilled operators. For instance, not every type of component can be monitored by PdM. Additionally, some devices

may not be suitable for PdM implementation due to shop floor space limitations.

Identifying criteria to be considered in the modern manufacturing era

The investigation in the second part focuses on identifying the criteria to be considered in the modern manufacturing era. Following the methodology outlined in Chapter 3, Section 3.2.2, the identified criteria are presented in Table 4-1.

Table 4-1 Part Two, Step A3 decision criteria identified

Decision Criteria	Paper
Human needs adoption	Zizic et al., 2022; Alves et al., 2023; Jafari et al., 2022; Hein-Pensel et al., 2023; Gladysz et al., 2023; Wang et al., 2024; Kasinathan et al., 2022; Destouet et al., 2023; Madzik et al., 2024
Human-machine integration	Zizic et al., 2022; Alves et al., 2023; Paschek et al., 2022; Jafari et al., 2022; Hein-Pensel et al., 2023; Fatima et al., 2022; Vyhmeister and Gabriele, 2024; Gladysz et al., 2023; Wang et al., 2024; Kasinathan et al., 2022; Destouet et al., 2023; Taj1 and Jhanjhi; Zafar et al., 2024; Gomathi et al., 2023; Tavares et al., 2022; Panagou et al., 2024; Madzik et al., 2024
Meaningful job creation	Zizic et al., 2022; Alves et al., 2023; Jafari et al., 2022; Hein-Pensel et al., 2023; Fatima et al., 2022; Vyhmeister and Gabriele, 2024; Gladysz et al., 2023; Wang et al., 2024; Kasinathan et al., 2022; Destouet et al., 2023; Madzik et al., 2024
Energy efficiency	Zizic et al., 2022; Jafari et al., 2022; Vyhmeister and Gabriele, 2024; Baig and Yadegaridehkordi, 2024; Destouet et al., 2023; Dhayal et al., 2023
Waste prevention	Paschek et al., 2022; Jafari et al., 2022; Vyhmeister and Gabriele, 2024;

	Baig and Yadegaridehkordi, 2024; Destouet et al., 2023; Gomathi et al., 2023; Tavares et al., 2022; Dhayal et al., 2023
Information logistic waste	Zizic et al., 2022
Technology ethical	Alves et al., 2023
People towards resilience	Zizic et al., 2022; Destouet et al., 2023
Technology toward resilience	Zizic et al., 2022; Destouet et al., 2023
Mass personalization	Paschek et al., 2022; Jafari et al., 2022; Taj1 and Jhanjhi

The detailed explanation of the identified criteria for modern manufacturing ear are presented as follow:

- *Human Needs Adoption:* Technology development in Industry 5.0 increasingly focuses on meeting human needs more effectively. Machine behaviour feedback, complementing sensor data, leads to more accurate failure predictions. Digital twins enable real-time monitoring of production processes and predictive analysis. Virtual training programs enhance worker safety by simulating hazardous scenarios, with VR/AR systems showing promise in construction safety. Artificial intelligence plays a central role, allowing machines to learn from human interaction and autonomously perform tasks (Nahavandi, 2019; Stjepandi'c et al., 2022; Li et al., 2018; Kim et al., 2018; Zizic et al., 2022).
- *Human-Machine Integration:* Efforts in human-robot collaboration emphasize the development of evaluation frameworks to assess interaction dynamics. Key dimensions such as workload, trust, robot design, physical ergonomics, and usability are crucial considerations. Additionally, trajectory prediction techniques help prevent collisions, while plan recognition enhances collaboration efficiency (Gervasi et al., 2020; Cheng et al., 2020; Aljinovic et al., 2020; Zizic et al., 2022).
- *Meaningful Job Creation:* Meaningful job creation in Industry 5.0 prioritizes human-centred production, supported by tools such as collaborative robots. This approach addresses consumer demands while

offering workers more fulfilling roles compared to traditional factory jobs. New roles focus on programming, organization, planning, training, and maintenance, highlighting the growing importance of data science, machine learning, and AI skills for future employment. While technological advancements may raise concerns about job displacement, they also create new roles to support automation. To remain competitive, businesses must adapt, requiring individuals skilled in navigating technological changes and transitioning seamlessly from technology to solutions and operations. Bridging the skills gap involves using technologies like augmented reality (AR) and wearables to enhance human performance and improve staff efficiency through real-time guidance (Ostergaard, 2018; Frey & Osborne, 2013; Spath et al., 2013; Broo et al., 2022; Ras et al., 2017; Zizic et al., 2022).

- *Energy Efficiency: The introduction of Industry 4.0 and 5.0 highlights the importance of energy efficiency. While these technologies consume energy, they also offer opportunities for conservation. This raises concerns about their environmental impact and society's readiness to address these challenges. New technologies may cause drawbacks like increased pollution and resource use, but these can be mitigated by optimizing energy use through data analysis. The technology selection process should prioritize sustainable options, even if they initially seem less productive (Bonilla et al., 2018; Oláh et al., 2020; Rocha et al., 2021; Celent et al., 2022; Zizic et al., 2022).*
- *Waste Prevention: The concept of waste prevention spans various dimensions, including process waste such as overproduction and overstock, social waste represented by individuals eager to work but lacking opportunities, and physical waste encompassing general trash and production line waste. Additionally, urban waste, which includes underutilized greenfield and inadequate infrastructure, contributes to inefficiencies in resource utilization Circular economy and environmental sustainability (Paschek et al., 2019; Paschek et al., 2022).*

- *Information Logistic Waste: Sustainability and technology intersect significantly in the realm of information logistics waste within processes. This issue arises across the design, production, and supply chain stages. Waste in data processing encompasses three main areas: data generation and transfer, data processing, and data storage and utilization. To address this, it's crucial to collect an optimal amount of data and evaluate it based on content, meaning, and source. Minimizing wait periods and optimizing data storage are vital, especially for ensuring real-time data availability (Tribelsky et al., 2010; Maurer, 2013; Meudt et al., 2016; Zizic et al., 2022).*
- *Ethical Use of Technology: Industry 5.0 emphasizes ethical technology use, prioritizing humans over technology, in contrast to Industry 4.0's focus on transhumanism and posthumanism (Longo et al., 2020). While Industry 4.0 often saw technology dominate human workers, Industry 5.0 advocates for technology serving humanity, as reflected in the European Commission's directive (Longo et al., 2020; Margherita et al., 2021; Kravchenko, 2019; Zizic et al., 2022).*
- *People Towards Resilience: Resilience, the ability to endure disruptions, has been underexplored in the context of Industry 4.0. The role of human resources in resilience is particularly overlooked. Research shows that people are essential for detecting anomalies, with training, education, awareness, leadership, skills, and talent enhancing resilience. Strategic human resource management is crucial for developing the necessary knowledge and skills and fostering resilience through collective routines and processes (Morisse and Prigge, 2017; Lengnick-Hall et al., 2011; Al-Ayed, 2019; Zizic et al., 2022). This approach strengthens maintenance systems, ensuring adaptability and prioritizing human well-being.*
- *Technology Toward Resilience: Organizational resilience is a multidisciplinary concept involving both internal and external factors. It is the ability to overcome challenges by understanding, adapting to, and managing vulnerabilities. Resilience is built upon organizational*

capabilities, routines, practices, and processes that help navigate challenges and promote adaptability. Internal factors such as risk management and information visibility are vital, with risk plans and prevention techniques being key components. The adoption of technologies enhances resilience by improving information tracking, though careful consideration of the data generated is required for organizational benefit (Lengnick-Hall et al., 2011; Marcucci et al., 2021; Zizic et al., 2022).

- *Mass Personalization:* In today's dynamic market, customers are inundated with cutting-edge innovations and products, posing a significant challenge for the manufacturing industry to meet personalized demands. The shift from mass customization to mass personalization is becoming increasingly imperative for manufacturing systems. This transition involves actively involving customers in the design phase to create customized products from the ground up. Human-robot collaboration plays a crucial role in enhancing operational flexibility, enabling versatile fabrication in a more efficient timeframe. While robots primarily handle the main tasks, human collaboration enhances problem-solving capabilities and process flows, fostering intelligence and innovation within manufacturing operations (Rossi, 2018; Paschek et al., 2022).

Identify limitations and challenges of PdM

The aim of the third phase of literature review is to identify the limitations and challenges of PdM. Following the methodology outlined in Chapter 3, Section 3.2.2, the identified criteria are presented in Table 4-2.

Table 4-2 Part Three, Step A3 decision criteria identified

Decision Criteria	Paper
Resource and knowledge limitation	Khan et al., 2022; Achouch et al., 2022; Sivanuja and Sandanayake,

	2022; Hassankhani Dolatabadi and Budinska, 2021; Cheng et al., 2022; Hubert and Kaledio, 2024
Data availability	Khan et al., 2022; Achouch et al., 2022; Sivanuja and Sandanayake, 2022; Ucar et al., 2024; Çınar et al., 2020; Mallioris et al., 2024; Hubert and Kaledio, 2024
Maintenance and production linkage	Zonta et al., 2020; Sivanuja and Sandanayake, 2022; Ucar et al., 2024
Model deployment	Achouch et al., 2022; Sivanuja and Sandanayake, 2022; Hubert and Kaledio, 2024
Fault diagnoses	Nunes et al., 2023; Sivanuja and Sandanayake, 2022; Hassankhani Dolatabadi and Budinska, 2021; Ucar et al., 2024; Hubert and Kaledio, 2024

- *Fault Diagnoses:* False fault warnings or untimely warnings can occur in predictive maintenance systems, as predictive tools may not always be accurate. Additionally, false alarms and untimely warnings can be triggered by cyber-attacks (Li et al., 2020; Roig et al., 2019; Yoo, 2020; Liu et al., 2020; ElMenshawy & Helmy, 2018; Peng et al., 2019; Cauteruccio et al., 2019; Nunes et al., 2023).
- *Data Availability:* Developing and testing anomaly detection techniques faces a significant challenge due to the scarcity of labeled data. To address this issue, some researchers resort to unsupervised techniques. While these methods yield promising results, the datasets used to evaluate their performance often incorporate explicit perturbations. For instance, in one study, sounds like gunshots, glass breaks, screams, and sirens were added to the background audio, while in another, sensors were disrupted with lighted bulbs and a silicon bag. However, real industrial environments may introduce perturbations that are less obvious

(Cauteruccio et al., 2019; Garg et al., 2020; Janjua et al., 2019; Nunes et al., 2023).

- *Resource and Knowledge Limitation:* The challenges facing PdM mainly result from companies' limited awareness, communication, and adaptation to evolving technology. Companies often lack knowledge of the latest solutions and innovations, as well as skilled individuals proficient in modern data-driven software. Outdated equipment in companies, which lacks sensors for generating necessary data, is a key reason for data unavailability. Implementing PdM in companies is hindered by a shortage of expert technicians capable of handling the technology's technical aspects. Furthermore, technical challenges intensify post-adoption, as system interruptions can halt production processes, reducing overall productivity.
- *Maintenance and Production Linkage:* Some articles have proposed integrating the maintenance process with production as a method of utilizing time-based PdM, aligning with the integration between industrial processes and intelligent automation, a fundamental aspect of Industry 4.0 (Jantunen et al., 2016; Jin et al., 2017; Kiangala & Wang, 2018; Lee, 2017; Nemeth et al., 2018; Qin et al., 2018; Wu et al., 2016; Zonta et al., 2020).
- *Model Deployment:* After developing intelligent failure prediction models, integrating them into industry, monitoring their updates, and maintaining their accuracy pose significant challenges. Integrating these models is often managed separately by IT teams, leading to labor-intensive efforts in building data pipelines often overlooked in project planning. Monitoring involves ensuring model updates through a feedback loop for new data, enabling continuous learning. However, this ongoing re-training risks reliability as data integrity isn't consistently verified, potentially introducing outliers that distort predictions over time. Updating models is essential to counter conceptual drift in machine learning, requiring simultaneous modifications to code, models, and data. This improvement cycle for

predictive maintenance models is notably more complex than traditional software updates (Paleyes et al., 2022; Achouch et al., 2022).

4.1.4 Step A4 Set up of the hierarchic tree

Based on the AHP methodology, the next step after identifying decision criteria is to set up a hierarchical tree. In this step, the decision criteria identified in **part two** and **part three**, Step A3, are classified into the decision criteria groups identified in **part one**, similar criteria are combined, as presented in Table 4-3, along with the decision goal and alternatives defined in Steps A1 and A2. Criteria "Data Availability" and "Resource and Knowledge Limitation" are combined with the criterion "Tech-Assessment," as they all express the company's capability to develop PdM technology.

Table 4-3 Defined decision goal, alternatives, and criteria

Goal and Alternative	Criteria	Sub-Criteria
Developing the AHP for maintenance strategy selection in the modern manufacturing era among CM, PM and PdM.	C_1 Cost	C_{11} Capital Investment
		C_{12} Annual Maintenance Cost
		C_{13} Training Cost
	C_2 Productivity	C_{21} Total Efficiency
		C_{22} Reduced Downtime
		C_{23} Flexibility and Customizability
		C_{24} People Towards Resilience
		C_{25} Technology Toward Resilience
		C_{26} Maintenance and Production Linkage
	C_3 Added Value	C_{31} Improved Product Quality
		C_{32} Increased Satisfaction and Loyalty
		C_{33} Human Needs Adoption
		C_{34} Human-Machine Integration
		C_{35} Meaningful Job Creation
		C_{36} Mass personalization

C_4 Safety	C_{41} Safety to People
	C_{42} Safety to Equipment
C_5 Environmental	C_{51} Environment Impact & Hazard
	C_{52} Carbon Emission
	C_{53} Energy Efficiency
	C_{54} Waste Prevention
C_6 Additional Factors	C_{61} Operator Confidence Level
	C_{62} Tech-Assessment
	C_{63} Information Logistic Waste
	C_{64} Technology Ethical
	C_{65} Fault Diagnoses
	C_{66} Model Deployment

Based on the defined goal, alternatives, and criteria, the hierarchical tree is presented as follows in Figure 4-2.

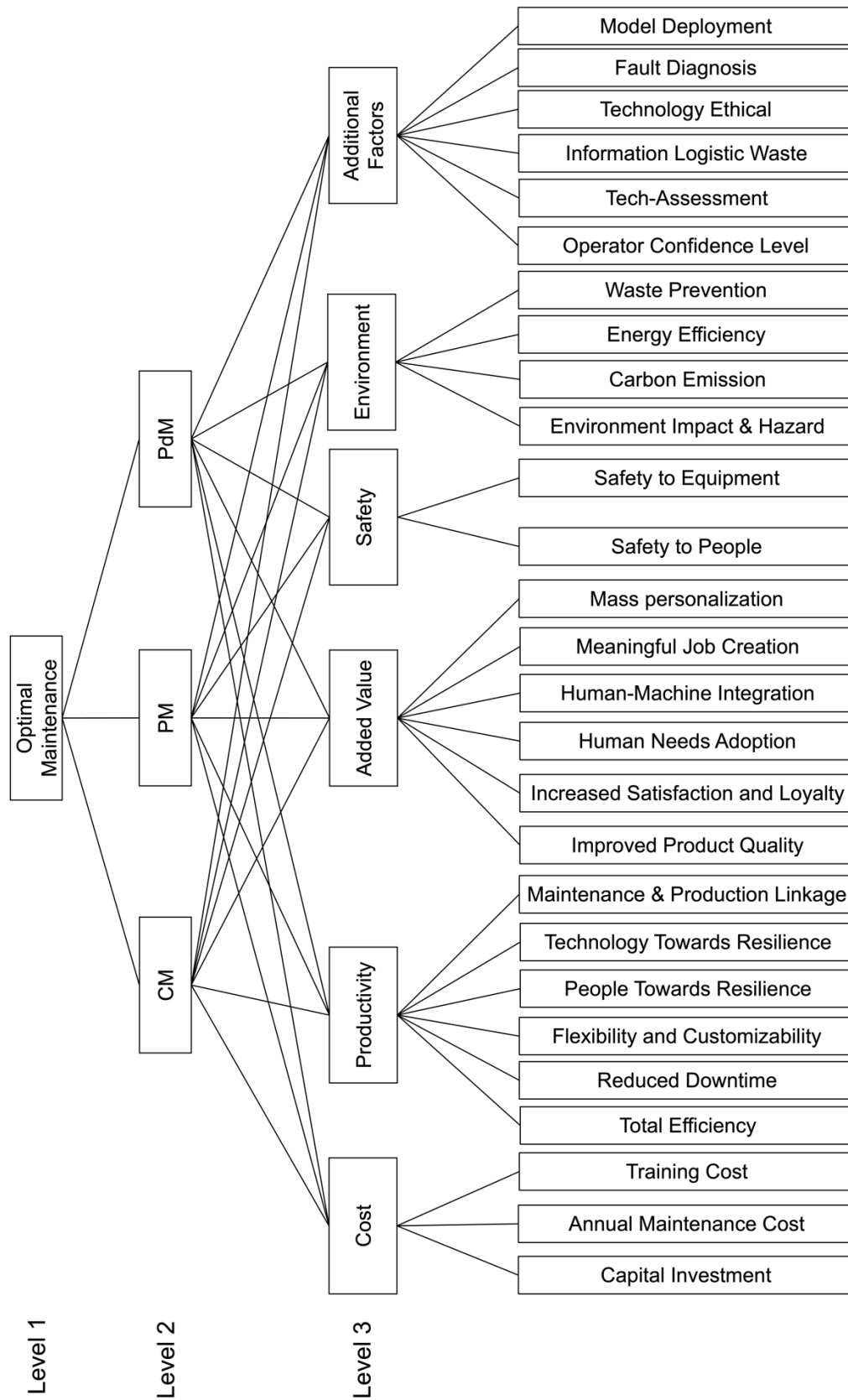


Figure 4-2 Hierarchical tree for maintenance strategy selection

Key Feedback and Refinements

Several key insights are obtained during the expert review based on the methodology introduced in Chapter 3, leading to meaningful refinements of the proposed hierarchy.

First, the sub-criterion C_23 Flexibility and Customizability is recommended to be more explicitly connected to the concept of mass customization, particularly under conditions of rapid production reconfiguration. In line with this suggestion, the explanation of C_23 is revised to emphasize adaptability for mass personalization, thereby linking it directly to evolving customer demands and product variability.

Second, conceptual overlap is identified between C_24 People Towards Resilience and C_34 Human-Machine Integration, raising concerns regarding potential confusion in pairwise comparisons. To resolve this, the definitions of the two sub-criteria are clarified: C_24 is specified to capture human cognitive adaptability and anomaly recognition, while C_34 is reframed to emphasize human-robot collaboration, ergonomics, and trust in automation.

Third, it is suggested that C_66 Model Deployment should differentiate between initial deployment and ongoing maintenance of AI/ML models, as these stages involve distinct technical and managerial challenges. Consequently, the explanation of C_66 is expanded to include both deployment and lifecycle management, covering aspects such as retraining, drift detection, and version control.

Additionally, the inclusion of Data Availability and Resource and Knowledge Limitation as separate sub-criteria is questioned, since their scope significantly overlaps with C_62 Tech-Assessment. To address this issue, these two sub-criteria are integrated into Tech-Assessment, resulting in a more concise and coherent representation of organizational capability to support PdM development and deployment.

4.2 Step B Case study – decision maker judgement

As presented in Figure 4-1, a case study is conducted to validate the AHP methodology for selecting the optimal maintenance strategy. The results of this case study are presented in Sections 4.2, 4.3, and 4.4.

4.2.1 Step B1 Decision maker gathering for maintenance strategy selection

As outlined in Chapter 3, Section 3.2.2, experts were selected to participate in the case study. These experts represent various industries and sectors, as shown in Table 4-4. Their diverse knowledge and experience are essential for making informed decisions in the case study.

Table 4-4 Expert participants information

Expert	Industry	Sector	Year of experience
Expert 1	Auto	Management	16
Expert 2	Iron and steel	Maintenance	7
Expert 3	Home application	Production	5
Expert 4	Auto	Production and Maintenance	9
Expert 5	Auto	Production	11

Rationale for Expert Selection in AHP Scoring Process

Five experts are selected to ensure that the AHP scoring process integrates both internal and external perspectives while capturing diverse industrial experiences.

Expert 1 (Automotive Management, 16 years – Case Company)

Extensive experience in automotive management is brought by Expert 1, ensuring that strategic and high-level operational insights from within the case company are reflected in the scoring. This insider perspective is used to align the PdM approach with long-term organizational goals and operational realities.

Expert 2 (Iron and Steel Maintenance, 7 years – External Company)

Experience in the iron and steel industry is contributed by Expert 2, providing an external viewpoint on the maintenance of high-impact industrial machinery. This expertise is considered particularly relevant to the case study, as it parallels the mechanical stresses experienced by the stamping machine.

Expert 3 (Home Appliance Production, 5 years – External Company)

A background in home appliance production is brought by Expert 3, offering insights into production optimization and PdM implementation outside the automotive sector. This external perspective is utilized to mitigate company-specific bias and to broaden the applicability of PdM integration across different manufacturing contexts.

Expert 4 (Automotive Production and Maintenance, 9 years – Case Company)

Hands-on experience in both production and maintenance within the case company is contributed by Expert 4. Their expertise ensures that the scoring reflects operational constraints while capturing the integration of PdM strategies into the company's specific production environment.

Expert 5 (Automotive Production, 11 years – Case Company)

Knowledge of automotive production and maintenance strategies is provided by Expert 5, whose insider experience supports the evaluation of PdM feasibility on the stamping machine. Their contribution ensures that the maintenance strategies under consideration are realistically aligned with the company's existing capabilities.

4.2.2 Step B2 Case introduction

The case study focuses on asset-level monitoring in a manufacturing production line. Typically, multiple devices are present in the production line, but PdM is applied selectively to critical assets. The case study aims to identify the most suitable maintenance strategy for a key asset in the manufacturing system.

The company specializes in vehicle structural parts, such as front side frames, floor frames, and wheelhouses. The case study centers on a stamping machine used to produce vehicle front bulkhead parts. This machine applies 2000 tons of force at a frequency of 10 to 15 strikes per minute and includes a storage system, a feeding system, and a transfer system.

Key components of the stamping machine susceptible to faults include:

Dies: These parts experience wear and cracking over time, leading to a decline in product quality.

Cutting Tools: These parts suffer from wear due to the stamping force, causing misalignment and poor cuts.

Guide Components: These parts assist the die's movement, but wear can result in inaccurate product dimensions.

The focus on these critical components aims to optimize asset performance, reduce downtime, and lower maintenance costs.

4.2.3 Step B3 Criteria pairwise comparison

The main criteria pairwise comparison is presented in Table 4-5.

Table 4-5 Main criteria pairwise comparison

	Cost	Productivity	Added Value	Safety	Environmental	Additional Factors
Cost	1	4	4	2	5	3
Productivity	0.25	1	2	0.333	2	0.25
Added Value	0.25	0.5	1	0.25	3	0.5
Safety	0.5	3	4	1	4	4
Environmental	0.2	0.5	0.333	0.25	1	0.333
Additional Factors	0.333	4	2	0.25	3	1

The comparison in Table 4-5 indicates that, for the evaluated alternatives, factors related to productivity and added value are considered more important than cost

or environmental impacts. This ranking reflects the prioritization of performance and value maximization over expense reduction or environmental concerns in the selected strategy. The sub-criteria pairwise comparisons are presented in Table 4-6 to Table 4-11.

Table 4-6 Cost sub-criteria pairwise comparison

Cost	Capital Investment	Annual Maintenance Cost	Training Cost
Capital Investment	1	0.5	5
Annual Maintenance Cost	2	1	4
Training Cost	0.2	0.25	1

The comparison in Table 4-6 indicates that, while capital investment is a key concern, ongoing maintenance costs and training expenses are considered significant but secondary in the decision-making process.

Table 4-7 Productivity sub-criteria pairwise comparison

Productivity	Total Efficiency	Reduced Downtime	Flexibility and Customizability	People Towards Resilience	Technology Toward Resilience	Maintenance and Production Linkage
Total Efficiency	1	2	3	4	5	4
Reduced Downtime	0.5	1	3	3	6	6
Flexibility and Customizability	0.333	0.333	1	1	4	3
People Towards Resilience	0.25	0.333	1	1	5	2
Technology Toward Resilience	0.2	0.167	0.25	0.2	1	3
Maintenance and Production Linkage	0.25	0.167	0.333	0.5	0.333	1

Table 4-6 indicates that Total Efficiency and Reduced Downtime are the highest-ranked criteria, underscoring their importance in maintenance strategy effectiveness. In contrast, Flexibility, Customizability, and Maintenance-Production Linkage are less prioritized, indicating they are secondary to

minimizing downtime and optimizing efficiency. The focus on Technology Toward Resilience reflects the growing importance of technological integration in productivity.

Table 4-8 Added-Value sub-criteria pairwise comparison

Added-Value	Improved Product Quality	Increased Satisfaction and Loyalty	Human Needs Adoption	Human-Machine Integration	Meaningful Job Creation	Mass personalization
Improved Product Quality	1	3	5	7	3	8
Increased Satisfaction and Loyalty	0.333	1	0.333	3	0.25	2
Human Needs Adoption	0.2	3	1	2	0.2	3
Human-Machine Integration	0.143	0.333	0.5	1	0.25	2
Meaningful Job Creation	0.333	4.000	5	4	1	3
Mass personalization	0.125	0.5	0.333	0.5	0.333	1

According to Table 4-8, it is suggested that, while customer satisfaction and meeting human needs are essential, they are secondary to delivering high-quality products and ensuring meaningful job creation. Human-Machine Integration, although relevant, is ranked lower, indicating it may not be as critical as other factors in driving added value.

Table 4-9 Safety sub-criteria pairwise comparison

Safety	Safety to People	Safety to Equipment
Safety to People	1	3
Safety to Equipment	0.333	1

According to Table 4-9, it is reflected that, the prioritization of worker well-being as the primary concern in maintenance strategies compare to equipment safety.

Table 4-10 Environmental sub-criteria pairwise comparison

Environmental	Environment Impact & Hazard	Carbon Emission	Energy Efficiency	Waste Prevention
Environment Impact & Hazard	1	3	0.2	2
Carbon Emission	0.333	1.1	0.167	0.5
Energy Efficiency	5	6	1	5
Waste Prevention	0.5	2	0.2	1

Table 4-10 underscores the significant importance of Energy Efficiency and Environmental Impact & Hazard in the environmental sub-criteria comparison. Energy Efficiency is highly ranked, highlighting its critical role in the environmental evaluation of maintenance strategies. Waste Prevention, while important, is given a lower weight, indicating its secondary consideration compared to reducing energy consumption and environmental impact.

Table 4-11 Additional Factors sub-criteria pairwise comparison

Additional Factors	Operator Confidence Level	Tech- Assessment	Information Logistic Waste	Technology Ethical	Fault Diagnoses	Model Deployment
Operator Confidence Level	1	0.167	4	4	0.333	2
Tech- Assessment	6	1	8	8	4	6
Information Logistic Waste	0.250	0.125	1	2	0.2	3
Technology Ethical	0.25	0.125	0.5	1	0.25	2
Fault Diagnoses	3	0.25	5	4	1	5
Model Deployment	0.5	0.167	0.333	0.5	0.2	1

Table 4-11 highlights the strong emphasis on Tech-Assessment and Fault Diagnoses, with Tech-Assessment ranked highest. While Operator Confidence

Level and Technology Ethics are considered, they are ranked lower, indicating their secondary importance in the decision-making process.

4.2.4 Step B4 Alternative performance marking

In this step, the performance of each alternative with regards to the criteria is presented.

Table 4-12 Cost sub-criteria performance

Capital Investment	CM	PM	PdM	Annual Maintenance Cost	CM	PM	PdM
CM	1	1	8	CM	1	0.25	0.167
PM	1	1	5	PM	4	1	0.5
PdM	0.125	0.2	1	PdM	6	2	1
Training Cost	CM	PM	PdM				
CM	1	3	7				
PM	0.334	1	4				
PdM	0.143	0.25	1				

In Table 4-12, pairwise comparisons for capital investment, annual maintenance cost, and training cost across the maintenance strategies CM, PM, and PdM are presented. PdM requires the highest capital investment and also incurs the highest training cost, reflecting its complexity and need for specialized skills. However, it performs best in terms of lower annual maintenance costs, offering potential long-term savings. CM has the lowest upfront cost, but results in higher recurring expenses, making it less efficient over time. PM presents a moderate trade-off between investment and operational cost.

Table 4-13 Productivity sub-criteria performance

Total Efficiency	CM	PM	PdM	Reduced Downtime	CM	PM	PdM
CM	1	0.2	0.143	CM	1	0.2	0.2
PM	5	1	0.5	PM	5	1	2

PdM	7	2	1	PdM	5	0.5	1
Flexibility and Customizability	CM	PM	PdM	People Towards Resilience	CM	PM	PdM
CM	1	0.25	0.167	CM	1	2	5
PM	4	1	1	PM	0.5	1	3
PdM	6	1	1	PdM	0.2	0.333	1
Technology Toward Resilience	CM	PM	PdM	Maintenance and Production Linkage	CM	PM	PdM
CM	1	1	0.143	CM	1	0.143	0.25
PM	1	1	0.2	PM	7	1	3
PdM	7	5	1	PdM	4	0.333	1

In Table 4-13, sub-criteria such as Total Efficiency, Reduced Downtime, Flexibility and Customizability, People Toward Resilience, Technology Toward Resilience, and Maintenance and Production Linkage are compared across CM, PM, and PdM. PdM outperforms CM and PM in most sub-criteria, including Total Efficiency and Reduced Downtime, highlighting its superior efficiency and ability to minimize downtime. CM is assigned the lowest values in Flexibility and Customizability, indicating limitations in adapting to changes. PdM also scores highest in People Toward Resilience and Technology Toward Resilience, demonstrating its strength in integrating technological solutions to enhance productivity.

Table 4-14 Added-value sub-criteria performance

Improved Product Quality	CM	PM	PdM	Increased Satisfaction and Loyalty	CM	PM	PdM
CM	1	0.167	0.125	CM	1	0.5	0.25
PM	6	1	0.5	PM	2	1	1
PdM	8	2	1	PdM	4	1	1
Human Needs Adoption	CM	PM	PdM	Human-Machine Integration	CM	PM	PdM

CM	1	0.333	0.25	CM	1	0.5	0.111
PM	3	1	0.333	PM	2	1	0.143
PdM	4	3	1	PdM	9	7	1
Meaningful Job Creation	CM	PM	PdM	Mass personalization	CM	PM	PdM
CM	1	1	0.167	CM	1	0.25	0.167
PM	1	1	0.2	PM	4	1	0.333
PdM	6	5	1	PdM	6	3	1

In Table 4-14, the added-value sub-criteria, including Improved Product Quality, Increased Satisfaction and Loyalty, Human Needs Adoption, Human-Machine Integration, Meaningful Job Creation, and Mass Personalization, are compared across CM, PM, and PdM. PdM consistently receives the highest ratings across all sub-criteria, indicating its superior added value in terms of product quality, customer satisfaction, and job creation. In contrast, CM ranks lowest in most areas, suggesting it provides less added value, particularly in aspects related to customer and employee satisfaction.

Table 4-15 Safety sub-criteria performance

Safety to Human	CM	PM	PdM	Safety to Machine	CM	PM	PdM
CM	1	0.143	0.125	CM	1	0.143	0.125
PM	7	1	1	PM	7	1	0.5
PdM	8	1	1	PdM	8	2	1

Table 4-15 is presented with the pairwise comparison values for the safety sub-criteria performance across the maintenance strategies CM, PM, and PdM. The two sub-criteria evaluated are Safety to Human and Safety to Machine.

For Safety to Human, PdM is rated highest, followed by PM, and CM receives the lowest ratings. A similar trend is observed in Safety to Machine, with PdM rated highest, PM rated second, and CM rated the lowest.

Table 4-16 Environmental sub-criteria performance

Environment Impact & Hazard	CM	PM	PdM	Carbon Emission	CM	PM	PdM
CM	1	0.25	0.2	CM	1	0.333	2
PM	4	1	1	PM	3	1	3
PdM	5	1	1	PdM	0.5	0.333	1
Energy Efficiency	CM	PM	PdM	Waste Prevention	CM	PM	PdM
CM	1	1	4	CM	1	0.2	0.143
PM	1	1	3	PM	5	1	0.333
PdM	0.25	0.333	1	PdM	7	3	1

In Table 4-16, the comparative results across four key sustainability criteria—environmental impact, carbon emission, energy efficiency, and waste prevention—indicate that PdM consistently outperforms both PM and CM. It achieves the highest overall scores, particularly in energy efficiency and waste prevention, reflecting its strong capability in reducing resource consumption and environmental burden. PM shows moderate performance, especially in environmental and carbon-related aspects, while CM ranks lowest in all categories, indicating limited effectiveness in supporting sustainable operations. These findings suggest that PdM is the most sustainable maintenance approach, offering significant advantages for organizations aiming to align maintenance practices with environmental and efficiency goals.

Table 4-17 Additional factor sub-criteria performance

Operator Confidence Level	CM	PM	PdM	Tech-Assessment	CM	PM	PdM
CM	1	4	6	CM	1	3	7
PM	0.25	1	4	PM	0.333	1	5
PdM	0.167	0.25	1	PdM	0.143	0.2	1
Information Logistic Waste	CM	PM	PdM	Technology Ethical	CM	PM	PdM

CM	1	0.25	0.125	CM	1	2	8
PM	4	1	0.2	PM	0.5	1	6
PdM	8	5	1	PdM	0.125	0.167	1
Fault Diagnoses	CM	PM	PdM	Model Deployment	CM	PM	PdM
CM	1	3	9	CM	1	2	9
PM	0.333	1	7	PM	0.5	1	7
PdM	0.111	0.143	1	PdM	0.111	0.143	1

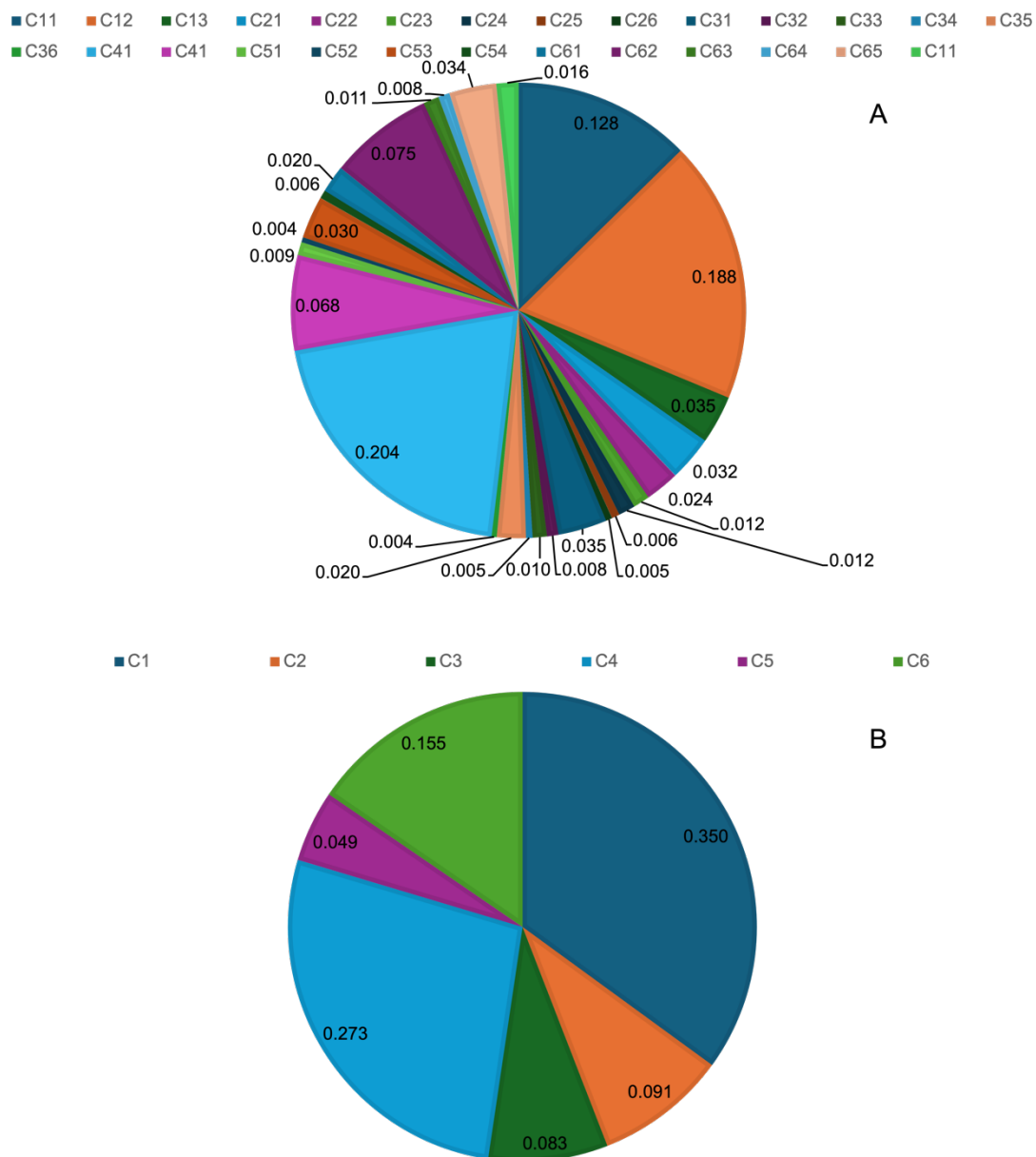
In Table 4-17, CM generally ranks first across all dimensions, performing the best with the lowest scores. PM ranks second in most dimensions, with moderate scores. PdM, with the highest scores in each dimension, typically ranks last, indicating the poorest performance. Specifically, PdM performs the worst in Operator Confidence Level, Tech-Assessment, Technology Ethical, Fault Diagnoses, and Model Deployment, while CM performs the best, with PM falling in between. In the dimension of Information Logistic Waste, CM ranks first, PM ranks second, and PdM ranks last.

4.3 Step C Case study – criteria importance, alternative performance and alternative mark calculation

In this section, the relative importance of criteria (Figure 4-3), alternative performance concerning criteria (Figure 4-4), and alternative rankings (Figure 4-5) are calculated following the methodology discussed in Chapter 3, Section 3.2.1, and presented following the methodology presented in Figure 4-1.

4.3.1 Step C1 Weight relative importance of criteria

Based on the pairwise comparison of criteria and sub-criteria presented in Section 4.2, Step B3, the relative importance of criteria and sub-criteria is calculated, as depicted in the following Figure 4-3.



highlighting the need for maintenance strategies that prioritize worker well-being and cost-effectiveness, in line with the Industry 5.0 trend toward human-centric and economically efficient approaches.

4.3.2 Step C2 Alternative performance with respect to criteria and alternative selection

The performance of each maintenance alternative was evaluated with respect to the defined criteria, based on Equations 3-1 to 3-7 outlined in Chapter 3. A detailed comparison is provided in Figure 4-4, where the relative performance of the three maintenance strategies—CM, PM, and PdM—is illustrated across various criteria. The performance of each maintenance strategy under each sub-criterion is represented by the bars in the figure. For instance, in C_{11} Initial Investment, CM was found to perform better than PM and significantly better than PdM. In contrast, for C_{34} Human-Machine Integration, PdM was shown to perform substantially better than both CM and PM. The results obtained are used as the basis for the calculation of the overall scores for each maintenance strategy.

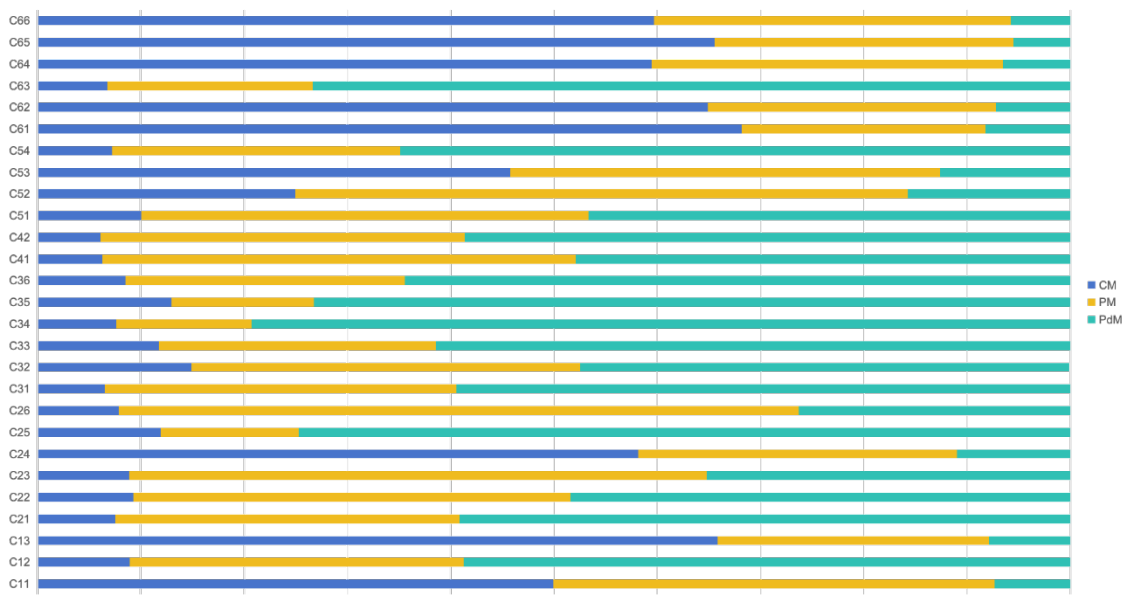


Figure 4-4 Alternative weight with respect to criteria

As depicted, superior performance is shown by PdM, particularly in reducing equipment downtime and operational risks. It is suggested that PdM offers a more proactive and reliable approach compared to the reactive nature of PM and CM,

which may result in higher costs and downtime over time. The figure highlights PdM's long-term advantages, particularly in minimizing downtime and reducing operational risks, supporting its selection as the preferred strategy.

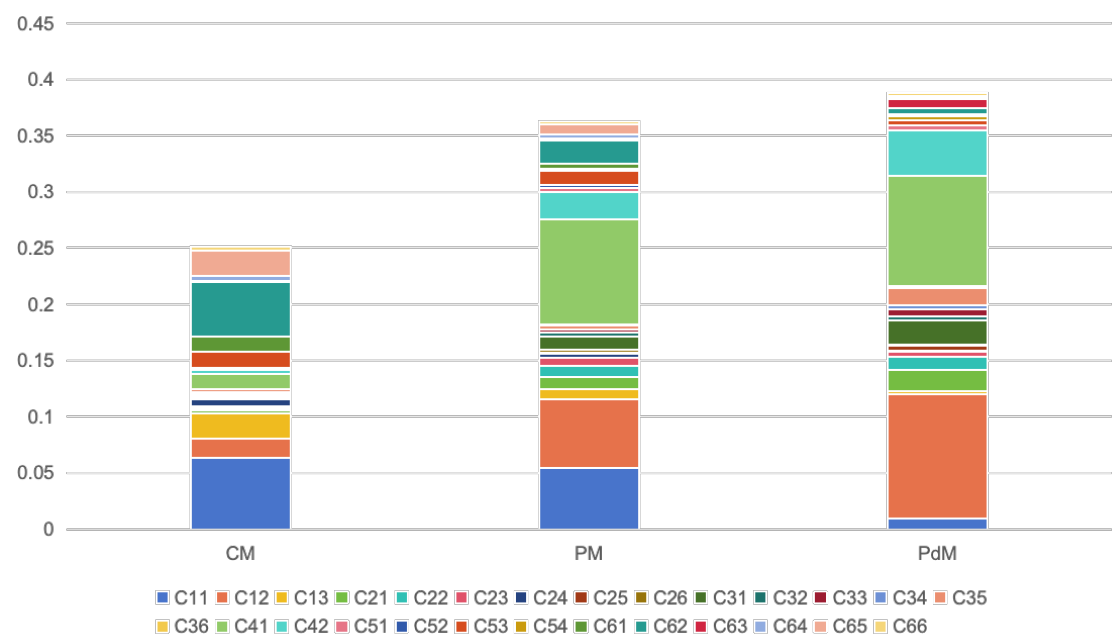


Figure 4-5 Alternative marks

In Figure 4-5, the scores of each alternative with respect to the sub-criteria are presented. It illustrates the evaluation of each maintenance strategy based on the specified criteria. Each bar is used to represent the cumulative scores for the three maintenance strategies—CM, PM, and PdM. Distinct colours are applied to indicate the respective scores of these alternatives for each criterion. It is shown that PdM achieves the highest overall score (0.385), followed by PM (0.362) and CM (0.251). Based on this result, it is indicated that PdM is identified as the most suitable strategy for the given case study. A margin of 0.023 is observed between the scores of PdM and PM, with PdM being ranked as the optimal strategy.

Further, specific factors contributing to these scores are highlighted. For criterion C_{11} (initial investment), a significantly higher score is achieved by PM compared to PdM, reflecting its cost advantage in terms of upfront implementation. However, for criterion C_{12} (annual maintenance cost), a much higher score is observed for PdM compared to PM, emphasizing its cost-effectiveness during long-term

operations. This contrast is identified as one of the primary reasons for PdM achieving the highest overall score despite its relatively higher initial investment. Through these findings, the trade-offs between initial and operational costs in the selection of maintenance strategies are addressed. The results show that PdM excels in reliability and cost-effectiveness, supporting the company's goals of reducing costs and improving safety. While PdM offers long-term benefits like reduced downtime and maintenance costs, the higher initial investment—covering technology, infrastructure, and training—presents a challenge. This highlights the trade-off between upfront costs and future savings. Businesses must carefully weigh short-term expenses against long-term benefits. If the long-term savings justify the initial investment, PdM proves valuable.

**4.4 Step D Sub-Criteria Weighted-Rank-Sum Ratio (WRSR)
Evaluation**

In this step, as presented in Figure 4-1, the WRSR approach is evaluated to refine the decision-making process. While AHP provides a structured ranking of maintenance strategies based on a set of decision criteria, it does not quantify the relative importance of these criteria in a statistically rigorous manner. This limitation may result in decision outcomes that do not fully reflect the nuances of the ranking process. In contrast, integrating WRSR with AHP enhances the prioritization of maintenance strategies by incorporating rank distributions. WRSR captures ranking variations, allowing for a more nuanced assessment of the decision criteria and their relative importance. This integration improves decision accuracy by accounting for variability in expert opinions and refining the prioritization process.

WRSR is utilized in this research to rank the sub-criteria. Followed by the steps, Frequency count (f), cumulative frequency ($\sum f$), frequency range (G), median cumulative frequency ($G/2$), the percentile 100% (G/N) and Probability are conducted and presented Table 4-18.

Table 4-18 Distribution Condition of Statistical WRSR

WRSR	Sub-criteria	f	$\sum f$	$\bar{R}$	$(\bar{R}/N) * 100\%$	Probit
0.0926	C_{52}	1	1	1	3.7	3.214
0.1481	C_{66}	1	2	2	7.4	3.554
0.1667	C_{26}, C_{36}	2	4	3.5	13	3.872
0.1852	C_{64}	1	5	5	18.5	4.104
0.2593	C_{25}, C_{54}	2	7	6.5	24.1	4.296
0.2778	C_{34}, C_{63}	2	9	8.5	31.5	4.518
0.3704	C_{61}	1	10	10	37	4.669
0.4074	C_{32}, C_{51}	2	12	11.5	42.6	4.813
0.5	C_{23}, C_{33}	2	14	13.5	50	5
0.537	C_{24}	1	15	15	55.6	5.14
0.5556	C_{65}	1	16	16	59.3	5.234
0.6667	C_{22}, C_{35}	2	18	17.5	64.8	5.38
0.7222	C_{13}, C_{53}	2	20	19.5	72.2	5.589
0.7593	C_{21}, C_{62}	2	22	21.5	79.6	5.828
0.8519	C_{31}	2	24	23.5	87	6.128
0.9259	C_{11}	1	25	25	92.6	6.446
0.963	C_{12}	1	26	26	96.3	6.786
1	C_{41}	1	27	27	99.1	7.355

Finally, the evaluation objects are sorted and classified based on their weighted rank sum ratio values. See following Table 4-19.

Table 4-19 Classification Results

Grade	Probit	WRSR	Sub-Criteria
High	> 6	< 0.231	$C_{11}, C_{12}, C_{41}, C_{31}$
Medium	6 ~	0.231 ~	$C_{13}, C_{21}, C_{22}, C_{23}, C_{24}, C_{25}, C_{32}, C_{33}, C_{34}, C_{35}, C_{42}, C_{51}, C_{53}, C_{54}, C_{61}, C_{62}, C_{63}, C_{64}, C_{65},$
Low	4 ~	0.760 ~	$C_{26}, C_{36}, C_{52}, C_{66}$

Sub-criteria C_{11} , C_{12} , and C_{41} are classified as High impact on maintenance alternative selection. C_{13} , C_{21} , C_{22} , C_{23} , C_{24} , C_{25} , C_{31} , C_{32} , C_{33} , C_{34} , C_{35} , C_{42} , C_{51} , C_{53} , C_{54} , C_{61} , C_{62} , C_{63} , C_{64} , and C_{65} are classified as medium impact sub-criteria, and C_{26} , C_{36} , C_{52} , and C_{66} are classified as low impact sub-criteria.

The results of this study are consistent with other studies, highlighting the advantages of PdM over traditional PM and CM in terms of operational efficiency, cost reduction, and asset lifespan. For instance, Zizic et al. (2022) demonstrated that PdM's ability to detect early faults significantly reduces unplanned downtime and maintenance costs, which is also consistent with the high ranking of PdM in this study. Their research indicates that by predicting potential faults, PdM can more effectively schedule maintenance interventions, thereby avoiding unnecessary work and minimizing operational disruptions.

Similarly, Zhang et al. (2021) claimed that PdM optimizes asset management by enhancing equipment reliability and prolonging mechanical lifespan. Their research results indicated that PdM is particularly beneficial for industries with high costs and high reliability, such as aerospace and the automotive manufacturing industry, because in these industries, the consequences of unplanned downtime are particularly severe. This is consistent with the outstanding performance of PdM in terms of safety and predictive diagnosis observed in this study.

Furthermore, Tamin et al. (2020) highlighted the economic impact of PdM, stating that companies adopting the PdM strategy can reduce maintenance costs by 15% to 30% compared to traditional PM and CM methods. This economic advantage is the key factor contributing to the high ranking of PdM in this case, as it ensures more efficient allocation of maintenance resources by reducing the frequency of failures.

4.5 Discussion

The AHP method is widely used in the maintenance selection process in the manufacturing sector. The AHP method demonstrates excellent practicality in the maintenance strategy selection process. Manufacturers are allowed to select the

most suitable maintenance strategy based on their own circumstances. Moreover, this method effectively integrates opinions from different departments within the company, such as production, maintenance, and management departments.

This chapter is characterized by several important contributions.

Methodological Advancement in Multi-Criteria Decision-Making for Maintenance Strategy Selection

The theoretical landscape of maintenance strategy selection is advanced in this research through the introduction of a hybrid Analytical Hierarchy Process–Weighted Rank-Sum Ratio (AHP–WRSR) method. While AHP is widely applied in maintenance-related multi-criteria decision-making (MCDM), its heavy reliance on subjective expert judgment is often noted to undermine reliability. This limitation is addressed by integrating WRSR, which refines priority rankings through statistical weighting and thereby enhances robustness and reproducibility. Through this combination, MCDM theory is enriched, as the combination of qualitative expert-based approaches with quantitative statistical adjustments is shown to yield more balanced and defensible outcomes in the application of maintenance strategy selection. The adaptability of the method is recognised as making it theoretically significant for evaluating complex, multi-dimensional decisions beyond maintenance strategy selection.

Expansion of Maintenance Strategy Evaluation Criteria to Align with Industry 5.0

A conceptual extension is also made through the incorporation of Industry 5.0-oriented criteria into traditional maintenance evaluation frameworks. Whereas conventional approaches emphasise cost, safety, and reliability, this research explicitly integrates human-centricity, sustainability, and resilience. By doing so, maintenance strategy research is repositioned within a broader socio-technical paradigm, where the intertwined importance of technological efficiency, environmental stewardship, and human well-being is acknowledged. This theoretical expansion bridges the gap between purely technical evaluations and

human–machine collaborative models, and the role of ethical and sustainable considerations in industrial decision-making theory is reinforced.

Integration of Implementation Barriers into the Evaluation Framework

A further theoretical contribution is made by embedding real-world PdM implementation barriers into the evaluation process. In much of the existing MCDM literature, evaluation is conducted under idealised assumptions of feasibility across all strategies. This research explicitly incorporates constraints such as high capital investment, diagnostic complexity, and integration challenges into the criteria hierarchy. As a result, decision-making theory is advanced toward a more context-sensitive and pragmatic orientation, ensuring that evaluative rigour is aligned with practical realities.

Reframing Predictive Maintenance as a Strategically Filtered Decision

Finally, predictive maintenance is reframed as a strategically filtered decision rather than a default, technology-driven choice. The AHP–WRSR method is presented as a formal mechanism for evaluating PdM alongside preventive and corrective maintenance strategies, with considerations of technological readiness, human alignment, and ethical implications systematically included in the decision process. These reframing challenges deterministic narratives in PdM literature and positions PdM adoption as a deliberate, contextually appropriate, and human-centred strategy consistent with the values of Industry 5.0.

Development of a Customizable and Transparent Tool for Maintenance Strategy Selection

From a practical perspective, this research provides a structured and adaptable decision-support tool through the hybrid AHP–WRSR method. The AHP component generates an initial ranking of criteria based on expert input, and the WRSR refinement quantifies relative importance without requiring additional data collection. This dual-layered approach enables decision-makers to visually interpret and quantitatively justify their choices, ensuring transparency and traceability in strategic planning.

Enhanced Flexibility in Strategy Prioritization across Industrial Contexts

Flexibility is further enabled through the adaptability of the framework, which allows organisations to align maintenance strategies with diverse operational priorities—such as cost reduction, safety improvement, energy efficiency, or workforce alignment. The weighting system is designed to be adjustable so that shifting business objectives can be accommodated. This adaptability is particularly valuable in dynamic manufacturing environments, where priorities evolve due to regulatory changes, market pressures, or technological advancements.

Strategic Filtering for Predictive Maintenance Adoption

The framework also functions as a contextual filter for determining the appropriateness of PdM adoption. In contexts where machine learning and deep learning models are costly, data-intensive, or insufficiently interpretable, the framework helps clarify whether PdM provides a strategic fit before substantial investment is made. This reduces the risk of misaligned technology adoption. Once appropriateness is confirmed, integration with data-driven optimisation models is facilitated, ensuring that PdM deployment is both targeted and value-driven.

Readiness for Integration with Emerging Industry 5.0 Technologies

Scalability toward emerging Industry 5.0 technologies is built into the design of the method. Real-time data from edge computing is capable of dynamically adjusting decision weights, digital twin simulations are enabled to explore alternative strategies, and explainable AI systems are suggested for improving operator trust and transparency. This forward compatibility ensures that the method acts as a bridge between current decision-making needs and future smart manufacturing ecosystems.

The limitations of the methods presented in this chapter are discussed as follow.

Subjectivity in Expert Judgement

A primary limitation is identified in the reliance on expert judgement during the AHP stage. Even when consistency ratio checks are applied, the ranking of criteria is inevitably shaped by experts' individual backgrounds, experiences, and cognitive biases. The outcomes are therefore influenced by the composition of the expert panel rather than by universally applicable priorities. Equal weighting is assigned to all participants, and variations in domain expertise are not reflected, which may reduce the impact of highly specialised insights.

Limited Diversity of Expert Representation

Another limitation arises from the relatively narrow scope of the expert panel in terms of both size and industrial diversity. While the participants contribute valuable perspectives from manufacturing contexts, the distinct requirements of other industries—such as energy, healthcare, or transportation—are not fully represented. As a result, the generalisability of the model beyond the sector in which it is applied is restricted.

Static Nature of the Evaluation Framework

The evaluation framework, although innovative in its integration of Industry 5.0 criteria, is applied in a static manner. The weights derived through AHP and refined by WRSR remain fixed within a given decision instance, and adaptation to changing operational conditions, technological developments, or evolving business priorities does not occur. This limitation reduces responsiveness in dynamic environments where maintenance requirements shift rapidly.

Lack of Longitudinal Validation

A further limitation is recognised in the absence of longitudinal testing. Although the method positions itself as a strategic filter for predictive maintenance adoption, no empirical validation is undertaken in scenarios where maintenance strategy outcomes are monitored over time. Without such validation, it cannot be assessed whether the framework consistently leads to superior operational or strategic outcomes in practice.

Absence of Real-Time Data Integration

Finally, the method does not yet incorporate direct integration of real-time data or predictive analytics into the decision-making process. While conceptual alignment with Industry 5.0 technologies is achieved, the current implementation continues to depend on static expert assessments. The potential offered by IoT-enabled assets, digital twins, or explainable AI systems remains unexploited, and applicability in fully automated and adaptive decision environments is thereby limited.

Chapter Summary

This chapter provides a comprehensive evaluation of maintenance strategy selection using the AHP framework, incorporating expert judgment, pairwise comparisons, and ranking distributions through the AHP-WRSR method. The results underscore the critical importance of aligning maintenance strategies with organizational goals and technical requirements. A structured methodology for selecting the most appropriate maintenance strategies is established, considering PdM. All relevant factors, including cost, safety, and downtime, are rigorously addressed in this analysis.

In Chapter 5, the results, validation, and discussion of the PdM technical selection method are presented, following the procedure outlined in Chapter 3, Section 3.3. The insights gained in this chapter form the foundation for Chapter 5, where a PdM technique selection framework for implementation is presented. If PdM is identified as the most suitable maintenance strategy, the framework can be used to identify the most appropriate PdM technique. Building upon the strategies identified here, the framework focuses on the practical application of PdM in real-world settings and addresses specific technical considerations.

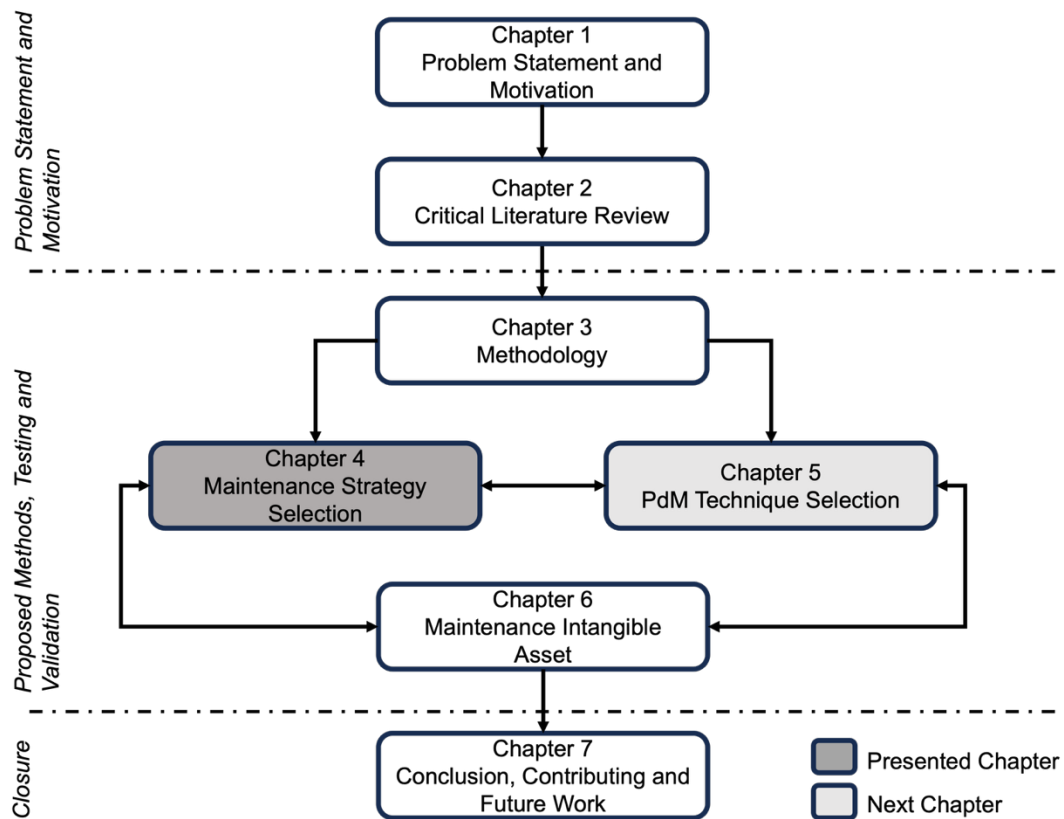


Figure 4-6 Organization of the Thesis – Presented and Next Chapter

CHAPTER 5 - A DECISION BASED FRAMEWORK FOR PREDICTIVE MAINTENANCE TECHNIQUE SELECTION

In this chapter, a decision-based framework for predictive maintenance technique selection is presented to answer the Research Question Two *What is the method that helps manufacturers evaluate the necessary tangible assets for PdM implementation, considering whether PdM is required and which PdM technique is needed?* introduced in Chapter 1, Section 1.3, and justified through critical literature review in Chapter 2, Section 2.3 The framework is the second objective for investigating PdM implementation tangible assets. In this chapter, three issues are addressed (1) lacking analysis of PdM technique capabilities, lacking analysis of PdM implementation objectives, and lacking analysis of PdM implementation attributes, (2) lacking linkage among PdM implementation attributes and objectives with PdM techniques, and (3) validation of the framework.

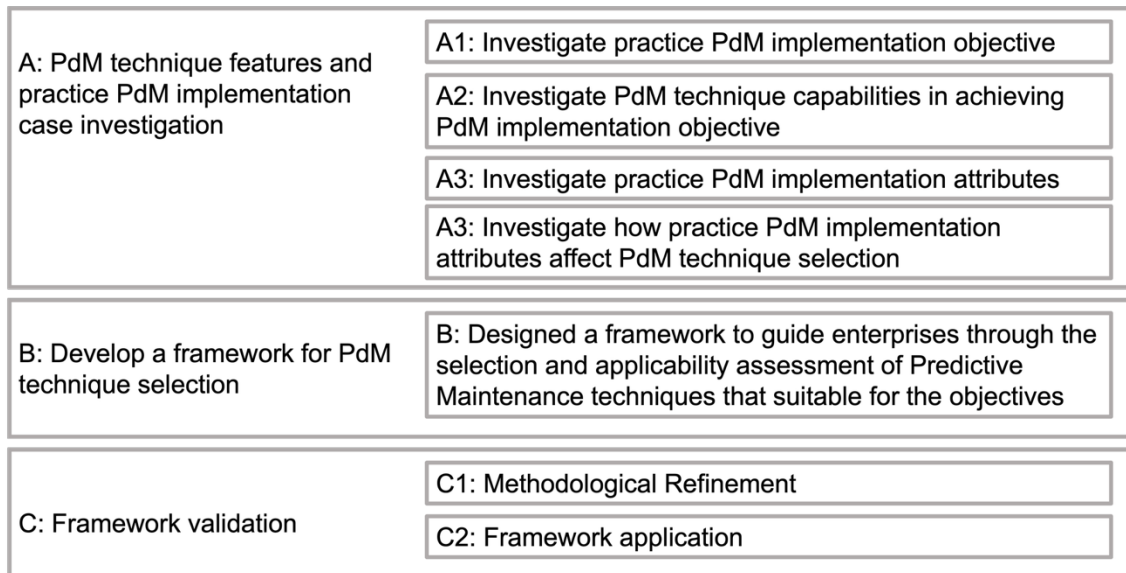


Figure 5-1 A framework for PdM technique selection – methodology

Following the methodology for designing the decision-based framework for PdM technique selection introduced in Section 3.3 and presented in Figure 5-1, the PdM technique capabilities, PdM implementation objectives, and PdM implementation attributes are included in the first section in this chapter (Section

5.1). The developed framework and support algorithms for establishing linkages among PdM implementation attributes and objectives with PdM techniques are presented in Section 5.2. The framework validation process is presented in Section 5.3.

5.1 Step A Analysis of PdM technique objectives, PdM implementation capabilities, and PdM implementation attributes

As presented in Figure 5-1, the initial step for developing the decision framework is to analyse the PdM technique objectives, PdM implementation capabilities, and PdM implementation attributes.

5.1.1 Step A1 Investigate practice PdM implementation objectives

In the research, the concept of "ambition level" (AL) is introduced to refer to the enterprise's specific objectives or goals for implementing PdM. When implementing PdM, enterprises must assess their level of ambition and determine the appropriate techniques that align with it. A systemic literature review is conducted to identified that, in practical PdM cases, while many enterprises may not explicitly state a specific ambition level, they do establish clear objectives for their PdM systems. These objectives often include accurate component diagnostics, reliable predictions of component Remaining Useful Life (RUL), and extending asset service life.

The requirements for achieving these ALs—in terms of cost, knowledge, skills, resources, and experience—vary on a case-by-case basis. To categorize different levels of ambition, four ambition levels based on the tasks enterprises aim to accomplish are defined in this research:

- AL 1: Diagnose assets' fuzzy future state.
- AL 2: Diagnose a single component's accurate future state and RUL.
- AL 3: Diagnose multiple components' accurate future state and RUL.
- AL 4: Extend assets' service life through optimized maintenance actions.

5.1.2 Step A2 PdM technique capabilities for achieving ALs

Based on the methodology presented in Chapter 3, Section 3.3, it is identified that each PdM technique has specific capabilities or suitable for specific ambition levels. These alignments provide a clear understanding of which PdM techniques are applicable based on an enterprise's AL (Ambition Level). The following PdM technique and AL map illustrate the capabilities of each PdM technique.

Experience-based	AL 1			
Model-based		AL 2	AL 3	
Physics-based		AL 2	AL 3	
Data-driven		AL 2	AL 3	AL 4
Hybrid approach			AL 3	AL 4

Figure 5-2 PdM technique and capability map

The experience-based technique aligns with **Ambition Level 1** (AL 1). Enterprises at AL 1 aim to predict the fuzzy future state of their systems or components without requiring highly accurate RUL predictions. The experience-based technique is the most cost-effective option for AL 1, as it involves relatively low development costs and effort. Other techniques, aside from experience-based, are not cost-effective for AL 1.

Ambition Level 2 (AL 2) is associated with model-based, physics-based, and data-driven techniques. Enterprises at AL 2 aim to accurately diagnose and predict faults in a single component. Successful implementations of these PdM techniques have been documented in various publications. However, model-

based and physics-based techniques may be limited by their ability to address only specific types of wear and tear. Although a hybrid approach can also achieve the goals of AL 2, it may increase implementation costs and complexity without significantly improving prediction accuracy for a single component.

Ambition Level 3 (AL 3) corresponds to model-based, physics-based, data-driven, and hybrid approaches. Enterprises at AL 3 seek to diagnose and predict faults in multiple components with high accuracy. These techniques have been shown to effectively diagnose and predict faults across various components. Compared to data-driven techniques and hybrid approaches, model-based and physics-based techniques are more limited in handling multiple components, as they focus on specific types of wear and tear.

Ambition Level 4 (AL 4) is linked to data-driven and hybrid approaches. Enterprises at AL 4 aim to extend the service life of assets through optimized maintenance strategies. This involves performing diagnostics and prognostics on several systems or components of assets and optimizing maintenance planning. The number of components monitored at AL 4 is typically greater than at AL 3. Model-based and physics-based techniques are generally unsuitable for predicting across multiple components, as they can only account for limited types of wear and tear. In such cases, a hybrid approach, combining various techniques, is often employed to overcome the challenges of predicting multiple components.

5.1.3 Step A3 Investigate PdM implementation attributes and investigate how practice PdM implementation attributes affect PdM technique selection

Based on the methodology presented in Chapter3, Section 3.3, the following attributes for PdM implementation are identified, these attributes represent the internal and external resources that a company needs to consider when implementing any PdM technique.

Data availability is a recurring theme in the reviewed literature and can be classified into two categories. The first category is historical data availability. In

the context of maintenance, historical data includes technical knowledge, inspection records, and past maintenance logs. For PdM within Industry 4.0, historical data encompasses recorded system conditions, such as operating parameters (e.g., speed, force), environmental factors (e.g., temperature, pressure, humidity), and fault records. Historical data is critical for developing data-driven PdM systems, as it is required to train and test predictive models (Wöstmann et al., 2019; Sai et al., 2019; Ramesh et al., 2020; Shamayleh et al., 2020).

The second category is data acquisition, which refers to the process of gathering the necessary data. Different PdM techniques—whether experience-based, data-driven, model-based, or physics-based—require varying amounts and types of data. During data acquisition, engineers must ensure that the required data is accessible, such as machine operation records (Woldman et al., 2015; Li et al., 2020; Florian et al., 2021) or data from sensors monitoring critical parameters (Wöstmann et al., 2019; Li et al., 2020; Gbadamosi et al., 2021). Data acquisition is crucial for selecting and implementing any PdM technique, as all methods depend on accurate data for making predictions.

Critical components in maintenance are those that significantly influence maintenance costs, system availability, product quality, and safety. Identifying the most relevant factors for each specific scenario is essential because each technique has limitations and distinct areas of applicability. Therefore, it is crucial to determine which components are critical before evaluating suitable PdM techniques.

Expert knowledge plays a pivotal role in the selection and implementation of PdM. It aids in identifying critical components, defining mathematical models in model-based systems (Yiwei et al., 2019), developing physical wear and tear models in physics-based systems (Rivera et al., 2018; Tinga et al., 2019; Aivaliotis et al., 2021), and creating data-driven predictive models (Wöstmann et al., 2019; Gbadamosi et al., 2021; LaRose et al., 2021). Most companies can leverage extensive internal expertise accumulated over years of experience.

However, if such knowledge is unavailable, it may be necessary to derive insights from past production and maintenance records or seek external support.

Secondary data plays a similar role to expert knowledge in PdM selection and implementation, though its sources differ. Secondary data may include findings from research publications, patents, or company reports (Woldman et al., 2015; Aivaliotis et al., 2021; Bonci et al., 2021).

Cost is another critical factor in PdM implementation. While many studies focus on verifying PdM techniques or systems in practical applications, they often overlook detailed cost considerations. From a cost-benefit or return-on-investment perspective, cost is a key element in successful PdM implementation. Costs include sensors, system installation, IT infrastructure for data analysis, operator training, and consulting services. If the costs are not justifiable, PdM may not be the most suitable maintenance approach.

External support refers to assistance from research organizations or professional consultants. Enterprises may require external help at any stage of the PdM selection and implementation process, particularly when internal expertise and experience are insufficient to manage the entire process.

This review of publications related to real-world PdM applications identified six key factors that influence PdM technique selection: data availability, critical components, expert knowledge, secondary data, cost, and external support. However, no research explicitly connects these factors with technique selection. The following section introduces a PdM technique selection framework that links these factors to the decision-making process for selecting PdM techniques.

5.2 Step B Establish the decision-based framework for PdM techniques

The Decision-Based Framework for PdM Technique Selection (Figure 5-3) is presented in this section. The purpose of this framework is to link the attributes influencing PdM technique selection and implementation with the appropriate PdM techniques. Companies can use this framework to assess their specific needs and choose the most suitable PdM technique for their operations. The

foundation for this framework is established in Chapter 3, Section 3.3, where key attributes for successful PdM implementation are identified. These attributes, reflecting both internal and external resources, are critical factors that must be considered when adopting any PdM technique.

By applying this framework, companies can gain a structured understanding of how to align their PdM techniques with their operational goals, ensuring the selected technique not only meets their current needs but also supports future growth and adaptability

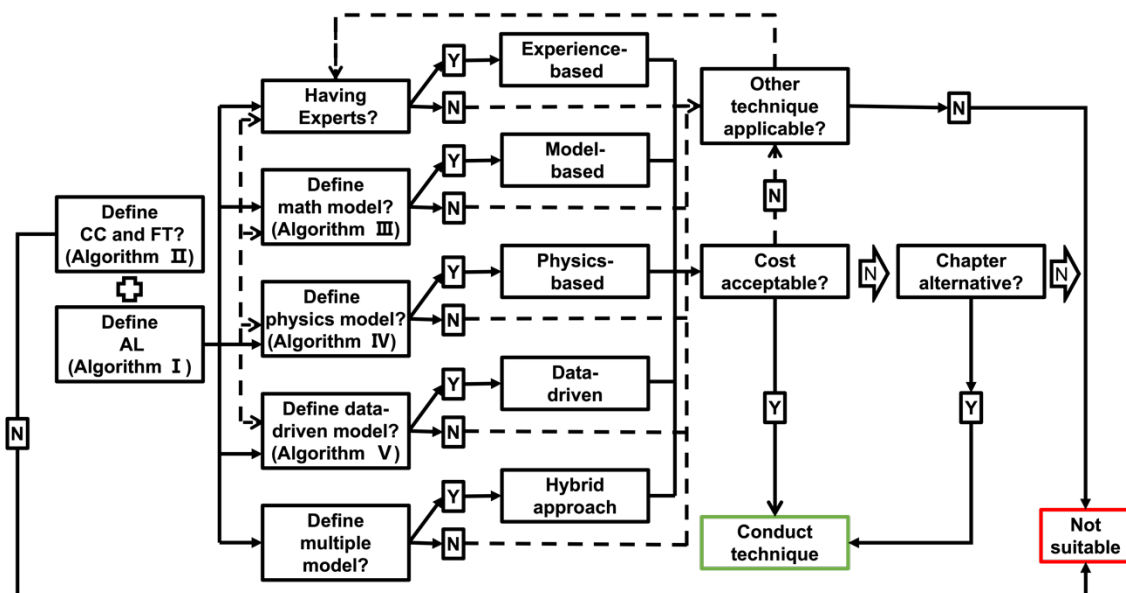


Figure 5-3 The Decision-Based Framework for Predictive Maintenance Technique Selection

As presented in Figure 5-3, the PdM technique selection and implementation process is supported by five key algorithms that guide critical decision-making. These algorithms play an essential role in determining the appropriate PdM techniques and include:

- **Algorithm I:** Algorithm to Define PdM Implementation Ambition Level
- **Algorithm II:** Algorithm to Define PdM Implementation Critical Component
- **Algorithm III:** Algorithm to Check if Model-Based PdM Technique is Applicable

- **Algorithm IV:** Algorithm to Check if Physics-Based PdM Technique is Applicable
- **Algorithm V:** Algorithm to Check if Data-Driven PdM Technique is Applicable

Each of the algorithms (Algorithms II to V) follows a structured, step-by-step process to evaluate the suitability of a specific PdM technique, as illustrated in Figure 5-3. These processes involve defining critical components, utilizing model-based methods, applying physics-based approaches, or adopting data-driven strategies. This hierarchical structure ensures that each decision point is evaluated based on the enterprise's available resources and needs, allowing a streamlined assessment and clear pathways for action.

The initial steps in each algorithm assess the enterprise's current capabilities, such as the presence of historical data, maintenance records, or existing mathematical models. These first steps determine if the enterprise has sufficient internal resources to proceed with implementing a PdM technique. If such resources are unavailable, the algorithm directs the enterprise toward assessing alternative resources or methods. Each algorithm includes a contingency for cases where internal resources (e.g., expert knowledge or historical data) are insufficient. These alternatives involve leveraging secondary data (such as industry publications or research) or seeking external support from research organizations or consultants. By introducing these pathways, the algorithms offer multiple solutions to bridge resource gaps, maintaining the feasibility of implementing PdM techniques even with limited internal resources.

5.2.1 Algorithm to Define PdM Implementation Ambition Levels (Figure 5-4, Algorithm I)

As discussed in Chapter 3, Section 3.3, the first algorithm enables enterprises to analyse their specific needs and clearly define their PdM implementation goals, which is defined as AL in this research. The algorithm used for defining PdM implementation ALs is illustrated in Figure 5-4 below.

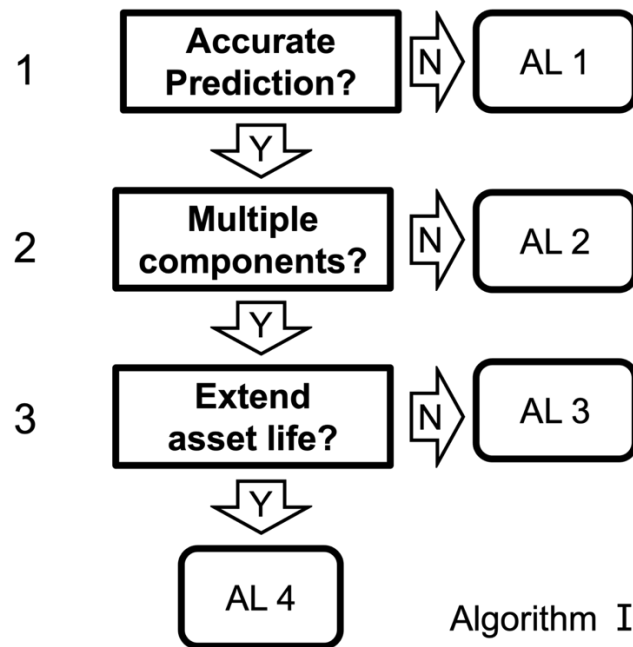


Figure 5-4 Algorithm for defining PdM implementation ALs

As shown in Figure 5-4, the first step in determining the AL is to decide whether there is a need to accurately predict the future state of the system. If there is no such need, the ambition level is AL 1. If accurate prediction is required, the next step is to assess whether there is a need to predict the condition of multiple components, such as the tools, spindle, and bearing of a milling machine. If predicting multiple components is not necessary, the ambition level is AL 2. However, if multiple components need to be predicted, the following step is to consider whether extending the asset's service life is a priority, such as delaying the retirement of a machine. If extending the service life is not a requirement, the ambition level is AL 3. Otherwise, the ambition level is AL 4.

Algorithm to Define PdM Implementation Critical Component (Figure 5-5, Algorithm II)

The second algorithm supporting PdM technique selection is the Algorithm to Define PdM Implementation Critical Component (Figure 5-5). Critical components are vital in selecting appropriate PdM techniques because each technique has specific characteristics, and some types of wear and tear may not be accurately captured by physical laws or mathematical models. Therefore, it is

crucial to define critical components before evaluating which PdM techniques are suitable.

As presented in Figure 5-5, Algorithm II, the algorithm begins with Step 1, which involves determining whether the enterprise possesses the internal knowledge to define critical components and fault types. This can be done by leveraging expert knowledge and organizational experience (Florian et al., 2021; Gbadamosi et al., 2021; LaRose et al., 2021). If the enterprise lacks this internal capability, the process moves to Step 2, where the availability of maintenance records is assessed to define critical components and fault types. Identifying components with high maintenance rates, costs, or efforts from maintenance records is a common approach to pinpointing critical components (Gbadamosi et al., 2021; Rivera et al., 2018; LaRose et al., 2021).

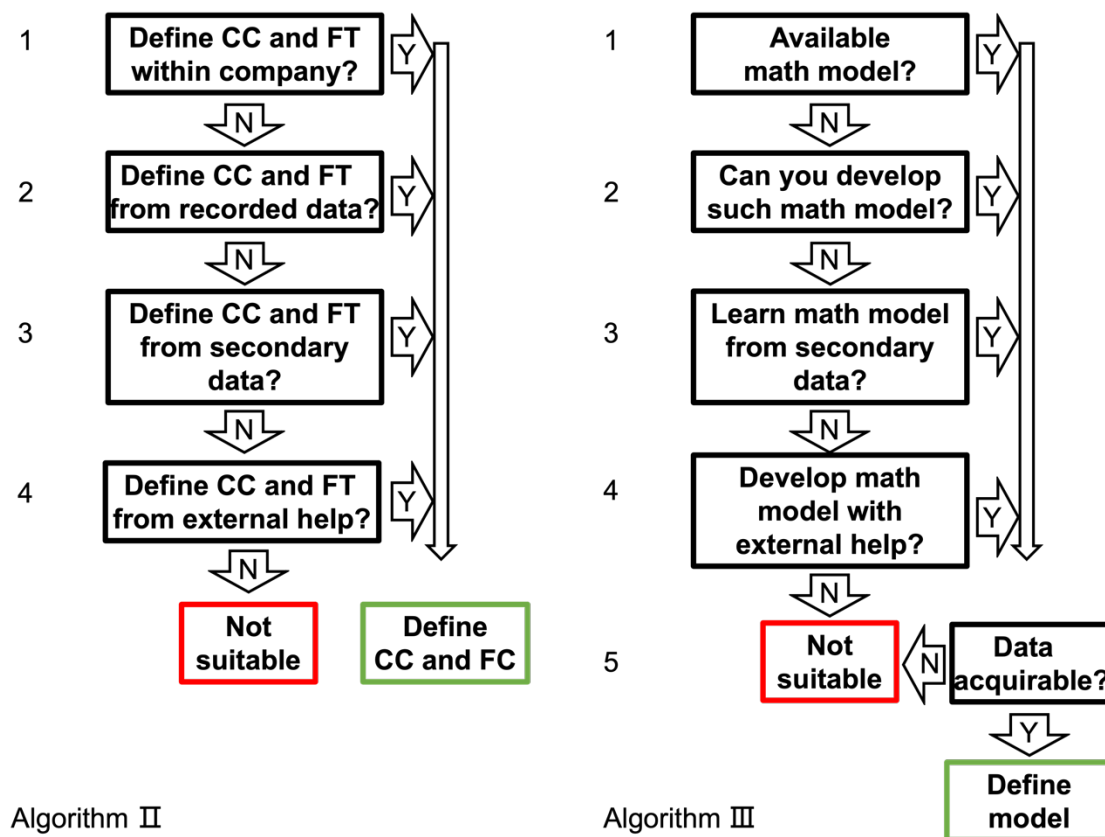


Figure 5-5 Algorithm to Define PdM Implementation Critical Component (Algorithm II) and Algorithm to Check if Model-based PdM Technique is Applicable (Algorithm III)

If maintenance records are not available, the next step, Step 3, involves using secondary data, such as published research or industry reports, to identify critical components and fault types. Engineers can draw insights from existing studies or industry reports to inform their decisions. Finally, if secondary data is also unavailable, Step 4 suggests engaging external research groups or consultants to assist in defining critical components and fault types.

By following this algorithm, enterprises can systematically define critical components and fault types, which are essential for selecting and implementing the appropriate PdM techniques.

5.2.2 Algorithm to Check if Model-based PdM Technique is Applicable (Figure 5-5, Algorithm III)

The third support algorithm is the Algorithm to Check if Model-Based PdM Technique is Applicable (Figure 5-5). This algorithm aids in determining the applicability of model-based PdM techniques. It begins with Step 1, which involves checking whether any existing mathematical models are available within the enterprise for predicting component states. It is crucial to assess the reusability of previously developed mathematical models for new applications.

If no mathematical models are available, the process moves to Step 2, where the enterprise evaluates its expertise in developing the necessary mathematical models. This assessment may include evaluating the capability to create models such as Markov chains, Gaussian models, linear systems, or Wiener part wear models.

If the enterprise lacks the expertise to develop these models, checking whether such mathematical models can be derived from secondary data is involved in Step 3. This refers to exploring published mathematical models in research papers or industry reports. For instance, if the enterprise aims to predict fatigue crack growth in fuselage panels, it can consult relevant literature (Yiwei et al., 2019).

If secondary data is also unavailable, the following Step 4 is for evaluating the possibility of seeking assistance from external research groups or consultants to help define the necessary models as presented in Figure 5-5, Algorithm III.

Once the model is defined, in Step 5, the data required to run the model is determined. This includes examining the types of sensors needed and their locations within the system to ensure the availability of necessary data for model-based PdM techniques.

By following this algorithm, enterprises can systematically assess the applicability of model-based PdM techniques based on the availability of mathematical models, internal expertise, secondary data, and data acquisition needs.

5.2.3 Algorithm to Check if Physics-based PdM Technique is Applicable (Figure 5-6, Algorithm IV)

The next algorithm supporting PdM technique selection is the Algorithm to Check if Physics-Based PdM Technique is applicable (Figure 5-6).

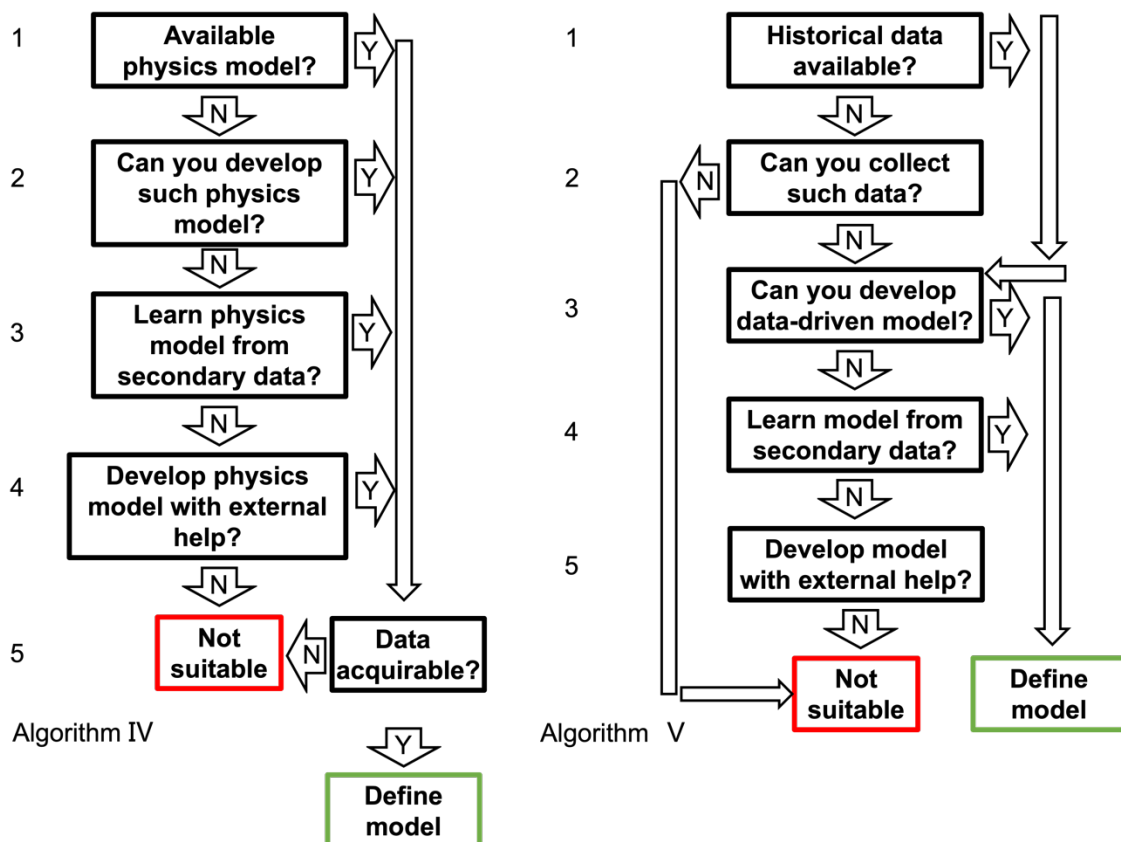


**Figure 5-6 Algorithm to Check if Physics-based PdM Technique is Applicable
(Algorithm IV) and Algorithm to Check if Data-driven PdM Technique is
Applicable (Algorithm V)**

This algorithm follows the same phases as Algorithm III but specifically focuses on assessing the applicability of physics-based PdM techniques. The key difference is in evaluating the availability of physics wear and tear models, existing knowledge, secondary data, and the potential for external assistance in developing these models.

**5.2.4 Algorithm to Check if Data-driven PdM Technique is Applicable
(Figure 5-6, Algorithm V)**

The final algorithm supporting PdM technique selection is the Algorithm to Check if Data-Driven PdM Technique is Applicable (Figure 5-6). This algorithm evaluates the feasibility of applying data-driven PdM techniques within the enterprise. It consists of several steps that assess the availability of historical data, the ability to record new data, the development of data-driven prediction models, and the potential for leveraging secondary data or seeking external assistance.

As presented in Figure 5-6, Algorithm V, the algorithm begins with Step 1, which involves checking for recorded historical data that can be used to train a data-driven model within the enterprise. If the necessary historical data is unavailable, the next step is Step 2. In this step, the enterprise evaluates whether it can collect and record the required data over a specified period. If data collection is feasible, Step 3, the enterprise's capability to develop a data-driven prediction model is assessed. This includes considering the expertise, resources, and tools needed to create an effective model.

If the enterprise cannot develop the data-driven model internally, the possibility of learning from secondary data is examined in Step 4. This involves exploring models available in open-source databases or those published by researchers and companies. The enterprise can leverage these existing models to inform its own data-driven approach. If secondary data is also unavailable or not applicable, the final step, Step 5, the option of seeking external assistance from research

groups or consultants is considered. These external experts can provide valuable guidance and support in developing and implementing the data-driven PdM technique.

It is important to note that while Algorithms III, IV, and V assist in determining the applicability of specific PdM techniques (model-based, physics-based, and data-driven), they do not offer guidance on selecting the specific mathematical, physics, or data-driven models to be used within each technique.

5.3 Step C Framework validation (Figure 5-1)

5.3.1 Step C1 Description of the case study

The case study focuses on a large automotive manufacturing company facing several challenges, including enhancing production efficiency, reducing maintenance costs, and maintaining product quality. The company primarily manufactures precision mechanical automotive parts and operates several automated production lines. It uses a variety of equipment, such as CNC machines, industrial robots, stamping machines, and injection molding machines. The production processes are diverse, including metal cold stamping, metal casting, plastic injection molding, metal punching, and polishing. Given the complexity of the equipment, downtime caused by failures has a significant impact on overall production efficiency.

Currently, the company employs PM. However, as production has scaled and automation has increased, the issues of over-maintenance and unexpected equipment failures have become more evident. To address these problems, reduce costs, and improve equipment reliability, the company decided to trial PdM on key equipment, focusing on a CNC machine used for precision finishing of holes in cast automotive engine parts.

The company's objectives for implementing PdM are to:

1. Reduce unexpected equipment failures and increase production line efficiency.

2. Optimize maintenance frequency, avoiding over-maintenance and wasted resources.
3. Lower maintenance costs while extending equipment life.
4. Improve Overall Equipment Effectiveness (OEE) by minimizing downtime and failures, thus enhancing production capacity.

5.3.2 Step C2 Framework application

Based on an analysis of these objectives and by applying Algorithm I (Figure 5-1), the company's AL is determined to be AL 4. According to the PdM technique map (Figure 5-2), the most appropriate approaches are data-driven, or hybrid methods as shown in Figure 5-7. This analysis is based on the company's PdM implementation objectives. As outlined in the objectives, the second goal—"Optimize maintenance frequency, avoiding over-maintenance and wasted resources"—necessitates precise fault prediction for its successful realization. Furthermore, the objective to improve the overall OEE of the production line implies the need for predictive capabilities extending beyond a single machine. Lastly, the third objective highlights the company's intent to extend the lifespan of its machinery. As a result, the final AL determined for the company is AL4. The next steps of the case study involve using Algorithm II to identify which critical components of the CNC machine should be monitored. Since extending equipment life is one of the company's objectives, the focus will then shift to Algorithm V to evaluate the company's ability to develop a data-driven PdM technique.

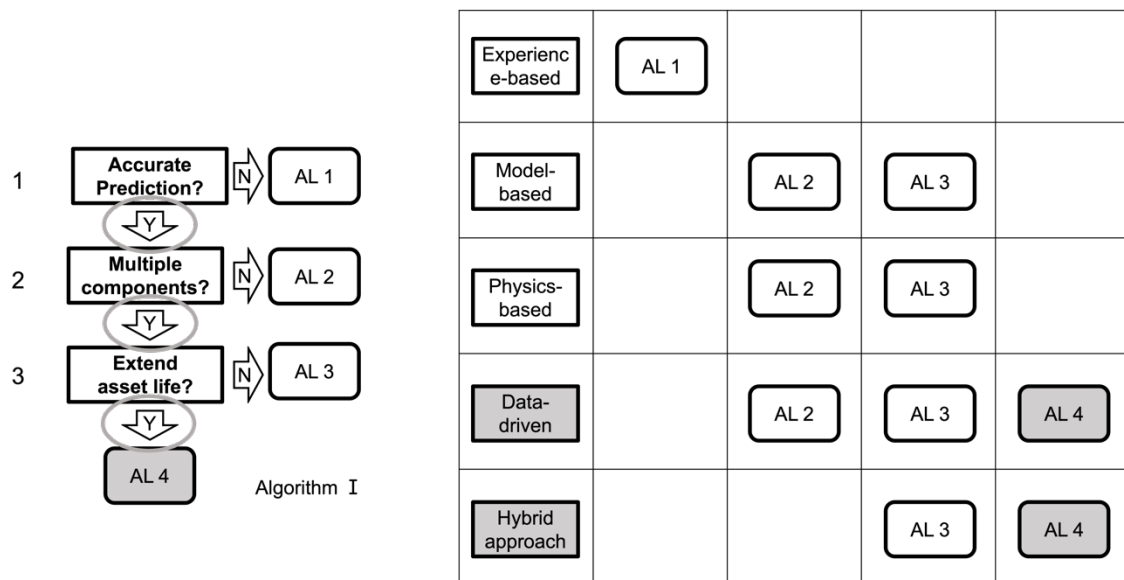


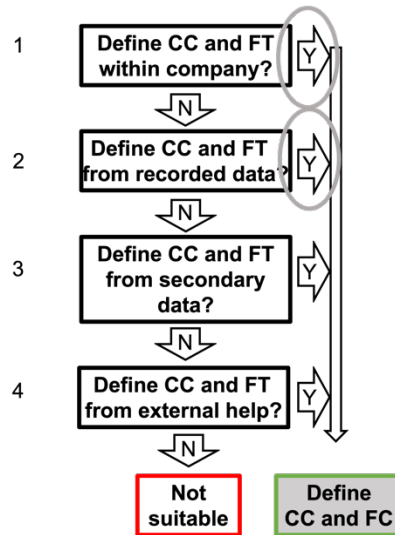
Figure 5-7 Case study AL and suitable PdM technique define

Defining Critical Components and Fault Types (Figure 5-5, Using Algorithm II)

The first step is to evaluate if the company has the internal capability to define critical components and fault types (Figure 5-8).

The company has a long history of implementing PM, and it maintains detailed maintenance records that include:

- Maintenance dates, personnel involved, and the type of maintenance (e.g., routine inspection, planned maintenance, or emergency repairs).
- Detailed descriptions of maintenance steps, such as inspection, cleaning, and parts replacement, with reasons for part replacements, model numbers, and serial numbers.
- Performance test results before and after maintenance, materials and lubricants used, critical parameter readings, post-maintenance inspections, and recommendations for further action.



Algorithm II

Figure 5-8 Critical component and fault type define procedure

Based on these records, along with data like mean time to failure (MTTF) and maintenance costs, as well as expert advice, the following critical components and fault types are defined for the CNC machine:

- Spindle:
 - Bearing wear or failure: This results in vibrations, noise, and reduced machining precision.
 - Spindle motor failure: Can cause the machine to stop or run at inconsistent speeds.
- Cutting Tool:
 - Tool wear: The cutting edges wear down over time, leading to poor surface finish and increased cutting forces.
 - Tool breakage: This can occur due to excessive cutting forces or incorrect tool selection, leading to unexpected downtime.
 - Chipping or fracturing: This is often caused by improper feed rates, speeds, or tool misalignment, resulting in a shorter tool lifespan.

Assessing the Feasibility of Developing a Data-Driven PdM Technique (Using Figure 5-6, Algorithm V)

Once critical components and fault types are defined, the next step is to assess the feasibility of developing a data-driven PdM technique (Figure 5-9). The first consideration is whether the company has access to, or can collect, relevant historical data. The company already records operational data during equipment failures, including parameters such as: Spindle Speed, Feed Rate, Cutting Depth (Axial and Radial), Cutting Speed, Torque, Force, Power Consumption, Positioning Accuracy and Repeatability. This data provides the foundation for developing a predictive model.

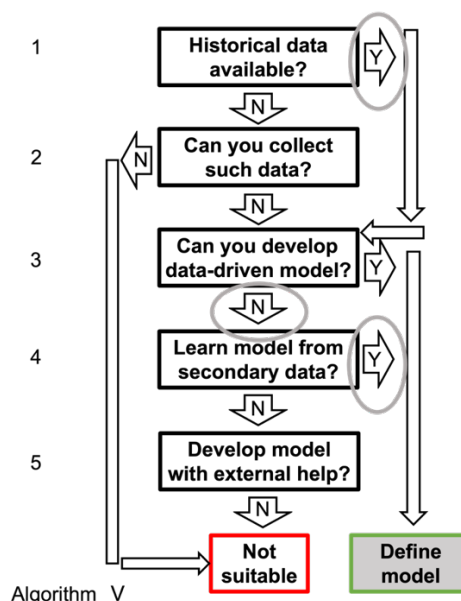


Figure 5-9 Data-driven PdM technique developing procedure

Next, the company needs to thoroughly assess whether it has the capability to develop a data-driven PdM model. Given that the company has never previously implemented any form of data-driven technology in its operations, this represents a significant shift in its approach to maintenance. Furthermore, none of the staff have prior experience in developing data-driven models, which adds complexity to the task. Without in-house expertise in areas such as machine learning, data analytics, or predictive modeling, the company faces a steep learning curve.

As a result, the next logical step is to explore the possibility of learning from secondary data. By leveraging existing models developed by other companies or researchers, the company could significantly shorten its development time and reduce the need for internal expertise. A comprehensive search of open-source databases was conducted, revealing several pre-built models that have been successfully applied to CNC machine data-driven predictive maintenance. The identified pre-built models are listed in Table 5-1. The source code and documentation for these models are provided in Appendix B, offering the company a valuable resource for accelerating its PdM development efforts. The idea behind using open-source data to develop PdM models is that many PdM models, particularly data-driven ones, are designed with the capability to be retrained. This is largely because PdM models are often trained on generic, similar types of data, such as vibration, temperature, voltage, and pressure, making them broadly applicable across different types of equipment. Most PdM models that use machine learning algorithms are set up for continuous training and retraining. These models are trained on historical data to predict a machine's remaining useful life and potential failures.

By changing the training data and retraining the original algorithm on data from new machines, the algorithm can adapt to identifying the operational patterns of the new equipment. However, several factors need to be considered in this retraining process. First, a sufficient amount of historical data from the new machine is necessary for effective training. Additionally, since PdM models often rely on machine learning algorithms, particularly regression or classification, labeling the data is essential so the algorithm can analyze features within the data. Lastly, as each machine has unique characteristics, variations in data or working environments should be represented in the new dataset to capture these differences accurately. According to Table 5-1, the company in the case study possesses historical data, which was also highlighted in the case analysis earlier. Regarding the second condition for algorithm retraining, data labelling, the company records not only machine operation parameters but also fault times, fault types, and mean time to failure, which effectively addresses the data labelling requirements. Finally, on the matter of data types, there is significant

overlap between the data used by the company and that used in open-source models, though some differences remain. These distinctions will require attention during the retraining process.

Table 5-1 Identified data-driven PdM model

Model Type	Accuracy	Required data	Available data
Random Forest Regression	99.94%	Actual Position, Actual Velocity, Actual Acceleration,	Actual Position, Actual Velocity, Actual Acceleration,
Gradient Boosting Regression	99.96%	Command Position, Command Velocity, Command	Command Velocity, Command Acceleration, Current
Logistic Regression	58.74%	Acceleration, Current Feedback, DC Bus	Feedback, Current Feedback, Output
Support Vector Classification	63.70%	Voltage, Output Current, Output Voltage, ... DC Bus	Power, System Inertia, Current Program Number, Sequence
Gaussian Classifier	54.61%	Voltage, Output Power, System Inertia, Current Program Number,	Number, Current Federate, Material, Spindle vibration
KNN Classifier	76.02%	Sequence Number,	
Decision Tree Classifier	87.31%	Current Federate	
Random Forest Classifier	99.35%		
Optimizing Random Forest Classifier	99.35%		
XG Boost Classifier	97.71%		
Ensemble modelling	97.94%		

Once potential models have been identified, the company must also assess the financial feasibility of implementing a data-driven PdM technique. While the company does not need to allocate additional resources for data acquisition—since the necessary machine data (e.g., spindle speed, feed rate, torque) is already being recorded—there are still costs associated with edge/cloud computing infrastructure and software licensing or purchases. These expenses could include cloud-based services for real-time data processing, specialized PdM software tools, or even computing hardware upgrades to support the increased data processing demands.

With the goal of reducing unexpected downtime, improving Overall Equipment Effectiveness (OEE), and optimizing maintenance scheduling, the company expects to see substantial long-term savings through reduced maintenance costs and improved machine reliability. Consequently, after considering both the technical and financial aspects, the company concluded that the costs involved were acceptable. This case study demonstrates a successful evaluation and selection of a data-driven PdM technique for implementation, paving the way for more efficient and reliable operations.

5.3.3 Evaluation of Machine Learning Models for PdM Implementation

The feasibility of identified data-driven models is analyzed in this section.

Random Forest Regression

The random forest regression model demonstrates outstanding performance in terms of prediction accuracy and has high feasibility in implementation. The data required for this model include vibration, position, and speed of the main shaft, etc. These data are currently stored within the company, making data acquisition relatively straightforward. Although this algorithm may become computationally intensive when dealing with large-scale data, it can effectively share the computing burden by leveraging cloud computing or edge computing platforms to ensure processing efficiency. The random forest model has excellent scalability and can easily be applied to other devices by making minimal

adjustments to the existing data input features. Although the implementation process is relatively simple and there are mature machine learning libraries available to support its development, certain machine learning expertise is still required to optimize the model's performance (Jogdeo et al., 2024). Overall, with sufficient computing resources and technical support in place, the random forest regression model can be successfully implemented in such environments.

Gradient Boosting Regression

The gradient boosting regression model outperforms the random forest regression in terms of prediction accuracy, but it poses certain challenges in terms of computational complexity. The data required by this model include spindle speed, cutting depth, and torque, etc. These data are already prepared within the company and thus obtaining them is not difficult. However, due to the iterative calculation method adopted by the gradient boosting algorithm, it consumes more resources computationally compared to the random forest and requires stronger computing capabilities. Although this model has certain scalability, when applied to new equipment or different production environments, it may require re-training or fine-tuning of the model. Although gradient boosting regression can be implemented through existing machine learning libraries, to achieve the best performance, hyperparameter tuning and cross-validation are usually required, which undoubtedly increases the complexity of model implementation (Carvalho et al., 2019). Overall, although the gradient boosting regression model performs well in terms of accuracy, its high computational cost and implementation complexity in large-scale applications may become major obstacles in the implementation process. Therefore, when deciding whether to adopt this model, it is necessary to comprehensively consider the availability of computing resources and the complexity of the implementation process, especially in large-scale applications.

Logistic Regression

Logistic regression is an algorithm with a relatively light computational burden. The data it requires include cutting speed, feed rate, and torque, etc., which are all available in the current production environment. However, the accuracy of

logistic regression is relatively low, so it is not very applicable in this case study. Although the model is simple to implement and requires fewer computing resources, its performance is limited in complex industrial environments. The simplicity of logistic regression gives it an advantage in terms of scalability, but its low prediction accuracy indicates that its value in predictive maintenance is limited (Silvestrin et al., 2019). Given its poor performance, logistic regression is not a practical choice in this case study.

Support Vector Classification

Support Vector Machine Classification (SVC) requires data such as force, power consumption and spindle position. These data can be obtained in this case study, but for achieving the best performance, certain preprocessing may be necessary. Although SVC is feasible in some scenarios, it is computationally resource-intensive, especially when dealing with large-scale datasets or using complex kernel functions, which may affect the scalability and real-time prediction capability of the model. Although SVC is theoretically feasible, its relatively low prediction accuracy and high computational cost make it less applicable in the predictive maintenance requirements of companies (Wu et al., 2017). To improve performance, detailed tuning and parameter optimization of the model may be required, which undoubtedly increases the complexity of implementation.

Gaussian Classifier

The Gaussian classifier requires the use of spindle speed and torque data. However, it performs poorly in terms of accuracy, making it infeasible for the company's predictive maintenance implementation. Although the algorithm does not require high resources computationally and can be implemented quickly, it relies on assumptions about the data distribution, which limits its effectiveness when dealing with complex real-world datasets. Given its low accuracy and scalability limitations, the application value of the Gaussian classifier in this case study is not significant (Susto et al., 2014).

KNN Classifier

The K-Nearest Neighbour classifier (KNN) has moderate accuracy and requires data such as principal shaft vibration, cutting force, and torque, which are available within the company. However, since KNN needs to calculate the distance between the test point and the training data points in real time, this makes its computational burden heavy during the prediction process. Although the implementation of KNN is relatively simple and it can effectively handle high-dimensional data, its scalability is limited as the size of the data set expands. With the increasing demand for predictive maintenance in the company, the computational cost of KNN during prediction may become unaffordable, and thus it is not suitable for use in large-scale application scenarios (Chazhoor et al., 2020).

Random Forest Classifier

The random forest classifier is another feasible option applicable for predictive maintenance, with high accuracy and relatively easy implementation through existing machine learning libraries. This model requires data such as torque, feed rate, and spindle position, which are available within the company. Although the random forest involves significant computational load, these costs can be managed through appropriate infrastructure. The model has excellent scalability and can be applied to different types of equipment, requiring only minor adjustments to the input features. With its high accuracy and flexibility, the random forest classifier is highly suitable for application in complex industrial environments (Chazhoor et al., 2020).

XGBoost Classifier

The XGBoost Classifier is a model with high accuracy. It requires the use of shaft vibration and cutting force data. Compared with Gradient Boosting, it is more computationally efficient, but still requires a significant amount of computing resources, especially during model training and tuning. XGBoost has good scalability and can be applied on different devices, although certain adjustments need to be made based on the data. Additionally, its performance is highly dependent on data quality, so preprocessing (Salim et al., 2022) is necessary. Although XGBoost is relatively simple to implement and can be accomplished

using existing libraries, the tuning and optimization process may take a considerable amount of time. Overall, XGBoost provides a good balance between accuracy and computational efficiency but requires more expertise than simple models.

Ensemble Modelling

Ensemble Modelling combines multiple models to enhance accuracy and robustness. During implementation, data such as spindle speed, position, and torque are required. Although this method has high computational demands, the higher accuracy justifies the additional cost. Ensemble models have high scalability across different devices, but as the predictive maintenance system of the company continues to expand, the increase in computational requirements may pose some challenges. Nevertheless, the ensemble approach remains a reliable and efficient predictive maintenance option (Beretta et al., 2021).

5.3.4 Alternative PdM Strategies in the Context of the Case Study

The case study focuses on the implementation of a data-driven PdM technique, but alternative strategies could have been considered based on the company's existing conditions and resources. Three alternative PdM strategies are discussed below, highlighting their advantages and limitations while considering the company's specific circumstances.

Model-based PdM

Advantages

Model-based PdM technologies (such as using Markov chains or failure rate models) have high accuracy in predicting faults, especially when the known processes and fault modes are clear. Considering the company's existing historical data of machine parameters (such as spindle speed and cutting depth), model-based technologies can utilize the existing data to develop precise fault prediction models. The CNC machines used by the company are usually for precision processing and have clear operating parameters, making them suitable for developing customized model-based PdM systems.

Limitations

Developing a model-based PdM system requires a high level of mathematical expertise, but the company currently lacks sufficient technical reserves in this regard. The lack of internal expertise will increase the complexity of the development and lead to higher costs, such as hiring consultants or training employees, which may delay the implementation progress. Moreover, developing such a system is both time-consuming and expensive. In contrast, data-driven PdM methods can be deployed more quickly by leveraging existing data and tools. Given the company's limitations in terms of time and resources, the feasibility of adopting the model-based approach is relatively low.

Physics-based PdM

Advantages

The physics-based PdM model relies on the understanding of the physical behaviour of components and can provide powerful predictive capabilities for known fault patterns. Taking the company's CNC machine tools as an example, operational parameters such as cutting force and spindle speed can be used to predict foreseeable wear patterns. The physics-based model can effectively predict faults caused by material fatigue or wear by applying mature physical principles. Moreover, these models typically offer long-term reliability, thus having significant value in long-term asset management.

Limitations

Developing a physics-based PdM model requires not only detailed machine data but also a deep understanding of physical processes (such as the influence of cutting force on tool wear). Although the company has collected operational data, it lacks the in-depth data (such as material properties and failure mechanisms) needed for developing such models, thus requiring significant additional investment. Besides, integrating the physics-based model with real-time data for continuous monitoring is also complex and costly. To capture real-time physical parameters, specialized hardware or sensors are needed, which further increases costs and complexity. Given the company's lack of sufficient physical

data and expertise, implementing the physics-based PdM method will face considerable challenges.

Hybrid approach

Advantages

The hybrid PdM system integrates the advantages of data-driven methods and model-based or physics-based methods. For instance, data-driven models can be used to identify patterns in machine data, while model-based methods can optimize predictions based on known fault patterns. This integration can enhance the overall accuracy of predictions. In this case, data-driven models can predict the likelihood of faults occurring, while the physics-based models can strengthen these predictions by considering specific operating conditions.

Limitations

The hybrid approach requires integrating two distinct systems, which is technically complex and resource intensive. Managing and integrating data-driven models with physical models will increase the complexity of the implementation process and the risk of errors. Moreover, the cost of implementing a hybrid system may be high as it requires sufficient expertise in both fields and investment in software and hardware. For companies, this will lead to higher initial investment and maintenance costs, making it a less feasible option compared to data-driven methods.

Based on the actual situation of the company, data-driven PdM technique is the most feasible approach. Although model-based and physics-based strategies have advantages in terms of accuracy and long-term reliability, they require professional knowledge that the company currently lacks. Moreover, the time and financial investment needed to develop these models make them unsuitable for immediate implementation. The complexity and higher cost of the hybrid method make it a less attractive option.

In contrast, data-based PdM technology offers the best balance among implementation speed, scalability and cost-effectiveness. The company has collected relevant operational data and can solve problems more quickly and

cost-effectively by leveraging existing open-source models, without having to develop custom model-based or physics-based systems from scratch.

5.3.5 Practical and Organizational Considerations for PdM Implementation

A thorough cost-benefit analysis justifies the adoption of a data-driven PdM technique, ensuring that the company makes an informed decision by evaluating the financial and operational implications of this transition.

Costs

The company already collects substantial operational data, such as spindle speed, feed rate, and torque, from various sensors installed in the machinery. As no new data collection systems are required, the immediate financial burden is reduced. However, data quality remains a key issue. To ensure the accuracy of the model, data cleaning and preprocessing must be carried out. Poor data quality or missing data may lead to prediction errors. Therefore, data cleaning tools and periodic data audits are indispensable.

Data-driven PdM systems usually require powerful computing capabilities to process and analyse large amounts of real-time data. This may require the company to invest in upgrading its computing infrastructure. Especially in terms of data storage and real-time data processing, cloud computing and edge computing solutions may be necessary. For the demand of storing and processing large amounts of data, costs can be initially reduced through cloud platforms, and then gradually transition to local deployment or a hybrid model as the company expands. For cloud services, the pay-as-you-go model can control costs in the initial stage, but long-term costs also need to be evaluated as the data volume and computing volume increase.

Developing, training, and deploying data-driven PdM models usually require dedicated machine learning platforms and data analysis tools. Although open-source tools such as Python's Scikit-learn or TensorFlow can help reduce initial costs, some advanced platforms (such as Azure Machine Learning, Google Cloud AI, etc.) may require subscription purchases. To reduce costs, companies

can consider sharing costs with cloud service providers or adopting appropriate open-source tools to reduce licensing fees.

Currently, the company lacks sufficient machine learning and data processing skills, so it must provide professional training for existing employees or hire external data science experts to support the development and implementation of the PdM system. The cost of training and recruiting data scientists may be high, but this is a necessary investment for long-term sustainability and self-sufficiency. Initially, training and knowledge accumulation can be carried out through small teams, and then the team can be gradually expanded to reduce reliance on external consultants.

Benefits

Predictive maintenance enables companies to intervene promptly by predicting when equipment is likely to fail, thereby reducing unplanned downtime. Unplanned downtime is typically the costliest form of disruption in manufacturing. By addressing potential issues before they escalate into larger and more expensive malfunctions, companies can ensure more reliable operation of machinery and equipment, thereby enhancing production efficiency and reducing production disruptions. As unplanned downtime decreases, production efficiency significantly improves, and operational continuity is guaranteed.

By shifting maintenance strategies from time-based to condition-based, companies can ensure that maintenance is performed only when equipment is needed, thereby avoiding unnecessary maintenance costs. By accurately predicting when maintenance is required, companies can optimize maintenance plans to ensure that equipment is maintained at the most suitable time rather than over-maintaining or neglecting maintenance. This optimized maintenance scheduling helps to reduce operational costs related to labour, parts replacement, and equipment downtime during maintenance.

Early detection of equipment problems allows for timely repairs to prevent problems from escalating into larger and more costly malfunctions. Predictive maintenance helps to extend equipment lifespan, providing more accurate

equipment replacement predictions and reducing the frequency of capital expenditures on new equipment or spare parts. Companies will benefit from long-term cost savings and be better able to predict future equipment replacement and repair costs.

By reducing downtime, improving equipment reliability, and optimizing maintenance plans, data-driven PdM methods will directly enhance overall equipment efficiency (OEE). OEE is a comprehensive indicator for measuring the effectiveness of manufacturing processes, considering equipment availability, performance, and quality. An increase in OEE means improved production capacity and profitability, and better utilization of existing resources reduces the need for expansion investments, thereby improving the company's financial situation.

5.4 Discussion

In this section, the main conceptual and methodological contributions of the study are presented, aiming to enhance the decision-making process for predictive maintenance technique selection and implementation.

Structured Definition of Ambition Levels

A structured definition and operationalization of Ambition Levels (ALs) for predictive maintenance (PdM) implementation is presented as one of the central contributions. In much of the existing PdM literature, technological maturity is commonly represented through generic readiness indices or capability maturity models, where a linear progression towards advanced solutions is often assumed. This assumption is challenged here, as the AL framework is conceptualized as a goal-oriented and asset-specific process. By doing so, the possibility of parallel ambition levels across different systems within the same organization is acknowledged.

Through this discussion, it becomes evident that PdM implementation is rarely uniform in practice. Companies tend to pursue fully data-driven, AI-enhanced approaches for critical assets, while simpler, rule-based solutions are often maintained for less critical equipment. The AL classification is derived from a

synthesis of literature and practical considerations, and it is used to simplify the decision-support process by directing organizations toward an appropriate class of PdM solutions without requiring exhaustive technical modelling at the initial stage. Organizational objectives such as cost reduction, reliability improvement, or regulatory compliance are explicitly linked to feasible technology classes, and a transparent logic path from strategic goals to technology choice is thereby ensured. In this way, a persistent gap in the literature is addressed, where technology selection is typically technology-driven rather than goal-driven, and the connection between business strategy and technical feasibility remains weak.

Development of a Three-Hierarchical Framework for PdM Technology Selection

A coherent, three-hierarchical framework for systematically selecting PdM techniques is developed as another significant contribution. Prior approaches in the literature usually focus on individual elements maintenance strategy selection, condition-based maintenance evaluation, or technology adoption readiness but their integration into a unified process is often absent. In response, this framework is designed to operate modularly, so that ambition level identification, feasibility assessment, and knowledge-source-based substitution can be applied either sequentially or independently.

This structure ensures that decision-making remains transparent, traceable, and adaptable across different levels of organisational maturity. Each hierarchy follows a consistent logic: criteria are derived from structured literature, transported into operational decision steps, and applied to both strategic and tactical planning. The first hierarchy aligns organisational objectives and capabilities with an appropriate ambition level; the second evaluates feasibility of PdM techniques based on those ALs; the third identifies substitution pathways when key resources are lacking, using the Knowledge Source algorithms. In this way, a gap in the literature is addressed, since feasibility assessments are usually presented without clear contingency mechanisms. By adopting a resource-aware, action-oriented design, this framework connects abstract strategy with the operational realities of PdM adoption in industry.

Integrating PdM Technology Selection with Digital Transformation and Asset Management Frameworks

PdM technique selection is explicitly situated within broader agendas of digital transformation and asset management. In much of the PdM literature, the technology is treated as an isolated initiative, often assessed primarily by algorithmic performance or cost outcomes. In contrast, this research positions PdM within the strategic continuum of digital transformation, where it is regarded as both a driver and a beneficiary of digital capability development.

The ambition level framework is used to map PdM maturity onto stages of digital transformation, ensuring alignment between technology adoption and organisational digital roadmaps. For example, organisations in early stages are guided towards lower-complexity solutions compatible with their infrastructure, while digitally mature enterprises are directed to AI-enabled PdM embedded in an Industry 4.0 ecosystem.

Furthermore, PdM evaluation is linked to asset management standards, such as ISO 55000, by incorporating asset criticality, lifecycle cost, and performance targets. This ensures that PdM choices are not only technically feasible but also optimised for long-term asset value preservation and risk mitigation. By embedding asset-centric metrics and governance principles, the framework bridges maintenance engineering with asset management practice, thereby supporting a holistic view of reliability and investment planning.

Advancing Beyond Existing PdM Evaluation Methods through Structured, Goal-Oriented Integration

An advancement beyond existing evaluation methods is achieved by integrating the strengths of multi-criteria decision-making (MCDM), analytic hierarchy processes (AHP/ANP), and data-driven auto-selection systems while addressing their limitations. Traditional MCDM and AHP approaches provide rigorous mathematical structure, but they rely heavily on expert judgement and are difficult to scale across diverse organisations. Conversely, purely data-driven selection

methods achieve objectivity but demand large, high-quality datasets, which are rarely available, especially in SMEs.

These limitations are mitigated here through a hybrid approach that combines structured criteria with goal-oriented adaptability. Organisational objectives, constraints, and asset-specific requirements are first identified, and these inputs guide the progression through ambition level classification, feasibility assessment, and conditional substitution pathways. This ensures transparency and interpretability while keeping recommendations realistic even under limited data availability.

The framework's modularity also allows flexible use: it can serve as a stand-alone tool in low-data environments or as a front-end to data-intensive optimisation methods when readiness improves. By being both immediately deployable and extensible, the framework provides a rare bridge between theoretical rigour and operational practicality. In doing so, it fills a significant gap in PdM research, where most approaches remain either too abstract or too data-dependent for broad applicability.

The framework presented in this chapter are also subject to the following limitations.

Dependence on the Scope and Quality of the Systematic Literature Review

One methodological limitation of this research is acknowledged to lie in the reliance placed on the scope and quality of the literature captured through the systematic literature review (SLR). Although the SLR provides a structured and replicable means of identifying PdM-related objectives, organisational attributes, and capability factors, the comprehensiveness and representativeness of the framework are inevitably constrained by the availability, quality, and accessibility of published studies. The decision to focus primarily on peer-reviewed sources ensures academic rigour, but it may also lead to the omission of valuable insights contained in grey literature, industry reports, or proprietary documents. In addition, the exclusion of simulation-based or laboratory-only studies helps preserve industrial relevance, yet it may filter out emerging approaches not widely

deployed in practice. Reliance on published industrial case studies also risks survivorship bias, since unsuccessful implementations are rarely documented. These constraints highlight the need for complementary evidence from targeted surveys or expert interviews.

Subjectivity and Complexity of the Hierarchical Framework

Another limitation is associated with the subjectivity and complexity inherent in the hierarchical decision framework. Although ambition level classification and feasibility algorithms are designed to provide structured and repeatable guidance, their thresholds, weights, and categorical boundaries are influenced by expert judgement and author-defined parameters. Variability may therefore arise across organisations or among decision-makers. The multi-layered structure, while beneficial for nuanced analysis, can also pose challenges for organisations with limited expertise or decision-support infrastructure. Small and medium-sized enterprises in particular may struggle to navigate the framework without external support, and the learning curve may deter adoption in contexts where decision-making speed is prioritised. These concerns point to the importance of developing streamlined, user-friendly interfaces or automated decision-support tools.

Representativeness of the Demonstrative Case Study

The demonstrative case study used to illustrate the framework's application provides valuable insights but also introduces limitations regarding representativeness. Because the study focuses on a single organisation operating at a relatively high level of digital maturity, the findings cannot easily be generalised to enterprises with different levels of capability, asset classes, or regulatory environments. The case study is designed as a demonstration rather than as a validation exercise, meaning that tactical implications are explored rather than statistically verified. Broader empirical validation through multi-case, cross-sectoral, or longitudinal evaluations is therefore needed to ensure robustness and transferability.

Lack of Standardised Criteria for Assessing Internal Modelling Capability

The evaluation of internal modelling capability represents another concern, as the framework currently lacks fully standardised criteria. Users are asked to determine whether predictive modelling capability exists, yet no baseline set of technical competencies, process maturity indicators, or tooling requirements is provided. This ambiguity risks inconsistent assessments across organisations and undermines comparability. Although flexibility is preserved through qualitative judgement, objectivity and repeatability are reduced. A more granular capability maturity model aligned with digital skills assessments or asset management frameworks is therefore suggested for future refinement.

Adaptability and Risk in Using External Data and Pre-Trained Models

Further limitations are recognised in the consideration of external datasets and pre-trained models. While the potential value of such resources is acknowledged, adaptation requirements and risks are addressed only at a high level. In practice, differences in data sources, environmental conditions, and asset characteristics often necessitate significant preprocessing, retraining, or feature engineering. The absence of a formalised evaluation process for compatibility gaps or risk assessment may lead to overestimation of benefits and underestimation of hidden costs. The development of a standardised adaptation checklist or risk-scoring mechanism is therefore recommended.

Insufficient Formalisation of Accuracy–Complexity Trade-Offs

The framework does not fully formalise the trade-offs between predictive accuracy and implementation complexity in model selection. Although feasibility confirmation precedes detailed model choice, no structured process is provided to balance accuracy against cost, interpretability, or maintainability. Organisations may therefore overinvest in unnecessarily complex models or underutilise simpler ones. This limitation highlights the need for a dedicated model selection sub-framework that captures both quantitative and qualitative trade-offs.

Chapter Summary

In this chapter, as presented in Figure 5-10, the results, validation, and discussion of the PdM technique selection method are presented, adhering to the steps outlined in Section 3.3. To support PdM technique selection, Section 5.1 identifies the critical elements of PdM technique capabilities, PdM implementation objectives, and PdM implementation attributes. A structured framework and associated algorithms are developed in Section 5.2, establishing linkages among PdM implementation attributes, objectives, and specific PdM techniques.

In summary, this chapter outlines the contributions of the research in addressing the gaps identified in Chapter 2: the analysis of PdM technique capabilities, alignment of implementation objectives, evaluation of implementation attributes, and linkage of these factors to PdM techniques. These contributions provide a comprehensive framework for selecting and implementing PdM systems. In Chapter 6, the results, validation, and discussion of the PdM operation intangible assets evaluation method are presented, following the approach outlined in Chapter 3, Section 3.4.

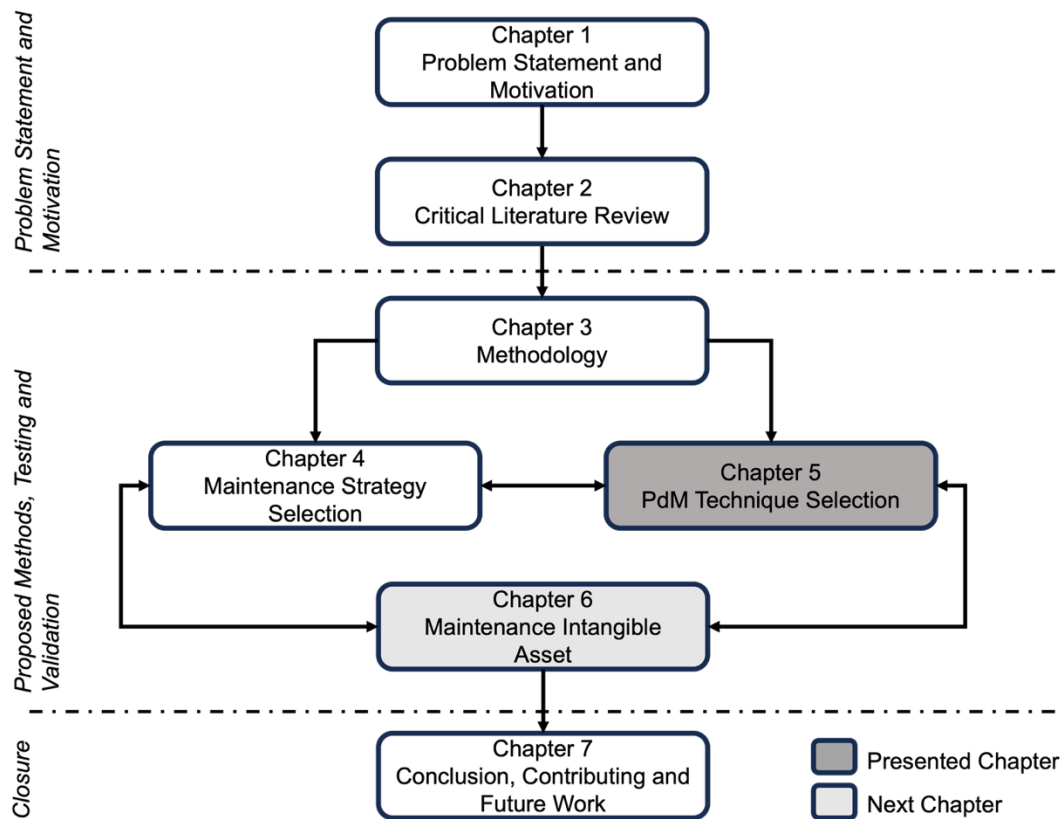


Figure 5-10 Organization of the Thesis – Presented and Next Chapter

CHAPTER 6 - INVESTIGATION ON PREDICTIVE MAINTENANCE IMPLEMENTATION INTANGIBLE ASSETS

In this chapter, a method termed “Investigation on Predictive Maintenance Implementation Intangible Assets” is presented. This method is developed to address Research Question Two *What is the method that helps evaluate the necessary intangible assets for PdM implementation, taking into account the enterprise's specifications, before the actual implementation?*, as outlined in Chapter 1, Section 1.3, and its relevance is substantiated through a critical review of the literature provided in Chapter 2, Section 2.4. The method for investigation on predictive maintenance implementation intangible assets is the third objective for investigating PdM implementation cost-benefit. In this chapter, five aspects are addressed (1) PdM implementation and operation intangible assets type investigation; (2) establish PdM implementation and operation maturity model; (3) PdM implementation and operation intangible assets quantification equations; (4) PdM implementation and operation intangible assets marking scale; and (5) method validation.

Following the methodology for designing the maintenance implementation and operation intangible asset evaluation method introduced in Section 3.2 and presented in Figure 6-1, in which the method development logic is outlined, the first section of this chapter (Section 6.1) is dedicated to the identification of intangible asset types required for the implementation and operation of maintenance strategies. In Section 6.2, the maintenance implementation and operation maturity model is introduced, while in Section 6.3, the intangible assets quantification equations and the intangible assets marking scale are explained. In Section 6.4, a case study is conducted for method validation. Finally, in Section 6.5, a discussion of the chapter is provided.

A: PdM implementation and operation intangible assets investigation	A1: Evaluate required intangible assets for manufacturing
	A2: Evaluate required intangible assets for maintenance implementation and operation
B: Establish PdM implementation and operation maturity model	B1: Investigate PdM capabilities and capability levels
	B2: Classify PdM capabilities and capability levels and define maturity model
C: PdM implementation and operation intangible assets quantification equation development	C1: Develop equation to express PdM implementation and operation intangible assets dimension and sub-dimension
D: PdM implementation and operation intangible assets sub-dimension marking scale	D1: Expert selection and survey
	D2: Expert intangible assets sub-dimension description and explanation
	D3: Data analyse and marking scale development
E: Method validation	E1: Case define
	E2: Intangible assets marking
	E3: Target maturity level selection
	E4: Target level and existing mark comparison
	E5: Expert development plan

Figure 6-1 Method for PdM implementation and operation intangible assets evaluation

6.1 Step A PdM implementation and operation intangible assets type investigation

Following the methodology presented in Chapter 3, Section 3.4, and presented in Figure 6-1, the intangible asset types for PdM implementation are investigated in this section.

6.1.1 Step A1 Evaluate required intangible assets for manufacturing

A systemic literature review is conducted to investigate the required intangible assets for manufacturing industry first. The result is presented in Table 6-1. The intangibles assets identified can be classified into five main dimensions, which

are Human Capital (HC), Structural Capital (SC), Relational Capital (RC), Research and Development (R&D), and Information and Technology (IT). Each intangible asset dimension includes several sub-dimensions. providing a foundation for the assessment of maintenance intangibles.

HC can be general defined as the summation of a number of elements to carry out work which can produce economic value including competencies, knowledge and skills (Wright et al. 1994).

Enterprises consider HC a critical factor for gaining competitive advantage (Cricelli and Grimaldi, 2009; Lepak and Snell, 1999; Nakamura, 1981) and for sustaining their performance (Ambrosini et al., 2009; Becker, 1962; Mincer, 1958; Schultz, 1961; Wernerfelt, 1984), regardless of their size. At the same time, HC is recognized as having the capability to make an enterprise distinct from others, as it is valuable, rare, non-substitutable, and inimitable (Delery and Shaw, 2001; Newbert, 2007). According to Mubarik et al. (2018), the critical dimensions of HC still lack clarity. They investigated the most important dimensions of HC for the manufacturing sector. The identified critical dimensions are education, experience, training, skills, attitude, personal attributes, stability, health, and compliance. A similar point can be seen in Mubarik (2016).

The second type of intangibles for maintenance implementation and operation is structural capital (SC). It is difficult to give structure capital a general valid definition because of its nature of adopting to the market's demand primarily involves flexibility Gogan et al., (2016). According to Van Caenegem (2002), it is the knowledge that remains within the company when employees leave for the day, such as database structures, manuals, and training materials. This indicates that the company retains ownership of these assets. A same description can be seen in Pablos (2004). Structural capital is also the embodiment, empowerment, and supportive infrastructure of human capital (Chatzkel, 2002). It may have some overlap with human capital but generally it is the knowledge at organization level.

RC arises from the value an organization derives through its relationships with external stakeholders, such as customers, suppliers, partners, and regulatory

bodies. It encompasses the goodwill, trust, loyalty, and reputation that the company builds through these interactions (Nakatani, 2021; Ferdaous and Rahman, 2019).

Research and development (R&D) in intangible assets is a critical area of focus in modern economies, play an increasingly important role in creating value. R&D in this area leads to the development of unique products, brands, and processes that are difficult for competitors to replicate (Corrado et al., 2022; Hsiao et al., 2021).

IT often play a supportive and foundational role in building a company's intangible assets. For example, in managing human capital and structural capital, the assistance of information and technology is indispensable (Ocak and Findik, 2019; Niebel et al, 2017).

Table 6-1 Identified intangible assets dimensions for manufacturing

Intangible Assets Dimensions	Sub-Dimensions	Literature
Human Capital	Education	Bryl et al., (2019); Wendra et al., (2019); SEO and KIM (2020); Postuła and Chmielewski (2019); Fu and Ghauri (2019); Ocak and Findik (2019); Cheng and Krumwiede (2017); Nnado Ifeanyi and Ozouli Caroline (2016); Niebel et al (2017); Corrado et al., 2022; Hsiao et al., (2021); Shakina and Barajas (2015); Krusinskas et al., (2015); Muntean (2014); Roth et al., (2023); De Ridder (2014); Li and Wu (2018)
	Experience	
	Training	
	Skills	
	Attitude	
	Personal Attributes	
	Stability	
	Health	
Structural capital	Database structures	Bryl et al., (2019); Wendra et al., (2019); Kaus et al., (2020); Qureshi and Siddiqui (2020); Turovets (2021); Ocak and Findik (2019); Niebel et al (2017); Corrado et al., 2022; Hsiao et al., (2021); Shakina and Barajas (2015); Krusinskas et al., (2015); Muntean (2014); De Ridder (2014); Li and Wu (2018)
	Process/Routine	
	Supply chains, and distribution	

Relational capital	Goodwill	Nakatani (2021); Ferdaous and Rahman (2019); Trequattrini et al., (2022); Bryl (2019); Wendra et al., (2019); Qureshi and Siddiqui (2020); Turovets (2021); Ionita and Elena Dinu (2021); Fu and Ghauri (2019); Ocak and Findik (2019); Niebel et al (2017); Corrado et al., 2022; Hsiao et al., (2021); Yeşim, and Kılıçaslan (2016); Shakina and Barajas (2015); Krusinskas et al., (2015); Muntean (2014); Roth et al., (2023); Teece (2015); Li and Wu (2018)
	Brand	
	Trademarks	
	Advertising	
Research and Development	Patents	Nakatani (2021); Ferdaous and Rahman (2019); Trequattrini et al., (2022); Kaus et al., (2020); Qureshi and Siddiqui (2020); Turovets (2021); SEO and KIM (2020); Postuła and Chmielewski (2019); Ionita and Elena Dinu (2021); Fu and Ghauri (2021); Ocak and Findik (2019); Niebel et al (2017); Corrado et al., (2022); Hsiao et al., (2021); Yeşim, and Kılıçaslan (2016); Muntean (2014); Roth et al., (2023); Teece (2015); Li and Wu (2018)
	Research expenses	
	Expenditure for market development	
Information and Technology	Copyrights	Nakatani (2021); Ferdaous and Rahman (2019); Trequattrini et al., (2022); Kaus et al., (2020); Qureshi and Siddiqui (2020); Turovets (2021); Postuła and Chmielewski (2019); Ionita and Elena Dinu (2021); Fu and Ghauri (2021); Ocak and Findik (2019); Niebel et al (2017); Corrado et al., 2022; Hsiao et al., (2021); Muntean (2014); Li and Wu (2018)
	Software	
	IP	
	Licenses	

6.1.2 Step A2 Evaluation on required intangible assets for maintenance implementation and operation

Following the methodology discussed in Chapter 3, Section 3.4. A questionnaire survey is conducted to receive expert judgements to identify the required intangible assets for maintenance implementation and operation. Totally 13 experts participated on the survey, the result is present in the Table 6-2.

Table 6-2 Intangible assets relevancy to maintenance

Intangible Assets Dimensions	Sub-Dimensions	Positive	Negative	Natural
Human Capital	Education	3	4	6
	Experience/Knowledge	10	0	3
	Training	13	0	0
	Skills	13	0	0
	Attitude	9	2	2
	Personal Attributes	2	9	2
	Stability	0	8	5
	Health	2	8	3
Structural capital	Database structures	3	1	9
	Process/Routine	10	1	3
	Supply chains, and distribution	1	9	3
Relational capital	Goodwill	0	11	2
	Brand	0	13	0
	Trademarks	0	13	0
	Advertising	0	13	0
Research and Development	Patents	8	2	3
	Research expenses	9	0	4
	Expenditure for market development	2	9	2
Information and Technology	Copyrights	1	10	2
	Communication and Software	13	0	0
	IP	0	12	1
	Licenses	0	13	0

To assess the relevance of each sub-dimension, it is essential to establish a threshold for positive responses. If a sub-dimension receives more than 50%

positive feedback (7 or more affirmative responses), it cannot be deemed sufficiently supported and is thus recommended for retention. In a similar manner, it is beneficial to set a threshold for negative responses. If a sub-dimension is met with a significant proportion of negative feedback (more than 50%), it may warrant consideration for removal from the evaluation. It's also important to analyze the number of neutral responses as they can provide insights into the overall assessment. A high prevalence of neutral responses might suggest weak relevance for that particular sub-dimension, indicating a lack of strong opinions from experts. Therefore, the retaining intangible asset dimension for maintenance implementation and operation are presented in the following Table 6-3.

Table 6-3 Intangible assets for maintenance implementation and operation

Intangible Assets Dimensions	Sub-Dimensions
Human Capital	Experience/Knowledge Training Skills Attitude
Structural Capital	Process/Routine
Research and Development	Research expenses
Information and Technology	Communication and Software

6.2 Step B Maintenance implementation and operation maturity model

Following the methodology outlined in Chapter 3, Section 3.4, and presented in Figure 6-1, a maturity model for maintenance implementation and operation is developed. This model allows for the assessment of the current state of intangible assets and identification of the maturity level to be achieved. The purpose of developing this maturity model is to differentiate between various maintenance strategies based on their capabilities. Often, the descriptions of maintenance strategies are not sufficient to clearly explain their capabilities. This is particularly important for PdM, as numerous models corresponding to this strategy have been published, each with different levels of capability. Without distinguishing between

these models, manufacturers applying PdM may struggle to understand the specific benefits that a PdM system can bring to their operations. The maintenance maturity model addresses this by using capability levels to distinguish between different maintenance strategies. This approach allows users to understand the potential benefits at each maturity level before implementing PdM, helping to avoid situations where the required capabilities are not met or where resources are wasted after implementation.

In addition, by integrating the maintenance maturity model with an intangible asset evaluation method (Section 6.3), enterprises can examine their existing intangible assets and identify the additional assets required to reach their desired maturity level. Five maintenance maturity levels are identified, ranging from Level One to Level Five. As the levels increase, more capabilities can be obtained, but greater costs and efforts are required for implementation, as presented in Figure 6-2.

LEVEL 5	Beyond the capability of Level four, at this level, the company have started to extract value from data.
LEVEL 4	The process is continuously analysed, and failure is predicted by collecting and monitoring operation data.
LEVEL 3	Periodical component/device monitoring is taken, and component/device state is analysed.
LEVEL 2	Maintenance operation is planed; maintenance operations are taken after specific working time.
LEVEL 1	At maturity level one, maintenance operation is poorly planned or unplanned.

Figure 6-2 Maintenance maturity levels

The detailed descriptions of each maturity level are presented as follows. These maturity levels have been developed based on a study of maintenance and predictive maintenance practices, as outlined in Chapter 3, Section 3.4. The

maturity levels are grounded in the maintenance practice capabilities discussed in various publications. Two rationale tables for the maturity levels, presented in Table 6-4 and Table 6-5, serve as supplements to the descriptions and define the rationale behind each level. The rationale not only outlines the benefits of each maturity level but also serves as a measurement and assessment tool for evaluating maturity levels, assisting organizations in assessing their current maturity status. These tables also include the sources of the publications referenced to establish the maturity levels.

Maturity level one

Maintenance is reactive, occurring only when equipment fails. No planning or tools are in place.

Maturity level two

Maintenance is planned with scheduled tasks, but unexpected breakdowns can still occur.

Maturity level three

Periodic monitoring and analysis of components/devices are performed. Maintenance is data-driven but lacks real-time prediction.

Maturity level four

Continuous monitoring enables real-time failure prediction. A data-driven decision-making process is established, replacing a manager-driven approach.

Maturity level five

A fully integrated data-driven maintenance process is in place, linked with other business functions, allowing real-time updates and coordination across the value chain.

To better distinguish the five maturity levels, their rationale is presented in this section. Two dimensions are considered for their assessment, namely: “Basic Function”, and “Additional Functions”. Both dimensions include multiple sub-

dimensions. Besides the types of sub-dimensions, sub-dimension capability levels are also included to justify their rationale. Sub-dimension capability levels describe the capability of each maturity level in terms of each dimension.

“Basic Function” refers to the fundamental function for maintenance tasks including productivity improvement, safety improvement, quality improvement and ensure functionality. Since the sub-dimensions for “Basic Function” are qualitative in nature, a marking scales is employed to quantify them. The marking is based on the description of PdM capabilities in terms of the sub-dimensions published by researchers. The marking scale for Basic Function is presented in Table 6-4.

Table 6-4 Maturity level basic function rational

Basic Functions						
	Maturity Levels					
	Level 1	Level 2	Level 3	Level 4	Level 5	
Ensuring function	Retraining the device to a functional state	Retraining the device to a functional state	Retraining the device to a functional state	Retraining the device to a functional state	Retraining the device to a functional state	
Productivity	The production process can be interrupted by unexpected shutdowns (Löfsten, 2000).	Productivity improves, the number of unexpected shutdowns decreases, and production typically runs smoothly (Löfsten, 2000).	Fuzzy state prediction enables device inspection, fault estimation, and prevention of unexpected shutdowns before job completion (Tiddens et al., 2020).	Accurate fault prediction is achieved, enabling the accurate prediction of remaining useful life for parts. (Saez et al., 2018).	Accurate fault prediction is achieved, and possible faults can be detected and predicted in real-time (Daily and Peterson, 2016).	

Quality	May lead to defects or inconsistencies in production (Gouiaa-Mtibaa et al., 2018)	Produce higher-quality products, and improve overall production efficiency (Gouiaa-Mtibaa et al., 2018)	Product quality is improved, and any uninspected tool or device defect is minimized before completing a specific job (Tiddens et al., 2020).	Product quality is further improved, and uninspected tool or device defects are predicted and resolved in advance (He et al., 2018).	Product quality is improved to the greatest extent, as uninspected tool or device defects are predicted and resolved in advance. (Lu et al., 2021).
Safety	Often deals with unexpected failures, which can introduce higher safety risks (Parida et al., 2009)	Reduces the occurrence of emergency repairs and unsafe conditions (Erwin and Susan, 2008)	The device is anticipated to operate normally until a specific job is completed, aiming to enhance safety (Compare et al., 2019).	Safety for the operator, device, and customer is further enhanced with the expectation of normal device operation (Yoon et al., 2017).	Theoretically, any potential safety risk is predicted in real-time and resolved in advance (Gorür et al., 2021).

“Additional Functions” refers to the functions related to or enabled by maintenance tasks including production management improvement, logistic improvement, transparency improvement, and sustainability improvement. The same marking method as in the case of “Basic Function” marking is employed, and the marking scale for Additional Functions is presented in Table 6-5.

Table 6-5 Maturity level additional functions rational

Additional Functions					
Maturity Levels					
	Level 1	Level 2	Level 3	Level 4	Level 5
Production		The production plan optimized alongside the maintenance plan, but it may be disrupted by unexpected shutdowns.	The production plan will not be affected since device shutdown can be avoided before a specific job is finished (Tiddens et al., 2020).	Production plans are automatically conducted by production management software using device operation data (Lee et al., 2017).	Management software automatically conducts production plans using real-time device data. If stakeholders change, plans can be instantly re-optimized (Einabadi et al., 2019).

Logistic	The raw material and spare part purchase plan, as well as the product delivery plan, can be optimized (Irawan et al., 2017).	Software automatically optimizes raw material and spare part purchase, storage plans, and product delivery plans (Hribernik et al., 2018).	The raw material and spare part purchase and storage plan, as well as the production delivery plan, are automatically optimized by software based on real-time device operation data. (Proto et al., 2020).
Sustainability		The waste of energy and raw materials is reduced since the productivity and product yield are improved (Çınar et al., 2020)	The waste of energy and raw materials is reduced to the largest extent since the productivity and product yield are improved to the largest extent (Rødseth et al., 2016)
Transparency		Any stakeholder is allowed to access the production, purchase storage plan, and delivery plan (Sang et al., 2020)	Any stakeholder is allowed to access and work on the production, purchase storage plan, and delivery plan in real-time (Rødseth et al., 2016)

Section 6.3 follows, outlining the tools and equations required to quantify intangible assets, facilitating the transition from conceptual understanding to practical assessment.

Expert Contributions to Model Refinement

The refinement of the maturity model is undertaken with input from the academic and industrial experts listed in Table 6-6. Their contributions influence both the descriptions of the maturity levels and the rationale tables (Tables 6-4 and 6-5), with particular emphasis on the integration of intangible assets.

Maturity level definitions

Academic experts emphasize that the distinction between Levels 2 and 3 must be clarified. Based on their input, “periodic monitoring and analysis” is more explicitly positioned as data-driven but not predictive, while “real-time prediction” is reserved for Level 4. Industry experts confirm that in practice, many

organizations remain at Level 2 despite partial monitoring, which justifies the stricter boundary between these levels. Maintenance engineers highlight that troubleshooting experience and tacit knowledge still dominate at Levels 1–2, and this observation is incorporated into the intangible asset requirements for early stages.

Basic Function refinements

In the “Productivity” sub-dimension, production managers stress that the reduction of shutdowns at Level 2 is often accompanied by improved scheduling discipline rather than advanced technology. This refinement ensures that Level 2 reflects managerial effort as much as technological development. For the “Safety” sub-dimension, maintenance engineers emphasize that informal safety practices (e.g., operator vigilance, communication across shifts) play a critical role at Levels 1–3. As a result, intangible assets such as communication flow and experiential awareness are integrated into the rationale. Academics contribute by linking the progression of safety practices to published evidence, ensuring alignment with scholarly sources.

Additional Function refinements

For “Production,” lecturers in manufacturing engineering suggest clarifying that automatic production planning at Level 4 depends not only on data integration but also on cultural readiness to delegate planning decisions to software. Production managers confirm that in practice, trust in system recommendations is a gradual process, which justifies the placement of this capability at higher maturity. In “Logistics,” maintenance engineers highlight the importance of tacit coordination with suppliers in Levels 2–3, which precedes full system-driven optimization. This refinement ensures that intangible assets such as supplier relationships and collaborative skills are acknowledged. In “Transparency,” associate professors emphasize the role of organizational culture and leadership support in allowing stakeholders to access data openly, and this requirement is added to the intangible assets for Levels 4–5.

6.3 Maintenance intangible assets evaluation method

In Section 6.2, the maturity model introduced serves as the foundation for the intangible asset evaluation method presented in this chapter. By utilizing this model, manufacturers can select the maturity level they wish to achieve based on their capability needs. The next step is to apply the maintenance intangible assets evaluation method detailed in this section to assess the types and amounts of intangible assets they currently possess and those required to reach the desired maturity level.

The maintenance intangible assets evaluation method consists of two parts: the Maintenance Intangible Assets Quantification Equation (Section 6.3.1) and the Maintenance Intangible Assets Quantification Marking Scale (Section 6.3.2). These tools enable manufacturers to evaluate their current intangible assets for maintenance and identify those needed for future development. After selecting the desired maturity level, they can use these tools to assess both the types and amounts of intangible assets currently in their possession and those necessary to achieve their target maturity level. This process also allows them to identify specific gaps between their existing intangible sub-dimensions and the requirements for their desired maturity level.

This chapter employs the interval scale method to evaluate intangible assets. This method is applied in two keyways. First, it is used to model attributes where zero is relative, such as temperature or efficiency. Second, it transforms qualitative data captured by ordinal word scales into a numerical interval scale. As discussed in Chapter 2, Section 2.4, this scaling method is the only approach that enables the quantification of intangible assets prior to any investment actions.

6.3.1 Step C Maintenance intangible assets quantification equations

This section presents the introduction of the Equation (Equation 6-1 to Equation 6-11) for maintenance intangible assets quantification following the methodology presented in Figure 6-1. The principle behind the Intangible Assets Quantification Equation is that the value of Maintenance Intangible Assets is equal to the

aggregate value of each Maintenance Intangible Assets dimension. The following equations express the measurement of enterprises' intangibles for maintenance implementation and operation:

$$I = \{I_{HC}, I_{SC}, I_{RD}, I_{IT}, \}$$
 (6-1)

Here, I represents the total measurement of an enterprise's intangible assets related to maintenance implementation and operation. The components $I_{HC}, I_{SC}, I_{RD}, I_{IT}$ correspond to measurements of four distinct intangible dimensions: I_{HC} represents Human Capital, I_{SC} represents Structural Capital, I_{RD} represents Research and Development, and I_{IT} represents Information and Technology.

The four dimensions of intangibles for maintenance implementation and operation are measured by the following equations 6-2 to 6-6.

$$I_{HC} = \{i_{HC1}, i_{HC2}, i_{HC3}, i_{HC4}, \}$$
 (6-2)

Where $i_{HC1}, i_{HC2}, i_{HC3}$, and i_{HC4} are the four sub-dimensions of Human Capital. Specifically, i_{HC1} is the sub-dimension Experience, i_{HC2} is the sub-dimension Training, i_{HC3} is the sub-dimension Skills and i_{HC4} is the sub-dimension Attitude of dimension Human Capital.

$$I_{SC} = \{i_{SC1}\}$$
 (6-3)

Where i_{SC1} is the sub-dimension Process/Routines of dimension Structural Capital.

$$I_{RD} = \{i_{RD1}\}$$
 (6-4)

Where i_{RD1} is the sub-dimension Research Expenditure of dimension Research and Development.

$$I_{IT} = \{i_{IT1}\}$$
 (6-5)

Where i_{IT1} is the sub-dimension Communication and Software.

The equation (6-1) is transferred to

$$I = \{i_{HC1}, i_{HC2}, i_{HC3}, i_{HC4}, i_{SC1}, i_{RD1}, i_{IT1}\} \quad (6-6)$$

The intangible sub-dimensions are measured using the Maintenance Intangible Assets Marking Scale presented in Section 6.4. When the measurements of all dimensions of Human Capital, Structural Capital, Research and Development, and Information Technology in an enterprise are equal to or greater than 1, the enterprise has achieved Maintenance Maturity Level 1:

$$I_{L1} = \{i_{HC1} \geq 1, i_{HC2} \geq 1, i_{HC3} \geq 1, i_{HC4} \geq 1, i_{SC1} \geq 1, i_{RD1} \geq 1, i_{IT1} \geq 1\} \quad (6-7)$$

When the measurements of all dimensions of Human Capital, Structural Capital, Research and Development, and Information Technology in an enterprise are equal to or greater than 2, the enterprise has achieved Maintenance Maturity Level 2:

$$I_{L2} = \{i_{HC1} \geq 2, i_{HC2} \geq 2, i_{HC3} \geq 2, i_{HC4} \geq 2, i_{SC1} \geq 2, i_{RD1} \geq 2, i_{IT1} \geq 2\} \quad (6-8)$$

When the measurements of all dimensions of Human Capital, Structural Capital, Research and Development, and Information Technology in an enterprise are equal to or greater than 3, the enterprise has achieved Maintenance Maturity Level 3:

$$I_{L3} = \{i_{HC1} \geq 3, i_{HC2} \geq 3, i_{HC3} \geq 3, i_{HC4} \geq 3, i_{SC1} \geq 3, i_{RD1} \geq 3, i_{IT1} \geq 3\} \quad (6-9)$$

When the measurements of all dimensions of Human Capital, Structural Capital, Research and Development, and Information Technology in an enterprise are equal to or greater than 4, the enterprise has achieved Maintenance Maturity Level 4:

$$I_{L4} = \{i_{HC1} \geq 4, i_{HC2} \geq 4, i_{HC3} \geq 4, i_{HC4} \geq 4, i_{SC1} \geq 4, i_{RD1} \geq 4, i_{IT1} \geq 4\} \quad (6-10)$$

When the measurements of all dimensions of Human Capital, Structural Capital, Research and Development, and Information Technology in an enterprise are equal to or greater than 5, the enterprise has achieved Maintenance Maturity Level 5:

$$I_{L5} = \{i_{HC1} \geq 5, i_{HC2} \geq 5, i_{HC3} \geq 5, i_{HC4} \geq 5, i_{SC1} \geq 5, i_{RD1} \geq 5, i_{IT1} \geq 5\} \quad (6-11)$$

It is important to note that to reach a maturity level, all dimensions must be equal to or greater than the required measurement number. Any dimension falling below the required number will result in the maturity level not being achieved. However, the fewer dimensions that fall below the required number, the closer the enterprise is to achieving the maturity level.

6.3.2 Step D Maintenance intangible assets marking scale

To further develop the marking scale necessary for evaluating intangible assets, interviews are conducted following the methodology outlined in Chapter 3, Section 3.4, and presented in Figure 6-1 (see Appendices 6-1 and 6-2). The second part of the intangible asset evaluation method was contributed to by these interviews, as they provided a systematic approach for assigning marks to the intangible asset sub-dimensions critical for maintenance implementation and operation. Information about the participants, including their roles and areas of expertise, is presented in Table 6-6, while the results of the interviews, highlighting key findings and insights, are summarized in Table 6-7. While the quantification equations provide a numerical basis for measuring intangible assets, the marking scale offers a detailed evaluation approach, categorizing competencies into five levels. This enables a nuanced understanding of intangible asset maturity. Both the quantification equations and the marking scale are utilized to identify intangible asset gaps, providing a clear path for achieving the target maturity level.

Table 6-6 Interview participant information

Participant	Age	Education	Occupation	Industry/ Specialty
1	43	PhD	Associate Professor	Mechanical Engineering
2	52	Undergraduate	Production Manager	Auto
3	39	PhD	Associate Professor	Industry Design
4	37	PhD	Lecturer	Manufacturing Engineering

5	45	Postgraduate	Maintenance Engineer	Auto
6	33	PhD	Lecturer	Manufacturing Engineering
7	49	Postgraduate	Maintenance Engineer	Small Application

Table 6-7 is designed to evaluate maintenance experience and knowledge assets within an organization, with competencies categorized into five progressive levels (Marks 1 to 5). At Mark 1, foundational skills are assessed, including the identification of failures, understanding of their impacts, and effective communication. At Mark 2, the ability to conduct preventive maintenance and develop scheduling plans is evaluated. At Mark 3, diagnostic skills, such as the recognition of operational indicators and the estimation of maintenance timing, are measured. At Mark 4, the interpretation of PdM system alerts, assessment of impacts, and decision-making based on severity are examined. At Mark 5, strategic tasks, including the evaluation of PdM-based plans and the optimization of stakeholder collaboration, are required

Table 6-7 Maintenance experience/knowledge assets marking scale

Experience/Knowledge Description	Marks
<ul style="list-style-type: none"> • Identify the root cause of failure: Recognize underlying issues that lead to equipment malfunctions (Q16A5). • Understand the effects of failure: Comprehend how failures impact operations and productivity (Q16A6). • Prevent future failures: Implement strategies to avoid recurrence of similar issues (Q16A7). • Communicate and report issues: Clearly convey problems and findings to team members for effective resolution (Q16A1). 	Mark 1
<ul style="list-style-type: none"> • Understand the maintenance scheduling plan: Laborers have a clear understanding of the maintenance scheduling plan (Q19A1). • Conduct preventive maintenance: They carry out proper preventive maintenance according to the established plan (Q19A1). 	Mark 2

- **Develop a preventive maintenance schedule:** Management develops the preventive maintenance plan (Q19A1).
- **Plan based on operational factors:** The schedule is designed based on factors such as machinery, production, and storage needs (Q19A1).
- **Identify potential component damage:** Laborers can identify potential critical component damage by analyzing machine operation parameters and monitoring conditions (Q5A1, Q5A5). Mark 3
- **Recognize operational indicators:** They recognize signs such as noise, abnormal vibration, and product defects as possible indicators of machine issues (Q5A2, Q5A5).
- **Use experience for assessments:** Employees use their experience and machine observations to evaluate if the machine is operating normally (Q5A3).
- **Estimate maintenance timing:** Based on their assessments, they can estimate the time remaining until the next required maintenance task (Q5A5).
- **Fault recognition and action:** Laborers can recognize potential machine issues and understand the corresponding actions required for faults detected by the PdM system (Q9A1). Mark 4
- **Impact assessment:** They possess the knowledge to assess the potential impacts of faults reported by the PdM system (Q9A1).
- **Procedure familiarity:** Laborers are familiar with the appropriate procedures to follow when receiving PdM system alerts (9QA2).
- **Decision-making on severity:** They can determine whether to double-check the device, report detected faults, continue production while inspecting, or immediately shut down the device based on the severity of the alert (Q9A3, Q9A4).
- **Higher standards for management:** At Mark 5, the management team is held to higher expectations in responding to PdM system alerts or external stakeholder changes (Q13A6). Mark 5
- **Evaluating maintenance plans:** When the PdM system detects potential future machine failures or stakeholder requirement changes,

managers must evaluate new alternative maintenance plans provided by PdM systems (Q13A6).

- **Optimized collaboration:** Ensures effective collaboration between internal and external stakeholders, optimizing production and maintenance plans while minimizing disruptions (Q13A6).

Table 6-8 is structured to evaluate maintenance skills assets, categorizing competencies into five progressive levels (Marks 1 to 5). At Mark 1, fundamental skills are assessed, including performing corrective repairs and understanding the tools required for such operations. At Mark 2, the ability to execute preventive maintenance actions, conduct inspections, apply lubrication, and replace worn parts is evaluated. At Mark 3, skills in identifying fault types, implementing appropriate maintenance actions, ensuring device functionality, and utilizing inspection tools are examined. At Mark 4, workers are evaluated on their ability to interpret PdM fault reports, resolve system issues, communicate effectively across departments, and make decisions based on key factors like costs and inventory. At Mark 5, advanced responsibilities are assessed, such as making critical decisions regarding production and maintenance planning, supervising teams, and communicating with external stakeholders to implement alternative plans effectively.

Table 6-8 Maintenance Skills assets marking scale

Skills Description	Mark
<ul style="list-style-type: none"> • Corrective repair skills: Labor should have the essential skills to perform corrective repairs or replacements on machinery (Q15A1, Q16A1). • Understanding of tools: Workers must have a thorough understanding of the tools required for these operations, they should be able to utilize the right equipment effectively for specific tasks (Q16A1, Q16A2, Q16A3). 	Mark 1
<ul style="list-style-type: none"> • Carry out preventive maintenance actions: Implement scheduled maintenance to ensure optimal machine performance (Q20A1, Q20A2). 	Mark 2

- **Conduct regular inspections:** Perform systematic checks on equipment to identify any potential issues before they escalate (Q20A2).
- **Execute planned lubrication:** Apply lubricants at scheduled intervals to reduce friction and wear (Q20A2).
- **Timely replace worn parts:** Identify and replace parts that have reached the end of their useful life to maintain machine efficiency (Q20A2).
- **Identify fault types:** Recognize different types of faults that may occur in devices (Q5A5). Mark 3
- **Conduct appropriate maintenance actions:** Implement suitable maintenance procedures based on the identified fault types (Q5A7).
- **Ensure device functionality:** Take corrective and preventative actions to maintain or restore the functionality of the devices (Q5A6, Q5A7).
- **Inspection tool operation:** Use tool to conduct inspection actions (Q7A1).
- **Understand fault reports:** Interpret the fault reports generated by the PdM system and respond promptly to these alerts (Q9A1). Mark 4
- **Resolve PdM system issues:** Address and correct issues related to the PdM system, such as sensor faults and network delays (Q9A2).
- **Communication skills:** Effectively report and communicate potential device faults to relevant departments (e.g., production planning, logistics, management) using internal information and management systems. This includes basic data input and processing skills (Q9A5).
- **Decision-making:** Evaluate and select alternative action plans recommended by the system (Q9A4).
- **Consideration of key factors:** Managers need to assess various factors such as costs, inventory, and labour when evaluating the options (Q9A4).
- **Departmental collaboration:** They must determine which departments (e.g., production, maintenance, quality control) should implement the new maintenance alternatives (Q9A5).

- **Critical decision-making:** Make informed decisions regarding production and maintenance planning based on information from PdM system alerts, customer requirements, spare part inventory, workforce availability, and other relevant factors (Q13A1). Mark 5
- **Supervision:** Oversee production, maintenance, and logistics teams to ensure the effective implementation of these alternative actions (Q13A1, Q13A2).
- **Communication with stakeholders:** Effectively communicate with external stakeholders regarding the proposed alternative plans (Q13A3).

Table 6-9 is structured to evaluate maintenance training assets, categorizing competencies into five progressive levels (Marks 1 to 5). At Mark 1, training focuses on improving efficiency, enhancing safety, reducing downtime, and promoting better tool management. At Mark 2, workers are trained to recognize early signs of equipment issues and proactively schedule maintenance tasks. At Mark 3, comprehensive training on maintenance operations is provided, with an emphasis on hands-on experience and the "learning by doing" approach. At Mark 4, training shifts to understanding predictive maintenance systems, including data interpretation and alert handling. At Mark 5, the focus is on fostering a digital culture, building trust in data-driven systems, and understanding information security procedures.

Table 6-9 Maintenance training assets marking scale

Training Description	Mark
<ul style="list-style-type: none"> • Increased Efficiency: Proper training in tool usage leads to more efficient maintenance activities, allowing tasks to be completed more quickly and effectively (Q16A3). • Enhanced Safety: Training promotes safety by ensuring that workers understand how to use tools correctly, reducing the risk of accidents and injuries during maintenance tasks (Q16A4, Q16A5). 	Mark 1

-
- **Reduced Downtime:** Well-trained personnel can perform maintenance tasks more swiftly, minimizing equipment downtime and maintaining operational productivity (Q16A3).
 - **Better Tool Management:** Understanding how to use tools appropriately aids in their maintenance and care, prolonging their lifespan and reliability (Q16A3).
 - **Sign Recognition:** Workers should be trained to identify early signs of wear and tear, such as unusual noises, vibrations, or performance drops, which can indicate potential equipment issues (Q19A3). Mark 2
 - **Proactive Maintenance Scheduling:** Training empowers workers to schedule maintenance activities proactively, reducing the likelihood of unexpected equipment failures (Q19A3).
 - **Training on Maintenance Operations:** The company provides comprehensive training focused on maintenance operations, covering topics such as work orders and maintenance techniques (Q6A1, Q6A2, Q6A5, Q6A6). Mark 3
 - **Hands-On Experience:** Training is delivered through practical, hands-on experiences alongside maintenance experts (Q6A3).
 - **Learning by Doing:** The "learning by doing" methodology allows operators to gain practical experience (Q6A4).
 - **System Understanding:** In addition to Level 3, training for Level 4 focuses on understanding and operating predictive maintenance and communication systems (Q10A1). Mark 4
 - **Data Interpretation:** Employees learn to interpret data and alerts generated by PdM systems (Q10A1).
 - **Digital Culture:** In addition to Level 4, training for Level 5 emphasizes building a digitalized culture within the company (Q13A1). Mark 5
 - **Trust in Data-Driven Systems:** The aim of this training is to ensure that both operators and the management team trust the alternative providers recommended by data-driven systems (Q13A1).
 - **Information Security:** Familiar with information security management procedures (Q14A3).

Maintenance attitude assets are evaluated in Table 6-10, categorized into five progressive levels (Marks 1 to 5). At Mark 1, a basic attitude toward corrective maintenance is deemed sufficient, without requiring openness to new technologies. At Mark 2, a positive attitude is emphasized toward preventative maintenance and adherence to established schedules. At Mark 3, team collaboration and trust in expert judgments for condition monitoring are required. At Mark 4, openness toward PdM systems, trust in their alerts and plans, and a willingness to learn digitalization technologies are expected. At Mark 5, strong communication and trust between teams are fostered, alongside openness to integrated digitalized processes.

Table 6-10 Maintenance attitude assets marking scale

Attitude	Mark
<ul style="list-style-type: none"> • Attitude Towards Technology: Employees and the management team do not need to maintain an open attitude toward new maintenance management technologies (Q16A8). • Focus on Skills: They only need to possess the skills required to effectively execute corrective maintenance (Q16A8). 	Mark 1
<ul style="list-style-type: none"> • Positive Attitude: Employees must have a positive attitude toward implementing preventative maintenance and adhering to the maintenance schedule (Q16A8). • Task Compliance: It is essential to ensure that maintenance tasks are performed according to the established schedule (Q16A8). 	Mark 2
<ul style="list-style-type: none"> • Team Collaboration: The maintenance, production, and management teams need to trust expert judgments and maintain an open attitude toward condition monitoring (Q5A8). 	Mark 3
<ul style="list-style-type: none"> • Open Attitude: Production and maintenance workers, along with the management team, must maintain an open attitude towards the PdM system, trust the alerts and plans provided by the PdM system (Q11A1). • Learning and Adaptation: The team needs to be willing to learn about digitalization technologies and knowledge believe that these tools can improve efficiency and reduce costs (Q11A2). 	Mark 4

- **Positive Mindset:** Both the workforce and management team must maintain a positive attitude towards PdM systems trust the predictions generated by these systems (Q11A3).
- **Learning and Adaptation:** At this stage, the company has digitized and integrated multiple processes in addition to implementing PdM. Mark 5
- **Openness:** Openness from Level 4 is essential (Q13A9).
- **Communication and Trust:** Strong communication and trust between teams are necessary when addressing changes and requests from different departments (Q13A9).

Table 6-11 is designed to evaluate maintenance process and routine assets, categorizing them into five progressive levels (Marks 1 to 5). At Mark 1, basic process design is not required, but failures are expected to be reported promptly, and relevant details are to be recorded accurately. At Mark 2, timely record-keeping, process establishment for planning and communication, and root cause analysis are prioritized. At Mark 3, preventive maintenance is emphasized, with inspections carried out continuously, potential failures reported immediately, collaborative plans developed, and data stored for future optimization. At Mark 4, PdM-driven processes are implemented, including data collection, standardization, secure sharing, and decisions made based on equipment life and fault alerts. Communication protocols and feedback mechanisms are also established to ensure smooth adjustments. At Mark 5, collaboration mechanisms with internal and external stakeholders are established, dynamic adjustments to plans are enabled, a data-driven decision-making process is implemented, and new strategies are communicated effectively by the management team.

Table 6-11 Maintenance process/routines assets marking scale

Process/Routines	Mark
<ul style="list-style-type: none"> • Process Design: At this level, the company does not require much process design (Q15A1). • Effective Corrective Maintenance: To perform corrective maintenance more effectively, it is essential to promptly report failures (Q15A2, Q15A3). 	Mark 1

-
- **Detailed Recording:** In addition to reporting, it is necessary to record the time, type, and other relevant details of the failure(Q15A2).
 - **Timely Record-Keeping:** At this level, there is a need to promptly record the failure type, time, and other relevant details (Q18A1, Q18A4). Mark 2
 - **Process Establishment:** Establish processes for timely planning, deployment, and communication of the maintenance plan based on order requirements (Q18A2).
 - **Root Cause Analysis:** Conduct root cause analysis to optimize processes and reduce losses (Q18A1).
 - **Preventive Maintenance Focus:** The primary focus at this level is on preventive maintenance (Q1A2, Q3A1). Mark 3
 - **Continuous Inspections:** Planned inspections of machines or condition parameters are carried out continuously (Q3A2).
 - **Immediate Reporting:** When potential failures are detected, they must be reported immediately (Q3A2).
 - **Collaborative Planning:** Maintenance experts and the management team should collaborate on the subsequent production/maintenance plan, which will then be communicated to all departments (Q3A3, Q3A4).
 - **Data Storage for Optimization:** Data on failures and inspections should be stored to optimize processes in the future (Q3A5).
 - **Data Collection and Standardization:** At this level, the PdM system will collect necessary data, which will be standardized and securely handled to ensure data sharing across departments while maintaining data security (Q8A1, Q8A2). Mark 4
 - **Continuous Improvement of Predictions:** The collected data, including machine operation and degradation data, will continuously enhance the accuracy of PdM predictions (Q8A10, Q8A11).
 - **Comprehensive Data Management:** During the design and implementation of PdM, plans for data storage, access, and security must also be established (Q8A2).

- **Critical Decision-Making:** Decisions regarding maintenance and production workflows will be based not only on orders but also on the remaining useful life of device components and fault alerts (Q8A3).
- **Dynamic Planning Adjustments:** Maintenance and production plans will be adjusted based on orders and the remaining useful life of the equipment (Q8A4, Q8A5, Q8A6, Q8A7).
- **Replanning and Task Allocation:** When a potential failure is detected, the management team must replan production, maintenance, logistics, and allocate new tasks to departments (Q8A4, Q8A9).
- **Established Communication Protocols:** In addition to the tools, communication rules and routines are established within the company, such as setting time limits for operators to report device conditions, deadlines for management decisions, and time limits for operators to respond to alternative plans. These rules and routines ensure smooth communication among departments (Q8A13).
- **Feedback Mechanism:** A timely feedback mechanism must be established to ensure that all departments adjust their tasks and plans accordingly (Q8A10, Q8A11, Q8A12).
- **Internal and External Collaboration:** Building on Level 4, the key addition at this level is the establishment of collaboration mechanisms that engage both internal and external stakeholders, allowing them to actively participate and upload their changes and requirements (Q13A1, Q13A2, Q13A3). Mark 5
- **Dynamic Planning Adjustments:** This collaboration enables dynamic changes in production and maintenance plans to meet the needs of both internal departments and external stakeholders (Q13A1, Q13A2).
- **Data-Driven Decision-Making:** A data-driven decision-making process is established, with maintenance and production plans formulated based on orders and the remaining useful life of the equipment (Q13A1).
- **Management Team Responsibilities:** The management team must select the most suitable alternative plan and communicate the new plan effectively with all stakeholders (Q13A1).

In Table 6-12, the allocation of maintenance research expenses is presented across five progressive levels (Marks 1 to 5). At Mark 1, expenses are allocated to reactive maintenance, with efforts directed toward resolving failures, minimizing downtime, and restoring functionality. At Mark 2, funding is allocated for optimizing maintenance scheduling and preventive methods to reduce unplanned downtime. At Mark 3, costs are incurred for assessing machine conditions and researching the integration of maintenance operations with production scheduling. At Mark 4, investments are made in the development and implementation of PdM systems, including technical setup, staff training, and workflow adjustments. At Mark 5, funding is directed toward the development of integrated systems, ensuring synchronization of PdM data with production, logistics, and supply chain operations, and enabling holistic decision-making and seamless communication between internal and external stakeholders.

Table 6-12 Maintenance research expense assets marking scale

Research Expense	Mark
<ul style="list-style-type: none"> • Reactive Maintenance Focus: These expenses primarily focus on reactive maintenance, which is a response to equipment failures (Q20A1, Q20A2). • Cost Considerations: Costs may be incurred to determine how to detect and resolve unexpected failures (Q20A2). • Restoration of Functionality: The goal of research is to restore functionality as quickly as possible to minimize downtime and operational disruptions (Q20A2). 	Mark 1
<ul style="list-style-type: none"> • Optimizing Maintenance Scheduling: Research funding might be allocated towards optimizing maintenance scheduling management and technology (Q21A3, Q21A4). • Exploration of Effective Methods: This includes exploring methods for more effective preventive maintenance (Q21A5). • Avoiding Unplanned Downtime: Optimizing maintenance scheduling helps to avoid unplanned downtime, enhancing overall operational efficiency (Q21A4, Q21A5). 	Mark 2

- **Costs Related to Machine condition Assessment:** In addition to Mark 3
costs related to determining the health condition of machines based on
experience and condition-monitoring data (Q21A6, Q21A7, Q21A8).
- **Expenses for Integration Research:** There may also be expenses
dedicated to researching how to better integrate maintenance
operations with production scheduling (Q21A8, Q21A9).
- **Investment in PdM Systems:** Costs will be directed towards Mark 4
developing, fine-tuning, and promoting the adoption of PdM systems
within the company (Q21A10, Q21A11, Q21A12, Q21A13).
- **Technical Implementation:** This includes not only the technical
implementation of the PdM system also other support technology
(Q21A11).
- **Staff Training:** Investment will also focus on training staff to ensure
they are equipped to use the new system effectively (Q21A12).
- **Workflow Adjustments:** Additionally, workflows will be adjusted to
leverage the PdM system effectively (Q21A13).
- **Investment in Integrated Systems:** Expenses will focus on Mark 5
developing, refining, and promoting the use of integrated systems that
enable seamless communication between internal departments and
external stakeholders (Q21A14, Q21A18, Q21A19).
- **Data Synchronization:** This includes ensuring that data from PdM
systems, production, logistics, and supply chain operations are fully
synchronized (Q21A15-A17).
- **Holistic Decision-Making:** The goal is to enable more holistic
decision-making and collaboration both within the company and with
partners (Q21 A19).

The allocation of communication and software assets is presented in Table 13 across five progressive levels (Marks 1 to 5). At Mark 1, basic communication methods, such as oral or written exchanges, are utilized without specific technology requirements. At Mark 2, maintenance and production planning software may be required, along with data storage systems for maintenance records. At Mark 3, IoT systems may be installed to collect and visualize machine condition data, though real-time monitoring and fully digital processes are not yet

implemented. At Mark 4, PdM system-based maintenance plans necessitate IoT and data visualization software, machine-to-machine communication, and digital tools for internal communication and decision-making. At Mark 5, digital communication tools and standardized software are used to enable seamless connectivity with external stakeholders, facilitating efficient information sharing across internal and external entities.

Table 6-13 Maintenance communication and software assets marking scale

Communication and Software	Mark
<ul style="list-style-type: none"> • Communication Methods: At Level 1, there is no need for any specific communication technology. Information can be conveyed orally or in writing (Q17A1, Q17A2). 	Mark 1
<ul style="list-style-type: none"> • Software Requirements: At Level 2, maintenance planning and production planning software may be required (Q20A1). • Data Management: Additionally, data storage systems might be used to store maintenance records (Q20A1). 	Mark 2
<ul style="list-style-type: none"> • Communication Tools: Similar to Level 2, at Level 3, fully digitalized or data-driven maintenance and production processes have not yet been implemented, so the company does not need to adopt specific communication tools (Q7A2). • Information Sharing: Maintenance-related information (such as maintenance plans, device condition, production plans, and spare part availability) can be communicated face-to-face, through documentation, phone calls, text messages, or social media among departments, as real-time monitoring and decision-making are not yet in place (Q7A2). • IoT Implementation: However, since regular inspections are required at this level, it may be necessary to install IoT systems on machines and use software to collect, visualize, and record machine condition data (Q7A3). 	Mark 3
<ul style="list-style-type: none"> • Data-Driven Maintenance Plans: By Level 4, maintenance plans are based on PdM system monitoring and predictions (Q12A4). 	Mark 4

- **IoT and Data Visualization:** IoT system software needs to be installed to standardize and visualize the collected data, which is analyzed in real-time by PdM model software to predict the remaining useful life (RUL) of equipment (Q12A1, Q12A6).
- **Data Management Systems:** Given the large amount of data collected and processed, storage systems and data transmission systems must also be installed (Q12A1, Q12A2, Q12A3).
- **Machine-to-Machine Communication:** Machine-to-machine data exchange becomes essential to ensure the efficient transfer and use of data, enabling automated communication between machines without human intervention. This allows machines to directly update systems, schedule maintenance, or request parts (Q12A1).
- **Digital Communication Tools:** A specific digital communication tool is used within the company to convey maintenance information. Operator responses and management decisions (such as alternative maintenance, production, or logistics plans) are also transmitted and reported through this tool, which could be an app, website, or digital platform (Q12A5, Q12A6).
- **Enhanced Connectivity with External Stakeholders:** Building on Level 4, at Level 5, digital communication tools enable the company to connect with external stakeholders, including suppliers, customers, and supply chains (Q14A2, Q14A4). Mark 5
- **Standardized Information-Sharing Software:** Additionally, standardized information-sharing software is needed to facilitate communication regarding orders and service requirements between internal teams and external stakeholders (Q14A1, Q14A3).

6.4 Step E Maintenance intangible assets quantification case study and implementation strategy

Following the methodology presented in Figure 6-1, the maintenance intangible assets quantification case study and implementation strategy is presented in this section.

6.4.1 Case study introduction

Purpose and Scope

This case study assesses the intangible assets required for implementing PdM in a large Chinese automotive manufacturing company. The research objectives are twofold: to evaluate the necessary intangible assets for PdM and to create a strategy map to guide successful adoption.

Company Background and Challenges

The company is a major manufacturer of precision automotive parts, operates several automated production lines and employs diverse equipment types, including CNC machines, industrial robots, stamping machines, and injection molding machines. Its production processes—such as metal stamping, casting, plastic injection molding, and polishing—require high operational efficiency to minimize downtime and maximize output quality. Equipment failure currently impacts production significantly, which motivates the company to implement PdM as a proactive solution.

6.4.2 Step E2 – Step E4 Intangible assets evaluation

First, the case study analyses the current state of the company's maintenance operations and the goals for PdM implementation. Detailed information from the case study is provided in Table 6-14.

Table 6-14 Case study maintenance operation function analyze

Themes	Present	Target
Productivity	– Corrective maintenance actions sometimes required	– Reduce corrective maintenance number and time.
	– Regular preventative, inspection, lubrication, replacement are	– Reduce the required PM number.
		– Reduce preventative replace frequency.

	conducted to minimize unexpected shutdown.	– Increase the total machine available time.
Quality	– Regular product inspections are conducted.	– Reduce product defect.
		– Reduce the cost of product inspection.
	– Machine degradation analysis is performed when product defects are identified.	– Enable automated product quality inspection
		– Enable automated product defect detection and root cause analysis.
Safety	– Ensure operator safety	– Ensure operator safety
Production	– Production plan based on order information and integrated with maintenance plan.	– Adapt of order change and optimize production plan and maintenance plan in short time.
	– Ensure order delivery.	– Production plan optimized dynamically with the change of order, storage and logistic information.
Logistic	– Spare parts, raw material are purchased in advanced based on order information.	– Dynamic spare part, raw material purchase, reduce storage room waste and enhance cashflow.
	– Final products are packed and stored in warehouse and wait for delivery.	– Dynamic logistic planning for product delivery, ensure on time delivery and quickly adapt to order change.
Sustainability	– None	– Raw material saving by reducing low quality product.

Transparency	– Internal multidepartment transparency	– Receive order and perchance information on time.
		– Allow share of production, process, and delivery information.

Based on the maturity level functions outlined in Tables 6-4 and 6-5, the current maintenance operation functions and the target PdM implementation functions for the company are shown in Figure 6-3.

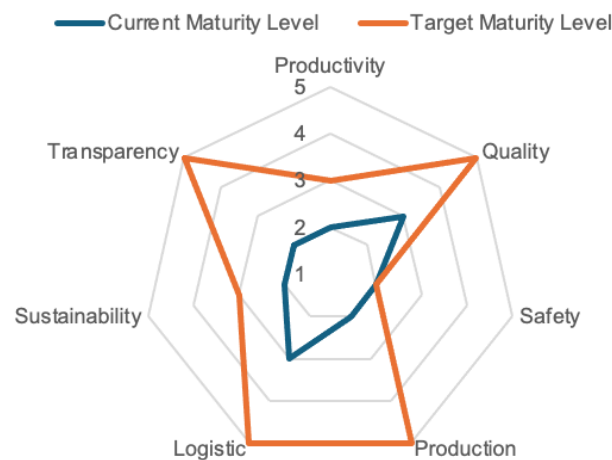


Figure 6-3 Case study current and target maintenance maturity level

According to the results in Figure 6-3, the company's maintenance maturity has currently reached Level 2. However, it is evident that the company has achieved Level 5 in four of the seven target functions. To fully meet its objectives, the company needs to elevate its maintenance maturity level to Level 5.

The next step involves analyzing the current state of the company's intangible assets, as detailed in Table 6-15.

Table 6-15 Analysing the current state of the company's intangible assets

Intangible Asset	Description
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Experience/Knowledge	<ul style="list-style-type: none"> – Laborers are fully aware of the maintenance scheduling plan to ensure smooth operations. – They are responsible for conducting preventive maintenance in line with the established schedule. – This involves adhering to a structured preventive maintenance routine developed based on key operational factors. – The preventive maintenance schedule is designed to minimize downtime and optimize the efficiency of equipment and processes.
Skills	<ul style="list-style-type: none"> – Laborers possess the skills to perform corrective repairs or replacements on machinery to minimize downtime. – They follow the preventive maintenance schedule to ensure machines operate efficiently. – Timely replacement of worn parts is conducted to maintain equipment functionality. – Laborers can identify and address different types of faults to prevent further issues.
Training	<ul style="list-style-type: none"> – Proper training in tool usage is conducted, enabling tasks to be completed more quickly and effectively. – Workers develop essential skills and knowledge to handle tools correctly. – Understanding proper tool use ensures better tool management, aiding in their care and maintenance. – Proper management ultimately extends the lifespan and reliability of the tools.
Attitude	<ul style="list-style-type: none"> – Poor trust on AI based tool. Fear of being replaced by AI.

Process/Routines	<ul style="list-style-type: none"> – Laborers promptly record the failure type, time, and relevant details to facilitate accurate tracking and resolution. – Established processes for timely planning, deployment, and communication of the maintenance plan are essential, aligning it with order requirements. – Conducting root cause analysis is necessary to optimize processes and minimize losses. – Continuous planned inspections of machines and condition parameters help maintain operational efficiency.
Research Expense	<ul style="list-style-type: none"> – Budget for IoT based technology.
Communication and Software	<ul style="list-style-type: none"> – Maintenance planning and production planning software are implemented. – Data storage systems are established to efficiently store maintenance records, ensuring easy access to historical data. – Improved access to historical data supports better decision-making and process optimization.

Based on the descriptions in Table 6-15 and the marking scale provided in Table 6-7 to Table 6-13, the company's current and target intangible asset scores are presented in Figure 6-4.

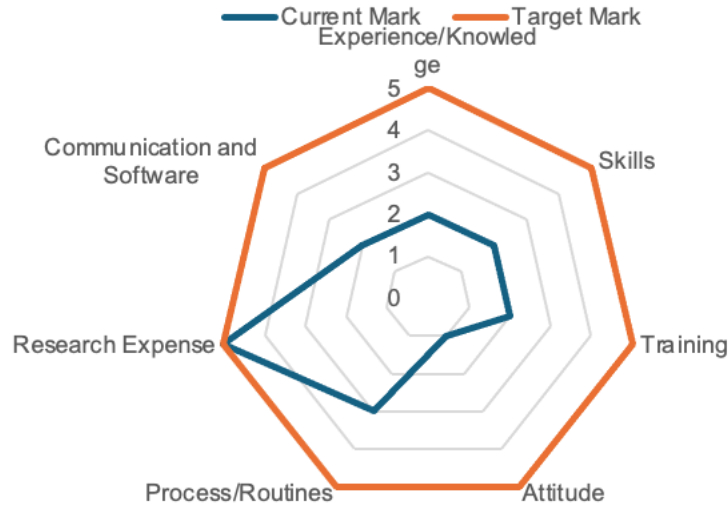


Figure 6-4 Case study current and target intangible marks

As depicted in Figure 6-4, among the seven intangible sub-dimensions, the company has sufficient research expenses to serve as a foundation for reaching maturity level 5. However, there are significant gaps in areas such as communication and software, experience/knowledge, skills, and training, which are currently only at level 2. Additionally, the attitude dimension is still at the most basic level, level 1. The process/routines dimension is relatively more developed, reaching level 3. Therefore, according to Equation 6-6, the company's maintenance intangible assets value is represented as:

$$I = \{i_{HC1}, i_{HC2}, i_{HC3}, i_{HC4}, i_{SC1}, i_{RD1}, i_{IT1}\} \quad (6-12)$$

$$I = \{2, 2, 2, 1, 3, 5, 2\}$$

In contrast, achieving maturity level 5 requires intangible assets values meeting the following targets as outlined by Equation 6-11:

$$I_{L5} = \{i_{HC1} \geq 5, i_{HC2} \geq 5, i_{HC3} \geq 5, i_{HC4} \geq 5, i_{SC1} \geq 5, i_{RD1} \geq 5, i_{IT1} \geq 5\} \quad (6-13)$$

Once the current and target intangible asset scores are compared, companies can then proceed to develop a personalized maintenance intangible asset development plan. To aid in the implementation of maintenance intangible assets, an implementation strategy map is provided in Section 6.4.2.

6.4.3 Step E5 Intangible asset implementation strategy

The final step of the methodology (Step E5) is to develop a strategy for implementing maintenance intangible assets for the company as introduced in Chapter 3, Section 3.4. Beyond the case study, to further explore effective strategies for implementing maintenance intangible assets and to assist more companies at different maturity levels, the authors and participants expanded on the case study rationale to present a comprehensive strategy map covering Levels 3 to 5. Through interviews (Appendix C, D) and based on participants' responses, Figure 6-5 is designed to support the implementation of maintenance intangible assets from Maturity Levels 3 to 5. Each level includes specific goals, processes, and resources for implementing various intangible asset dimensions.

This holistic strategy map is designed to guide organizations in improving their maintenance practices, regardless of their current maturity level. Levels 1 and 2 are excluded because there are extensive open-source resources available for achieving these levels. Additionally, manufacturers typically provide guidance for Levels 1 and 2 when companies purchase machines, spare parts, or tools. By following the outlined strategies, companies can implement necessary improvements and ultimately reach their desired maturity level. This approach ensures that each organization can tailor its efforts to its unique context, maximizing efficiency and effectiveness in maintenance operations.

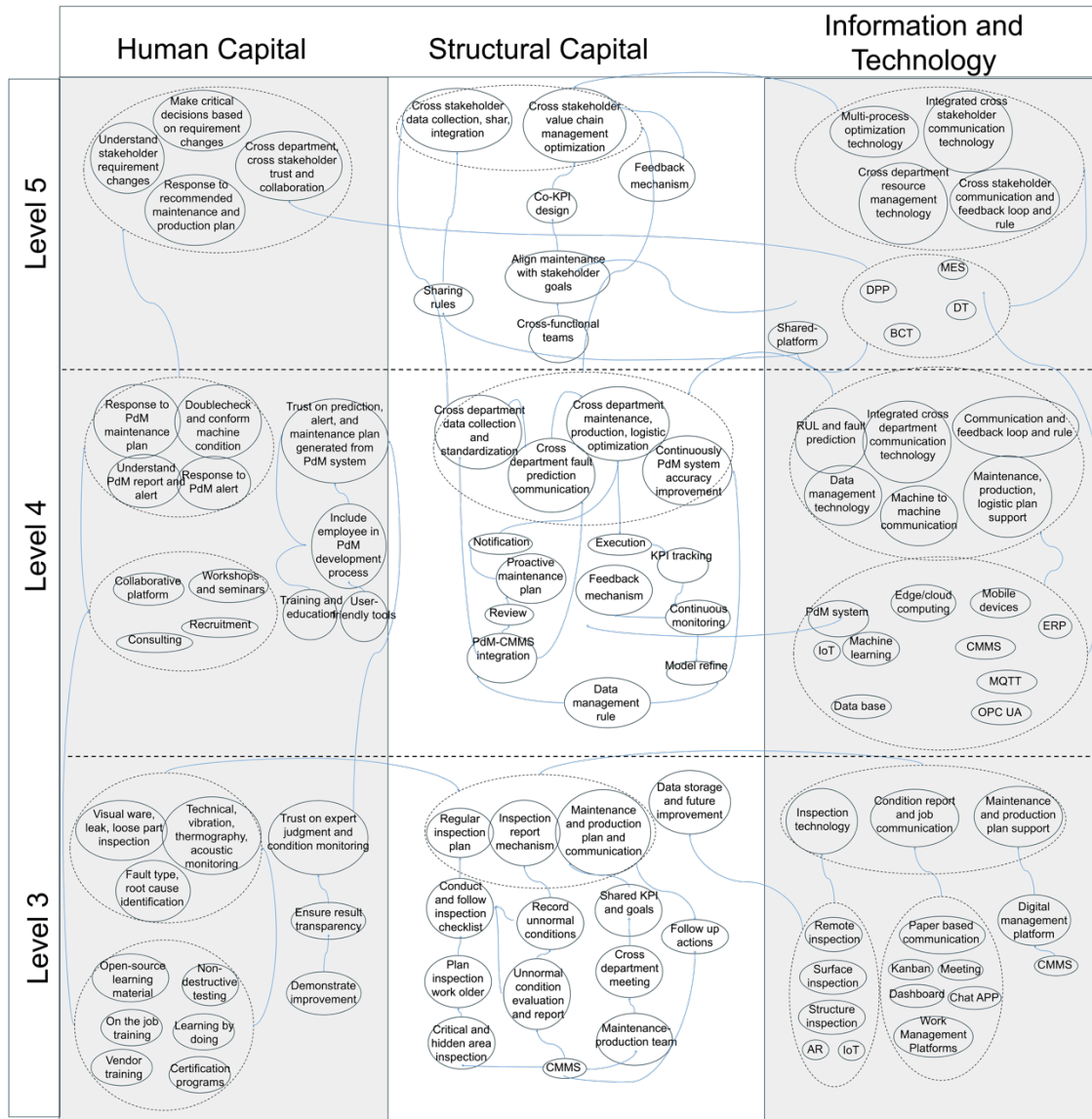


Figure 6-5 Maintenance intangible assets implementation strategy map

For Level 3, the primary goal is to implement experience-based PdM. This type of PdM cannot accurately predict a machine's Remaining Useful Life (RUL), but it can prevent unexpected shutdowns from interrupting production when performing specific tasks. Experience-based PdM is achieved through machine inspection, which can be either manual inspection (Q2A1, Q2A3) or monitoring of machine operating conditions (Q2A2). The purpose of inspection is to assess the machine's current status and predict performance over time (Q1A1), based on operational observations and historical experience.

For implementing Human Capital for Level 3, the company's human capital requirements focus on four primary objectives:

1. Visual wear, leak, and loose part inspection – enables manual inspection for assessing machine condition (Q2A3).
2. Technical monitoring using vibration, thermography, and acoustic monitoring – supports condition assessment using monitoring technologies (Q2A1, Q2A2).
3. Fault type and root cause identification – allows identification of the exact location of issues for quick corrective action (Q5A7).
4. Trust in expert judgment and condition monitoring – ensures effective adoption of experience-based PdM within the company (Q5A8).

The first three objectives are achievable through similar strategies. Companies that meet these goals can provide training through on-the-job learning or “learning by doing” methods for staff training. For companies that have not yet achieved these targets, there are various open-source manuals and resources available, as well as options like vendor training, non-destructive testing, or certification programs (Q6A1-Q6A6). The fourth objective, Trust in expert judgment and condition monitoring, ensures workers understand and trust the inspection results. Strategies for this include ensuring result transparency, so workers can see how inspection conditions were determined, and demonstrating improvements to show how experience-based PdM improves maintenance outcomes (Q5A8).

To support Level 3, the company should achieve four structural capital goals:

1. Conducting a regular inspection plan – ensures maintenance conditions are monitored in a timely manner to identify potential issues. Strategies include critical and hidden area inspection, planned inspection work orders, and inspection checklists to ensure important parts are effectively monitored and recorded (Q4A1-A8).
2. Developing an inspection reporting mechanism – records all observed conditions for reporting to maintenance and production teams to optimize scheduling. Processes include recording abnormal conditions and evaluating

and reporting abnormal conditions, both of which can be included in the inspection checklist (Q4A8-Q4A10).

3. Achieving maintenance and production plan communication – ensures alignment of maintenance and production plans. Processes include forming maintenance-production teams, cross-department meetings, and establishing shared KPIs and goals to synchronize maintenance conditions and allow scheduling adjustments across both sectors (Q4A11-Q4A14).
4. Implementing data storage and future improvement processes – stores maintenance and machine condition records to optimize future maintenance operations. Processes such as follow-up actions are crucial to arrange repairs, replacements, or other maintenance tasks based on inspection results and ensure that any potentially critical issues have been fully addressed (Q4A15-Q4A16).

In addition, all four goals can be supported by a Computerized Maintenance Management System (CMMS), which automates maintenance workflows, including work order creation, scheduling, inventory management, and reporting (Q4A9, Q4A10, Q4A15).

Technology and communication resources are essential for achieving three primary objectives:

1. Implementing inspection technology – in addition to manual visual inspections, technologies like remote inspection, surface inspection, structural inspection, AR, and IoT can be used (Q7A1).
2. Achieving condition reporting and job communication – ensures that monitored conditions and maintenance-production plans flow smoothly across departments. Available processes and resources include paper-based communication, Kanban, meetings, dashboards, chat apps, and work management platforms. Since real-time monitoring and reporting are not yet implemented at this stage, these methods are sufficient (Q7A2).
3. Maintenance and production plan support – to optimize production by integrating maintenance and production plans. Processes include implementing digital management platforms and CMMS (Q7A3).

In Level 4, the focus shifts to fully automating the prediction of Remaining Useful Life of machines and components. At this stage, RUL predictions are generated by the PdM system, relying on machine condition data processed through advanced machine learning algorithms and predictive models. These predictions can be real-time or generated at regular intervals, depending on the data acquisition methods and the sophistication of the modelling. Maintenance plans are no longer manually created; instead, they are developed through an integrated PdM system that collaborates with other digitalized automated systems, such as production, logistic, resource, and human capital management systems. Human roles at this level primarily involve decision-making, supervision, and execution rather than manual data analysis.

To effectively implement Human Capital for Level 4, organizations should focus on four key objectives:

1. Understanding PdM reports and alerts (Q9A1)
2. Responding to PdM alerts (Q9A2, Q9A3, Q9A4)
3. Double-checking and confirming machine conditions (Q9A3)
4. Trusting PdM system-generated predictions, alerts, and plans (Q11A1)

The first four objectives ensure operators can interpret alerts from the PdM system and carry out maintenance operations as recommended. Additional strategies, beyond those introduced in Level 3, include setting up collaborative platforms for support, organizing workshops and seminars to share successes, experiences, and explore the use of digital systems. By Level 4, digitalized platforms may have become highly customized to meet company-specific needs, so sourcing processes from open databases may no longer suffice. Recruitment and consulting may be necessary to meet these advanced human capital needs (Q10A1, Q10A2). The final objective, trusting the PdM system and integrated maintenance management, ensures smooth adoption of PdM within the company. Additional strategies include involving employees in the PdM development process to increase familiarity and utilizing user-friendly tools to encourage system acceptance (Q11A1).

The primary function of structural capital at this level is to ensure that machine conditions are continuously monitored, RUL predictions are based on machine condition data, and maintenance and production plans are optimized in collaboration with other company departments. Key objectives for structural capital include:

1. Data collection and standardization: Enables consistent data collection, formatted for the PdM system. Strategies include integrating CMMS with PdM systems to allow monitoring of machine RUL while optimizing maintenance and production schedules based on production orders, raw material inventory, and other factors (Q12A1-A3).
2. Cross-department fault prediction communication: Once the production schedule is created, it typically undergoes management review before implementation. This also enables cross-department optimization of maintenance, production, human resource and logistics (Q12A5-A9).
3. Continuous PdM system accuracy improvement: Feedback mechanisms ensure that the PdM system's accuracy continues to improve as it gathers more data. Strategies include KPI tracking, continuous monitoring, and model refinement to monitor and measure PdM system performance, ensuring it continuously adapts and improves based on operational data (Q12A10-A12).

A Data management rule is essential to ensure secure and appropriate data use across these structural capital objectives (Q12A13).

Technologies and communication in Level 4 support the various PdM processes. Achieving effective predictive maintenance requires not just one or a few isolated technologies, but rather the integration of multiple systems to support the comprehensive set of processes. For instance, to achieve RUL and fault prediction, it is also essential to establish data acquisition, management, and processing capabilities. Another key objective is to implement integrated maintenance, production, and logistics plan support to optimize the entire company's information resources and workflow. This requires Integrated Cross-

Department Communication Technology (Q12A1). The following technologies are normally required for this level.

1. RUL and Fault Prediction: Machine learning, IoT sensors, and advanced computing predict equipment failure by analysing machinery data, helping prevent unplanned downtimes.
2. Integrated Cross-Department Communication: Mobile devices, ERP systems, and CMMS enable seamless data exchange across departments, aligning maintenance, production, and logistics teams to adjust plans based on real-time information.
3. Data Management: Efficient data acquisition, storage, and processing are key to managing large volumes of data, improving decision-making, and enhancing RUL and fault predictions.
4. Communication and Feedback Loop Rules: Structured communication protocols ensure that maintenance, production, and logistics teams can adjust strategies in real time, reducing delays and improving responsiveness.
5. Maintenance, Production, and Logistics Plan Support: Integrating PdM systems with planning tools helps align maintenance with production and logistics schedules, minimizing downtime and boosting productivity.

At this point, relying solely on individual technologies is insufficient; the objectives require integrated technological solutions. For example, PdM systems require a combination of machine learning, IoT, and computing technologies, etc., for RUL prediction, integrated cross-department communication relies on mobile devices, ERP systems, and CMMS technologies to ensure seamless information flow (Q12A1-A6).

In Level 5, the integration of maintenance and production planning extends beyond internal departments to include stakeholders and customers. For example, changes in order quantities or logistics from stakeholder's prompt adjustments to maintenance and production plans, which are optimized in real time based on RUL predictions and other data inputs. At this level, intangible assets emphasize enhancing communication and data-sharing across stakeholders. Alongside advanced technology, this level promotes trust among

stakeholders to encourage data sharing, ensuring transparency and data security (Q13A1, Q13A2, Q13A5).

Human Capital implementation goal for Level 5 include (Q13A1, Q13A2, Q13A5, Q13A6):

1. Understanding stakeholder requirements and changes
2. Making critical decisions based on requirements
3. Responding to recommended maintenance and production plans
4. Building cross-department and cross-stakeholder trust and collaboration

The first three objectives align closely with Level 4 goals but additionally incorporate changes in stakeholder requirements. The fourth objective, Trust and collaboration across departments and stakeholders, can be achieved by utilizing technology implementation strategies such as DPP and BCT to enhance transparency, trust, and accuracy in data sharing (Q13A9).

The Structural Capital implementation goals for Level 5 centre around two main objectives:

1. Cross-stakeholder data collection, sharing, and integration: Ensures information flows smoothly among stakeholders. Strategies include creating data-sharing rules and mechanisms to define which data to share, sharing methods, formats, access permissions, and security protocols. With a data-sharing platform, this process can become automated (Q13A1-A3).
2. Cross-stakeholder value chain optimization: Adjusts production and maintenance plans according to stakeholder changes. Processes may include co-KPI design, alignment of maintenance goals with stakeholder objectives, and cross-functional teams (Q13A2, Q13A4).

Technologies required at Level 5 focus on enabling data-sharing and interaction among stakeholders. Objectives include (Q14A1-A4):

1. Cross-stakeholder communication and feedback loops
2. Integrated cross-stakeholder communication

Beyond technologies used in Level 4, Level 5 introduces tools like DPP, BCT, DT, and MES, which enhance stakeholder trust and encourage data sharing, fostering transparency and data security in shared operations (Q14A1-A4).

6.5 Discussion

The focal point in this chapter is to understand the intangible assets required for PdM implementation, develop a method to quantify these intangibles, and clarify the strategic logic that manufacturers use when implementing necessary intangible assets for PdM. The contributions of this chapter are as follow.

Development of a Structured Intangible Asset Evaluation Methodology

A structured method for evaluating intangible assets that are critical for implementing predictive maintenance (PdM) in manufacturing environments is developed in this research. Unlike existing approaches where intangible assets are discussed broadly or framed generically, the methodology is tailored specifically to PdM requirements. Expert assessments and interviews are integrated so that intangible resources such as human capital, organizational culture, technological infrastructure, and knowledge management systems are identified, validated, and quantified systematically. By explicitly linking intangible assets to PdM, a gap in the literature is addressed, where tangible assets such as machinery and technology tend to dominate while human and organizational resources are often overlooked. The theoretical framework extends the resource-based view (RBV) by suggesting that intangible resources, rather than physical assets alone, are key drivers of competitive advantage in high-tech domains such as PdM. From a practical perspective, organizational readiness for PdM adoption is assessed systematically through this method, ensuring that critical intangible assets are highlighted and developed as part of the decision-making process.

Integration of Intangible Asset Evaluation into a PdM Maturity Model

The integration of intangible asset management into the PdM Maturity Model constitutes a significant theoretical contribution. Five levels of PdM maturity are linked to the corresponding development of intangible assets required at each stage, creating a roadmap that guides organizations along their PdM journey.

Traditional frameworks, which typically emphasize technical infrastructure, sensors, and data analytics, are extended by incorporating intangible resources such as leadership, knowledge management, and employee skills. The theoretical scope of dynamic capabilities theory is broadened by demonstrating that the ability to manage intangible resources dynamically is essential for progressing through PdM maturity levels. For practitioners, this approach provides a tangible tool for assessing current PdM capabilities and a structured path for continuous improvement. Intangible assets such as organizational culture, skills, and data-driven decision-making are prioritized at each maturity level, and their development is explicitly aligned with technical progress.

Critical Theoretical Insights into the Role of Intangible Assets in PdM Success

The research also provides critical theoretical insights into the underexplored role of intangible assets in PdM success. Traditional PdM models emphasize tangible factors such as hardware, sensors, and algorithms, while the importance of organizational and human elements is often downplayed. By positioning knowledge, skills, and organizational culture as central drivers, the theoretical understanding of PdM adoption is reframed. Dynamic capabilities theory is expanded by showing that successful PdM outcomes are achieved not only through technological innovation but also through the effective management of intangible resources. Organizational learning, employee training, and leadership are highlighted as being as critical as technical systems, thereby promoting a more holistic perspective. For practice, this insight provides organizations with a roadmap that balances technological investment with the cultivation of human and cultural readiness.

Establishing a Roadmap for Continuous Improvement in PdM Implementation

A roadmap for continuous improvement in PdM implementation is also established, emphasizing the incremental development of intangible assets in parallel with technical capabilities. This roadmap is structured around maturity levels, ensuring that PdM practices evolve in tandem with the development of

human and organizational resources. Organizational development theory is extended through this contribution by demonstrating how intangible resources must be reconfigured continuously in response to changing operational contexts. From a practical perspective, PdM is treated as a long-term strategic initiative rather than a short-term technological solution. This ensures that organizational readiness is built gradually and that the risks associated with overemphasizing technology at the expense of human capabilities are avoided.

Contribution to PdM, Digital Transformation, and Industry 5.0

The research contributes to the evolving fields of PdM, digital transformation, and Industry 5.0 by explicitly linking intangible resources to technological adoption and organizational transformation. In much of the existing literature, PdM adoption is framed primarily in terms of algorithms, hardware, and data systems, while the human and organizational dimensions remain underexplored. This research addresses that gap by emphasizing the importance of leadership, knowledge management, and employee skills in sustaining PdM systems. In the context of digital transformation, the findings demonstrate that technologies such as IoT, AI, and big data require strong organizational preparedness, including cultural readiness and leadership, to be leveraged effectively. Theoretical contributions are made by extending digital maturity models to account for intangible assets as a core determinant of success. In Industry 5.0, where human-centric and sustainable approaches are prioritized, the research reinforces the perspective that PdM adoption is not only a technical process but also a socio-technical transformation shaped by people and culture. By doing so, alignment with Industry 5.0 values of inclusivity, collaboration, and sustainability is ensured.

Contribution to Enhancing and Complementing Existing Frameworks

The study also enhances and complements established performance and process frameworks such as the Balanced Scorecard (BSC), Capability Maturity Model Integration (CMMI), and Key Performance Indicators (KPIs), addressing their limited treatment of intangible resources.

Complementing the Balanced Scorecard (BSC)

The BSC provides a structured approach to performance across financial, customer, internal process, and learning dimensions, but its treatment of intangible resources remains broad. This research complements the BSC by offering a framework that quantifies specific intangible assets such as knowledge management, leadership, and human capital. By aligning these resources with PdM maturity levels, greater granularity is added, enabling a deeper understanding of how organizational readiness drives long-term performance improvements.

Extending the Capability Maturity Model Integration (CMMI)

CMMI focuses on process maturity but underrepresents the role of human and organizational factors. This research extends CMMI by embedding intangible asset evaluation into process improvement pathways. It is argued that true process maturity requires investment in organizational culture, leadership, and training. By integrating these dimensions into PdM maturity, CMMI is enhanced with a more holistic orientation that combines technical maturity with organizational capacity development.

Refining Key Performance Indicators (KPIs)

KPIs provide output-oriented measures of efficiency and performance, but they often overlook underlying cultural and organizational drivers. This research refines KPIs by incorporating intangible asset measures, such as leadership effectiveness, employee engagement, and knowledge-sharing practices. By doing so, KPIs are transformed into a more comprehensive performance management tool that acknowledges the human and organizational resources necessary for successful PdM and digital transformation.

Although several theoretical and practical contributions are achieved by this study in understanding and evaluating intangible assets in the context of predictive maintenance (PdM), a number of methodological and contextual limitations are acknowledged. These limitations influence how the findings are interpreted and the extent to which they can be generalized.

Subjectivity in Expert Assessments

The first limitation is related to the subjectivity inherent in expert evaluations and the use of a majority rule to identify critical intangible assets. In this approach, assets are classified as significant when more than half of the consulted experts agree on their importance. While this method provides a practical way to prioritize factors, the diversity of expert perspectives is inevitably simplified, and nuances in individual judgments are downplayed. Minority views, especially those representing niche expertise or highly context-specific knowledge, may be overlooked. As a result, intangible assets that could be essential in specialized PdM contexts may be missed, even though they are not widely recognized across the broader expert group.

Linear Assumptions in the PdM Maturity Model

A second limitation is found in the assumptions of the PdM maturity model developed in this research. The model is designed around a linear, stage-by-stage progression toward higher maturity levels, which facilitates benchmarking and provides organizations with a roadmap for improvement. However, this design may oversimplify the complex and non-linear nature of organizational development. In practice, progress in PdM adoption is rarely sequential: organizations may advance unevenly across different dimensions, regress due to internal or external setbacks, or even leapfrog certain stages. Consequently, the structured progression of the model may fail to capture the adaptive strategies employed by some organizations and may generate misalignments between the model's recommendations and real-world organizational capabilities.

Limited Generalizability of Findings

Another limitation concerns the generalizability of the findings. Validation is carried out through a single case study in the manufacturing sector, which enables a deep and context-specific understanding of intangible asset evaluation. However, the extent to which the results apply to other industries remains uncertain. Different organizational sizes, sectoral regulations, technological infrastructures, and workforce cultures may lead to varying priorities in managing intangible resources. For example, intangible asset requirements in sectors such as healthcare, energy, or transportation may differ significantly from those

identified in manufacturing. While the framework demonstrates utility in the studied context, its broader applicability requires further comparative studies across multiple industries.

Rigidity of the Roadmap for Continuous Improvement

A further limitation is linked to the relative rigidity of the roadmap for continuous improvement in PdM adoption and intangible asset development. Although clear and actionable steps are provided, the design assumes a structured progression and does not fully account for the unpredictability of organizational change. In practice, PdM implementation is frequently affected by sudden disruptions such as market volatility, leadership turnover, technological breakthroughs, or operational challenges. Because flexibility is not embedded in the roadmap, organizations may find adaptation constrained, and innovation may be slowed or progress delayed when deviations from the prescribed path are necessary.

Temporal Constraints of the Framework

The final limitation arises from the temporal scope of the framework. The study primarily reflects the current technological and organizational landscape of PdM, but the rapid pace of technological advancement introduces new requirements continuously. Emerging technologies such as artificial intelligence, Internet of Things, and blockchain bring with them intangible asset needs such as advanced data governance, AI ethics management, and human-machine collaboration skills. While the framework captures intangible assets relevant to today's practices, its applicability may decline over time unless it is regularly updated. This temporal limitation emphasizes the importance of adopting a forward-looking perspective and ensuring that future work integrates emerging technological and organizational competencies.

Chapter Summary

In this chapter, as presented in Figure 6-6, the results, validation, and discussion of the maintenance strategy operation intangible assets evaluation method are presented, following the steps outlined in Section 3.4. Section 6.1 begins by identifying various intangible asset types relevant to the implementation and

operation of maintenance strategies. Section 6.2 introduces a maintenance implementation and operation maturity model designed to support companies in self-evaluation and target setting. Section 6.3 provides the equations necessary for quantifying intangible assets, while Section 6.4 details a marking scale to assign values to these assets.

In Section 6.5, the applicability of this quantification method is validated through a case study, and strategies for implementing maintenance intangible assets are explored. This section also presents a strategy map for maintenance intangible asset implementation, outlining goals, processes, and resource requirements across different maturity levels.

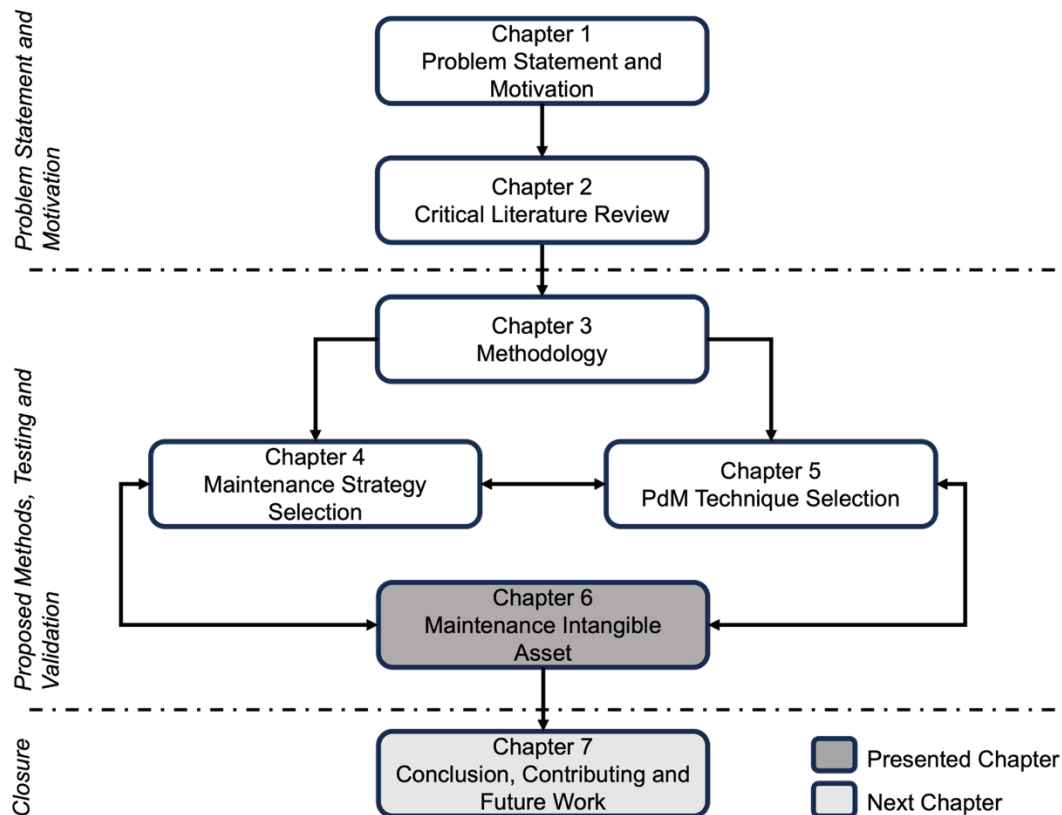


Figure 6-6 Organization of the Thesis – Presented and Next Chapter

CHAPTER 7 - CLOSURE

The primary goal of this research is to establish a systematic methodology to aid the manufacturing industry in evaluating the cost-benefit of PdM implementation, tailored to each organization's specific needs and circumstances. This research delves into the motivations behind PdM adoption and the unique aspects of its cost-benefit evaluation, including the assessment of both tangible and intangible assets, therefore, frame the problem, identify research gaps in this thesis, and define research questions that will be further addressed in future work.

In this chapter, a summary of the thesis is presented in Section 7.1. The research questions and research objectives introduced in Chapter 1 are revised and critically evaluated with a special emphasis on the validity of the research objectives in Section 7.2. Further, expected contributions and identified limitations are presented in Section 7.3. Lastly, the motivation for a way forward, research gaps and research questions that will be addressed in future work are proposed in Section 7.3.

7.1 Summary of thesis

In conclusion, as manufacturing industries transition to Industry 4.0, the increasing complexity and criticality of maintenance practices are being recognized for their role in sustaining competitiveness and operational efficiency. PdM has been identified as a promising solution to the challenges of Industry 4.0, as it enables efficient and proactive maintenance, cost reduction, productivity improvement, and enhancements in performance indicators such as safety, quality, and customer satisfaction. However, despite the potential offered by PdM, its adoption has been impeded by uncertainties related to cost-benefit justification. Significant barriers, including the high initial investment required for technology, infrastructure, and training, as well as the absence of systematic evaluation methods for cost-effectiveness, have been observed.

To address these challenges, the development of a structured framework for evaluating the cost-benefit of PdM implementation has been undertaken in this research. Tailoring has been conducted to meet the unique needs and conditions

of individual companies. Through this framework, clarity on the financial and operational impacts of PdM is provided to guide manufacturers in making informed decisions regarding PdM investments. Support is intended for a smoother and more successful transition to Industry 4.0. Both tangible and intangible aspects of PdM have been incorporated into the framework, to provide industries with a comprehensive tool for optimizing maintenance outcomes.

The necessity of comprehensively evaluating tangible assets, intangible assets for successful PdM implementation has been demonstrated. Tangible assets, such as IoT systems and data processing tools, are shown to require significant financial commitments. Therefore, the necessity of assessing these assets and selecting the most suitable PdM techniques for ensuring cost-effectiveness is emphasized. Intangible assets, including specialized knowledge, skills, and expertise, are identified as vital for the effective operation of PdM systems, although a structured method for their assessment has not yet been established. By addressing these overlooked areas, this research is positioned to offer a robust and holistic approach to PdM evaluation, ensuring feasibility and alignment with the objectives of modern manufacturing.

In addition to PdM implementation cost-benefit, when implementing PdM systems, businesses must consider costs such as equipment acquisition, data storage, and employee training. On the benefit side, PdM can reduce equipment failure rates, extend asset lifecycles, and improve operational efficiency, with the ROI formula providing insights into the investment-return relationship.

However, the initial implementation can be costly, with expenses for equipment, sensor installation, and data systems creating short-term financial pressure. Thus, organizations should take a long-term view, accounting for potential savings in maintenance and extended equipment lifespans.

Real-world challenges include data quality, technological integration, and organizational alignment. High-quality data systems and cross-department collaboration are essential for success. In industries with high operational costs, such as oil and gas, PdM systems can significantly reduce downtime and maintenance costs, improving efficiency and supporting sustainability goals.

7.1.1 Evaluating required tangible for PdM implementation

Maintenance strategy selection method in modern manufacturing era

In modern manufacturing, selecting the optimal maintenance strategy is crucial to achieving long-term success, as it directly influences cost, productivity, quality, and safety. Traditional strategies such as CM and PM are now complemented by PdM, which leverages data-driven insights to anticipate failures. Despite its potential, PdM presents significant challenges, including high initial costs, technical complexities, and operational uncertainties that can hinder effective implementation, particularly for small and medium-sized enterprises. In addition to technical factors, manufacturers must consider evolving market demands, environmental pressures, and emerging human-centred and sustainable manufacturing practices in Industry 5.0, which add further complexity to maintenance strategy selection.

This research addresses these multifaceted challenges by introducing a refined decision-making method for maintenance strategy selection that integrates AHP with WRSR. The research's contributions are threefold: it establishes relevant decision criteria that align with Industry 5.0's focus on human-centricity, sustainability, and resiliency; it facilitates a structured (Chapter 4, Section 4.1), AHP-based approach to navigate complex maintenance decisions (Chapter 4, Section 4.2 and 4.3); and it provides a pioneering method that combines AHP and WRSR to deliver a clear and customizable prioritization of criteria based on individual organizational goals (Chapter 4, Section 4.4). This innovative approach not only supports more effective maintenance strategy selection but also guides manufacturers in aligning with broader industry and environmental goals. Future studies applying this AHP-WRSR method across diverse manufacturing contexts can further validate and expand its applicability, offering valuable insights for optimizing maintenance practices across the industry.

Decision based framework for PdM technique selection

The implementation of PdM holds great potential for enhancing efficiency and reducing operational costs in manufacturing, yet significant challenges hinder its widespread adoption. Chief among these challenges is the lack of a systematic,

practical approach to help companies select the most suitable PdM technique from a range of options—experience-based, model-based, physical-based, data-driven, and hybrid techniques—each with varying requirements in hardware, software, and expertise. This gap in methodology complicates the decision-making process, often leading to suboptimal technique selection, which can result in higher costs, longer implementation times, and diminished returns on investment.

To address these challenges, a structured framework that aids enterprises in selecting the optimal PdM technique based on specific operational conditions and maintenance objectives is introduced in this research. The framework contributes in three key areas: PdM techniques are aligned with ALs that correspond to specific implementation goals (Chapter 5, Section 5.1); key attributes, such as data availability and system complexity, are identified as factors influencing the suitability of these techniques (Chapter 5, Section 5.2); and a decision-making framework is established to connect these ambition levels and attributes with the most appropriate PdM technique (Chapter 5, Section 5.3). By providing a comprehensive, step-by-step methodology for PdM selection, this research facilitates informed, context-specific decisions, optimizing maintenance performance and promoting sustainable operational benefits over the long term.

7.1.2 Evaluating required intangible assets for PdM implementation

The successful implementation of maintenance strategies, particularly PdM, relies not only on tangible assets like sensors and tools but also on intangible assets such as knowledge, skills, and organizational expertise. While tangible assets are often prioritized, it is clear that the appropriate type and quantity of intangible assets are crucial for effective maintenance operation and strategy execution. However, there exists a significant challenge in evaluating and quantifying these intangible assets, with manufacturers currently lacking a systematic approach to assess the specific intangible requirements for PdM implementation. Without this understanding, companies risk misallocating resources, facing budget overruns, or failing to meet maintenance objectives effectively.

This gap is addressed in by identifying the essential intangible assets for PdM implementation and operation and developing a comprehensive method for their quantification. The research presents a maintenance implementation maturity model, categorizing PdM practices into five levels based on their capabilities, and outlines a framework to define the types and quantities of intangible assets required at each level. Additionally, a strategy map is introduced in this research, that guides companies in aligning their intangible asset investments with their business goals, ensuring efficient resource allocation and successful maintenance strategy implementation.

The significance of this research lies in its practical contributions to the manufacturing sector. It enables companies to make informed decisions about the intangible resources necessary for PdM adoption, reducing the risks associated with investing in these assets (Chapter 6, Section 6.1-6.3). Furthermore, a clear pathway for organizations to progress through different stages of maintenance maturity, from reactive to advanced predictive maintenance is provided (Chapter 6, Section 6.2). By offering a strategic, structured approach to intangible asset management, the research enhances the understanding of how these assets contribute to long-term maintenance success, providing valuable insights for industrial managers aiming to optimize their PdM strategies (Chapter 6, Section 6.3).

7.2 Answering the research questions and objective achievement

The motivations behind PdM adoption are delved into, and the unique aspects of its cost-benefit evaluation, including the assessment of both tangible and intangible assets are examined. These aspects are explored within the context of the primary research question presented in Chapter 1, Section 1.3.

Primary Research Question: *What is the method that helps evaluate the cost-benefit for predictive maintenance implementation that takes into account the investment in tangible and intangible assets of PdM?*

Furthermore, as discussed in Chapter 1, Sections 1.2.2 to 1.2.5, there is a related set of challenges tied to assessing the necessary tangible and intangible assets before the actual implementation. These challenges form the sub-research problems addressed in this thesis as outlined below:

Secondary Research Question One: *What is the method that helps manufacturers evaluate the necessary tangible assets for PdM implementation, considering whether PdM is required and which PdM technique is needed?*

Two research objectives are achieved to answer Research Question One and validate Research Hypotheses One and Two, which are:

Objective One: *Create an AHP-based MCDM method tailored for manufacturing enterprises. This method should enable these enterprises to choose the most appropriate maintenance strategy in modern manufacturing while considering the technical, environmental, and market challenges they face.*

Objective Two: *Develop a comprehensive framework to assist enterprises in selecting the most suitable Predictive Maintenance Technique. This framework should consider the unique characteristics of each PdM technique and evaluate their alignment with the specific conditions and needs of the enterprise.*

Secondary Question Two: *What is the method that helps evaluate the necessary intangible assets for PdM implementation, taking into account the enterprise's specifications, before the actual implementation?*

One research objective is achieved to answer Research Question Two and validate Research Hypothesis Three, which is:

Objective Three: *Develop a method for manufacturers to accurately assess the required intangible assets necessary for successfully implementing and operating their maintenance strategies regarding their needs and situations.*

The research objectives are designed to answer the secondary research questions and support the principal goal of this thesis. The ultimate outcome is the development of new knowledge: a systematic methodology to assist the manufacturing industry in evaluating the cost-benefit of PdM implementation,

tailored to the specific needs and circumstances of individual organizations. The validation of these methods is discussed in detail within each chapter, following the validation roadmap outlined in Chapter 1, Section 1.4. Additionally, the validation of hypotheses is revisited and summarized in Tables 7-1 to 7-3, as detailed in Sections 7.2.1–7.2.2.

7.2.1 PdM implementation tangible assets evaluation method validation

APH based method for maintenance strategy selection

In this section, Objective one is discussed in order to answer the Research Question one. Objective one is introduced in Chapter 1 and further addressed in Chapter 4 as presented in Table 7-1.

The development of an AHP-based MCDM method for the selection of maintenance strategies in modern manufacturing is validated through a comprehensive, multi-layered process. Theoretical structural validation is conducted first, where the motivation for an advanced maintenance selection method is addressed, as outlined in Section 1.2.2. An introduction to the AHP approach is provided in Section 3.2.1, and its relevance to current manufacturing challenges is highlighted. The mathematical foundation of AHP is detailed in Section 3.2.2, and gaps in the existing literature are justified through a review conducted in Section 2.2.

Table 7-1 Summary of validation of objective one

Objective	Validation	Details
Create an Analytical Hierarchical Process (AHP)-based Multi-Criteria Decision-Making (MCDM) method tailored for manufacturing enterprises. This method should enable these enterprises to	Theoretical Structural Validation	
	Motivation for maintenance strategy selection method in modern manufacturing ear	S 1.2.2
	Introduction to AHP method for maintenance strategy selection	S 3.2.1
	Mathematical background of AHP method	S 3.2.2
	Literature review	S 2.2

Empirical Structural Validation

Case study example	S 4.2.2
Decision maker gathering	S 4.2.1
Defined decision goal, alternatives, and criteria	S 4.1.4, Table 4-3
Maintenance strategy selection hierarchic tree	S 4.1.4, Fig 4-2
Alternative and criteria marking	S 4.3.1 Fig 4-3, 4-4

Empirical Performance Validation

Maintenance strategy selection method in modern manufacturing era	S 4.1, Fig 4-2
Maintenance alternative performance marking	S 4.3.4, Fig 4-5
Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) Evaluation	S 4.4, Table 4-19

Subsequently, empirical structural validation is performed to assess the structural integrity of the AHP-based method through real-world applicability. A case study is presented in Section 4.2.2 to demonstrate the practical application of the method. The involvement of decision-makers in establishing essential parameters for the AHP process is documented in Section 4.2.1. Goals, alternatives, and criteria are defined in Section 4.1.4 (Table 4-3), and a hierarchical decision tree for organizing maintenance strategy selection is illustrated in Fig. 4-2. The marking and categorization of alternatives and criteria are detailed in Section 4.3.1 (Figures 4-3 and 4-4), ensuring that the method's structural completeness for practical implementation is established.

Finally, empirical performance validation is conducted to evaluate the method's effectiveness in real-world maintenance strategy decision-making within modern manufacturing contexts. The adaptability and relevance of the method to current industrial needs are evaluated in Section 4.1 (Fig. 4-2). The performance marking of maintenance alternatives is presented in Section 4.3.4 (Fig. 4-5), and the method's capability to optimize maintenance strategy selection among

differentiated options is demonstrated. Further validation is provided through the Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) evaluation in Section 4.4 (Table 4-19), where prioritization capability based on criteria importance is established.

The development of an AHP-based MCDM method for selecting maintenance strategies in modern manufacturing requires a multi-layered validation process, starting with theoretical structural validation. This first stage establishes a robust foundation by addressing the motivation for an advanced maintenance selection method as outlined in Section 1.2.2 and provides an introduction to the AHP approach in Section 3.2.1, highlighting its relevance to current manufacturing challenges. The mathematical foundation of AHP is detailed in Section 3.2.2, and a literature review justifies the gaps identified.

The empirical structural validation phase follows, evaluating the structural integrity of the AHP-based method through real-world applicability. A case study example is presented in Section 4.2.2, in which the method's practical application is demonstrated, while the involvement of decision-makers is documented in Section 4.2.1, and essential parameters for the AHP process are established by them. This validation is further supported by the definition of goals, alternatives, and criteria (Section 4.1.4, Table 4-3) and the hierarchical decision tree illustrated in Fig. 4-2, which organizes maintenance strategy selection. The marking and categorization of alternatives and criteria (Section 4.3.1, Figures 4-3 and 4-4) ensure the method's structural completeness for practical implementation.

Finally, empirical performance validation assesses the method's effectiveness in real-world maintenance strategy decision-making within modern manufacturing contexts. The adaptability and relevance to the current industrial landscape of the method are evaluated in Section 4.1 (Fig. 4-2). The performance marking of each maintenance alternative in Section 4.3.4 (Fig. 4-5) is demonstrated to showcase the method's capacity for optimizing maintenance strategy selection among different options, while the Sub-Criteria Weighted-Rank-Sum Ratio (WRSR) evaluation in Section 4.4 (Table 4-19) is conducted to further validate its ability to prioritize based on criteria importance. A decision-based framework for PdM technique selection

In this section, Objective Two is discussed in order to answer the Research Question 1. Objective Two is introduced in Chapter 1 and further addressed in Chapter 5 as presented in Table 7-2.

The development of a comprehensive framework to assist enterprises in selecting the most suitable PdM technique is validated through three main forms, beginning with **theoretical structural validation**. This initial stage establishes the foundational motivation for creating a PdM technique selection method, as detailed in Section 1.2.2, explaining the need for alignment between PdM techniques and enterprise-specific needs. Context is provided in the literature review in Section 2.3, where existing methods are surveyed, and a theoretical basis is established to underscore the necessity of this framework within the broader predictive maintenance research landscape.

The framework undergoes further scrutiny through **empirical structural validation**. A case study in Section 5.3.1 applied the framework, demonstrating its alignment with practical PdM implementation objectives as outlined in Sections 3.3.1 and 5.1.1. Additionally, the framework’s capacity to address specific predictive maintenance technique capabilities and ALs is evaluated in Sections 3.3.1 and 5.1.2 and visualized in Figure 5-2. Sections 3.3.1 and 4.3.1, along with Figures 4-3 and 4-4, provide a detailed assessment of PdM implementation attributes and effects, establishing a structured, decision-based approach for PdM technique selection (Sections 3.3.1, 5.2.1, Figures 5-4 to 5-6) that ensures the framework’s operational feasibility.

Table 7-2 Summary of Validation of Objective Two

Objective	Validation	Details
Develop comprehensive framework to assist enterprises in selecting the most suitable	Theoretical Structural Validation	
	Motivation for developing PdM technique selection method	S 1.2.2
	Literature Review	S 2.3
	Empirical Structural Validation	
	Case study example	S 5.3.1

practice PdM implementation objectives	S 3.3.1, S 5.1.1
PdM technique capabilities for achieving ALs	S 3.3.1, S 5.1.2, Fig 5-2
PdM implementation attributes and affect	S 3.3.1, S 4.3.1 Fig 4-3, 4-4
Establish the Decision-Based Framework for Predictive Maintenance Technique Selection	S 3.3.1, S 5.2.1, Fig 5-4 to 5-6

Empirical Performance Validation

Decision-Based Framework for Predictive Maintenance Technique Selection	S 5.2.1, Fig 5-4 to 5-6
Framework case study application	S 5.3.2, Fig 5-7 to 5-9
Identified possible Data-driven PdM model for case study	S 5.3.2, Table 5-1, Appendix B

Finally, **empirical performance validation** assesses the framework's effectiveness through application and case-specific evaluations. The operational application of the framework within the case study is detailed in Sections 5.2.1 and Figures 5-4 to 5-6, with further case study results shown in Section 5.3.2 and Figures 5-7 to 5-9. In Section 5.3.2, Table 5-1, and Appendix B, a possible data-driven PdM model for the case study is identified and recommended by the framework, thereby demonstrating its performance in accurately aligning PdM technique selection with real-world enterprise needs.

7.2.2 PdM implementation intangible assets evaluation method validation

In this section, Objective 3 is discussed in order to answer the Research Question 2. Objective 3 is introduced in Chapter 1 and further addressed in Chapter 6 as presented in Table 7-3.

The development of a method for manufacturers to assess the intangible assets required for successfully implementing and operating their maintenance strategies is validated through three primary stages, starting with **theoretical structural validation**. This stage provides the foundational rationale for the

method, explaining the need for a structured approach to evaluating intangible assets in PdM as discussed in Section 1.2.3. The literature review in Section 2.4 supports this by exploring existing methodologies and highlighting the gaps this method aims to address, ensuring its theoretical relevance within the broader context of maintenance strategy evaluation.

Empirical structural validation tests the applicability and feasibility of the method in practical settings. A case study example illustrating the quantification of intangible assets for maintenance is presented in Section 6.4, providing a real-world demonstration of the method's operational relevance. Various intangible asset types specific to maintenance are identified in Sections 3.4.1 and 6.1 (Table 6-3), while a maintenance maturity model, which helps assess the current state of maintenance practices within organizations, is introduced in Section 3.6.2 and Section 6.2 (Tables 6-4 and 6-5). Further, the method's precision in quantifying intangible assets is supported by equations in Sections 3.4.3 and 6.3.1, while a marking scale to classify and evaluate the identified assets is defined in Section 3.4.4 and Section 6.3.2 (Table 6-7, Appendix C, D).

Table 7-3 Summary of Validation of Objective Three

Objective	Validation	Details
Develop a method for manufacturers to accurately assess the required intangible assets necessary for successfully implementing and operating their maintenance strategies	Theoretical Structural Validation	
	Motivation for developing PdM intangible evaluation method	S 1.2.3
	Literature Review	S 2.4
	Empirical Structural Validation	
	Maintenance intangible assets quantification case study example	S 6.4
	Identified intangible asset types for maintenance	S 3.4.1, S 6.1, Table 6-3
	A maintenance maturity model	S 3.6.2, S 6.2, Table 6-4, 6-5
	Maintenance intangible assets quantification equations	S 3.4.3, S 6.3.1

Maintenance intangible assets marking scale	S 3.4.4, S 6.3.2, Table 6-7, Appendix C, D
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Empirical Performance Validation

The method for evaluating intangible assets for maintenance implementation and operation	S 6.3.1, S 6.3.2
Framework case study application	S 6.4, Table 6-8, 6-9, Fig 6-3, 6-4
Intangible asset implementation strategy	S 6.4.2, Fig 6-5 Appendix C, D

Empirical performance validation evaluates the actual effectiveness of the method in practice. The capability of the method to evaluate intangible assets within maintenance operations is validated in Sections 6.3.1 and 6.3.2, ensuring that it aligns with real-world implementation requirements. The case study application in Section 6.4, supported by Tables 6-8 and 6-9 and Figures 6-3 and 6-4, demonstrates the performance of the method in a practical environment. Additionally, a strategy for implementing intangible asset evaluation within the maintenance process is outlined in Section 6.4.2 (Figure 6-5, Appendix C, D), further proving the effectiveness of the method in aligning maintenance strategies with organizational needs and capabilities.

7.3 Achievements, contributions, and limitations

In this section, the achievements, contributions, and limitations of this research are outlined. In Section 7.3.1, the contributions of the tangible asset evaluation method for PdM implementation, which are related to Research Question One and Objectives One and Two as discussed in Chapter 1, Section 1.3.1, are included. In Section 7.3.2, the contributions of the intangible asset evaluation method for PdM implementation, which are related to Research Question Two and Objective Three as discussed in Chapter 1, Section 1.3.1, are presented.

7.3.1 PdM implementation tangible assets evaluation

7.3.1.1 Maintenance strategy selection method in modern manufacturing era

To achieve the objective of developing a comprehensive method for selecting the most appropriate maintenance strategy in the modern manufacturing era, the research systematically evaluates the unique characteristics of different maintenance approaches and their alignment with the specific conditions and needs of enterprises. As presented in Table 7-4, this objective is accomplished through the following key contributions:

Table 7-4 Summary of contributions — AHP–WRSR method

Contribution	Novelty / Advancement Beyond Prior Work
Integration of AHP with Weighted Rule-based Reasoning (WRSR)	Bridges quantitative AHP weighting with qualitative rule logic, reducing pairwise complexity and improving interpretability.
Formalization of evaluation attributes (cost, data sufficiency, feasibility)	Provides consistent structure to assess interdependent factors in maintenance strategy selection.
Incorporation of domain knowledge substitution rules	Introduces flexibility by allowing internal, external, or secondary data sources to compensate for expertise gaps.
Clarification of rule logic and sequencing	Establishes transparent evaluation chain for improved decision traceability.

Methodological Advancement in Multi-Criteria Decision-Making for Maintenance Strategy Selection

The theoretical landscape of maintenance strategy selection is advanced through the introduction of a hybrid Analytical Hierarchy Process–Weighted Rank-Sum Ratio (AHP–WRSR) method. Although AHP is widely applied in maintenance-related multi-criteria decision-making (MCDM), reliance on subjective expert judgment is often observed to limit reliability. This limitation is addressed through the integration of WRSR, whereby priority rankings are refined by statistical

weighting and both robustness and reproducibility are enhanced. MCDM theory is enriched through this hybridization, as the demonstration is made that the combination of qualitative expert-based approaches with quantitative statistical adjustments can yield more balanced and defensible outcomes. The adaptability of the method is recognized as making it theoretically significant for evaluating complex, multi-dimensional decisions beyond maintenance strategy selection.

Expansion of Maintenance Strategy Evaluation Criteria to Align with Industry 5.0

From a conceptual standpoint, traditional maintenance evaluation frameworks—which historically emphasize cost, safety, and reliability—are extended through the incorporation of Industry 5.0-oriented criteria such as human-centricity, sustainability, and resilience. Through this extension, maintenance strategy research is repositioned within a broader socio-technical paradigm, and acknowledgment is made of the intertwined importance of technological efficiency, environmental stewardship, and human well-being. This theoretical expansion is seen as bridging the gap between purely technical evaluations and human-machine collaborative models, and the role of ethical and sustainable considerations in industrial decision-making theory is reinforced.

Integration of Implementation Barriers into the Evaluation Framework

A further theoretical contribution is made through the explicit inclusion of PdM implementation challenges such as high capital investment, diagnostic complexity, and integration constraints within the criteria hierarchy. In existing MCDM literature, evaluation is often treated in an idealized context, with assumptions of optimal feasibility for all strategies. By embedding real-world barriers into the theoretical model, decision-making theory is advanced toward a more context-sensitive and pragmatic orientation, and evaluative rigor is aligned with practical constraints.

Reframing Predictive Maintenance as a Strategically Filtered Decision Rather Than a Default Choice

A contribution to PdM theory is made by positioning it not as an inevitable, technology-driven adoption but as a strategy that should be selectively deployed based on contextual appropriateness. The AHP–WRSR method is presented as a formalized mechanism for the assessment of PdM alongside preventive and corrective maintenance strategies, with technological readiness, human alignment, and ethical considerations integrated into the decision process. A reframing of deterministic narratives in PdM literature is thereby achieved, and support is provided to a more deliberate and human-centered adoption model consistent with Industry 5.0 values.

Development of a Customizable, Transparent Tool for Maintenance Strategy Selection

Practically, a clear, structured, and adaptable decision-making tool is offered to manufacturers through the hybrid AHP–WRSR method. An initial ranking of criteria based on expert input is generated by the AHP component, while relative importance is quantified in the WRSR refinement stage without the requirement of additional data collection. Through this dual-layered approach, decision-makers are enabled to visually interpret and quantitatively justify their choices, and transparency and traceability in strategic planning are promoted.

Enhanced Flexibility in Strategy Prioritization for Diverse Industrial Contexts

Flexibility in maintenance strategy selection is enabled through the tool, allowing organizations to tailor decisions to their specific operational priorities—whether focused on cost reduction, safety improvement, energy efficiency, or workforce alignment. Adjustment of the weighting system is permitted so that shifting business objectives are accommodated. This adaptability is particularly valuable in dynamic manufacturing environments where priorities evolve due to market pressures, regulatory changes, or technological advancements.

Strategic Filtering for Predictive Maintenance Adoption

The AHP–WRSR framework is positioned as a contextual filter for determining when PdM adoption is justified, particularly in environments where machine

learning and deep learning tools are costly, data-intensive, or insufficiently interpretable. Clarification of the strategic fit of PdM before investment in advanced analytics is enabled, and the risk of misaligned technology adoption is reduced. Once appropriateness is confirmed, integration of data-driven models for operational optimization is facilitated, ensuring that PdM deployment is targeted and value-driven.

Readiness for Integration with Emerging Industry 5.0 Technologies

Scalability toward future technologies is built into the method's design. Real-time data from edge computing is capable of dynamically adjusting decision weights, digital twin simulations are enabled to explore alternative maintenance strategies, and explainable AI systems are suggested for enhancing operator trust and transparency. This forward compatibility ensures that the method functions as a practical bridge between current decision-making needs and future smart manufacturing ecosystems.

Through the development and application of the proposed method, the following limitations are identified and summarised in Table 7-5:

Table 7-5 Limitations of the maintenance strategy selection method

Limitation	Source / Cause	Implication / Impact
Subjectivity in Expert Judgement	Reliance on expert judgment in AHP stage; equal weighting assigned to all experts	Rankings influenced by experts' backgrounds; reduces generalizability and robustness
Limited Diversity of Expert Representation	Small expert panel, limited industrial scope	Nuances from other industries not captured; applicability beyond tested sector limited
Static Nature of the Evaluation Framework	Weights derived through AHP–WRSR remain fixed for a given decision instance	Reduces responsiveness in dynamic environments; unable to adapt to changing priorities or technology

Limitation	Source / Cause	Implication / Impact
Lack of Longitudinal Validation	No monitoring of maintenance strategy outcomes over time	Cannot confirm framework's consistent operational or strategic effectiveness
Lack of Real-Time Data Integration	Current implementation relies on static expert assessments	Limits applicability in fully automated, adaptive decision environments
Demonstrative Rather Than Validatory Nature of the Case Study	Case study designed to illustrate method, not validate statistically	Cannot establish predictive accuracy or generalizability across industries
Generalizability and Feasibility	Framework developed primarily for manufacturing; requires adaptation for other sectors	May need modifications for healthcare, aerospace, etc.; expert weighting may introduce bias

Subjectivity in Expert Judgement

First, subjectivity is inevitably introduced by reliance on expert judgment in the AHP stage. Even when consistency ratio checks are applied, rankings of criteria are influenced by experts' individual backgrounds, experiences, and cognitive biases. Results are therefore shaped by the specific composition of the panel rather than by a universally applicable prioritization. Furthermore, equal weighting is assigned to all experts' opinions, and variations in domain expertise are not accounted for, which may inadvertently diminish the influence of highly specialized insights.

Limited Diversity of Expert Representation

Second, a relatively narrow scope is observed in the composition of the expert panel, both in size and industrial representation. Although valuable perspectives from manufacturing contexts are contributed by the participants, the nuances of other industries such as energy, healthcare, or transportation, where maintenance requirements, operational risks, and human–technology interactions differ significantly are not fully captured. This limited diversity restricts the generalizability of the model beyond the sector in which it is tested.

Static Nature of the Evaluation Framework

Third, the evaluation framework although innovative in its integration of Industry 5.0 criteria is applied in a static context. The weights derived through AHP and refined by WRSR remain fixed for a given decision instance, and dynamic adaptation to changing operational conditions, emerging technologies, or evolving business priorities does not occur. Responsiveness in highly dynamic environments, where maintenance priorities shift rapidly, is thereby reduced.

Fourth, although the method is positioned as a strategic filter for PdM adoption, empirical testing in longitudinal decision-making scenarios—where outcomes of maintenance strategy selection are monitored over time—is not undertaken. Without longitudinal validation, assessment of whether the model's recommendations consistently lead to superior operational or strategic outcomes in practice cannot be achieved.

Lack of Longitudinal Validation

Finally, direct integration of real-time data or predictive analytics into the decision-making process is not yet realized in the current implementation. Although conceptual alignment with Industry 5.0 technologies is achieved by the framework, execution continues to rely on static expert assessments. Potential offered by data streams from IoT-enabled assets, digital twins, or explainable AI systems is not yet leveraged, and current utility in fully automated, adaptive decision environments is thereby limited.

Demonstrative Rather Than Validatory Nature of the Case Study

A further limitation relates to the scope and purpose of the case study employed to illustrate the AHP–WRSR method. The case study is designed to be demonstrative, showcasing how the hybrid framework can be operationalised in practice and providing illustrative insights into decision-making processes. It does not serve as a formal validation exercise and therefore cannot confirm the generalisability or predictive accuracy of the model across industries, organisational contexts, or time horizons. While valuable for illustrating practical applicability, this demonstrative focus underscores the need for complementary

empirical studies such as comparative cross-industry analyses or longitudinal validations to establish the method's robustness and effectiveness in diverse operational settings.

Epistemic Limitations

The hybrid AHP–WRSR framework, while recognized as providing a structured and transparent approach for maintenance strategy selection, is subject to epistemic limitations. Inherent subjectivity is introduced through reliance on expert judgment for criteria weighting and ranking, as outcomes are influenced by the composition, experience, and cognitive biases of the expert panel. The applicability of the framework is illustrated through the demonstrative case study, but formal validation across industries or organizational contexts is not provided. Additionally, responsiveness to dynamic operational conditions or evolving strategic priorities is limited by the static nature of the model, which comprises fixed criteria weights and decision pathways. Finally, the epistemic breadth of the method may be constrained by the scope of the literature reviewed and the number of experts involved, with atypical industrial scenarios or emerging maintenance strategies potentially overlooked. These limitations underscore the context-dependent boundaries of the framework and the necessity for broader empirical testing and longitudinal studies.

Generalizability and Feasibility

The AHP-based method for maintenance strategy selection offers a versatile framework for industries where maintenance is essential for minimizing downtime and optimizing operational efficiency. Originally developed for manufacturing, this method can be extended to sectors such as aerospace, energy, automotive, and mining, where complex equipment is vital to operations. The AHP approach prioritizes maintenance strategies by evaluating criteria such as cost, reliability, and equipment condition through a structured decision-making process. Its flexibility allows for adaptation to different operational environments, supporting both large-scale industrial plants and small-to-medium enterprises (SMEs). The scalability of the method makes it valuable for organizations of various sizes, optimizing resource allocation and selecting the most appropriate maintenance

strategies to enhance equipment reliability, reduce unplanned downtime, and improve long-term sustainability.

While highly adaptable, the AHP method may require modifications for industries with specialized maintenance needs. In sectors like healthcare, where safety and equipment reliability are paramount, additional criteria related to safety and compliance must be considered. The application of AHP in complex industries such as aerospace or nuclear power may be challenged by the large number of factors involved. Additionally, the reliance on expert judgment for assigning criteria weights may introduce bias, requiring careful expert selection and the potential integration of objective decision-support tools. Despite these challenges, the method's ability to standardize decision-making makes it a feasible solution for industries with complex, asset-intensive operations.

Future Research Directions

Mitigating Subjectivity in Expert Judgment

First, future studies should explore mechanisms for mitigating the subjectivity inherent in expert judgment. One promising direction is the implementation of weighted expert input, where contributions are adjusted according to the depth and relevance of each expert's domain expertise, rather than treating all inputs equally. Additionally, structured bias detection tools or AI-assisted validation methods could be applied to identify inconsistencies in responses and minimise the influence of cognitive biases on the ranking process.

Such refinements are essential because expert input will remain a cornerstone of multi-criteria decision-making in contexts where reliable datasets are scarce. By ensuring that expert assessments are both weighted and validated, the robustness of the decision process can be enhanced and the credibility of the framework in high-stakes strategic planning can be reinforced.

Expanding Diversity and Scale of Expert Panels

Second, expanding the diversity and scale of expert panels is critical for improving the robustness and generalisability of the framework. Multi-sector

panels including representatives from manufacturing, energy, healthcare, and transportation would allow the criteria hierarchy to be stress-tested under varying operational contexts. Cross-industry benchmarking could further distinguish universal drivers of maintenance strategy selection (such as safety and reliability) from sector-specific priorities (such as regulatory compliance in healthcare or sustainability in energy).

This expansion is important because maintenance challenges are highly context-dependent, and a more inclusive expert base would enable the framework to better reflect diverse industrial realities while avoiding biases associated with a narrow sectoral focus.

Developing Dynamic Weighting Mechanisms

Third, the development of dynamic weighting mechanisms should be prioritised. Future research could integrate the framework with real-time data streams such as equipment health monitoring systems, production scheduling updates, and environmental condition sensors so that criteria weights are continuously updated in response to evolving operational contexts. This would transform the model from a static decision-support tool into a continuously adaptive system capable of responding to both gradual changes and sudden disruptions.

The significance of this direction lies in its capacity to bridge the gap between predictive analytics and strategic decision-making. By embedding real-time responsiveness, organisations would be able to maintain alignment between maintenance strategies and shifting business priorities, thereby enhancing resilience and operational efficiency.

Conducting Longitudinal Validation Studies

Fourth, longitudinal studies should be undertaken to empirically validate the practical impact of the AHP–WRSR method over time. Tracking key performance indicators such as equipment availability, downtime reduction, maintenance cost savings, and workforce satisfaction before and after strategy adoption would generate evidence on the framework’s long-term effectiveness. Moreover, such studies could uncover potential trade-offs among human-centric, sustainability,

and resilience objectives, which are often difficult to capture in cross-sectional analyses.

This line of research is crucial because the value of decision-support frameworks ultimately depends on sustained improvements in operational and strategic outcomes. Longitudinal validation would therefore provide a stronger empirical basis for the framework’s adoption and continued refinement.

Integrating Industry 5.0 Technologies and Ethical Considerations

Finally, deeper integration with Industry 5.0 technologies offers a promising path forward. Coupling the decision framework with digital twin simulations would allow decision-makers to explore “what-if” scenarios under varying constraints, while incorporating explainable AI modules could enhance transparency and trust in the decision logic. Furthermore, embedding ethical governance mechanisms for example, accountability in AI-driven recommendations or human-in-the-loop safeguards would align the framework with Industry 5.0’s human-centric values.

This integration is significant because the next generation of maintenance strategy selection tools will need to balance technological sophistication with interpretability and ethical responsibility. By positioning the AHP–WRSR method within a broader intelligent and ethically guided decision-support ecosystem, future research could ensure that maintenance strategy selection not only optimises technical performance but also strengthens social legitimacy and stakeholder acceptance.

7.3.1.2 A decision-based framework for PdM technique selection

To achieve the objective of developing a comprehensive framework for selecting the most suitable Predictive Maintenance technique, the research systematically addresses the unique characteristics of each PdM technique and their alignment with the specific conditions and needs of enterprises. As presented in Table 7-6, this objective is accomplished through the following key contributions:

Table 7-6 Summary of Contributions — PdM Technology selection framework

Contribution	Novelty / Advancement Beyond Prior Work
Introduction of “Ambition Levels” for PdM readiness	Establishes hierarchical link between digital maturity, data readiness, and strategic ambition.
Modular, goal-oriented decision logic	Enables flexible configuration of PdM pathways aligned with organizational goals.
Substitution mechanism for hybrid data and domain sources	Provides methodological bridge between data-driven and knowledge-driven PdM approaches.
Visualization and simplification of decision pathways	Enhances usability for practitioners through structured flow representation.

Structured Definition of Ambition Levels (ALs)

A structured definition and operationalisation of Ambition Levels (ALs) for predictive maintenance (PdM) implementation is provided as one of the central contributions of this research. In existing PdM decision-support models, technological maturity or readiness is typically categorised through generic readiness indices or capability maturity models, and a single linear progression towards advanced solutions is often assumed. In contrast, the AL framework developed in this thesis is conceptualised as a goal-oriented and asset-specific process, so that parallel ambition levels across different systems within the same organisation are allowed. Through this conceptualisation, it is acknowledged that PdM implementation is rarely uniform, with companies often pursuing a fully data-driven, AI-enhanced approach for critical assets while simpler, rule-based approaches are retained for less critical equipment. The AL classification is derived from a synthesis of literature and practical considerations, and the decision-support process is simplified by guiding organisations towards an appropriate class of PdM solutions without the need for exhaustive technical modelling at the initial stage. Organisational objectives—such as cost reduction, reliability improvement, or regulatory compliance—are explicitly connected by the AL framework to feasible technology classes, and a transparent logic path from strategic goals to technology choice is thereby provided. In this way, a persistent

gap in the literature is addressed, where technology selection is often technology-driven rather than goal-driven, and the linkage between business strategy and technical feasibility remains weak.

Development of a Three-Hierarchical Framework for PdM Technology Selection

A coherent, three-hierarchical framework for systematically screening and selecting suitable PdM techniques is developed as another significant contribution. In prior literature, frameworks for maintenance strategy selection, condition-based maintenance evaluation, or technology adoption readiness are presented individually, but their integration into a unified decision-making process is lacking. In this study, ambition level identification, feasibility assessment for PdM techniques, and knowledge-source-based resource substitution are designed to operate either in sequence or independently, depending on organisational needs. This modular structure ensures that the decision-making process is kept transparent, traceable, and adaptable to different levels of organisational maturity. In each hierarchy, a consistent design logic is embodied: criteria are drawn from a structured literature review, operationalised into decision steps, and applied to both strategic and tactical planning. In the first hierarchy, organisational objectives and capabilities are aligned with an appropriate ambition level; in the second, the feasibility of applying different PdM techniques based on defined ALs is evaluated; in the third, viable substitution options are identified when key resources are missing, drawing on the Knowledge Source Triad concept. In this way, a gap in existing PdM literature is addressed, as feasibility assessment is often presented without clear contingency pathways when constraints are present. By providing a methodologically consistent, resource-aware, and action-oriented framework, this research bridges the gap between abstract strategic frameworks and the practical realities of PdM adoption in industrial settings.

Integrating PdM Technology Selection with Digital Transformation and Asset Management Frameworks

PdM technology selection is explicitly positioned within broader organisational agendas of digital transformation and asset management, addressing a gap in both theory and practice. In much of the existing PdM literature, predictive maintenance is treated as an isolated technical initiative, evaluated primarily on algorithmic performance or maintenance cost savings. In contrast, PdM is situated within the strategic continuum of digital transformation, and it is recognised as both a driver and a beneficiary of broader digital capability development. The ambition level framework is used to map PdM maturity to stages of digital transformation, ensuring that technology adoption decisions are aligned with the organisation's overarching digital roadmap. For example, organisations at early digital stages are guided to low-complexity PdM solutions that match their existing data infrastructure, whereas more digitally mature enterprises are directed towards advanced, AI-enabled PdM systems within a fully connected, Industry 4.0 ecosystem.

Furthermore, a clear operational link between PdM technology selection and asset management best practices—as formalised in standards such as ISO 55000—is established. Asset criticality, lifecycle cost considerations, and performance targets—core components of asset management—are incorporated into the PdM evaluation process. In this way, technology choices are ensured to be not only technically feasible but also optimised for long-term asset value preservation and risk reduction. By embedding asset-centric metrics and governance principles into the selection logic, the framework bridges the disconnect between maintenance engineering and asset management disciplines, enabling a more holistic approach to operational reliability and investment planning.

Through the integration of PdM decision-making with digital transformation strategy and asset management frameworks, theoretical integration is strengthened, practical cross-domain alignment is provided, and the strategic relevance of PdM adoption decisions beyond the maintenance function is enhanced.

Advancing Beyond Existing PdM Evaluation Methods through Structured, Goal-Oriented Integration

An advancement beyond existing technology evaluation methods—such as multi-criteria decision-making (MCDM), analytic hierarchy processes (AHP/ANP), and purely data-driven auto-selection systems—is achieved through the integration of their strengths while mitigating their respective limitations. In traditional MCDM and AHP-based frameworks, a rigorous mathematical structure is offered for ranking technology options, but heavy reliance on subjective weighting from domain experts is observed to limit scalability and adaptability across diverse organisational contexts. In purely data-driven selection methods, such as model recommendation engines trained on historical PdM datasets, high objectivity is achieved, but large, high-quality datasets are required and are rarely available in industrial practice, particularly for SMEs.

These shortcomings are addressed by combining the systematic, criteria-based structure of MCDM methods with the contextual adaptability of goal-oriented decision models. Organisational objectives, resource constraints, and asset-specific requirements are first identified, and these inputs are then used to navigate through ambition level classification, feasibility assessment, and conditional pathways for PdM technique substitution. This process preserves the interpretability and transparency valued in AHP-like approaches while ensuring recommendations remain realistic even when complete data or expert panels are unavailable.

The framework's modularity also allows use as a stand-alone decision-support tool or as a complementary front-end to advanced, data-intensive optimisation methods when organisational readiness and data availability improve. By ensuring immediate deployability in low-data environments and extensibility to high-data, algorithmic optimisation contexts, a rare bridge between theoretical rigour and operational practicality is created. This hybrid capability fills a notable gap in the PdM literature, where existing methods are often either too abstract for field use or too data-dependent for broad applicability. The applicability of the framework is illustrated through a demonstrative case study, designed to

showcase operationalisation and practical insights rather than to serve as a statistical validation of the proposed approach.

Through the development and application of the proposed method, the following limitations are identified and summarised in Table 7-7:

Table 7-7 Limitations of the PdM technique selection framework

Limitation	Source / Cause	Implication / Impact
Dependence on the Scope and Quality of the Systematic Literature Review	Limited to peer-reviewed studies; exclusion of grey literature and lab studies	Potential omission of emerging PdM techniques; survivorship bias towards successful implementations
Subjectivity and Complexity in the Hierarchical Decision Framework	Reliance on expert judgment and author-defined parameters; multi-layered structure	May vary in application across organizations; small or low-tech SMEs may find it complex to use
Representativeness and Scope of the Demonstrative Case Study	Single organisation with high digital maturity	Findings may not generalize to organizations at lower maturity or in other sectors
Lack of Standardised Criteria for Assessing Internal Modelling Capabilities	User interpretation required; no baseline for technical competencies	Inconsistent cross-organisational assessment; reduced repeatability
Adaptability and Risk Considerations in the Use of External Data and Pre-Trained Models	Differences in sensor configurations, asset conditions, environmental factors	Transferability limited; may require extensive preprocessing or retraining; legal/IP issues not fully addressed
Insufficient Formalisation of Accuracy–Complexity Trade-Offs in Model Selection	No structured process to weigh accuracy against cost/risk/maintainability	Risk of overinvesting in complex models or underutilising advanced options

Limitation	Source / Cause	Implication / Impact
Limited Granularity and Interaction Analysis in Attribute Structuring	Attributes treated as largely independent	Limits trade-off and scenario analysis; interactions between attributes not captured
Demonstrative Rather Than Validatory Nature of the Case Study	Case study intended for illustration	Does not establish predictive accuracy or generalizability

Dependence on the Scope and Quality of the Systematic Literature Review

One methodological limitation is acknowledged to lie in the reliance placed on the scope and quality of the literature captured through the systematic literature review (SLR). Although the SLR is used to provide a structured and replicable means of extracting PdM-related objectives, organisational attributes, and capability factors, the comprehensiveness and representativeness of the framework are inevitably constrained by the availability, quality, and accessibility of published studies. Because the review focuses primarily on peer-reviewed sources from mainstream academic databases, valuable insights from grey literature, industry reports, and proprietary studies—often containing practical details absent from academic publications—may be overlooked. Furthermore, simulation-based or laboratory-only studies are intentionally excluded to maintain industrial relevance; however, emerging PdM approaches that have not yet been widely deployed in operational settings may be filtered out inadvertently.

The reliance on published industrial case studies is also recognised to create the potential for survivorship bias, as unsuccessful implementations are less likely to be documented in accessible literature. Consequently, the criteria and decision pathways in the framework may implicitly reflect characteristics of more successful PdM projects, limiting their applicability to organisations operating under more challenging or atypical conditions. While these methodological choices are taken to ensure focus on real-world applicability, they also restrict theoretical breadth and point to the need for complementary studies, such as targeted industry surveys or expert interviews, to further validate and enrich the decision criteria.

Subjectivity and Complexity in the Hierarchical Decision Framework

A second limitation is acknowledged to arise from the inherent subjectivity and operational complexity within the hierarchical decision framework. Although ambition level classification and multi-step feasibility algorithms are designed to offer structured, repeatable guidance, the thresholds, weights, and categorical boundaries assigned within the framework rely in part on expert judgement and author-defined parameters. This qualitative interpretation is necessary in the absence of large-scale empirical calibration datasets, but it introduces potential variability in application across organisations or among decision-makers within the same organisation.

Additionally, the multi-layered structure, while beneficial for nuanced decision-making, is recognised as potentially complex for organisations with limited technical expertise or decision-support infrastructure. Small and medium-sized enterprises (SMEs) may face challenges in navigating the full set of decision pathways without external facilitation, which could limit adoption in resource-constrained settings. Although modularity and adaptability are built into the framework, the learning curve associated with mastering its terminology, logic flow, and interdependencies may deter usage in contexts where decision-making speed takes precedence over methodological thoroughness.

Representativeness and Scope of the Demonstrative Case Study

A further limitation is recognised in relation to the nature and scope of the demonstrative case study used to test the applicability of the framework. While the case study provides valuable, context-rich insights into the application of ambition level classification and decision algorithms, its focus on a single organisation—operating at a relatively high digital maturity—restricts the generalisability of the findings. The organisational conditions, asset types, and operational constraints in this case may not fully represent those of enterprises at lower maturity levels, in other industrial sectors, or under different regulatory and economic pressures.

Moreover, the case study is explicitly positioned as demonstrative rather than as a formal validation exercise. Its role is to illustrate operationalisation of the framework and explore tactical-level implications, rather than to statistically verify predictive or prescriptive accuracy across diverse contexts. Without a broader set of comparative or longitudinal case studies, there remains a risk that observed implementation pathways, prioritisation rules, or adaptation strategies are specific to the case setting.

Lack of Standardised Criteria for Assessing Internal Modelling Capabilities

The assessment of an organisation's internal modelling capabilities is acknowledged to be limited by the absence of fully standardised evaluation criteria. In the feasibility algorithm, users are asked to determine whether internal capability for developing predictive models exists, yet the definition of "capability" is left largely to user interpretation. At present, no baseline set of technical competencies, tooling requirements, or process maturity indicators is specified to enable consistent and replicable assessments across organisations.

This ambiguity can produce inconsistent results in cross-organisational comparisons or benchmarking. Furthermore, organisational processes essential for effective model development—such as experimental design competence, validation procedures, and integration of modelling workflows into maintenance operations—are not explicitly addressed. By retaining a qualitative approach, adaptability is preserved, but objectivity and repeatability are reduced.

Adaptability and Risk Considerations in the Use of External Data and Pre-Trained Models

The recognition of the potential value of external datasets and pre-trained models is acknowledged to be addressed only at a high level, without detailing the associated adaptation requirements and risks. In practice, such datasets and models often differ substantially from a target organisation's environment in terms of sensor configurations, sampling rates, asset conditions, environmental factors, and failure mode distributions. These differences can limit transferability and necessitate significant preprocessing, feature engineering, or retraining.

The methodology does not include a formalised evaluation process for quantifying compatibility gaps prior to adoption, nor does it systematically address risks such as sample bias, reduced interpretability, or hidden adaptation costs. Legal and intellectual property issues are also not explicitly incorporated into the decision pathways. Leaving these considerations to informal judgement risks overestimating benefits and underestimating costs.

Insufficient Formalisation of Accuracy–Complexity Trade-Offs in Model Selection

Although comparative results from different machine learning models are included in the case study, the framework is acknowledged not to fully formalise how trade-offs between predictive accuracy and implementation complexity should be managed. In practice, models with marginally higher accuracy may require disproportionately greater resources, while simpler models may underperform in capturing complex patterns.

The framework currently suggests that feasibility confirmation should precede detailed model selection, but no structured process for weighing accuracy against cost, risk, or maintainability is provided. Without such guidance, organisations risk overinvesting in overly complex models or underutilising advanced options.

Limited Granularity and Interaction Analysis in Attribute Structuring

The attribute classification within the framework is acknowledged to operate at a relatively high level of abstraction and with limited treatment of interdependencies. Certain attributes, such as “cost,” are not disaggregated into specific subcomponents, making trade-off analysis less precise. Furthermore, attributes are presented as largely independent, whereas in practice they often interact.

The absence of explicit modelling of these interactions limits the framework’s capacity for “what-if” scenario analysis. Future work could address this by introducing hierarchical or network-based models to map causal relationships and improve predictive depth.

Demonstrative Rather Than Validatory Nature of the Case Study

A key limitation lies in the nature and purpose of the case study presented in this research. The case study is explicitly designed to be demonstrative, serving to illustrate the operationalisation of the proposed framework and to provide exploratory insights into its practical application. It is not intended as a formal validation exercise, and therefore does not establish generalisable evidence of predictive accuracy or effectiveness across industries and organisational contexts. While this approach supports clarity and transparency in showcasing framework use, it also highlights the need for further empirical studies across diverse organisations, sectors, and maturity levels to formally validate and refine the framework.

Epistemic Limitations

The decision-based PdM technology selection framework offers goal-oriented, modular guidance for selecting appropriate PdM techniques. However, epistemic limitations arise from several sources. The hierarchical classification of Ambition Levels and feasibility assessments rely on expert interpretation and author-defined thresholds, introducing subjectivity. The demonstrative case study, focused on a single organization with relatively high digital maturity, restricts generalizability to other sectors or organizations with differing capabilities. Furthermore, the absence of fully standardized criteria for evaluating internal modeling capabilities, as well as the qualitative treatment of external datasets and pre-trained models, limits the objectivity and reproducibility of recommendations. The static treatment of accuracy–complexity trade-offs and the limited modeling of interdependencies among attributes further constrain the framework’s epistemic robustness. These considerations highlight the need for expanded cross-industry validation and formalization of evaluation procedures.

Generalizability and Feasibility

The decision-based predictive maintenance technology selection framework provides a structured approach for selecting the most suitable PdM technologies for various industries. The applicability of this framework is not limited to the

industries presented in the case studies; it also covers areas such as automotive, energy, chemical, and healthcare, where PdM technologies are crucial for enhancing equipment reliability, reducing downtime, and ensuring operational continuity. The flexibility of the framework enables the assessment of various PdM technologies ranging from basic condition monitoring to advanced AI-driven predictive analytics based on factors such as data availability and operational costs. This ensures that industries can choose the most cost-effective and technically appropriate strategies, whether for large-scale operations or small enterprises, and achieve goals in terms of cost efficiency, sustainability, and compliance.

From a feasibility perspective, this framework is most effective in industries that have ample data access and technical infrastructure, such as aerospace, automotive, and energy sectors. However, for industries with limited resources or low digital maturity (such as small manufacturing plants), its application might be more complex. Additionally, for industries with special equipment or strict regulatory requirements (such as pharmaceuticals or food processing), challenges might arise when interfacing with specific regulations. Despite these limitations, the adaptability of this framework makes it still a suitable solution for a wide range of industries, helping them improve predictive maintenance practices.

Future Research Directions

Expanding Empirical Validation Across Diverse Industrial Contexts

A key avenue for future research lies in expanding the empirical validation of the proposed framework. At present, the attribute set, and decision pathways are primarily derived from a structured literature review and tested through a single demonstrative case study. While this approach ensures methodological consistency and practical illustration, it inevitably limits generalisability. Multi-case studies conducted across diverse industrial sectors such as energy, healthcare, and transportation together with varying asset classes and organisational maturity levels, are therefore required. Complementary methods, including structured industry surveys or Delphi-based expert panels, could further

support the assessment of attribute relevance, threshold calibration, and inter-attribute interactions. Such empirical expansion would enable refinement of the framework to ensure its robustness and applicability across a wide range of organisational contexts, including small and medium-sized enterprises (SMEs) that often operate under severe resource constraints.

Formalising Data Readiness and Quality Assessment

Another promising direction is the formalisation of data readiness and quality evaluation within the framework. Although data sufficiency and representativeness are recognised as critical enablers of predictive maintenance, their assessment in this research is primarily qualitative and context-dependent. Future work could incorporate automated dataset profiling tools capable of assessing completeness, representativeness, labelling accuracy, and signal integrity. Additionally, diagnostic indicators could be developed to detect systematic biases and data imbalances that may compromise predictive performance. By embedding explicit, context-sensitive benchmarks into the decision process, organisations would benefit from greater transparency and consistency in evaluating data readiness, thereby facilitating more precise alignment between dataset characteristics and the choice of appropriate PdM modelling approaches.

Developing a Model Selection and Trade-Off Analysis Sub-Framework

A further research priority concerns the development of a structured sub-framework for model selection and trade-off analysis. While the current framework highlights the importance of balancing predictive accuracy against implementation complexity, it does not provide a systematic procedure for operationalising this trade-off. Future research could design a dedicated module that formalises decision rules for phased adoption strategies, interpretability requirements, computational resource availability, and lifecycle cost implications. Such a sub-framework would not only support organisations in selecting models that are technically feasible but also ensure alignment with strategic priorities such as cost-efficiency, risk management, and regulatory compliance. By making explicit the trade-offs inherent in model choice, this extension would enhance the

practical usability of the framework and reduce the risk of over- or under-investment in particular predictive solutions.

Strengthening Adaptation Protocols for External Data and Models

Building on the recognition of transferability challenges, future research should focus on developing formalised adaptation protocols for the use of external datasets and pre-trained models. In the current framework, the potential of such resources is acknowledged, but systematic evaluation mechanisms are lacking. A standardised “external model adaptation checklist” could be introduced to guide practitioners through critical considerations, including compatibility assessments with local sensor configurations and operating conditions, preprocessing and feature engineering requirements, and retraining demands. In addition, compliance with intellectual property rights and licensing restrictions should be explicitly addressed. By embedding such structured protocols, organisations would be better positioned to exploit open-source and third-party solutions while minimising risks associated with hidden costs, reduced interpretability, or degraded performance. This extension would significantly enhance the framework’s practical robustness in environments where external knowledge reuse is essential for accelerating PdM adoption.

Modelling Attribute Interdependencies and Dynamic Scenarios

Another direction for future research lies in the explicit modelling of interdependencies among attributes and the incorporation of dynamic scenario analysis. In the present framework, attributes are treated largely as independent variables, which simplifies decision pathways but overlooks the complex causal relationships often observed in real-world PdM adoption. Future iterations could employ network-based modelling approaches, such as Decision-Making Trial and Evaluation Laboratory (DEMATEL) or system dynamics, to map the interactions and feedback loops between critical factors, for example, how data availability influences cost structures, or how organisational culture affects investment decisions. By incorporating scenario-based planning tools, decision-makers would gain the ability to explore how changes in one attribute such as budget constraints, regulatory shifts, or workforce turnover cascade through the system

to alter technology selection outcomes. Such dynamic modelling would not only enhance the predictive depth of the framework but also improve its capacity to support resilient and adaptive decision-making under conditions of uncertainty.

7.3.2 PdM implementation intangible assets evaluation

To achieve the objective of developing a method for manufacturers to accurately assess the intangible assets necessary for successfully implementing and operating their maintenance strategies, as presented in Table 7-8, the research contributes the following:

Table 7-8 Summary of Contributions — Intangible Asset Evaluation Framework

Contribution	Novelty / Advancement Beyond Prior Work
Integration of intangible assets into PdM maturity assessment	Connects human, organizational, and knowledge resources with PdM capability progression.
Differentiation of maturity levels across intangible dimensions	Clarifies role of communication, learning, and cultural readiness in PdM evolution.
Systematic mapping between intangible resources and technical outcomes	Establishes causal link between soft and hard success factors.
Development of continuous improvement roadmap	Provides structured guidance for developing intangible enablers over time.

Development of a Structured Intangible Asset Evaluation Methodology

A novel, structured method for the evaluation of intangible assets that are critical for the implementation of predictive maintenance (PdM) in manufacturing environments is presented in this research. Unlike existing studies in which intangible assets are discussed broadly or general frameworks are applied, the methodology is tailored to PdM-specific requirements. Expert assessments and interviews are integrated into the method so that intangible assets such as human capital, organizational culture, technological infrastructure, and knowledge management systems, which are essential for PdM success, are identified,

validated, and quantified. By explicitly linking intangible assets to PdM, a gap in the literature is filled, since such assets are often treated generically or overlooked in favor of tangible assets such as machinery and technology. A clear theoretical framework is provided, and the resource-based view (RBV) of firms is extended with the proposition that intangible resources, rather than physical assets alone, are positioned as key drivers of competitive advantage and success in high-tech domains such as PdM. From a practical standpoint, organizational readiness for PdM adoption is assessed systematically through this method, and critical intangible assets are identified. A practical tool that directly supports manufacturers in their decision-making process is offered, and the development and deployment of necessary intangible resources are guided effectively. Furthermore, the crucial intangible elements that contribute to successful PdM implementation are ensured not to be overlooked.

Integration of Intangible Asset Evaluation into a PdM Maturity Model

A significant theoretical contribution is made through the integration of intangible asset management into the PdM Maturity Model. Five levels of PdM maturity are linked with the corresponding development of intangible assets required at each stage. A clear roadmap that guides organizations through their PdM journey is provided, and the development of necessary intangible resources at each maturity level is highlighted. Existing frameworks of PdM maturity, which often focus solely on technical infrastructure, sensors, and data analytics, are enhanced. By incorporating intangible assets such as leadership, knowledge management, and employee skills, theoretical understanding of organizational capabilities required for digital transformation is broadened. Dynamic Capabilities Theory is extended through the proposition that the ability to manage intangible assets dynamically is a critical factor for successful progression through PdM maturity levels. For practitioners, a tangible tool for assessing the current state of PdM capabilities is offered, while a clear and structured path for continuous improvement is also provided. Necessary intangible assets (e.g., skills, organizational culture, data-driven decision-making) are identified at each maturity level, and their development is prioritized accordingly. This alignment

between maturity progression and intangible asset development is established as a unique contribution that facilitates smoother PdM adoption across organizations.

Critical Theoretical Insights into the Role of Intangible Assets in PdM Success

Beyond the development of a specific methodology, a critical theoretical contribution to the field is made by emphasizing the underexplored role of intangible assets in predictive maintenance success. In traditional models of PdM implementation, tangible factors such as hardware and software are focused on, and the significance of human and organizational factors is often overlooked. By placing emphasis on intangible resources such as knowledge, skills, and organizational culture, new insights into the key drivers of PdM success are provided. The understanding of Dynamic Capabilities Theory is expanded with the suggestion that PdM success is achieved not merely through technological innovation but also through the ability of organizations to manage and leverage intangible assets effectively. Organizational learning, employee training, and leadership are argued to be as crucial as sensor technologies and predictive algorithms, and a shift to a more holistic view of PdM adoption is proposed. For practitioners, a roadmap for approaching PdM implementation with a balanced perspective is provided, with the understanding that PdM success is contingent not only on advanced technologies but also on the cultivation of organizational capabilities and a culture of continuous learning and knowledge sharing.

Establishing a Roadmap for Continuous Improvement in PdM Implementation

Another contribution is made through the establishment of a roadmap for continuous improvement in PdM adoption, in which the incremental development of intangible assets over time is emphasized. Based on a maturity model, the roadmap is aligned with the development of PdM capabilities and the maturation of intangible assets, ensuring that continuous improvement of PdM practices is achieved while necessary human and organizational resources are developed simultaneously. Organizational development theory is extended by this

continuous improvement framework, as a structured approach to the evolving nature of PdM capabilities and the role of intangible assets is provided. The dynamic capabilities perspective is strengthened with the proposition that organizational capabilities must be constantly reconfigured and adapted in response to changing environments. PdM practices are ensured to evolve in tandem with intangible resource development, thereby maintaining relevance and effectiveness over time. From a practical standpoint, PdM is managed as a long-term strategic initiative through this roadmap, and the common pitfall of overemphasizing short-term technological solutions at the expense of organizational readiness is avoided. Organizations are encouraged to invest in intangible resources gradually, and sustained success and adaptability in PdM practices are ensured as they mature.

Contribution to the Existing Knowledge in PdM, Digital Transformation, and Industry 5.0

A contribution to the evolving body of knowledge in PdM, digital transformation, and the emerging paradigm of Industry 5.0 is made by linking intangible assets to successful PdM adoption and organizational transformation. In existing research in these fields, technological and data-driven aspects of PdM or digital transformation are often emphasized, while the role of intangible resources in sustaining these processes is given limited attention. This gap is bridged by emphasizing how critical organizational elements such as knowledge management, leadership, and employee skills are essential for successful PdM and digital transformation initiatives.

Traditional PdM research is often centered on hardware, sensors, data analytics, and predictive algorithms. However, the intangible resources necessary for implementing and sustaining PdM systems are typically overlooked. By integrating intangible assets such as human capital, organizational culture, and leadership into PdM models, a broader and more holistic understanding of PdM adoption is provided. This approach moves beyond a purely technical perspective and incorporates organizational capabilities that are required for PdM success. This contribution aligns with the recent shift in PdM research towards people-

centric approaches, in which it is recognized that PdM adoption cannot be realized fully without attention to the human and organizational factors that drive it.

In the field of digital transformation, technological innovations such as IoT, AI, and Big Data, and their impact on business processes and operations are often emphasized. However, organizational preparedness, including cultural readiness, leadership, and employee capabilities, is frequently not addressed. In this research, these elements are integrated into the digital transformation framework, and it is demonstrated that advanced technologies must be supported by the development of intangible resources to be leveraged effectively. A clear theoretical extension to digital transformation research is provided, with the argument that the digital maturity of an organization is shaped significantly by its ability to manage and optimize intangible assets.

Industry 5.0, which emphasizes human-centric and sustainable manufacturing processes, is recognized as an emerging area of interest that extends beyond the automation- and efficiency-driven goals of Industry 4.0. While Industry 4.0 focuses on integrating advanced technologies such as AI and robotics into manufacturing processes, Industry 5.0 stresses the importance of collaboration between humans and machines, as well as the role of intangible human resources such as creativity, empathy, and knowledge. A contribution to Industry 5.0 is made in this research by emphasizing that successful PdM systems are enabled not only by machines and data but also by the people and organizational culture that support the effective use of these technologies. By focusing on intangible assets, alignment with Industry 5.0's vision of fostering human-centric, sustainable, and inclusive technology-driven transformations is achieved.

By addressing the interaction between intangible assets and technological systems in PdM, digital transformation, and Industry 5.0, a novel perspective that integrates human and technological factors is introduced. The theoretical framework in these fields is enriched by the suggestion that the effective implementation of advanced technologies depends not only on hardware and software but also on organizational and human resources. A move is made

beyond the technological determinism approach, and the critical role of organizational capabilities and leadership in guiding technology adoption is highlighted.

Contribution to Enhancing and Complementing Existing Frameworks (BSC, CMMI, KPIs)

An important extension and enhancement to well-established frameworks such as the Balanced Scorecard (BSC), Capability Maturity Model Integration (CMMI), and Key Performance Indicators (KPIs) is made by addressing the significant gap in these models regarding the evaluation of intangible assets. These existing models, although widely used in performance management and process optimization, are often focused on tangible outputs or efficiency metrics, while the crucial role of intangible assets—such as organizational culture, leadership, employee skills, and knowledge management—in the successful adoption of complex systems such as PdM and digital transformation is overlooked.

Complementing the Balanced Scorecard (BSC)

The Balanced Scorecard (BSC) provides a comprehensive approach to performance measurement across four key dimensions—financial, customer, internal processes, and learning and growth. While BSC includes a focus on learning and growth, specific intangible resources that drive these areas, such as leadership capabilities, knowledge sharing, or organizational culture, are not sufficiently detailed or quantified. BSC is complemented in this study through a standardized framework for quantifying intangible assets such as human capital, knowledge management, and employee skills. Unlike the generalized approach of BSC to learning and growth, clear and measurable dimensions of intangible resources that directly impact PdM implementation are provided. By aligning these resources with PdM maturity levels, additional granularity is added to BSC, which allows a deeper understanding of how organizational capabilities support long-term performance improvements, especially in technology adoption and digital transformation.

Extending the Capability Maturity Model Integration (CMMI)

The Capability Maturity Model Integration (CMMI) provides a structured approach to process management, focusing on process improvement and maturity in organizational capabilities, particularly in areas such as software engineering and systems development. However, the model emphasizes process maturity without fully accounting for the human and organizational resources necessary to sustain such processes. The role of intangible assets in advancing process maturity is also not emphasized. In this research, CMMI is extended by integrating the evaluation of intangible assets into the process improvement framework. A people-centric dimension is added through the PdM maturity model, with the argument that process maturity cannot be achieved without investment in human capital (e.g., employee training, leadership development) and organizational culture (e.g., knowledge-sharing practices). By aligning PdM maturity with the development of these intangible assets, CMMI is enhanced by a holistic view that connects technical maturity with organizational capability readiness.

Refining Key Performance Indicators (KPIs)

Key Performance Indicators (KPIs) are widely used in performance management to track organizational success, but they typically emphasize output-driven metrics such as production efficiency, cost reduction, and uptime. Deeper organizational and cultural factors that drive these outcomes are often overlooked. While KPIs provide valuable quantitative insights, qualitative aspects of organizational development that are essential for long-term success—such as employee engagement, leadership quality, and innovation capacity—are frequently omitted. In this research, KPIs are refined by incorporating the quantification of intangible assets such as leadership effectiveness, employee skills, and organizational culture into performance evaluation. By aligning KPIs with intangible asset evaluation, a more comprehensive performance management system is offered, recognizing that long-term success is influenced as much by intangible resources as by operational outcomes. This broader view enhances the relevance of KPIs in the context of PdM adoption and digital transformation, where success is driven not only by measurable efficiencies but

also by the capabilities of the workforce and the organizational culture that supports technological advancement.

Through the development and application of the proposed method, the following limitations are identified and summarised in Table 7-9:

Table 7-9 Limitations of the PdM intangible asset evaluation framework

Limitation	Source / Cause	Implication / Impact
Subjectivity in Expert Assessments	Expert assessment and majority-rule approach; minority viewpoints underrepresented	Certain critical intangible assets may be overlooked; reduces robustness of evaluation
Linear Assumptions in PdM Maturity Model	Assumes stage-by-stage progression	May not capture non-linear organizational development; roadmap flexibility limited
Limited Generalizability of Findings	Single case study in manufacturing sector	Findings may not apply to other industries, sectors, or organizations with different digital maturity
Rigidity of the Roadmap for Continuous Improvement	Structured, stage-based design	Organizations may struggle to adapt to sudden changes or disruptions
Temporal Constraints of the Framework	Rapid evolution of AI, IoT, and human-machine collaboration	Framework may require periodic updates; limits predictive validity over time
Demonstrative Rather Than Validatory Nature of the Case Study	Case study intended for illustration, not statistical validation	Generalizability and predictive accuracy across industries are not established

Subjectivity in Expert Assessments

The first limitation is associated with the subjectivity inherent in the expert assessment process and the use of a majority-rule approach for the identification of critical intangible assets. In this study, assets are classified as significant when their importance is agreed upon by more than half of the consulted experts.

Although a consensus-based approach is provided as a practical and efficient method for prioritizing key factors, the diversity of perspectives is inevitably simplified and the nuances of individual expert opinions are downplayed. Minority viewpoints, particularly those representing niche expertise or highly context-specific knowledge, may be underrepresented. This simplification, while necessary for feasibility, creates a risk that intangible assets which may be vital in specialized PdM scenarios but are not widely recognized across the broader expert group are overlooked.

Linear Assumptions in the PdM Maturity Model

A second limitation is related to the applicability of the PdM maturity model developed in this research, which assumes a linear, stage-by-stage progression toward higher levels of maturity. Although benchmarking is facilitated and a clear roadmap for improvement is provided to organizations through this design, the complex and often non-linear nature of organizational development may be oversimplified. In practice, a perfectly sequential path is rarely followed in PdM adoption; uneven progress across different dimensions may be made by organizations, regressions may occur due to internal or external setbacks, or certain stages may be bypassed altogether. As a result, the structured progression of the model may fail to capture fully the dynamic and adaptive strategies employed by some organizations, and potential misalignments between the model's recommendations and an organization's real-world capabilities may be created.

Limited Generalizability of Findings

The third limitation concerns the generalizability of the findings, as validation is conducted through a single case study in the manufacturing sector. Although a rich and contextualized understanding of intangible asset evaluation within a specific organizational environment is enabled by this in-depth examination, the applicability of the results to other industries or operational contexts is limited. Variations in organizational size, sector-specific regulations, technological infrastructure, and workforce culture mean that different priorities and management practices of intangible assets may exist in other settings such as

energy, healthcare, or transportation. Consequently, although clear utility is demonstrated by the proposed framework in the examined context, its broader applicability remains to be tested through comparative studies across multiple industries.

Rigidity of the Roadmap for Continuous Improvement

Another limitation is connected to the relative rigidity of the roadmap for continuous improvement in PdM adoption and intangible asset development. Although clear and actionable steps are provided to organizations by the roadmap, its design around a structured progression does not fully account for the unpredictability of large-scale organizational change. In reality, PdM implementation is often influenced by sudden shifts caused by market volatility, leadership turnover, technological breakthroughs, or unforeseen operational challenges. Because flexibility is not incorporated into the roadmap, organizational adaptation to these changes may be hindered, and innovation may be constrained or progress delayed when deviations from the prescribed path become necessary.

Temporal Constraints of the Framework

Finally, the framework is focused primarily on the current technological and organizational landscape of PdM, while the rapid pace of technological change and the emergence of new capabilities that may reshape the field in the near future are not fully addressed. Rapid evolution is experienced by technologies such as artificial intelligence, the Internet of Things, and blockchain, and new intangible asset requirements such as advanced data governance, AI ethics management, and human-machine collaboration skills are introduced by their adoption. Although the intangible assets relevant to today's PdM practices are captured by the present framework, its applicability may decrease over time unless periodic updates are made to reflect emerging competencies. This temporal limitation highlights the need for future research to be carried out with a forward-looking perspective that anticipates and integrates these technological and organizational developments.

Demonstrative Rather Than Validatory Nature of the Case Study

A further limitation lies in the nature of the case study applied to illustrate the intangible asset evaluation framework. The case study is intended to be demonstrative, showcasing the operationalisation of the proposed method and providing exploratory insights into its practical application, rather than serving as a formal validation exercise. As such, it does not establish generalisable or statistically verified evidence of the framework's predictive or prescriptive accuracy across industries or organisational contexts. While valuable for highlighting applicability, this demonstrative role underscores the need for broader validation through multi-industry comparative studies, longitudinal analyses, and empirical testing in varied organisational settings.

Epistemic Limitations

While systematically linking human, organizational, and knowledge resources to PdM success, the intangible asset evaluation methodology is subject to several epistemic limitations. Potential subjectivity and underrepresentation of minority or highly context-specific perspectives are introduced through expert assessments underpinning the identification and prioritization of critical intangible assets. Non-linear organizational development may be oversimplified by the linear assumptions embedded in the PdM maturity model, and generalizability across industries with differing operational, cultural, or regulatory conditions is limited by the demonstrative single-case study. Temporal constraints are also present, as the framework is anchored in current technological and organizational landscapes and may not fully capture emerging competencies or Industry 5.0 requirements. Finally, the roadmap for continuous improvement assumes structured progression, which may not reflect dynamic adaptation to sudden organizational changes. These limitations emphasize the need for adaptive, empirically validated approaches in future research.

Generalizability and Feasibility

The intangible asset evaluation method for PdM implementation is highly adaptable and particularly suitable for industries with complex operation and

maintenance requirements. This framework focuses on key factors such as knowledge management, professional skills of employees, organizational culture, and technology adoption, which are crucial for the successful implementation of PdM. It can be applied in multiple industries, especially in those such as energy, oil and gas, pharmaceuticals, and aerospace, where intangible assets (such as skilled labour, data management systems, and continuous employee training) are integrated during the PdM process to enhance maintenance efficiency and safety. The flexibility of this framework enables customization based on the operational characteristics of different industries, thereby better meeting specific needs. However, the actual effectiveness of the framework largely depends on whether industries can effectively invest in labour development and the construction of data-driven systems. In industries with limited resources, such as small and medium-sized enterprises or developing industries, adopting this framework may face greater difficulties. Moreover, the organization's preparedness and cultural differences may also affect the integration and implementation effect of intangible resources with PdM strategies.

Future Research Directions

Enhancing Expert Assessment and Reducing Subjectivity

To address the subjectivity inherent in expert assessments and the reliance on majority rule, future research should explore the integration of weighted scoring systems and advanced consensus-building techniques, such as Delphi rounds or fuzzy logic-based aggregation. These approaches would enable more nuanced representation of diverse expert opinions, ensuring that minority but potentially critical viewpoints are preserved. The incorporation of AI-assisted analysis tools is also recommended to detect cognitive biases and enhance the transparency and consistency of evaluation outcomes.

Such methodological refinements are particularly important because expert judgment remains indispensable in contexts where quantitative data are scarce. By improving the reliability of expert-derived inputs, the robustness of evaluation results can be increased, and the framework's credibility in high-stakes industrial decision-making can be strengthened.

Developing Dynamic and Non-Linear PdM Maturity Models

Current PdM maturity models often assume a linear progression toward advanced implementation. Future studies are encouraged to develop dynamic, non-linear models that reflect the adaptive and context-dependent nature of organisational growth. Real-time feedback loops, scenario planning, and contextual factors such as organisational culture, market conditions, and resource constraints could be integrated to provide a more personalised and flexible pathway for PdM adoption.

This evolution is significant because organisations rarely follow a uniform trajectory; they often progress unevenly across different assets or business units. A non-linear maturity model would capture this diversity, enabling decision-makers to design differentiated adoption strategies that better align with operational priorities and external pressures.

Expanding Cross-Sectoral Empirical Validation

To overcome the limited generalisability resulting from the single-case validation, future research should apply the methodology across multiple industries, including energy, healthcare, and transportation. Such cross-sectoral validation would allow for the identification of both commonalities and divergences in intangible asset management and provide insights into how the framework can be tailored to varying operational contexts. Broader empirical testing would also enable refinement of attribute definitions, threshold values, and decision pathways, thereby increasing the framework's robustness.

In particular, empirical expansion is essential for ensuring that the framework remains relevant across organisations with different regulatory environments, data availability conditions, and operational risks. By systematically testing the framework in diverse contexts, external validity can be established, and the model's adaptability can be demonstrated beyond manufacturing.

Designing Adaptive and Flexible Improvement Roadmaps

In response to the rigidity of the improvement roadmap identified in the current study, future research should focus on the development of adaptive roadmaps with built-in flexibility mechanisms. These mechanisms could include iterative reassessment cycles and adjustable milestones, enabling organisations to revise their strategies in light of emerging conditions or disruptive events. Such adaptive structures would foster resilience and innovation while maintaining strategic alignment over time.

This research direction is valuable because maintenance priorities are rarely static; they evolve in response to technological innovation, regulatory changes, and shifting market conditions. An adaptive roadmap would allow organisations to remain agile, ensuring that PdM implementation remains relevant and effective under uncertainty.

Integration of Emerging Technologies

Finally, to ensure the framework's relevance amid rapid technological advancements, future studies should proactively embed emerging technologies such as artificial intelligence, Internet of Things (IoT), and blockchain into intangible asset evaluation. The identification and integration of new competencies, including AI literacy, ethical governance, and advanced human-machine collaboration, will be essential. Through such forward-looking updates, the framework can remain a valuable guide for PdM adoption within the evolving paradigm of Industry 5.0.

This line of research is particularly critical because technological progress is not only reshaping maintenance practices but also redefining organisational capabilities and workforce roles. By explicitly aligning PdM adoption with the broader transformation agenda, future studies can help organisations balance efficiency with human-centric and ethical considerations, thereby reinforcing the long-term sustainability of Industry 5.0 strategies.

In summary, future validation and scalability pathways are considered to include longitudinal studies through which the frameworks' performance is observed over time in supporting organisational learning and adaptive capability development.

Cross-industry validation, particularly across sectors with differing digital maturity levels is regarded as a means of further strengthening evidence of robustness and generalisability. In addition, integration of quantitative performance indicators or simulation-based assessments is considered to complement expert-based evaluations, so that a more comprehensive understanding of the frameworks' long-term effectiveness and practical scalability is provided.

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Appendices

Appendix A Ethical approval letter



1 April 2025

Dear Mr Li ,

Reference: CURES/24708/2025

Project ID: 21781

Title: Investigation on Predictive Maintenance Implementation Cost-Efficiency

Thank you for your application to the Cranfield University Research Ethics System (CURES).

We are pleased to inform you your project title change request, reference CURES/24708/2025 has been approved.

If you have any queries, please contact CURES Support.

Regards,

CURES Team

Appendix B Open-source data-driven PdM model defined for Chapter 5 case study

This appendix provides supplementary resources to support the development of a data-driven Predictive Maintenance (PdM) model for the company, as discussed in Chapter 5. Given the company's lack of prior experience with data-driven technologies and its limited in-house expertise in machine learning, data analytics, and predictive modeling, leveraging secondary data is a critical step in overcoming these challenges.

Appendix B includes a comprehensive list of pre-built PdM models sourced from open-source databases, as summarized in Table 5-1 of Chapter 5. These models, successfully applied in similar contexts such as CNC machine predictive maintenance, come with source code and documentation to facilitate adaptation and retraining. Many data-driven PdM models are inherently designed for retraining on diverse datasets, making them applicable across various equipment types. By utilizing these resources, the company can significantly reduce development time and dependency on internal technical expertise.

The materials in this appendix serve as a valuable starting point, enabling the company to explore best practices in PdM modeling, understand the integration of secondary data, and accelerate its transition toward data-driven maintenance strategies.

Logistic Regression

```
: classifier = LogisticRegression(random_state = 0)
  classifier.fit(X_train, y_train)
  y_pred_1 = classifier.predict(X_test)
  acc = accuracy_score(y_test, y_pred_1)
  print("Accuracy: %.2f%%" % (acc * 100.0))
  cnf_matrix = confusion_matrix(y_test, y_pred_1)
  print(cnf_matrix)
```

Support Vector Classification

```
classifier = SVC(kernel = 'rbf', random_state = 0)
classifier.fit(X_train, y_train)
y_pred_2 = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred_2)
print("Accuracy: %.2f%%" % (acc * 100.0))
cnf_matrix = confusion_matrix(y_test, y_pred_2)
print(cnf_matrix)
```

Gaussian Classifier

```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
y_pred_3 = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred_3)
print("Accuracy: %.2f%%" % (acc * 100.0))
cnf_matrix = confusion_matrix(y_test, y_pred_3)
print(cnf_matrix)
```

KNN Classifier

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred_4 = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred_4)
print("Accuracy: %.2f%%" % (acc * 100.0))
cnf_matrix = confusion_matrix(y_test, y_pred_4)
print(cnf_matrix)
```

Decision Tree Classifier

```
classifier = DecisionTreeClassifier(max_depth=7)
classifier.fit(X_train, y_train)
y_pred_5 = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred_5)
print("Accuracy: %.2f%%" % (acc * 100.0))
cnf_matrix = confusion_matrix(y_test, y_pred_5)
print(cnf_matrix)
```

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier as RFC
classifier=RFC(n_estimators=100,criterion='entropy',random_state=0)

classifier.fit(X_train, y_train)
y_pred_6 = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred_6)
print("Accuracy: %.2f%%" % (acc * 100.0))
cnf_matrix = confusion_matrix(y_test, y_pred_6)
print(cnf_matrix)
```

Optimizing Random Forest Classifier

```
# Generate some random data for example purposes

# Define the parameters to tune
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 5, 10],
    'max_features': ['auto', 'sqrt', 'log2'],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
```



```

}

# Create a Random Forest Classifier
rf = RandomForestClassifier()

# Use grid search to find the best hyperparameters
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5,
n_jobs=-1)
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print("Best hyperparameters: ", grid_search.best_params_)
y_pred_6_5 = classifier.predict(X_test)

acc = accuracy_score(y_test, y_pred_6_5)
print("Accuracy: %.2f%%" % (acc * 100.0))
cnf_matrix = confusion_matrix(y_test, y_pred_6_5)
print(cnf_matrix)

```

XG Boost Classifier

```

classifier=XGBClassifier()
classifier.fit(X_train,y_train)
y_pred_7 = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred_7)
print("Accuracy: %.2f%%" % (acc * 100.0))
cnf_matrix = confusion_matrix(y_test, y_pred_7)
print(cnf_matrix)

```

Ensemble modelling

```
from statistics import mode
from scipy import stats as s

final_pred = np.array([])
for i in range(0, len(X_test)):

    final_pred = np.append(final_pred, s.mode([y_pred_7[i], y_pred_7[i], y_pred_7[i], y_pred_6[
i], y_pred_6[i], y_pred_5[i], y_pred_5[i]])[0])
```

```
c = accuracy_score(y_test, final_pred)
print("Accuracy: %.2f%%" % (c * 100.0))
cnf_matrix = confusion_matrix(y_test, final_pred)
print(cnf_matrix)
```

Source available: <https://www.kaggle.com/code/suriyaprakaash/tool-wear-detection-using-6-classification-models>

Appendix C Interview questions and answers translation (Part 1)

This appendix provides detailed supporting materials for the development of the marking scale used in evaluating intangible assets, as outlined in Chapter 6. The methodology for conducting interviews, described in Chapter 3, Section 3.4, was instrumental in shaping the second part of the intangible assets evaluation method. Appendices 6-1 and 6-2 contain the structured interview guides and related materials used during this process.

The interviews contributed significantly by offering a systematic approach to assigning marks to the sub-dimensions of intangible assets that are critical for the implementation and operation of maintenance practices. These insights were essential in refining the evaluation framework and ensuring its applicability in real-world contexts.

Details about the interview participants, including their professional roles and expertise relevant to intangible assets and maintenance practices, are presented in Table 6-6. Key findings and insights derived from the interviews, which informed the marking scale and its application, are summarized in Table 6-7. Together, this appendix provides a comprehensive view of the methodological rigor and practical contributions of the interview process to the thesis.

Q1: Could you describe the basic principle of machine condition inspection in relation to maintenance tasks for level 3 we discussed?

A1: I think the main idea behind machine condition inspection—or maintenance based on inspection results—is that we use inspection outcomes to evaluate the health of the equipment. Based on this health status, we identify any potential issues the equipment may have.

A2: Inspection personnel might assess the condition of the equipment by checking various indicators and doing some on-site inspections. The point is to find potential issues, but more importantly, to come up with preventive measures

based on those issues. If there's no follow-up, the inspection is pretty much pointless.

Q3: What's the maintenance process based on inspection results like?

A1: During machine inspections, we should mainly focus on preventive maintenance. The idea is to conduct preventive maintenance based on the equipment itself, standards, vendor suggestions, and specific production processes. Inspection mainly serves as a supplement or enhancement to preventive maintenance because, after all, preventive maintenance alone might still face issues due to component quality or handling errors.

A2: Well, the inspection process isn't just about doing it for the sake of doing it. This process is purposeful; it's there to understand the equipment's condition. So, all tasks during the inspection process should aim to learn about the equipment status and arrange maintenance tasks accordingly. That's why inspection must be consistent and planned. Problems should be caught early and addressed right away, or solutions should be proposed. That's the real purpose of inspection.

A3: Another thing—after identifying issues during inspection, it's crucial to base the maintenance plan on the inspection findings. For example, if a part needs immediate replacement, stick with the original plan, or make adjustments to the maintenance schedule.

A4: Just adjusting the maintenance plan alone doesn't fully capture the value of the inspection process. Sure, changing the maintenance plan can optimize operations, like reducing unexpected downtime or improving production safety. But unless we integrate maintenance and production planning, the value of inspection can't be fully realized. The production plan should also adjust according to inspection results and maintenance plans to maximize time, cost savings, and production efficiency.

A5: Another important point—each inspection's data and machine status should be recorded and stored to continuously improve operations. The company can learn from these records and even use them to train new employees in the future.

Q5: What knowledge, skills, and experience do employees need to perform these processes for level 3?

A1: First and foremost, workers must be able to assess which parts or equipment conditions might pose risks.

A2: They should also be able to detect abnormal conditions in the equipment or use operating parameters to judge potential failure risks.

A3: Experienced workers might even use sounds or visually check equipment vibrations to gauge its working condition.

A4: Another important skill is being able to plan maintenance effectively by using inspection data to arrange production schedules reasonably.

A5: Other skills include predicting potential faults based on inspection or parameter readings to estimate needed tools, spare parts, time, and personnel.

A6: The most crucial skill of all is the ability to troubleshoot faults.

A7: Naturally, having root cause analysis skills and troubleshooting abilities mentioned in level 1 are essential.

A8: Additionally, as we mentioned earlier, a good attitude matters. Operators need to trust inspection results and believe in the maintenance and production scheduling that follows. This can be achieved by ensuring transparency in the process so that both employees and managers trust it. Showing how inspection benefits them—like reducing workload and improving safety—helps foster trust in the system.

Q7: What technology is required throughout these processes for level 3?

A1: First up, inspection technology is key, such as technologies for structural inspections, like vibration, ultrasound, and thermal imaging, as well as sensors for remote monitoring. We also have IoT systems, augmented reality (AR), and similar technologies.

A2: Then there's communication tech, ensuring that inspection results and maintenance tasks are conveyed. Basic methods could include paper records, meetings, or tools like kanban boards, dashboards, or even messaging apps. Some advanced solutions use work management platforms to meet all needs, though those come at a higher cost.

A3: There's also technology for maintenance and production planning support, helping to plan inspection, maintenance, and production schedules—like CMMS (computerized maintenance management systems).

Q8: Could you introduce the real-time PdM (predictive maintenance) process and its integration across departments for level 4?

A1: When it comes to this kind of digitized, smart operation, everything starts with data collection. At this level, PdM integrates with other departments, so real-time equipment data supports not just predictive maintenance but also production, logistics, and warehousing.

In this process, IoT systems can be installed on equipment, vehicles (like forklifts), or key warehouse points. At this stage, all kinds of data—like equipment status (vibration, temperature), equipment parameters (production rate), and finished parts inventory—are collected in a data center and shared across departments.

A2: I think one key aspect of data collection is ensuring interconnectivity between departments. A unified data management platform is essential to integrate data from production equipment, logistics tools, and warehousing, providing a visual interface and standardizing data for easy understanding across departments.

A3: Next, using this data for equipment fault prediction. Predictive models—not manual labor—handle these predictions. PdM is not just a warning system at this level but also provides recommended maintenance plans, integrating PdM with CMMS and other departmental data.

A4: When the PdM system detects anomalies, it alerts the production management team to reschedule and minimize impact. Meanwhile, the maintenance team decides the optimal maintenance timing based on the equipment's condition to reduce production interference. Despite system recommendations, human decision-making remains crucial—especially for the management team to decide if they'll follow the suggested plan.

A5: Next, we need to use an integrated system for maintenance, production, logistics, and personnel. Once the system finalizes plans, management reviews them and assigns maintenance tasks to specific personnel. Advanced systems may even use operator training results and performance data to determine who should handle which tasks.

A6: Or, adjust the number of operators based on maintenance task specifics.

A7: Throughout this process, the system uses data from the warehousing department to generate spare parts requests, preventing delays due to missing components. The warehousing management system also adjusts inventory plans to ensure stock levels without excess.

A8: Early spare part requests also allow the purchasing department to place orders in advance, preventing parts shortages.

A9: Finally, on the execution side, operators carry out the necessary tasks.

A10: Just because maintenance and production plans are implemented doesn't mean the process ends here. Digitalized systems continuously monitor KPI changes (like IoT-monitored indicators) to enable real-time monitoring and adjustments.

A11: A feedback mechanism is also essential. Continuous model optimization is vital for digital models, as each department evaluates predicted faults for improvement. The PdM model continually adjusts based on the machinery it monitors.

A12: HR feedback is also crucial. By evaluating maintenance work execution, the HR team can identify additional skills or training employees might need.

A13: Communication routines and standards are established, like setting deadlines for operators to report equipment conditions, managers to make decisions, and operators to respond to revised plans.

Q9: What experience and skills are needed for Level 4 processes?

A1: The basics are straightforward: you need to be able to handle relevant maintenance tasks—this is foundational, no matter the maturity level. Beyond that, though, a key skill is understanding PdM system alerts. This means team members should be able to identify potential machine issues and know how to respond when the PdM system flags a fault.

- *Impact Assessment:* Workers also need to gauge the potential impacts of these faults accurately.

A2: It's also important to understand the full workflow of the PdM system. This includes the procedures to follow when receiving alerts, such as verifying the equipment's status since sensors can sometimes malfunction. It's essential to know the reporting process, follow-up steps, feedback channels, and optimization of the system after any troubleshooting.

A3: Workers should know how to decide the right response based on the alert's severity. This could mean double-checking the device, reporting issues, continuing production while monitoring, or even stopping the machine right away if necessary.

A4: Management, meanwhile, needs to make decisions based on these alerts and understand the digital tools involved.

A5: Lastly, it's important to communicate potential issues effectively to departments like production planning, logistics, and management. This requires basic skills in data entry and processing using the internal systems.

Q12: What technologies support a Level 4 system?

A1: At Level 4, it's not just about one or two specific technologies—it's more about integrating multiple systems to support all the processes we discussed. For example, to achieve Remaining Useful Life (RUL) and fault predictions, you need tech for data collection, management, and processing.

- Another priority is supporting integrated planning across maintenance, production, and logistics, so cross-departmental communication technologies are essential.

To keep the feedback loop going, here are some key technologies:

- **IoT and Sensor Technology:**

Industrial Sensors: These monitor critical metrics like temperature, vibration, pressure, humidity, and current in real-time, providing the PdM system with essential data on equipment health.

Edge Computing: This processes data locally at the sensor level to reduce delays, so only crucial information is sent to the central system, improving response times.

- **Industrial IoT (IIoT) Platforms:** Platforms like *Siemens MindSphere* or *GE Predix* enable device connectivity and data integration, making it easier to manage sensors and controllers from a single system.

A2: Data Processing and Modeling Tools:

- Tools like Python, R, and Matlab are essential for data cleaning, analysis, and modeling to ensure PdM data accuracy.
- *Machine Learning Platforms:* TensorFlow, PyTorch, and Scikit-Learn are used to build predictive maintenance models (like fault prediction and anomaly detection), helping to improve the reliability of equipment predictions.
- *AutoML Platforms:* H2O.ai and Google AutoML can handle data analysis and model building automatically, making PdM model training and optimization faster.

A3: Cloud and Edge Computing:

- *Cloud Platforms* (AWS, Microsoft Azure, Google Cloud): These are used to store, analyze, and manage large-scale PdM data, offering high-performance resources for computing and storage.
- *Edge Computing Devices:* Devices like NVIDIA Jetson and Raspberry Pi allow for on-site data processing, which reduces cloud load and speeds up response times.
- *Hybrid Cloud Architecture:* By combining edge computing with the cloud, you get real-time access to crucial data while leveraging the cloud for large-scale processing and model updates.

A4: Computerized Maintenance Management Systems (CMMS):

- *CMMS Software:* Tools like IBM Maximo, SAP EAM, and UpKeep keep track of maintenance activities, fault reports, equipment status, and spare parts, helping the team to plan more effectively.
- *Integration with PdM:* When PdM is integrated with CMMS, maintenance tasks can be generated and scheduled automatically, so any detected issue can trigger a maintenance action and notify the right people.

A5: ERP, MES, and SCM Systems:

- *ERP (Enterprise Resource Planning):* Systems like SAP ERP and Oracle ERP Cloud bring together equipment management, production planning, and inventory management to support data sharing and process optimization across departments.
- *MES (Manufacturing Execution Systems):* Tools like Siemens SIMATIC IT and Wonderware MES allow for real-time production monitoring and adjust production tasks based on PdM data.
- *SCM (Supply Chain Management):* Systems like Oracle SCM and SAP SCM help ensure PdM requirements (like parts replacement or equipment checks) are aligned with procurement and logistics for timely inventory replenishment.

A6: Data Visualization and Real-Time Monitoring Technology:

- *Data Visualization Tools:* Power BI and Tableau allow PdM data to be displayed in a way that's easy to understand, making it simpler for production, maintenance, and management teams to keep tabs on equipment status and predictions.
- *Business Intelligence (BI) Platforms:* Looker and Qlik integrate data from different parts of the organization, making it easy for management to view KPIs and make real-time decisions.
- *Real-Time Alert Systems:* PdM systems can be set up with alert functions that notify the right people by SMS, email, or app to reduce downtime when faults are detected.

Q13: So what should the workflow look like at Level 5?

A1: At Level 5, the fundamental workflow principles stay pretty much the same as at Level 4. We're still talking about data collection, predicting equipment lifespan and potential failures, and using that info to create maintenance and production plans, along with feedback processes.

A2: The big change here is the scope of the data we're integrating. Instead of just focusing on internal company data like production stats, maintenance records, HR info, and inventory, we're also bringing in insights from stakeholders

throughout the entire value chain. This means incorporating data from suppliers about inventory levels and pricing, customer orders from downstream clients, and logistics info from transport partners—all of which help us optimize the whole process.

A3: By this point, the company should have the workflows and technologies from Level 4 in place, giving it the ability to integrate all this data. But the real challenge is establishing clear rules for data sharing: what data each stakeholder needs to share, how they'll share it, who gets to use it, and how that data can be applied. Setting these rules is the heart of Level 5. Everyone needs to be on the same page about why we're sharing data to avoid misunderstandings that could hurt our collaboration.

On the tech side, we need to agree on data formats to ensure consistency across different systems—think XML, JSON, CSV, or EDI. We also need to choose the right transfer protocols based on the type of data we're dealing with, like RESTful APIs, SOAP, or FTP/SFTP. And let's not forget about data security—implementing authentication measures (like OAuth or SAML) to make sure only authorized users can access data, along with encryption methods (like SSL/TLS) during transmission to keep everything confidential.

A4: Of course, just like before, we'll be continually iterating and optimizing our models and processes.

A5: Now, when it comes to aligning maintenance and production plans, this isn't something we can do in a vacuum anymore. We need to consider our partners and clients too. If our partners have fluctuations in their orders or if there are changes in logistics, we need to adjust our maintenance and production plans in real time based on how long machines are expected to last and other relevant data. Keeping those lines of communication open with our partners becomes super important; trust and transparency are key. By the time we reach Level 5, management really has to be on their toes—if the predictive maintenance system sends out an alert or there's a change from a partner, they need to react immediately.

A6: If the predictive maintenance system indicates that a machine might fail or if there's a shift in partner demand, management needs to quickly assess whether the new maintenance plans provided by the system are viable. It's all about teamwork—internally and with our partners—to create efficient, low-error production and maintenance plans.

A7: The goal is to have our team and our partners working closely together, ensuring that both our production and maintenance plans run smoothly and avoid unnecessary complications.

A8: At this stage, the company has not only implemented predictive maintenance but has also digitized and integrated many other processes. Just like at Level 4, having an open mindset is crucial.

A9: When it comes to handling changes between departments or shifts in demand, trust and smooth communication among team members and across organizations are vital. This trust-building isn't just internal; it's about creating a shared sense of trust with external partners too. To achieve goals related to cross-departmental and cross-stakeholder collaboration, companies can use tech strategies like Digital Process Platforms (DPP) and blockchain to boost transparency in data sharing, enhance trust, and ensure information accuracy.

Q14: So what technologies will we need at this level?

A1: For starters, some basic communication protocols are really important, like MQTT. It's a lightweight messaging protocol perfect for IoT and real-time applications, making it a great fit here.

A2: We'll also need database and cloud storage technologies to handle data storage, transmission, and hosting services effectively.

A3: Data encryption is a must too. Nobody wants their data accessible to just anyone. We should use encryption protocols like SSL/TLS for secure internet communication and JWT (JSON Web Tokens) for safely exchanging information.

A4: In certain situations, blockchain technology can also come into play to decentralize data management and enhance the overall transparency of data handling.

Q15: We've talked a lot about PDM, but let's get back to the basics of maintenance operations. We all agree that both corrective maintenance (CM) and preventive maintenance (PM) require intangible assets to perform. So, what does the process of corrective maintenance look like?

A1: Well, when it comes to applying CM, a company doesn't really need a ton of processes or routines in place. Basically, it's all about fixing issues as soon as equipment goes down or malfunctions. That's why CM is often referred to as "run to failure."

A2: But you can still achieve high-quality CM. Besides the operator's individual skill level, consistently recording information like fault types and timestamps can really help improve CM performance.

A3: It's also crucial to report failures as soon as they're discovered during the CM process. Timely communication is key.

Q16: What kind of skills and technical knowledge are needed to carry out this process?

A1: First and foremost, the operators need the right skills to conduct CM, like troubleshooting and replacing parts. Communication skills are equally important for promptly reporting issues to prevent further damage.

A2: Operators should also be familiar with the tools they need when addressing failures or replacing components. Some issues require specific equipment for resolution, so they need to be trained in using those tools effectively.

A3: These are the basic skills, but if a company wants its staff to perform CM more efficiently, operators should also know how to manage their tools—like

keeping track of them to avoid loss—and be trained based on the specific context of their work, such as the type of equipment and shop flow layout. This not only helps them perform CM better but also ensures that the equipment runs safely and smoothly for longer, while reducing downtime.

A4: Safety training for employees should be a continuous and well-planned process. Whether they are new hires or seasoned workers, maintaining a strong safety awareness is critical.

A5: As for knowledge and experience, operators need to be able to conduct root cause analysis. Often, failures aren't just surface-level issues; especially in companies that focus on CM, identifying the true cause of failures is essential for completely resolving the issue and minimizing safety risks.

A6: They should also understand how failures impact production or operations so they can prepare for subsequent actions.

A7: Additionally, the causes of failures aren't always just due to equipment aging or natural wear and tear; sometimes, they stem from human factors like improper handling or bad operational habits. This is where identifying the root cause becomes crucial to avoid similar issues in the future.

A8: Ultimately, the attitude towards this is clear: there's no need to have any grand opinions about technology. The focus should be on mastering the techniques for troubleshooting and executing those effectively.

Q17: What technologies might be involved in this process?

A1: Generally speaking, when executing CM, there isn't a heavy reliance on technology. The primary focus is still on using the necessary tools and equipment for troubleshooting.

A2: When reporting failures for maintenance action, there's usually no need for specific communication software. More often than not, verbal communication or paper documentation will suffice.

Q18: So, when we get to Level 2, what kind of processes or routines do we need for preventive maintenance (PM)?

A1: First off, it's super important to understand that PM really builds on what we do in corrective maintenance (CM). Even if a company is all about PM, they can't avoid needing CM.

A2: Besides being ready to handle any CM that pops up, the biggest thing for PM is having a solid maintenance plan. This plan needs to take into account all sorts of factors like what kind of equipment you have, how much work it's doing, and what your order demands are. Usually, equipment suppliers give pretty thorough PM recommendations, telling you how long gear can run under certain conditions or how many cycles it can handle before it needs maintenance, parts replaced, or lubrication.

A3: You also want to make sure to keep track of when issues come up and what kind of maintenance you've done. That documentation is key for planning future maintenance.

A4: On top of what the suppliers suggest, you also want to keep your own maintenance records. The way your team works and the environment can really impact how long your equipment lasts, so figuring out your own issues with root cause analysis is super helpful.

Q19: What about the knowledge, skills, and training we need during this process?

A1: Operators need to really get the maintenance scheduling plan. They should know how to do the preventive maintenance that's laid out in that plan. For the management team, creating that preventive maintenance schedule is crucial. It should be based on things like the machinery, production needs, and storage requirements.

A2: As for skills, they need to know how to carry out the preventive maintenance tasks and keep everything running smoothly. It's also good to have regular inspections—basically, checking your equipment systematically to catch any potential issues before they become bigger problems.

A3: There are also specific skills they should have, like applying lubricants on schedule to cut down on friction and wear, and knowing when to replace worn parts to keep machines working efficiently.

A4: Plus, it's super important for workers to be trained to spot early signs of wear and tear, like odd noises or vibrations, which could mean something's about to go wrong with the equipment. Most importantly, they need to be able to schedule maintenance proactively, so they can avoid unexpected breakdowns. This training could come from outside suppliers, or it could be a mix of supplier advice and what the company has learned over time.

Q20: Finally, what kind of technology do we need to support the PM process?

A1: At Level 2, building off of what we've learned from CM, the key thing is probably maintenance planning and production planning software. These tools can really help you manage and plan maintenance schedules effectively.

A2: You might also want to use data storage systems to keep all your maintenance records organized and easily accessible. This way, you can track everything and make better decisions down the line!

Q21: Of course, whether we're talking about processes or technology, regardless of the level, we need a budget to implement everything. So, what kind of costs should we consider to enable all of this?

A1: Well, in maintenance operations, no matter what tech you're using or what maturity level you're at, there are some costs you just can't avoid. For instance,

you've got labor costs—like employee salaries—and then there are the tools you need for troubleshooting. Plus, you've got to think about replacing worn-out tools and spare parts. Don't forget the costs that come from reduced equipment lifespan and the documentation needed for audits, compliance, and certifications. Those are always there.

A2: For example, if we're using CM, we need to think about what equipment and tools we need to quickly troubleshoot and get things back up and running. That's definitely a cost to consider.

A3: Now, when we reach Level 2, which is PM, that's where you really start investing in optimizing maintenance and production scheduling. That's a big step up from Level 1.

A4: At this stage, we might need to use CMMS (Computerized Maintenance Management Systems) for scheduling, and you'll probably want to set up some databases and computational capabilities to manage and store those records.

A5: Besides scheduling, we need to invest in figuring out how to actually carry out PM. This includes understanding which equipment needs what kind of maintenance, how often it should happen, what the desired outcomes are, and how to continuously improve based on the company's specific needs.

A6: When we get to Level 3, we definitely need a solid budget for inspections. For example, we'll need inspection tools, which are those technologies we talked about earlier, and we'll also need to train employees on how to use those tools and equipment.

A7: You'll also want some software that can help with data visualization and monitoring. It's really important that the monitoring software or the IoT data we collect can integrate with our CMMS.

A8: Of course, the company needs to choose the right inspection methods based on its own circumstances—whether that's visual inspections, manual checks, or automated systems.

A9: Integration is crucial here. It needs to work with the feedback and reporting systems we mentioned earlier, which means we'll need software installations or process development to make that happen.

A10: For data collection and monitoring, we need to deploy high-quality sensors and IoT devices that can continuously monitor key parameters like vibration, temperature, and pressure. To collect and transmit data in real time, especially for large or remote facilities, we'll need to set up wireless networks and data transmission systems. It's also important to calibrate and maintain those sensors to ensure accuracy, which might increase our labor and resource investments. We need a solution that can handle large volumes of data and store it long-term—cloud storage is a good option. Additionally, we need a data processing system that can handle real-time data streams, especially when predictive models need immediate feedback to keep learning.

A11: We'll need some predictive modeling software and machine learning tools to help us spot trends, catch anomalies, and predict where things might go wrong. When we use these predictive maintenance (PdM) platforms, we'll have to pay for licenses and subscriptions. Those costs can cover complex data analysis, modeling tools, and the dashboards we use to visualize everything. Plus, if we want to connect the PdM software with our other systems—like maintenance management or production planning—that's going to add some extra costs too.

A12: We'll also need data scientists and machine learning experts to help us build, train, and fine-tune those predictive models. Our techs will need training too, so they can respond quickly to any alerts from the predictive maintenance system. And let's not forget that we have to stay on top of new technologies, software updates, and best practices to make sure our team knows what's what.

A13: Setting up and calibrating the PdM system can take time because the models need historical data to make good predictions. We'll need to run some pilot tests to make sure those models are accurate and properly adjusted for our facility's specific conditions. As data changes and new information comes in, we'll have to keep recalibrating those models to stay accurate. Regular maintenance and updates are key to keeping everything running smoothly. If there are any tech

issues, we need to tackle them quickly to avoid downtime. Plus, we should keep an eye on how the system is performing and make tweaks as needed to boost efficiency and accuracy.

A14: We need a solid data-sharing platform that lets suppliers, manufacturers, and customers exchange data in real time—think something like blockchain or a dedicated cloud platform. This way, our data becomes transparent and traceable. To make sure all our systems play nice together, we'll need to either develop or buy APIs and middleware to help integrate our ERP, CMMS, and SCM systems. When sharing information, we'll be dealing with sensitive business data, so we need to encrypt that data and manage access rights carefully to protect privacy and keep unauthorized eyes off our information. And when it comes to customer or supplier privacy, we have to follow regulations like GDPR, which might mean spending a little extra on things like data anonymization, encryption, and compliance checks.

A15: Companies will need to create data-sharing agreements that lay out how we access and use the data, and who's responsible for what. It's a good idea to get our legal and compliance teams involved in this. Different countries and industries have their own rules about data sharing, so we have to make sure we're compliant to avoid any legal headaches.

A16: Each company might use different data formats and standards, so we need to standardize everything before sharing to ensure it works across different systems. Throughout the data-sharing process, it's crucial to keep the data accurate and complete—that's how we ensure our predictive analysis is reliable. A data governance team should regularly clean up and monitor the data. Communication between companies is essential, so using collaboration tools like instant messaging, video calls, and shared platforms can really help keep everyone on the same page. We should also set up a feedback system to gather insights from our supply chain partners, which will help us improve our maintenance plans.

A17: Before we start sharing data, we might need to upgrade or tweak our existing systems to support cross-platform sharing and integration. To make sure

data stays current, we'll need to set up fast networks and synchronization tools, especially when handling real-time data from multiple companies. Low-latency communication protocols could come in handy here.

A18: Our employees will need training on how to operate and manage these sharing systems. This includes learning the steps for using the data-sharing platform, understanding security protocols, and picking up skills for cross-department collaboration.

A19: We should come up with joint performance metrics, like asset health, downtime, and delivery speed, to ensure our maintenance and production plans align with what our partners need. After we start sharing information, we may need to tweak our production and maintenance processes to effectively respond to the data we're getting from other companies. This could mean shifting equipment around, adjusting inventory, and optimizing our resources.

Appendix D Interview questions and answers translation (Part 2)

This appendix provides additional materials to support the development of a comprehensive strategy for implementing maintenance intangible assets, as discussed in Chapter 6. Building on the case study and interview insights (Appendices 6-1 and 6-2), the appendix expands the implementation framework to address organizations operating at Maturity Levels 3 to 5. This strategy map, presented in Figure 6-5, outlines specific goals, processes, and resources necessary for advancing maintenance practices at these higher maturity levels.

The holistic strategy map is designed to assist companies in tailoring their maintenance efforts to their unique operational contexts, ensuring targeted improvements and optimal use of intangible assets. It excludes Maturity Levels 1 and 2, as these foundational levels are widely supported by open-source resources and guidance from manufacturers when companies purchase machines, tools, or spare parts.

By following the strategies outlined in this appendix, organizations can systematically improve their maintenance capabilities, bridging gaps in their intangible assets and achieving their desired maturity level. This approach ensures an adaptable and efficient pathway for enhancing maintenance operations across diverse industries.

Q2: We just talked about monitoring indicators, so during the inspection process, how do we determine the condition of the machines? What indicators should we be monitoring?

A1: There are actually quite a few indicators we can monitor, but some of the most common ones include vibration analysis. This helps us spot issues with components like bearings or gears. We also check temperatures to assess the state of electrical equipment and monitor pressure levels, among other things.

A2: Besides keeping an eye on operational indicators, we can also track changes in certain parameters while the machine is running. For instance, we can monitor voltage levels or the coordinates of a CNC machine's axis to gauge its condition. However, sometimes this approach might not be super intuitive.

A3: I think we shouldn't overlook the basics, like visual inspections. This simple process can help identify issues, such as checking the lubrication status by eye. The level of lubrication often says a lot about how well the machine is running. If a company doesn't have the fancy monitoring equipment we talked about earlier, manual checks—like looking for leaks or missing parts—can still help us assess the machine's condition.

Q4: Now that we've discussed inspection and maintenance processes, how can we actually implement them? How do we establish these habits?

A1: To help the company develop a habit of inspections and set up a process, the first step is to have a clear inspection plan. We need to schedule inspections regularly or continuously. This means deciding how often to conduct inspections,

where to do them, and what specific tasks to perform—all of this should be planned out in advance.

Q4 Follow-up 1: So, what does this inspection planning process include?

A2: A key part of this process is figuring out when to conduct inspections, which is often done before a production schedule starts. This allows us to check various parts of the equipment and ensures safety.

A3: Next, we need to determine which locations, equipment, and components require inspections. We don't need to inspect every inch of the machine—that would take way too long and isn't necessary.

A4: For equipment that has sensors installed, we can monitor readings instead of doing onsite checks. In this case, we should place the same sensors on critical machines and parts, so we don't need to halt operations for inspections; we can just keep an eye on how the equipment is performing.

A5: As part of this process, we can create a checklist for inspections that outlines when and where to inspect. Giving the checklist to the people doing the inspections helps make it a regular habit.

A6: The checklist should also include a work order to ensure nothing gets overlooked during inspections.

A7: This checklist doesn't have to be on paper; it can be digital or even in an app.

A8: We can also use the checklist to record conditions, parameters, and even photos. These records ensure that inspection results are reported in a timely manner, allowing us to adjust maintenance plans as needed.

A9: Beyond just recording conditions, we need a reporting process. Otherwise, even the most thorough inspections won't mean much. We can use the checklist or rely on CMMS for this.

A10: Actually, everything from the checklist to recording and reporting processes can be managed through a CMMS.

A11: Once we get the inspection results, we should optimize our maintenance and production plans based on those findings. This is a crucial part of the whole inspection and maintenance process. Achieving this goal directly affects the performance of both inspections and maintenance efforts.

Q4 Follow-up 2: So, how can we typically achieve this goal?

A12: A common approach is to combine the maintenance and production teams so that the same group handles both tasks.

A13: If we have separate teams, we should hold joint meetings after inspections to discuss findings together.

A14: The most important thing is how we set up KPIs. They need to consider both departments, not just one, which is foundational for the previous two methods.

A15: Another crucial point is establishing a database, which can also be set up using a CMMS. This way, the CMMS connects the entire process, from planning inspections to carrying them out and recording the results.

A16: Finally, it's essential to have follow-up actions in place. This ensures the process is not just executed but also done well.

Q6: How can we gain the experience or skills needed for this?

A1: There are a lot of certification bodies out there that offer relevant certifications, like ISO CAT I-IV vibration analysis certification, which is highly recognized in the industry. Other certifications include non-destructive testing (NDT), thermal imaging, and ultrasonic testing.

A2: Tools like vibration analysis and infrared thermography are commonly used, and we can master their operation through specialized training. Many equipment manufacturers offer training and certification courses based on their products to help technicians learn how to operate the equipment and interpret the data.

A3: We can start from entry-level positions like maintenance technicians or inspectors and get hands-on experience with daily checks and maintenance tasks to build our understanding of how equipment runs and fails.

A4: Working alongside seasoned inspectors or experts in practice allows us to observe how they analyze data, troubleshoot issues, and make maintenance decisions—this is where we can pick up practical experience.

A5: Familiarizing ourselves with software like Maximo, SAP PM, or OSIsoft PI is also helpful. Learning how to operate these programs and understanding the processes for reading, processing, and analyzing monitoring data is crucial.

A6: We should stay updated with the latest research in the field to deeply understand how advanced technologies like vibration analysis, ultrasonic testing, and predictive maintenance are applied across different industries.

Q10: What methods can we use to gain the knowledge and skills required for Level 4?

A1: The methods for reaching Level 4 are generally similar to those for Level 3. We're talking about training and courses, but with a different focus—specifically on digital technologies. For example, we'll need to understand how to operate predictive maintenance and communication systems, as well as how to interpret the data and alerts generated by PdM systems.

A2: However, since digital technologies often change based on a company's needs, we might also need to look into hiring or consulting services to adapt to specific situations.

Q11: We know that employee attitudes are really important when it comes to implementing new technologies in a company. What kind of attitudes do employees need to ensure these processes run smoothly?

A1: Some effective methods include involving employees in the development process of PdM to help them feel more familiar with it and using user-friendly tools that encourage system acceptance. This way, employees can better understand how the PdM system works, which helps build trust. Additionally, having better operational methods can make it easier for employees to grasp the PdM processes, reducing any resistance they might feel.

Appendix D PdM Intangible Assets Evaluation Method Design Expert Contributions

The following section provides detailed information on the individual contributions of the experts who participated in the consultation process of PdM intangible assets evaluation method design. The panel includes seven participants with diverse academic and professional backgrounds. Each expert provides unique insights that support the refinement of the maturity model and the evaluation of intangible assets and associated capabilities.

- Participant 1 (Associate Professor, Mechanical Engineering, PhD, age 43)

Expertise in mechanical systems and engineering research contributes methodological rigor and theoretical depth. His academic position ensures that the model is evaluated against established engineering principles and aligns with current scholarly developments in predictive maintenance and system optimization.

- Participant 2 (Production Manager, Auto Industry, Undergraduate, age 52)

Extensive industrial experience in production management provides insights into workflow coordination, operational planning, and cross-departmental integration. His managerial perspective ensures that the model incorporates practical decision-making processes and reflects industrial realities.

- Participant 3 (Associate Professor, Industrial Design, PhD, age 39)

Expertise in industrial design supports the integration of human–machine interaction, usability, and organizational adoption into the maturity model. His contribution highlights the importance of intangible assets such as knowledge transfer, communication flows, and collaborative practices.

- Participant 4 (Lecturer, Manufacturing Engineering, PhD, age 37)

Research in manufacturing engineering provides systematic knowledge of industrial processes and emerging technologies. His input ensures that

technological progression and capability classification are addressed consistently across maturity levels.

- Participant 5 (Maintenance Engineer, Auto Industry, Postgraduate, age 45)

Practical expertise in automotive maintenance contributes detailed knowledge of reliability, equipment uptime, and troubleshooting strategies. His professional experience ensures that intangible resources such as experiential skills and safety-oriented practices are adequately represented.

- Participant 6 (Lecturer, Manufacturing Engineering, PhD, age 33)

Research expertise in digital manufacturing and Industry 4.0 technologies contributes a forward-looking perspective. His academic work strengthens the alignment of the maturity model with data-driven decision-making and digital integration practices.

- Participant 7 (Maintenance Engineer, Small Application Industry, Postgraduate, age 49)

Experience in smaller-scale industrial applications provides insights into adaptability, resource limitations, and context-specific maintenance practices. His contribution ensures that the maturity model remains relevant across different industrial scales, from large enterprises to specialized applications.

Collectively, these contributions establish a comprehensive basis for the refinement of the maturity model. Academic participants safeguard methodological rigor and theoretical grounding, while industrial participants ensure practical applicability and contextual relevance. This combination strengthens the evaluation of intangible assets and their associated capabilities across maturity levels.

Appendix E Summary of Expert Contributions Across Artefacts

Artefact / Validation Stage	Expert (Role / Affiliation)	Expertise Area	Artefact Component Validated
Maintenance Strategy Selection – AHP Structure	Senior Maintenance Engineer (Discrete Manufacturing – Automotive/Electronics)	Reliability management; preventive– predictive transition; production continuity	AHP hierarchy & evaluation criteria
	Professor of Industrial & Systems Engineering	Maintenance strategy optimisation; Industry 4.0/5.0 integration	Conceptual structure & methodological rigor
	Digital Transformation Consultant	AI/IoT PdM deployment; system integration; data governance	Feasibility of AHP structure in digitalised environments
Maintenance Strategy Selection – Case Study Validation	Expert 1 – Automotive Management (Case Company, 16 yrs)	Strategic operations & maintenance management	AHP scoring alignment with company goals

Artefact / Validation Stage	Expert (Role / Affiliation)	Expertise Area	Artefact Component Validated
	Expert 2 – Iron & Steel Maintenance (External, 7 yrs)	Heavy industrial equipment maintenance	External benchmarking for stamping-machine relevance
	Expert 3 – Home Appliance Production (External, 5 yrs)	Manufacturing system management	Cross-sector comparability
	Expert 4 – Automotive Production & Maintenance (Case Company, 9 yrs)	Operational practices; maintenance workflow optimisation	Feasibility of PdM adoption at shop- floor level
	Expert 5 – Automotive Production (Case Company, 11 yrs)	Production management & maintenance coordination	Resource alignment within existing systems
PdM Technique Selection – Methodological Refinement	Industry Expert (Manufacturing Sector)	Production & maintenance operations; decision sequencing	Rule sequencing (component clarity → data sufficiency → domain knowledge → infrastructure/cost)
	Academic Expert (Predictive Maintenance & Industrial AI)	Prognostics; MCDM theory;	Ambition-level classification;

Artefact / Validation Stage	Expert (Role / Affiliation)	Expertise Area	Artefact Component Validated
		hybrid model logic	domain knowledge substitution
Intangible Asset Evaluation	Associate Professors / Lecturers (Academia)	Organizational capability; manufacturing systems; knowledge management	Conceptual mapping of intangible assets; evaluation methodology
	Production Managers / Maintenance Engineers (Industry)	Production management; maintenance practice; resource allocation	Case-based validation; capability linkage
PdM Maturity Model	Participant 1 – Associate Professor (Mechanical Engineering, PhD)	Mechanical systems; engineering research	Theoretical alignment of maturity levels; methodological rigor
	Participant 2 – Production Manager (Automotive Industry, UG)	Production management; workflow coordination	Practical decision- making realism; cross-departmental integration

Artefact / Validation Stage	Expert (Role / Affiliation)	Expertise Area	Artefact Component Validated
	Participant 3 – Associate Professor (Industrial Design, PhD)	Human– machine interaction; organizational adoption	Intangible assets integration; usability and collaboration
	Participant 4 – Lecturer (Manufacturing Engineering, PhD)	Industrial process design; emerging technologies	Capability classification; technological progression
	Participant 5 – Maintenance Engineer (Automotive Industry, PG)	Reliability management; troubleshooting; safety	Representation of experiential knowledge and safety practices
	Participant 6 – Lecturer (Manufacturing Engineering, PhD)	Digital manufacturing; Industry 4.0 technologies	Data-driven and digital-integration aspects
	Participant 7 – Maintenance Engineer (Small Application Industry, PG)	Resource- limited maintenance practices; SME operations	Contextual adaptability and scalability