Towards Smart Maintenance

The Implementation of Predictive Maintenance in the Railway Industry

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by

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Kiet Foeken
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Executive summary

The thesis, *"Towards Smart Maintenance: The Implementation of Predictive Maintenance in the Railway Industry,"* examines the integration of predictive maintenance (PdM) technologies within railway operations, with a particular focus on freight rail. PdM leverages data analytics, machine learning, and advanced sensors to transition maintenance strategies from reactive or scheduled routines to a proactive, data-driven approach. This allows for predicting equipment failures before they occur, reducing unplanned downtime and optimizing maintenance schedules. However, despite its significant potential, the adoption of PdM in the railway sector remains limited due to technical, financial, and organizational barriers.

By employing advanced algorithms and continuous monitoring systems, PdM predicts component failure or degradation likelihood. Key technologies, including IoT-enabled sensors, machine learning, and big data analytics, facilitate real-time asset health assessment. Unlike traditional methods, which rely on fixed schedules or respond to failures after they happen, PdM prioritizes the actual condition of equipment. This approach minimizes resource waste, extends the lifespan of assets, and improves overall system reliability.

The literature review highlighted the disproportionate focus on technical advancements within PdM research for railways, with 58% of studies emphasizing data analytics, condition monitoring, and algorithm development. Comparatively, managerial aspects, such as cost-effectiveness and organizational readiness, received less attention, accounting for only 18% of research. This large proportion of technical research gives a preliminary insight into the technological readiness of PdM technology for the railway industry. Common challenges identified include issues with data standardization, the immaturity of predictive algorithms, and real-time data processing limitations.

The railway industry struggles with barriers that impede PdM's implementation. A statistical look at academic literature finds that technical issues such as integrating diverse data sources, the immaturity of predictive algorithms, and challenges with real-time data processing are seen as major hurdles. High initial costs for infrastructure upgrades, sensor deployment, and workforce training add financial hurdles, while organizational inertia and resistance to change exacerbate adoption difficulties. The lack of standardized regulatory frameworks further complicates large-scale deployment.

Drawing lessons from sectors like aviation, which has successfully employed standardized data protocols and advanced analytics, this research underscores the importance of clear frameworks and stakeholder collaboration. As seen in public infrastructure projects, a phased implementation approach highlights how incremental deployment can mitigate risks and build stakeholder confidence. These insights are critical to tailoring PdM strategies to the unique dynamics of the railway sector.

Analytical tools such as Interpretive Structural Modeling (ISM) and Fuzzy MICMAC analysis were employed in this study to map interdependencies among barriers and identify root causes. Economic viability, regulatory compliance, and alignment between business goals and technical capabilities emerged as pivotal factors for overcoming challenges. Cost-benefit analysis using Monte Carlo intervals revealed that PdM could reduce long-term maintenance costs between 31.3% and 47.8% with a median cost reduction of 39.5% over two decades, leaving room for a €0.6 billion investment in PdM technology for freight rail. Given this cost-reducing opportunity for train operators, the indirect benefits of PdM technology remain to be explored. Only when there is a full picture of who benefits and to what proportion can a sustainable investment consortium be initiated.

Addressing these challenges requires more than technical innovation. Establishing data standardization protocols and fostering collaboration among operators, manufacturers, and policymakers are critical. Additionally, workforce development programs must equip employees to interpret PdM data and integrate it into decision-making processes. This thesis emphasizes that adopting PdM in railways demands a phased, systematic approach informed by lessons from other industries. By prioritizing stakeholder alignment, regulatory clarity, and organizational transformation, the railway sector can unlock PdM's full potential, creating safer, more reliable, and cost-effective maintenance practices for the future.

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Nomenclature

Abbreviations

Abbreviation	Definition
BR	Barrier
DB	Deutsche Bahn
FDRM	Fuzzy Direct Reachability Matrix
IoT	Internet of Things
ISM	Interpretive Structural Modeling
MICMAC	Matrice d’impacts croisés multiplication appliquée á un classement
ML	Machine Learning
OEM	Original Equipment Manufacturer
PdM	Predictive Maintenance
ROI	Return on Investment
SSIM	Structural Self Interaction Matrix
TCO	Total Cost of Ownership
TM	Traditional Maintenance
WACC	Weighted Average Cost of Capital

1
Introduction

This chapter introduces the critical role of the railway industry in global transportation and the growing importance of robust maintenance practices to ensure safety and efficiency. It highlights the transformative potential of predictive maintenance (PdM) technology, which leverages advancements in data analytics, machine learning, and sensor technologies to predict equipment failures and optimize maintenance schedules. Despite these benefits, adopting PdM in the railway sector faces significant technical, financial, and organizational barriers. The chapter outlines the research problem, objectives, and questions, setting the foundation for exploring the feasibility of implementing PdM within the railway industry, specifically freight rail.

1.1. Introduction

The railway industry is a cornerstone of global transportation, ensuring the movement of people and goods efficiently across vast distances. Robust maintenance practices are essential to maintain such a critical infrastructure's safety, reliability, and operational efficiency. Traditionally, maintenance strategies in railways have relied on corrective or preventive approaches. While effective, these methods often result in unplanned downtime, higher operational costs, and inefficiencies in resource utilization [8, 13].

PdM has emerged as a transformative approach, leveraging advancements in data analytics, machine learning, and sensor technologies. PdM enables the prediction of equipment failures before they occur, optimizing maintenance schedules and minimizing disruptions. This innovation has the potential to revolutionize railway maintenance, reducing costs and enhancing reliability [44]. Integrating sensor technologies and energy harvesting methods further paves the way for more sustainable and cost-effective strategies [29, 74]. By enabling continuous monitoring of critical train components, PdM allows for the early detection of potential failures, facilitating timely interventions and improving overall operational efficiency.

Despite its transformative potential, the widespread adoption of PdM in the railway industry remains constrained by several challenges. These include technological limitations, significant initial investments, and the complexities of integrating PdM solutions into existing infrastructure while maintaining stringent safety standards [28, 68]. Addressing these barriers requires a comprehensive understanding of the technical, organizational, and economic factors that influence the adoption of PdM.

This thesis explores the fundamental barriers to implementing PdM in the railway industry, drawing insights from successful applications in comparable sectors such as aviation and infrastructure management. By identifying the key challenges and contextualizing them within the unique dynamics of railway operations, this study seeks to provide key action points for overcoming these obstacles. Ultimately, the research aims to streamline PdM adoption, fostering more resilient and efficient railway systems.

1.1.1. Background and significance

To establish a foundation for this research, an initial review of the current state of PdM technologies in the railway industry will be conducted alongside a comparative analysis of their implementation in other industries, notably aviation and public infrastructure. This contextual understanding will inform the problem statement and delineate the knowledge gap this thesis seeks to address.

The current state of predictive maintenance in railways

The global railway sector is transforming digitally, with PdM technologies at the forefront. These systems analyze data from train subsystems, enabling real-time monitoring and proactive maintenance. By doing so, they promise to improve fleet reliability, reduce the total cost of ownership (TCO), and enhance operational efficiency [44]. Condition-based maintenance has already demonstrated success in preventing equipment failures and optimizing maintenance schedules within the railway sector [28].

Nevertheless, the adoption of PdM in railways is still in its infancy. Key challenges include the need for more accurate predictive models, integrating disparate data sources, and deploying real-time monitoring capabilities across extensive and often aging railway networks [68]. Additionally, the high initial investment in technology and workforce training poses a significant barrier for many operators. The fragmented nature of railway operations, involving multiple stakeholders such as operators, equipment manufacturers, and regulators, further complicates PdM implementation.

While some countries, such as Japan, France, and Germany, have initiated strategies for PdM adoption under broader digitalization programs, these efforts are largely in pilot or early-stage deployment phases and focus on passenger rail [62, 64, 18]. This leaves a development gap for freight rail. Combined with the complexity of railway systems and the uneven pace of adoption, it highlights the need for a more structured approach to scaling PdM technologies.

Lessons from other industries

Other sectors, such as aviation and public infrastructure management, offer valuable insights into overcoming challenges related to PdM implementation. In aviation, PdM has optimized maintenance schedules, reduced aircraft downtime, and improved fault detection accuracy [65, 47]. Similarly, organizations like Rijkswaterstaat in the Netherlands have applied PdM to manage critical infrastructure assets such as bridges and tunnels, addressing challenges of standardization and stakeholder coordination [69, 39].

These examples underscore the potential of PdM to deliver significant benefits while also highlighting the importance of addressing technical, organizational, and financial barriers. Lessons from these sectors can inform strategies for the railway industry, particularly in overcoming fragmentation and achieving scalable implementation.

Problem statement and knowledge gap

Despite the demonstrated potential of PdM technologies, their adoption in freight rail is slow and uneven. This is primarily due to technical challenges, such as integrating diverse data sources and the immaturity of predictive models, organizational issues, including coordinating multiple stakeholders, and financial constraints related to high initial investments. Moreover, a lack of comprehensive cost-benefit analyses creates uncertainty around large-scale PdM implementation's return on investment (ROI) [72, 54].

The knowledge gap lies in identifying how these barriers interconnect and influence the adoption process and determining effective strategies to overcome them. By addressing these issues, this thesis aims to advance the understanding of PdM implementation in railways, contributing to developing more efficient and sustainable maintenance practices.

1.2. Research question

Given this background, the central research question of this thesis is:

What critical actions can enable the effective implementation of predictive maintenance technology in the freight rail industry?

Given the infant stage of digitization in the freight railway industry and the potential advantages of PdM technology, examining the barriers, opportunities, and steps needed for successful implementation is crucial. The railway industry, known for its complexity, asset diversity, and extensive stakeholder involvement, lags behind other sectors like aviation and infrastructure management, where PdM technologies are more advanced. This thesis aims to uncover the current state of PdM technology in the railway industry as a whole and how lessons from other industries can be tailored to overcome the specific challenges of railway systems. Additionally, input from the industry will be used to evaluate the current entrance barriers and economic feasibility of PdM technology in the freight rail sector.

Subquestions

1. *What is the current state of predictive maintenance technology in the railway industry?*

This question establishes the foundation by clearly understanding the existing technologies and their implementation levels in the railway industry as a whole. Understanding the state of PdM in the railway industry involves analyzing the specific applications within train subsystems, such as wheels, engines, and braking systems, to understand the possibilities for the freight rail sector. By assessing the progress made thus far, this subquestion will reveal the scope of PdM's adoption, providing insights into the most significant technological advancements and the limitations faced by the industry.

2. *What were the main entrance barriers for PdM technologies in similar industries, and how were these mitigated?*

   By investigating barriers in other industries, such as aviation and infrastructure management, this question identifies key factors and best practices that can be adapted to the railway sector. These industries share commonalities with railways, particularly in managing large, complex systems and ensuring safety through regular maintenance. Lessons from the aviation industry, which uses advanced sensor technology and machine learning for real-time fault detection and has to comply with rigorous safety requirements, or Rijkswaterstaat's infrastructure management framework, which involves coordinating among diverse stakeholders, offer valuable insights.

   Understanding how other industries overcame critical barriers to implement PdM provides actionable strategies for the railway sector's approach.

3. *What are the driving entrance barriers to implementing predictive maintenance technology on trains for freight rail operators?*

   Numerous challenges hinder the implementation of PdM in the railway industry. This subquestion explores these barriers, which may include technological issues (e.g., integration of real-time monitoring across multiple subsystems), financial constraints (e.g., high upfront investments in infrastructure and training), and organizational complexities (e.g., coordination among OEMs, rail operators, and regulators) and aims to find the driving barriers.

   Driving barriers refer to the key obstacles that slow or prevent the adoption of new technologies or processes and influence the state of other "dependent" barriers. Identifying these barriers is crucial for developing strategies to not only these driving barriers but also indirectly other barriers, thus paving the way for more streamlined implementation processes. By understanding these driving barriers, stakeholders can prioritize resources, tailor solutions to industry-specific needs, and accelerate the adoption of PdM technologies.

4. *What costs and benefits are associated with implementing predictive maintenance technology for wheel maintenance on trains for freight rail operators?*

   This subquestion aims to assess the economic implications of PdM adoption. It will delve into the immediate costs for cargo rail operators, such as maintenance costs, sensor installations, and workforce training, and the long-term benefits, including reduced downtime, lower operational costs, improved safety, and enhanced reliability. Given the limited time available for this research, certain assumptions will have to be made. Therefore, this model will incorporate confidence intervals using Monte Carlo Simulations.

   Understanding the financial impact of PdM technology will provide stakeholders with a clearer picture of its economic feasibility. It will also help justify the significant investments required for its implementation by showcasing the potential for long-term savings and improved operational efficiency.

1.3. Research proposal

1.3.1. Research objective

This research aims to find critical actions to facilitate the successful implementation of PdM technology in the freight rail industry. The study will examine the current state of PdM adoption across various subsystems, identify key advancements and limitations, and analyze best practices from similar sectors such as aviation and infrastructure management.

The research aims to find the contextual relations between the barriers to PdM deployment in railways by addressing technical, financial, and organizational barriers withholding the implementation of PdM technology. A cost-benefit analysis will further evaluate the economic feasibility of PdM, offering insights into the long-term gains in efficiency, safety, and reliability. Ultimately, the study will synthesize these findings into practical recommended actions for guiding operators, OEMs, and policymakers in adopting PdM technology.

1.3.2. Research design

For this research on facilitating the implementation of PdM technology in the freight rail industry, a mixed-methods research approach would be suitable [61]. This methodology combines qualitative and quantitative research, allowing for a comprehensive topic exploration.

Qualitative research

- **Case studies**: Case studies of PdM implementations in railways and similar industries (e.g., aviation, infrastructure) can provide valuable insights into best practices, challenges, and critical success factors.
- **Expert input**: Generating input from experts, policymakers, maintenance staff, and literature can uncover the nuanced challenges and perceptions of implementing PdM technology in the railway sector. Analyzing these results will highlight where the driving entrance barriers are for PdM technology.

Quantitative research

- **Statistical mapping of literature**: The statistics on the main topics and challenges found in academic literature will be used to identify the current development state of PdM technology for the railway industry and create an initial barrier list.
- **Cost-benefit analysis**: Quantitative analysis will be central to evaluating the economic impact of PdM adoption. This can include collecting and analyzing maintenance costs, downtime, failure rates, and overall ROI data to provide evidence-based recommendations for PdM implementation.

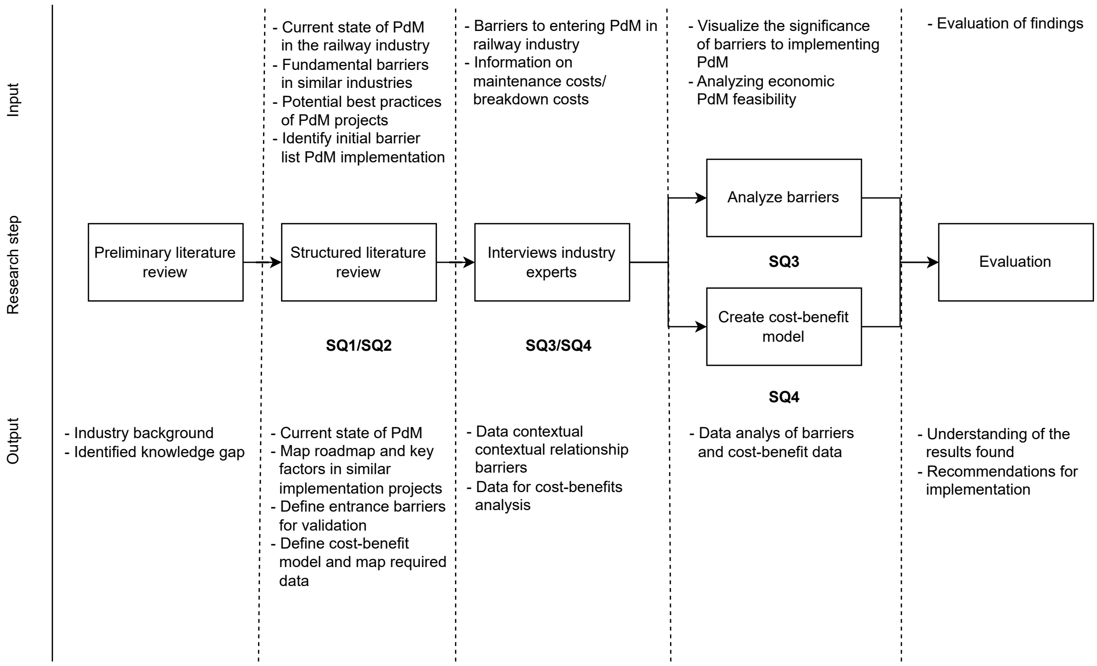

Figure 1.1: Proposed research design framework demonstrating the individual steps of this thesis.

1.4. Research framework

In Figure 1.1 of the proposal, the research steps are structured to guide studying PdM in the railway industry. The steps are laid out as follows:

1. **Preliminary literature review**: This initial step involves gathering information about the industry background and identifying the knowledge gaps related to PdM in the railway sector. It sets the foundation for the subsequent research by contextualizing the current state of the PdM technology.

2. **Structured literature review**: Building on the preliminary review, this step delves deeper into specific sources. It aims to establish an understanding of the current state of PdM and develop an initial entrance barrier list, analyze the implementation of PdM in other industries, and identify best practices that could be relevant to the railway sector.
3. **Analyze barriers**: After gathering data from the literature and interviews, this step analyzes the identified barriers to implementing PdM. This includes looking at organizational readiness, technological challenges, and economic factors impacting PdM adoption.
4. **Create cost-benefit model**: A detailed cost-benefit analysis model is developed to assess the financial viability of PdM technology in the railway industry. This model will be informed by the data collected in the previous steps.
5. **Evaluation**: This final step involves evaluating all the findings, including the barriers and cost-benefit analysis. It aims to draw conclusions and offer recommendations for a streamlined implementation of PdM technology based on the research results.

Each step is designed to feed into the next, ensuring a comprehensive exploration of the problem and the development of actionable recommendations for implementing PdM in the railway industry.

1.5. Research methods

A mixed-methods approach will be employed to achieve the objectives of this study on implementing PdM in the railway industry. This methodology allows for comprehensively exploring the topic by integrating qualitative and quantitative data.

1. **Literature review**: The literature review will focus on the implementation of PdM technologies across industries such as aviation, public infrastructure, and the current state of the railway industry. A structured review of academic and industry sources will identify fundamental success factors, challenges, and timelines. This will lay the groundwork for understanding the barriers and opportunities in the railway sector.
2. **Expert input**: Input from railway operators, technical experts, maintenance staff, and policymakers will be incorporated into the barrier analysis. The goal is to uncover the barriers faced in adopting PdM, such as technological, organizational, and financial barriers.
3. **Barrier analysis**: This analysis will focus on identifying and understanding the key barriers to PdM implementation in the railway industry. These barriers include technical integration challenges, financial constraints, and organizational complexities. Data collected through industry experts and academic literature will be used to map these barriers, which will then be analyzed using Interpretive Structural Modeling (ISM) and Fuzzy MICMAC to visualize the most significant factors impeding PdM adoption.
4. **Cost-benefit analysis**: A quantitative analysis will be conducted to evaluate the economic impact of PdM technology. This will compare the operating costs with and without PdM over a time span of 20 years and provide input on the bandwidth available for investing in PdM technology.

Link between the thesis and the Management of Technology (MOT) Program

The subject of this thesis, *“Towards Smart Maintenance: The Implementation of Predictive Maintenance in the Railway Industry”*, closely aligns with the objectives and themes of the MSc in Management of Technology (MOT) program at TU Delft. The program educates technology managers, market analysts, and entrepreneurs in technologically driven, competitive, and international environments. It focuses on the intersection of technological innovation, organizational strategy, and societal impact elements integral to this thesis.

Connection with the program's focus areas

Technology Analysis

- The thesis employs advanced analytical tools, such as Interpretive Structural Modeling and Fuzzy MICMAC analysis, to assess technological barriers and opportunities. This reflects the MOT program’s emphasis on equipping students with the ability to analyze technological trends and evaluate their viability.

- By exploring PdM, the thesis evaluates how advanced technologies like data analytics, machine learning, and IoT can transform railway maintenance. This mirrors the program's focus on leveraging technological opportunities to align with organizational goals and market needs.

Strategic decision-making in technological environments

- The research addresses strategic questions central to the MOT program, such as how and when to adopt new technologies and whether to build or acquire them. The comprehensive cost-benefit analysis in the thesis supports strategic decision-making by quantifying the economic impact of PdM implementation.
- The thesis explores challenges such as regulatory compliance, economic viability, and stakeholder alignment, providing insights into how organizations can navigate complex technological ecosystems.

Societal trends and technological integration

- The thesis underscores the societal benefits of PdM, such as enhancing railway safety, efficiency, and sustainability. Identifying these benefits aligns with the program's goal of preparing students to anticipate and adapt to societal trends influencing technological adoption.

Organizational context and innovation management

- The research investigates organizational resistance to change and the need for workforce development to enable PdM adoption, reflecting the MOT curriculum's focus on managing technological innovation within organizational structures.
- The recommendations for phased implementation and stakeholder collaboration illustrate the practical application of management theories taught in the program.

In summary, this thesis embodies the interdisciplinary and strategic approach central to the MOT program, integrating technical expertise with managerial insights to address real-world challenges in the railway industry. By bridging technological potential with organizational and societal considerations, this research highlights the transformative role of technology management.

2

Literature Review

This chapter examines the state of PdM technology's application in the railway industry, focusing on the technical, managerial, and combined implementation challenges. It identifies gaps in adopting PdM, including issues with data integration, sensor scalability, and organizational alignment. Drawing comparisons with successful implementations in aviation and infrastructure sectors, the chapter highlights key lessons, such as the importance of data standardization, phased deployment strategies, and stakeholder collaboration. These insights form the basis for identifying fundamental barriers and opportunities for PdM adoption in railways, offering a comprehensive foundation for the subsequent analysis in this thesis.

2.1. Introduction

PdM transforms asset management by shifting from traditional reactive and scheduled maintenance strategies to a proactive, data-driven approach. This paradigm leverages advanced analytics, machine learning (ML), and Internet of Things (IoT) technologies to anticipate equipment failures before they occur. By doing so, PdM minimizes unplanned downtime, optimizes maintenance schedules, and reduces operational costs.

PdM implementation in the railway industry as a whole is currently mostly focused on passenger rail and leverages sensor technologies and analytical techniques to maintain the integrity of critical components. Onboard and trackside sensors, as depicted in Figure 2.1, are integral to PdM systems, each catering to distinct yet complementary monitoring needs. Onboard sensors, mounted directly on rolling stock, provide real-time, high-resolution data about components such as wheels, bearings, brakes, and bogies. Accelerometers enable continuous monitoring of rolling stock, identifying issues such as wheel flatness or bearing overheating in real time. Recent advancements, such as the deployment of wireless sensor networks, have made onboard systems more accessible and efficient, particularly for vehicles like freight trains that often lack consistent onboard power [7, 31].

The placement of sensors on rolling stock can be categorized based on the number of sensors, resulting in three main classes: locomotives, carriages, and freight wagons. Among these, locomotives generally have the highest number of sensors due to their numerous moving and critical components and easier access to power. Carriages have fewer sensors, reflecting their simpler design and reduced power accessibility [37]. Their primary function of carrying passengers requires less intensive monitoring compared to locomotives. Freight wagons have the fewest sensors, largely because powering them requires batteries or energy-harvesting mechanisms, adding complexity [52, 9]. Despite these challenges, freight wagons present the greatest potential for improvement and demand the highest investment due to the complexities involved in implementing sensor technology. This makes them a particularly intriguing area for further exploration.

Trackside sensors, positioned strategically along railway infrastructure, complement onboard systems by monitoring multiple trains simultaneously. Infrared thermography, LIDAR, and acoustic monitoring assess rolling stock and infrastructure health, detecting issues like track, wheel, or bearing defects [3, 7].

Emerging technologies, such as energy-harvesting sensors and IoT-enabled condition monitoring systems [48, 49, 71], could further enhance PdM capabilities by enabling low-maintenance, real-time monitoring of both rolling stock and track infrastructure. The use of PdM technology helps detect existing faults and predict future failures, allowing operators to optimize maintenance schedules. This proactive approach could extend component lifespans, reduce operational costs, and enhance safety and reliability [31, 7].

By combining the strengths of onboard and trackside monitoring, modern PdM systems offer a comprehensive solution for managing rail assets, aligning with industry trends toward sustainable and efficient operations. These advancements underscore the transformative potential of predictive maintenance in reducing unplanned downtime, minimizing infrastructure wear, and preventing catastrophic failures [8, 30, 60, 7, 31, 3].

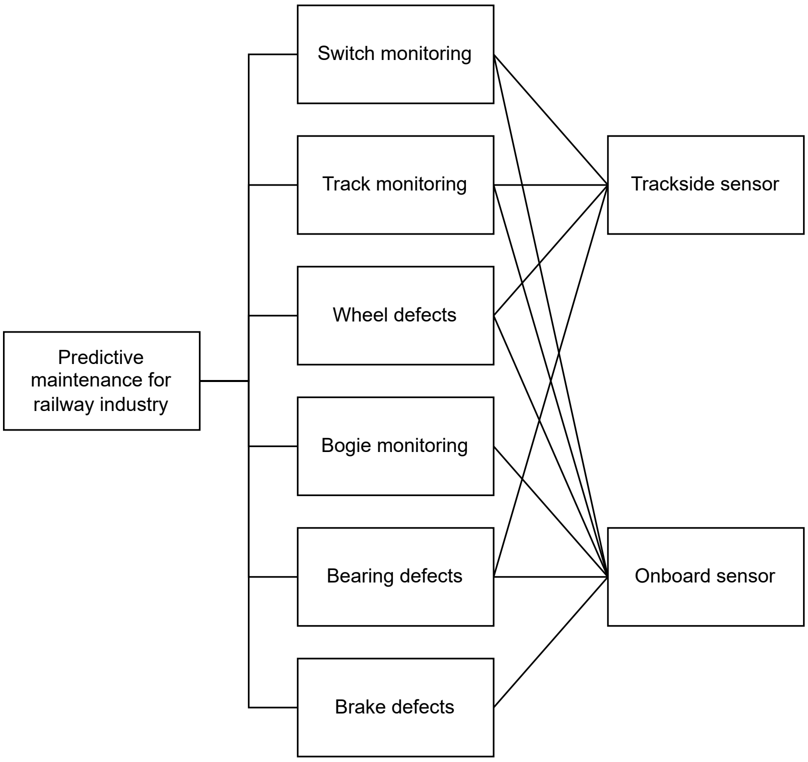

Figure 2.1: Overview of applications for predictive maintenance in the railway industry.

This chapter explores these challenges and compares them with other sectors, such as aviation and infrastructure, to identify strategies for overcoming barriers to successfully implementing PdM technology in the railway industry. The chapter is structured as follows: The first qualitative part analyzes the current state of PdM technology within the railway industry and compares the implementation of PdM across similar industries, including aviation and infrastructure, identifying lessons and best practices. In the second part, a quantitative analysis is conducted, identifying the current relevant subjects for PdM in the railway industry and finding the most prudent challenges identified in academic literature. The chapter concludes by discussing the common barriers to PdM adoption in the railway sector and outlining strategies that can help overcome these obstacles based on the successes of other industries. Finally, an initial entrance barrier list based on literature is presented.

2.2. Qualitative analysis

This section explores the qualitative dimensions of PdM technology, emphasizing its commercial applications and implementation across industries. By reviewing case studies from the railway sector and similar fields like aviation and public infrastructure, the analysis identifies key players, strategies, and challenges in PdM deployment. The insights highlight technological advancements while discussing the persistent barriers to large-scale adoption. This section provides a comparative foundation for understanding how lessons from other industries can guide and optimize PdM integration in the railway context.

2.2.1. Commercial implementation of predictive maintenance technology

A few key players lead the commercial adoption of PdM in the railway sector, although it remains fragmented and primarily in the pilot phase. All major initiatives mainly focus on passenger rail, leaving a large gap in freight rail monitoring. These major initiatives include Siemens' Railigent X Service [21], which utilizes cloud computing and big data analytics to offer PdM services for rail operators. The system collects sensor data and employs AI algorithms to predict maintenance needs, though challenges like hardware deployment, data integration, and standardization have limited its full potential.

Similarly, Hitachi's Lumada platform [24] applies digital twin technology to create virtual replicas of physical assets, enabling precise predictions of component failures. These digital twins help visualize asset health and optimize maintenance schedules, although the platform's efficacy in railway applications still requires broader validation.

Despite these technological advancements, large-scale commercial deployment of PdM in the railway industry faces significant hurdles, especially in freight rail. These include high implementation costs, technological complexities, and regulatory barriers. Additionally, resistance to change within the industry has slowed the adoption process. While industries like aviation and public infrastructure have seen more rapid adoption of PdM, the railway sector faces unique challenges due to its complex regulatory environment and legacy infrastructure.

2.2.2. Implementation of predictive maintenance technology in similar industries

PdM technologies have been widely explored in various industries, particularly critical operational efficiency and safety sectors. Aviation and infrastructure sectors offer valuable case studies for the railway industry due to their complex asset management, high safety standards, and extended asset life cycles. Analyzing these sectors can extract actionable insights for successfully adopting PdM in railways.

Aviation Sector

The aviation industry has a pioneering role in adopting predictive maintenance strategies due to its emphasis on safety and cost-efficiency. Airlines such as Delta Airlines and Lufthansa Technik have demonstrated the potential of PdM to reduce downtime and operational costs by leveraging advanced data analytics and machine learning.

Delta Airlines implemented a comprehensive PdM system in collaboration with Airbus, which processes real-time data from aircraft sensors to predict potential failures. This real-time data processing is most interesting for the railway industry, as airplanes generate many sensors in generating a substantial data flow [20]. This system allowed Delta to reduce maintenance-related cancellations by 99% and achieve substantial operational efficiency improvements [45, 14]. This collaboration between Delta and Airbus is critical as the wiring and placement of sensors require spec certifications.

Key takeaways for the railway industry include the importance of robust data infrastructure and integrating PdM systems into broader operational frameworks. Delta's success also underscores the need for a cultural shift towards data-driven decision-making and continuous improvement, which could be critical for rail operators aiming to adopt similar technologies.

Lufthansa Technik further emphasizes the advantages of PdM with its AVIATAR platform, which reduces unscheduled maintenance by up to 30% for aircraft like the Boeing 737. This demonstrates that PdM can optimize maintenance processes and reduce downtime in highly regulated industries [15, 41]. A similar focus on digital twin technologies and real-time data monitoring could transform maintenance practices in the railway sector.

Infrastructure Sector

The infrastructure sector, mainly through the initiatives of Rijkswaterstaat, the Dutch agency responsible for national infrastructure, has made significant strides in PdM adoption. Rijkswaterstaat's Data-Driven Asset Management (DGAM) [57] program focuses on monitoring the health of critical infrastructure assets, such as bridges, tunnels, and highways. The complexity of these assets, coupled with their decentralized maintenance processes, mirrors many of the railway industry's challenges.

A key aspect of Rijkswaterstaat's success is its focus on standardization across contractors and regions. By laying out a roadmap for gradually implementing a unified data collection and analysis system, Rijkswaterstaat managed to harmonize disparate systems and create a more cohesive maintenance strategy. The railway sector, which involves many stakeholders and asset types, could benefit from adopting similar standards to ensure consistency in PdM implementation [69].

2.3. Quantitative analysis

This section delves into the quantitative aspects of PdM research within the railway industry. By analyzing a curated dataset of 141 academic articles, the study categorizes insights into managerial, technical, and combined focus areas. Key trends, challenges, and thematic distributions are identified, offering a statistical overview of the field's current state. The analysis highlights predominant technical advancements, such as machine learning applications and data monitoring techniques, alongside managerial considerations like cost optimization and strategic decision-making. This section provides a data-driven foundation to assess the barriers and opportunities for PdM adoption in railways.

2.3.1. Methodology for quantitative analysis

The quantitative analysis aims to understand the railway industry's current entrance barriers for PdM from a technical and managerial focus. To visualize these trends, a dataset of articles is created using Scopus. Scopus is selected as it is among the largest curated scientific databases. The dataset combines search terms, filter criteria, and a set timeframe. Combined with manual curation, these selections create a dataset of 141 articles at the time of writing.

Table 2.1 provides an overview of the search criteria used to compile the dataset for the trend analysis in this paper. Several notable findings during the process necessitated the introduction of specific search criteria. Key points about the search criteria are explained below:

- **Interchangeable Terminology:** There are a lot of different terms for the word ”train” in literature, hence why these synonyms were adopted into the creation of the dataset. Notably, most results, including the word ”train,” are not relevant for trains but for the training of models, making it impractical to include this word in the search query. The same goes for the search term ”predictive”.
- **Language Limitation:** Articles in the dataset were limited to those published in English. This decision was made due to the authors' inability to interpret articles in languages other than English, such as German and Japanese, making collecting data from these articles impractical.
- **Timeframe:** Given the rapid advances in PdM technology, only articles from 2018 and newer were adopted into the dataset. This results in a more accurate overview of which barriers are relevant to the current state of technology.

Criterium	**Input**	**Total dataset**
Search items	”predictive maintenance” OR PdM OR ”preventive maintenance” OR ”prescriptive maintenance”	639 articles
	rail OR railway OR rolling stock	
Applied filters	Published articles only	268 articles
	English language only	
Timeframe	2018-2024	159 articles
Manual curation	Remove irrelevant literature and duplicates	141 articles

Table 2.1: Steps of search criteria followed to obtain a final dataset of 141 articles

2.3.2. Data acquisition from individual articles

The dataset consisted of 141 academic papers on predictive maintenance in the railway industry. A full reference list for the final 141 articles can be found in Appendix A. Note that the total number of articles depends on the availability of articles in the TU Delft library. The dataset is categorized into three focus areas:

- **Managerial focus**: Papers primarily discussed strategic, organizational, and business-related aspects of predictive maintenance.
- **Technical focus**: Papers focused on developing and implementing machine learning models, condition monitoring techniques, and predictive technologies.
- **Combined focus**: Papers that covered both managerial and technical aspects.

The articles were further classified into main topics within each focus area, and the challenges listed in each paper were identified. A statistical breakdown of the dataset was made, and the proportion of articles under each focus area was quantified. The frequency of key topics and challenges highlighted in the papers for each focus group was calculated. This breakdown was performed as follows:

- **Managerial focus**: Strategic decision-making, cost optimization, adoption barriers, compliance issues, and human factors.
- **Technical focus**: Machine learning techniques, data collection methods, digital twin technologies, and predictive model integration.
- **Combined focus**: Integration of technical frameworks with managerial decision-making, risk management, cost-benefit analysis, and adoption barriers.

To enhance the clarity of the data presentation, the following visualization techniques were used:

- **Pie charts**: used to visually represent the overall distribution of the papers across Managerial, Technical, and Combined focus areas. Pie charts were chosen to provide a clear, high-level view of the dataset's distribution.
- **Bar charts**: represents each focus area's main topics and challenges. These visualizations allow for an easy comparison of the different topics and challenges, showing the percentage distribution within each category.

2.3.3. Results quantitative analysis

This section presents the key findings derived from quantitative PdM literature analysis, focusing on its applications, challenges, and barriers within the railway industry. Three primary focus areas are identified by categorizing 141 academic articles into managerial, technical, and combined approaches. This analysis explores the predominant themes and obstacles associated with PdM, highlighting the distribution of research emphasis across these areas and identifying the primary technical challenges and managerial considerations required for effective implementation. The findings in this section offer a foundation for understanding the current landscape of PdM research in railways, setting the stage for targeted discussions on overcoming identified barriers to implementation.

2.3.4. Focus area distribution

The dataset of 141 academic papers was categorized into three main focus areas: Managerial, Technical, and Combined. As shown in Figure 2.2, most of the papers (58%) focused on Technical aspects, covering the development and implementation of machine learning models and condition monitoring techniques for predictive maintenance. Papers categorized as having a Managerial Focus constituted 18% of the total, discussing strategic and organizational aspects of implementing predictive maintenance. The remaining 24% were classified under Combined Focus, where managerial and technical considerations were addressed.

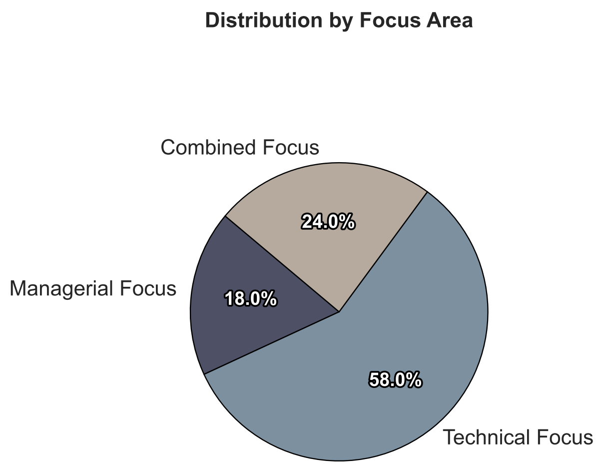

Figure 2.2: Distribution of papers by focus area

This breakdown indicates that most academic literature emphasizes technical advancements, with managerial perspectives and the integration of technical and strategic aspects receiving comparatively less attention.

2.3.5. Main topics in each focus area

The key topics within each focus area were consequently explored. The Managerial Focus papers primarily covered Strategic Decision-Making (40%), followed by Cost-Effectiveness & Budgeting (30%) and Adoption Barriers (15%). Regulatory Compliance and Human Factors were less frequently discussed, accounting for 10% and 5% of the papers, respectively (Figure 2.3).

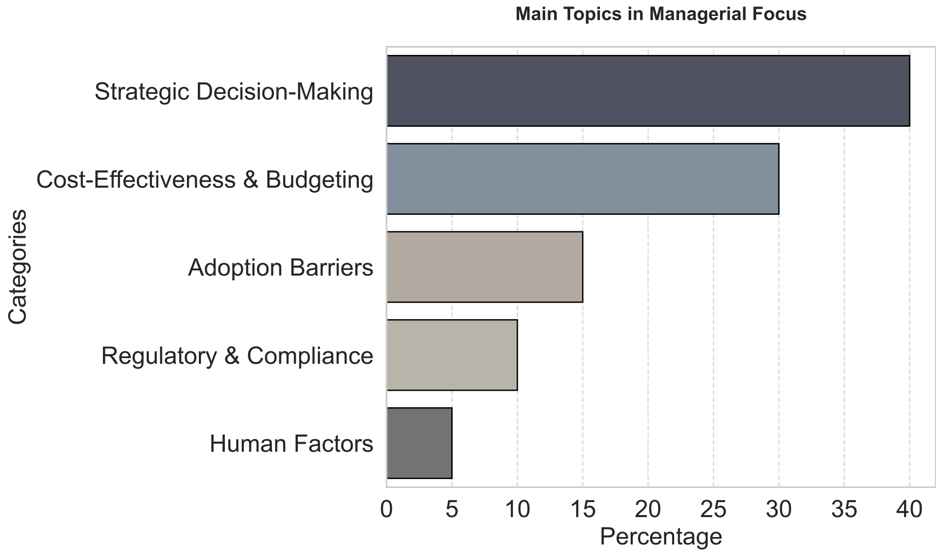

Figure 2.3: Main topics in managerial focus papers

For papers with a Technical Focus (Figure 2.4), the most prominent topics were AI & Machine Learning (50%) and Data Collection & Condition Monitoring (30%). Papers addressing Digital Twins & IoT and Predictive Model Integration comprised 10% and 10%, respectively.

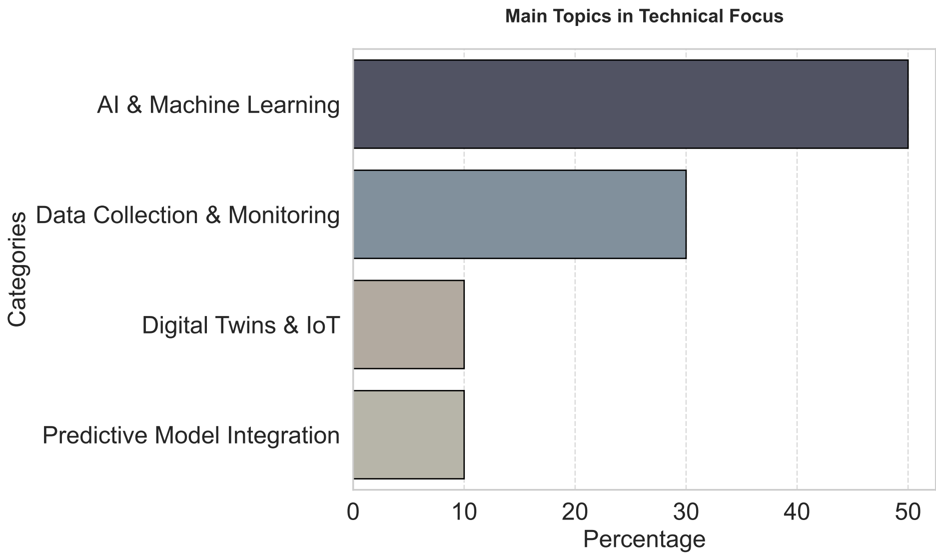

Figure 2.4: Main topics in technical focus papers

In the Combined Focus category (Figure 2.5), Framework Integration (40%) and Cost Optimization (30%) were the most frequently discussed topics, followed by Risk Management (20%) and Adoption Barriers (10%).

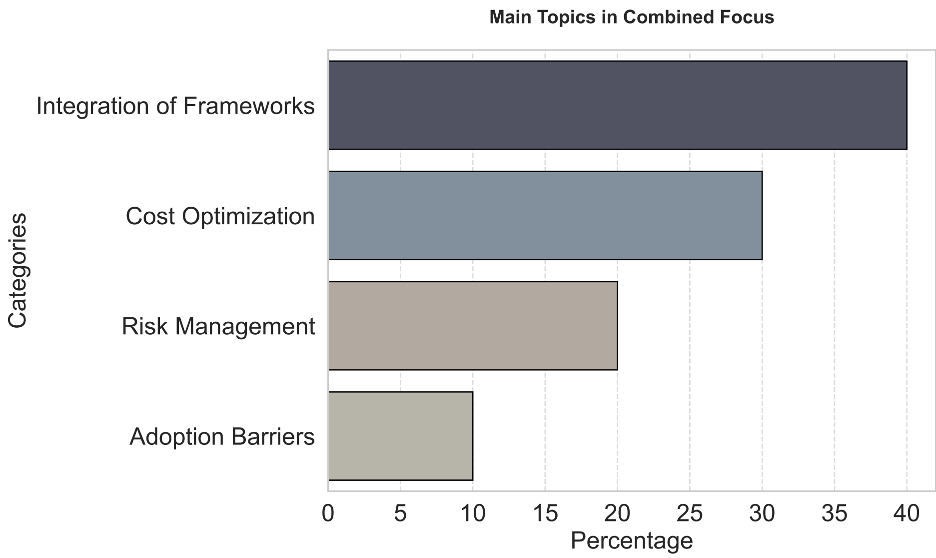

Figure 2.5: Main topics in combined focus papers

2.3.6. Challenges identified in each focus area

The challenges discussed in the articles were evaluated and were found to vary depending on the focus area. In the Managerial Focus papers, Data Availability (30%) and Organizational and Cultural Barriers (25%) were the most frequently cited challenges, followed by Budget Constraints (20%) and Regulatory Compliance (15%). A small percentage of papers (10%) discussed the challenges related to Human Expertise (Figure 2.6).

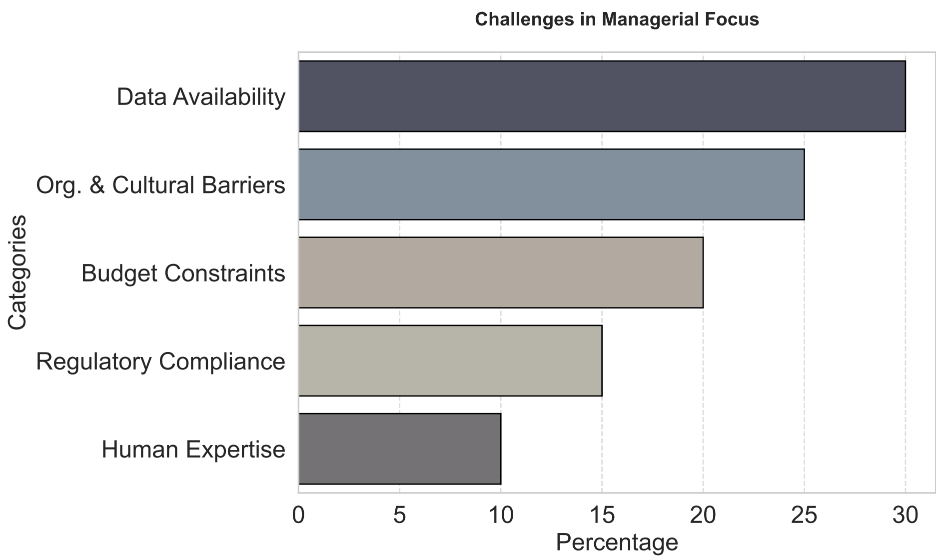

Figure 2.6: Challenges in managerial focus papers

In the Technical Focus papers (Figure 2.7), the primary challenges were related to Real-Time Data handling (30%) and Data Integration (25%). Issues surrounding the Scalability of Predictive Models and the need for Model Interpretability are 17% and 12% of the papers, respectively. At the same time, challenges involving Cybersecurity Risks also emerged in 11% of the documents.

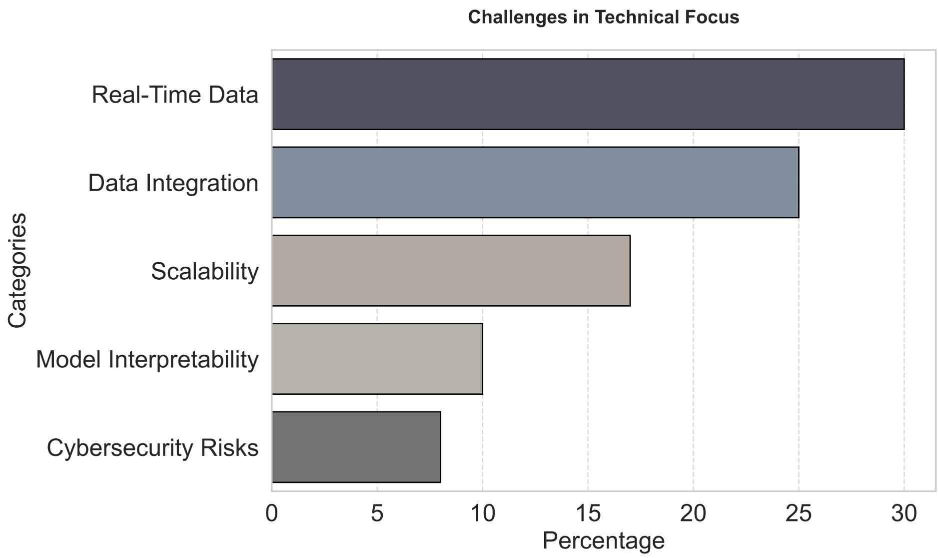

Figure 2.7: Challenges in technical focus papers

In the Combined Focus category (Figure 2.8), Business-Technical Alignment (35%) and Organizational and Technological Readiness (25%) were the most frequently mentioned challenges. Additional challenges included the need for a Skilled Workforce (17%), Infrastructure Complexity (12%), Data Ownership & Privacy (11%).

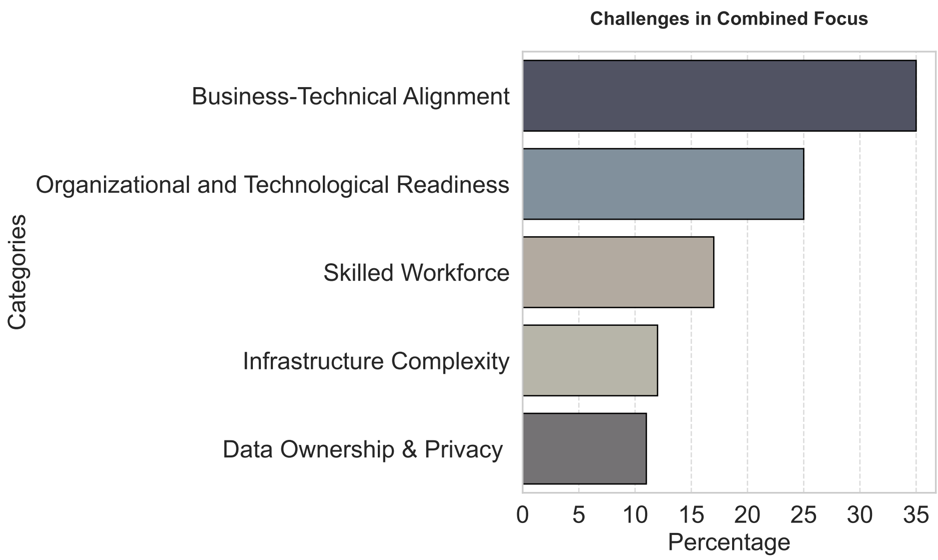

Figure 2.8: Challenges in combined focus papers

The results highlight a predominant focus on technical aspects of predictive maintenance in railway systems, particularly in developing machine learning models and condition monitoring techniques. Managerial and combined approaches, while less prevalent, emphasize the importance of strategic alignment, cost-effectiveness, and overcoming organizational barriers. Common challenges identified across all focus areas include data availability, model interpretability, and the alignment of technical and managerial strategies for effective implementation of predictive maintenance.

2.4. Discussion

This section discusses the results, and subquestions 1 and 2 are answered.

Subquestion 1: What is the current state of predictive maintenance technology in the railway industry?

The current state of PdM in the railway industry is characterized by promising technological potential with limited real-world application. Despite the demonstrated benefits of PdM in optimizing maintenance schedules and minimizing operational disruptions, the railway industry has not embraced PdM as readily as other sectors, such as aviation or infrastructure management. This section discusses the observed barriers to PdM adoption, drawing from both technical and managerial perspectives presented in this chapter.

Limited deployment and focus on technical research
An analysis of recent literature reveals that approximately 58% of PdM research in the railway industry over the past six years has been devoted to technical aspects, including data analytics, algorithm development, and condition monitoring techniques (Figure 2.2). By contrast, only 18% of studies emphasize managerial concerns, while 24% consider a combined focus that integrates both technical and managerial elements. This heavy technical emphasis suggests that PdM technology may still be in a development phase where technical bottlenecks dominate research efforts, limiting the industry's ability to shift toward deployment.

If PdM were closer to operational maturity, a more balanced research focus would likely emerge, with greater attention given to management, integration, and implementation strategies. The current focus on technical challenges points to ongoing algorithm accuracy, data processing, and sensor reliability issues. For instance, studies on condition monitoring frequently highlight the difficulty in achieving reliable and real-time data collection across railway assets such as wheels, tracks, and signaling systems, which are fundamental to effective PdM (Figure 2.7). These limitations underscore that PdM technology, in its current form, may not yet provide the consistent and actionable insights needed for full-scale deployment.

Technical Bottlenecks in Algorithms and Data Processing
One of the most critical barriers identified in this chapter is the challenge of processing and interpreting the massive volumes of data generated by PdM systems. Railway networks generate complex datasets through onboard and trackside sensors monitoring various components. However, the quality and integration of this data vary significantly, often leading to incomplete or inconsistent inputs for PdM algorithms. This lack of standardized, high-quality data complicates the development of accurate predictive models.

Further, real-time data processing remains an area where current PdM solutions fall short. As described in Figure 2.4, many algorithms used for predictive maintenance require substantial computational resources to analyze incoming data streams quickly enough to prevent component failures. However, most PdM systems are still limited in delivering real-time alerts with sufficient accuracy. For example, certain studies indicate that predictive algorithms for wheel and track degradation have yet to achieve the reliability needed to consistently forecast maintenance needs without generating false positives or missing critical faults.

Managerial and Economic Uncertainties
In addition to technical challenges, the chapter identifies significant managerial and economic concerns that hinder PdM adoption. On a management level, there is ongoing uncertainty about the financial feasibility of large-scale PdM implementation. While predictive maintenance promises reduced operational costs and improved asset longevity, its economic benefits are often speculative at this stage due to limited long-term studies and ROI analyses specific to railway applications.

A particular concern involves allocating responsibility for maintenance decisions based on PdM data. The decision-making authority in railways typically spans multiple stakeholders, including operators, original equipment manufacturers (OEMs), and regulatory bodies, all of whom may have differing priorities and risk tolerances. This fragmentation creates ambiguity regarding who will be accountable if PdM recommendations lead to unforeseen issues or failures.

Conclusion
In conclusion, PdM for railways remains a vibrant and growing research area, as demonstrated by the high level of technical innovation. However, the combined effects of technological immaturity and organizational uncertainty obstruct its broader adoption. This is especially true for the freight rail part of this industry. Until railway companies can resolve these issues, the industry will likely continue to

approach PdM cautiously. As such, the following steps should involve collaborative efforts between technical researchers and industry stakeholders to address the technical and managerial barriers that have hindered PdM implementation. Because the biggest hurdles are observed for freight rail, the following chapters will focus on this part of the railway industry.

Subquestion 2: What were the main entrance barriers for PdM technologies in similar industries, and how were these mitigated?

The barriers to implementing PdM in other sectors, such as aviation and infrastructure, offer valuable insights into potential obstacles for the railway industry. These industries have encountered similar challenges with high-stakes maintenance requirements, complex regulatory environments, and diverse stakeholders.

In the aviation sector, safety protocols are often stricter than those in the railway industry, influencing how PdM technology is integrated. Aviation benefits from placing sensors during production, bypassing additional certifications required for retrofitted components. This integration strategy reduces regulatory hurdles but is less applicable to railways, where retrofitting is more common.

Another critical barrier in aviation is the need for data standardization and frameworks, which are essential for managing the vast quantities and varied data sources generated by numerous sensors. Without standardization, data integration becomes challenging, leading to inefficiencies. While the aviation industry continues to address this need for uniformity, the railway sector could proactively adopt similar data standards to streamline PdM technology implementation.

Moreover, the aviation industry's closed nature, with restricted access to detailed information about specific barriers and mitigation outcomes, presents a challenge to identifying clear solutions. This opacity makes it difficult to grasp the complete picture of what is happening in the aviation sector. It introduces the question of whether there is more to learn from this industry.

The structure of Rijkswaterstaat in the infrastructure sector aligns closely with the fragmented nature of the railway industry. Rijkswaterstaat, a public entity responsible for Dutch national infrastructure, faces challenges such as fragmented maintenance practices due to the involvement of multiple subcontractors and regional divisions. This fragmentation leads to a viscous framework for introducing innovations like PdM, a constraint likely mirrored in the railway industry due to its similarly distributed structure across contractors and international borders in Europe. Rijkswaterstaat has focused on standardization and gradual PdM implementation with room for constant stakeholder feedback to mitigate this fragmentation. A phased approach, prioritizing data standardization alongside incremental technology deployment, has proven effective.

Conclusion
Overall, the experiences of the aviation and infrastructure sectors underscore the importance of data standardization and frameworks, phased implementation, and stakeholder involvement. For the railway industry, adopting these strategies will be essential for overcoming the technical and organizational barriers to PdM technology.

2.4.1. Initial entrance barrier list

Based on the quantitative analysis of challenges in the railway industry and the most stringent barriers in the aviation and infrastructure industries. Table 2.2 presents this barrier list, including each barrier's description. This initial list will form the foundation of the research conducted in Chapter 3.

Table 2.2: Barriers to the implementation of predictive maintenance technology in the railway industry

Barrier	Description
Scalability of IoT Sensors	Deploying IoT sensors across the railway network presents challenges related to their ongoing maintenance. Ensuring that these sensors consistently function requires additional sensor monitoring and maintenance efforts.

Regulatory Compliance	The absence of well-established legal frameworks and standardized government safety certification protocols complicates regulatory compliance. There is a need for a unified, clear, and easy-to-follow process for ensuring the technology meets safety requirements.
Economic Viability	Predictive maintenance requires a significant initial investment, and the return on investment (ROI) is often unclear. The long-term financial benefits, such as cost savings and risk reductions, must be demonstrated to justify the upfront costs.
In-House Expertise	Successful implementation of predictive maintenance technology requires training and developing in-house expertise. The workforce must be skilled in interpreting data from predictive models and making informed decisions based on that data.
Technological Maturity	Effective predictive maintenance relies on high-quality data from sensors, sufficient computational resources for real-time analysis, and the development of accurate predictive algorithms. The technology is still evolving, and achieving the necessary level of maturity remains challenging.
Data Standardization	Due to the variety of data sources (e.g., tracks, wheels, switches) and the fragmented nature of the maintenance industry, there is a need to standardize data formats. Without this, integrating data from multiple sources remains difficult and inefficient.
Data Responsibility and Security	As predictive maintenance depends on connected sensors, the risks of cybersecurity breaches increase. Clarifying data ownership and ensuring secure data handling protocols to protect sensitive information is essential.
Organizational Resistance	Resistance to change within organizations can slow the adoption of new technologies like predictive maintenance. Overcoming this inertia requires addressing concerns and fostering a culture of innovation.
Integration with Current Maintenance Flow	The current structure of contractors and subcontractors in railway maintenance may need to be restructured. Seamless integration of predictive maintenance technology will require adjustments to existing workflows, responsibilities, and contracts.

2.5. Conclusion

This chapter has provided an in-depth review of the literature on PdM technology's current state, challenges, and potential strategies relevant to the railway industry. The research identified a significant emphasis on technical challenges within PdM implementation, such as real-time data integration, scalability of sensors, and model interpretability. However, managerial and organizational issues, including regulatory compliance, economic viability, and data standardization, also pose considerable barriers. The largest gains in PdM adoption are observed specifically in freight rail, so the remainder of this thesis will focus on this area.

By examining implementations in similar sectors like aviation and infrastructure, this review highlights several critical lessons for the railway industry. In aviation, strategies such as robust data infrastructure, integration of PdM systems with operational frameworks, and standardized data protocols were instrumental in advancing PdM. Similarly, the infrastructure sector, exemplified by Rijkswaterstaat, emphasizes the importance of phased implementation and stakeholder alignment to overcome fragmented operational structures. These approaches provide a framework for addressing the unique challenges of PdM in railways.

The findings suggest that while PdM holds substantial promise for enhancing railway maintenance practices, its implementation requires systematically addressing both technical and managerial hurdles. The next chapter will delve into the contextual relationships between these identified barriers, providing a structured approach to prioritize and manage the challenges that currently limit the deployment of PdM in freight rail.

3

Contextual relations between barriers

This chapter explores the complex interdependencies among the barriers to implementing PdM in the railway industry. Using Interpretive Structural Modeling (ISM) and Fuzzy MICMAC analysis, this chapter identifies the contextual relations between barriers, categorizing them based on their driving and dependency powers. The study reveals foundational challenges such as economic viability, regulatory compliance, and business-technical alignment that significantly influence other barriers.

3.1. Introduction

This chapter delves into the intricate web of contextual relationships that underpin the barriers to implementing PdM within the railway sector. Understanding these relationships is crucial as it allows us to identify and prioritize the core factors that hinder PdM deployment. To accomplish this, Interpretive Structural Modeling (ISM) is utilized as a methodological framework, providing a systematic means of uncovering interdependencies among the barriers. ISM simplifies the complexity of these relationships, revealing which barriers are most influential and how they interact with and reinforce each other.

Further enhancing this analysis, fuzzy MICMAC (Matrix of Cross-Impact Multiplications Applied to Classification) is employed. This approach enables a nuanced categorization of barriers based on their driving and dependence power. By incorporating fuzzy logic, fuzzy MICMAC accounts for the inherent uncertainty and variability in expert assessments, thereby allowing a more precise identification of root causes. The combination of ISM and fuzzy MICMAC offers a comprehensive lens through which the underlying structure of these barriers is exposed, facilitating the identification of pivotal challenges that, if addressed, could accelerate the successful integration of PdM.

This analysis aims to identify the driving barriers that, if mitigated, could alleviate other related challenges, thus streamlining PdM adoption across the freight rail part of the railway industry. This chapter lays the groundwork for developing targeted strategies that address these root causes by identifying them, ultimately paving the way for a more resilient and efficient railway maintenance paradigm.

3.2. Methodology

This section details the methodological framework employed to identify, analyze, and prioritize the contextual relationships among barriers to implementing PdM in the railway industry. The study leverages ISM to explore interdependencies among barriers, enabling a structured visualization of their influence hierarchy. Complementing ISM, fuzzy MICMAC Analysis is applied to classify these barriers based on their driving and dependency powers. These approaches offer a robust approach for uncovering the critical obstacles to PdM adoption.

3.2.1. Interpretive structural modeling

ISM maps the relationship between different variables introduced during the literature and desk research. ISM is selected to determine the interrelation between variables holistically. The strengths of this model are found in the presentation of a complex system in a simplified way, thereby helping in answering what and how in theory building [66]. The method consists of the following steps [70, 66]:

Variable identification

- Determining contextual relationships
- Structural self-interaction matrix
- Reachability matrix
- Partitions on the reachability matrix
- Digraph for ISM

3.2.2. Variable identification

The barriers were identified through an extensive literature review as presented in chapter 2, policy documents, and relevant reports. This process aimed to gather a comprehensive list of variables associated with potential barriers. Initially, variables were drawn from diverse sources, broadly capturing relevant factors. Each variable underwent a frequency assessment to determine its relevance and consistency across sources.

Following the literature review, the flowchart in Figure 3.1 provided a structured approach for validating the identified variables. According to the flowchart, only frequently occurring variables proceeded to the initial list. This list was then refined through expert approval. If experts found the list lacking, improvements were made, and the process was repeated until a final approved list of barriers was established. This systematic approach ensured that each barrier was validated, contributing to the robustness of the final selection.

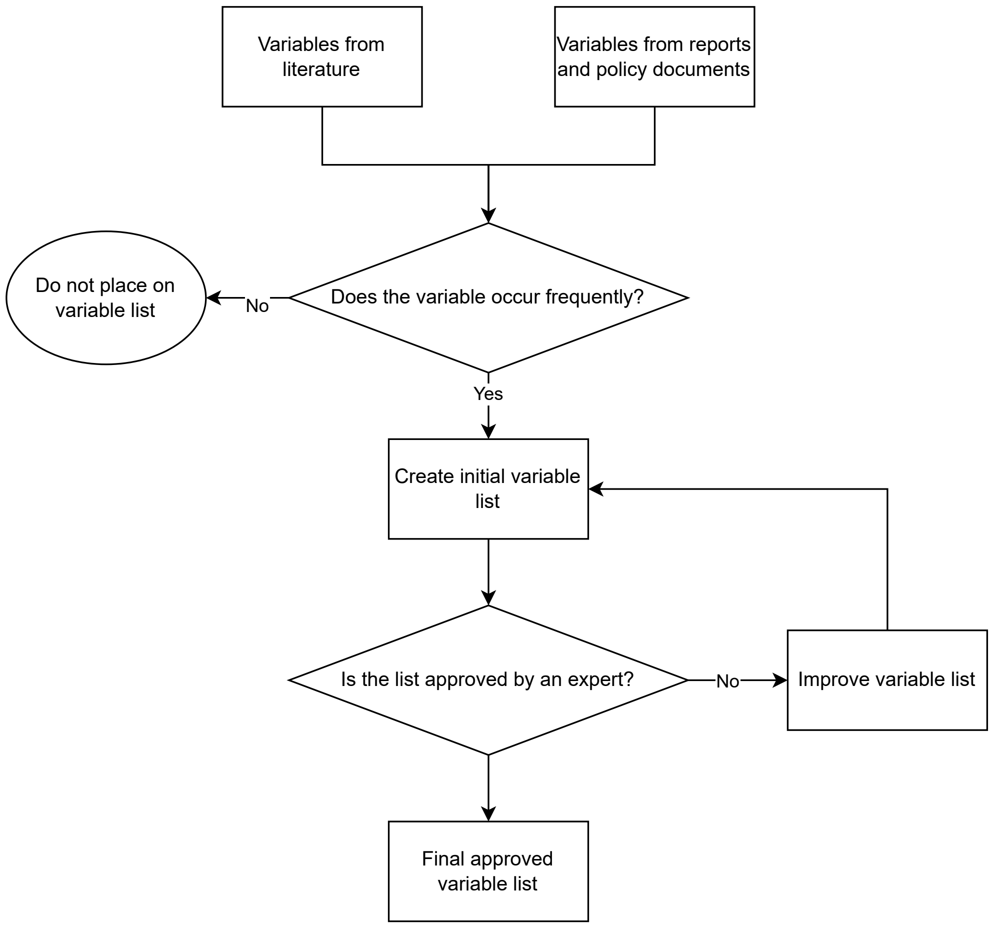

Figure 3.1: Method for gathering entrance barriers.

3.2.3. Determining contextual relationships

The contextual relationship between any two barriers (i and j) is ascertained using experts' opinions. The literature describes several methods of obtaining these opinions. These methods include individual interviews, questionnaires, focus group sessions, and literature syntheses [51].

A main advantage of group discussions is the interaction among participants, leading to new ideas and perspectives that might not surface in one-on-one interviews [51]. A significant weakness of group discussions is that group dynamics can introduce biases, such as conformity or dominance by certain individuals, which may distort the data. Strategic group biases and expectations influence the results, especially if participants know the researcher's objectives [51]. The reduced bias and dependence on group dynamics is one of the key advantages of individual interviews [6]. On the other hand, individual interviews introduce a loss of context and detail. Individual interviews may lack the richness of context and detail that can emerge from group interactions. Important nuances and insights from group dynamics, such as consensus-building and the expression of diverse perspectives, might be missed in individual settings [6].

A combination of existing research and expert opinion was chosen for this research to reduce bias created within group discussions. Additionally, the complexity of arranging a group discussion with relevant experts and the limited time available during this master's thesis made this combination the most realistic.

3.2.4. Structural self-interaction matrix (SSIM)

To determine the relationship between the variables, the parameters i and j have been associated with four symbols, as follows [4]:

- V: variable i will influence variable j, but variable j is not influenced by variable I.
- A: variable j will influence variable i, but variable i is not influenced by variable j.
- X: variables i and j will influence each other.
- 0: variables i and j are unrelated.

Amrina and Oktora (2020) considered the SSIM matrix and adhered to two guidelines [4]: For the aggregated SSIM, the symbol (V, A, X, or O) with the highest frequency of occurrence was chosen first. Second, precedence was assigned in the following order: V, A, X, and O if the frequency of a certain relation was equal for two or more symbols.

3.2.5. Reachability matrix

By converting the data in each SSIM entry into 1s and 0s in the reachability matrix, the SSIM format is converted into the reachability matrix format. This leads to the following four situations [42]:

- If the (i, j) entry in the SSIM is a V, the (i, j) entry in the reachability matrix becomes 1, and the (j, i) entry becomes 0.
- If the (i, j) entry in the SSIM is an A, the (i, j) entry in the reachability matrix becomes 0, and the (j, i) entry becomes 1.
- If the (i, j) entry in the SSIM is an X, both the (i, j) entry and the (j, i) entry of the reachability matrix becomes 1.
- If the (i, j) entry of the SSIM is 0, then both the (i, j) and (j, i) entries of the reachability matrix become 0.

3.2.6. Level partitions on the reachability matrix

After constructing the reachability matrix, the next step involves partitioning it into levels to understand the hierarchy and interactions between elements. This level of partitioning helps identify the layers within the structure by categorizing elements based on their reachability and dependability [70]. In ISM, each element's reachability and antecedent sets determine its level.

The reachability set and antecedent sets were obtained from the final reachability matrix. Variable i and every other variable that variable i would affect made up the reachability set. The variables that influenced variable i were included in the antecedent set, which also contained variable i. A differentiation between several levels was formed based on the intersection of these reachability and antecedent sets. Each variable's reachability, antecedent, and intersection sets were determined before the levels were created. After that, the top level is occupied by the variables for whom the antecedent and reachability sets were identical. The variables that have no variables ”above” them that have an impact on them occupy the top level. After removing these top-level variables from every other set of reachability, antecedent, and intersection variables, the procedure was repeated until every variable was assigned a level.

Assume, for instance, that BR5 has an antecedent set (1, 2, 5, 7, 11), which indicates that barriers 1, 2, 7, and 11 have an impact on BR5, and a reachability set (4, 5, 6, 12), which indicates that BR5 influences obstacles 4, 6, and 12. It is now possible to establish that BR5 does not affect any new variables; rather, it only affects those that it is influenced by.

The variables on the same level are arranged horizontally adjacent to one another in the diagram, and arrows are added between them to indicate the direction of the relationship.

3.2.7. Fuzzy MICMAC analysis

Fuzzy MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement) is an advanced method used to classify barriers based on their driving and dependency powers, incorporating fuzziness to manage the uncertainty inherent in expert judgments. This approach refines the analysis by converting influence levels into a continuous scale, allowing a more nuanced understanding of relationships within complex systems. The methodology involves several key steps, as outlined below.

Steps in fuzzy MICMAC

1. **Normalization of influence (fuzzification)**: Influence levels between barriers, provided in a tally matrix, are transformed into a fuzzy influence matrix. This process involves converting linguistic terms to corresponding numerical values, as detailed in Table 3.1. If the influence score meets or exceeds the set threshold of 60%, it is divided by the highest score in the matrix. Scores below the threshold are zero, indicating minimal or no influence.
2. **Multiplication of fuzzy influence matrix and calculating driving power and dependency**: There are three different compositions to ascertain the strength of the indirect relation from variable i to variable j: max-min, max-product, and max-average [73]. Since the maximum of all potential minimal influences from variable i to variable j indicates the minimal intensity of the indirect relationship between the two, the max-min option was used for this study [34]. Following the procedures outlined in Khan & Haleem (2012) [35], which were modified from Kandasamy et al. (2007) [34], the matrix is multiplied using the max-min approach using the function that follows:

$$C = A, B = \max k \left[\left(\min \left(a_{ik}, b_{kj} \right) \right) \right], A = [a_{ik}] \,\mathrm{and}\, B = [b_{kj}] \tag{3.1}$$

   According to Equation 3.1, the matrix is multiplied recursively, beginning with the Fuzzy Direct Reachability Matrix (FDRM), until the driving and dependent powers stabilize. The sum of the power of the variables influencing variable i, or the sum of all entries for row i, is the driving power of variable i. The total of all the variables affected by variable i, or the sum of all the entries in column i, yields the depending power [23]. The matrix is stable if, for every variable, the hierarchy of driving power and dependent power stays constant across the many multiplication steps [59]. The numpy package was used in Python to carry out these computations.
3. **Clustering of barriers**: Based on the median values of fuzzy driving power and dependency, barriers are classified into four key clusters:
   - **Autonomous Variables**: Barriers with low driving power and low dependency, generally peripheral to the system.
   - **Dependent Variables**: Barriers with low driving power but high dependency are heavily influenced by others.
   - **Linkage Variables**: Barriers with high driving power and high dependency, showing significant reciprocal influence within the system.
   - **Independent Variables**: Barriers with high driving power but low dependency, critical drivers with minimal external influence.

   The boundaries of these barriers are determined by taking the median driving power and dependency power of the barriers.
4. **Visualization of fuzzy MICMAC clusters**: A 2D scatter plot is created to display the distribution of barriers based on their fuzzy driving power and dependency. The plot is divided into four quadrants

by the median values, separating barriers into four clusters. Each barrier is color-coded to represent its classification.

Linguistic and numerical values for strength of relationships

In fuzzy MICMAC, linguistic terms represent the strength of relationships between barriers. Each term corresponds to a numerical value on a normalized scale, allowing experts to express varying degrees of influence, as shown in Table 3.1. The FDRM was produced by calculating each relation's "strength" value and superimposing it on the total BDRM. In earlier studies that used fuzzy MICMAC, these data were aggregated in two ways: the strength with the highest frequency was used to estimate the strength of the association [33, 63] or just one fuzzy matrix was offered, which was produced by consensus among the experts by asking them for their input a second time following the development of the BDRM [35, 42, 53] if any explanation was given at all [23, 16]. Time restrictions led to the decision to limit the number of interactions with the experts and the fuzzy connection was selected as the initial approach to assess strength. Furthermore, the ISM section already included the percentage of experts who stated a relationship using a 60% criterion.

Table 3.1: Linguistic and numerical values for strength of relationships

Linguistic Term	Description	Numerical Value
No Influence	Indicates no significant influence	0.0
Very Low	Very minimal influence	0.1
Low	Weak influence	0.3
Medium	Moderate influence	0.5
High	Strong influence	0.7
Very High	Very strong influence	0.9
Full Influence	Maximum possible influence	1.0

Relationship influence classification

Fuzzy MICMAC enables the classification of barriers based on driving and dependency power, helping to identify key drivers and reactive barriers in complex systems. Table 3.2 summarizes the characteristics of each relationship type.

Table 3.2: Relationship influence types in fuzzy MICMAC

Relationship Influence Type	Description	Driving Power	Dependency
Autonomous	Minimal influence and minimally influenced; peripheral	Low	Low
Dependent	Heavily influenced by others, with limited influence itself	Low	High
Linkage	High influence both exerted and received; reciprocal interactions	High	High
Independent	Strong influence on others, with minimal external influence	High	Low

Advantages of fuzzy MICMAC

The fuzzy MICMAC method enhances traditional analysis of driving power and dependency by capturing varying intensities of influence and accommodating uncertainties in expert judgments. Using linguistic terms and corresponding numerical values, fuzzy MICMAC provides a detailed, flexible analysis of relationships within complex systems. This method supports strategic decision-making by identifying key drivers within the system and clarifying influence dynamics visually and intuitively, making it invaluable for prioritizing resources and interventions.

3.3. Results

The results section begins by presenting the variables and their contextual relationships identified using ISM. The ISM process organizes these barriers into levels, illustrating their hierarchical influence and the interdependencies among them. Next, the fuzzy MICMAC analysis is applied to categorize barriers based on their driving and dependence power, providing a nuanced understanding of each barrier's impact on PdM adoption. Through these analyses, this section identifies driving barriers that play a critical role in shaping the freight rail's readiness for PdM implementation.

3.3.1. Variables

The selection of barriers listed in Table 3.3 emerged from an approach combining the literature research of chapter 2 with expert input and validation. Reviewing existing studies and industry reports initially provided a foundation for identifying common challenges in IoT adoption and analytics-driven decision-making. This research allowed the mapping of recurring barriers, such as data integration issues, model interpretability challenges, and infrastructure complexity, ensuring the list encompassed well-documented and relevant concerns.

Following this literature review, domain experts were approached to refine and validate the list. Through conversations with these experts, insights into practical challenges were obtained that were not always captured in existing research. For instance, it became evident that the absence of a robust, working product product is another relevant barrier. This barrier can be brought back entirely on technological challenges, so it was not included in the final barrier list.

Code	Barrier
BR1	Scalability of IoT sensors
BR2	Data integration and standardization
BR3	Model interpretability
BR4	Real-time data processing
BR5	Organizational and cultural barriers
BR6	Regulatory compliance
BR7	Economic viability
BR8	Data availability
BR9	Business-technical alignment
BR10	Data ownership and privacy
BR11	Infrastructure complexity
BR12	Skilled workforce

Table 3.3: List of barriers used for the ISM analysis.

3.3.2. Determining contextual relationships and SSIM

The contextual relationships were determined by examining the direction of influence between each pair of variables. Table 3.4 presents the aggregated SSIM barriers. As laid out in subsection 3.2.4, the following rules were followed to construct the SSIM from the collected data:

- V: variable i will influence variable j, but variable j is not influenced by variable I.
- A: variable j will influence variable i, but variable i is not influenced by variable j.
- X: variables i and j will influence each other.
- 0: variables i and j are unrelated.

In table 3.4, only the relationship (V, A, X, or O) with the highest frequency is presented.

	BR1	BR2	BR3	BR4	BR5	BR6	BR7	BR8	BR9	BR10	BR11	BR12
BR1	-	A	A	A	A	A	X	O	A	O	A	O
BR2		-	X	O	X	X	V	A	X	X	A	V
BR3			-	A	O	O	V	X	V	O	A	A
BR4				-	A	X	X	O	A	O	A	O
BR5					-	X	X	X	X	O	O	A
BR6						-	V	V	O	V	O	V
BR7							-	O	V	O	O	A
BR8								-	A	A	A	A
BR9									-	O	O	O
BR10										-	A	O
BR11											-	O
BR12												-

Table 3.4: Aggregated SSID Matrix

	BR1	BR2	BR3	BR4	BR5	BR6	BR7	BR8	BR9	BR10	BR11	BR12
BR1	-	13	9	15	7	5	11	14	8	6	10	12
BR2		-	16	18	14	13	17	20	11	19	10	7
BR3			-	13	8	5	9	15	6	7	12	14
BR4				-	7	5	11	14	8	6	10	12
BR5					-	13	11	12	10	9	11	8
BR6						-	17	10	10	15	6	9
BR7							-	12	15	8	7	9
BR8								-	16	9	10	11
BR9									-	14	8	10
BR10										-	11	10
BR11											-	12
BR12												-

Table 3.5: Tally Matrix with the number of times an SSIM relation was identified.

3.3.3. Developing reachability matrix

The SSIM is transformed to the initial Binary Direct Reachability Matrix (BDRM) by substituting V, A, X, and O by either 0 or 1, as described in subsection 3.2.5. Only the association with the highest frequency for each pair of variables is shown in the previous section.

BR1	BR2	BR3	BR4	BR5	BR6	BR7	BR8	BR9	BR10	BR11	BR12
22	30	27	35	19	18	18	26	15	23	20	20

Table 3.6: Number of times a barrier is mentioned in any contextual relationship.

The interviews for this study were conducted in an unstructured format. Due to time limitations, experts were asked to describe the relationships between six specific barriers and other barriers based on their area of expertise. A total of 47 experts contributed to the study. However, because certain fields were disproportionately represented among the experts, some barriers received more input than others. The frequency of expert input for each barrier is summarized in Table 3.6.

In this study, the choice was made for a threshold of 60%; i.e., if 60% of the experts say the relationship holds, the relationship is included in the aggregated matrix. Each barrier's total number of experts is presented in Table 3.6. Table 3.5 tracks how often a barrier relation is mentioned. Consequently, if for BR1 (22/100x60 = 15.4), the number in the tally matrix has a value of 15 or higher and a value of 1 on place (i, j) in their individual BDRM, a value of 1 is assumed on place (i, j) in the aggregated BDRM. If the corresponding value on the tally matrix is lower than the threshold and there is a value of 1 at place (i, j), the aggregated BDRM has a value of 0 at place (i, j).

	BR1	BR2	BR3	BR4	BR5	BR6	BR7	BR8	BR9	BR10	BR11	BR12
BR1	0	0	0	0	0	0	0	0	0	0	0	0
BR2	0	0	0	0	0	0	1	0	0	1	0	0
BR3	0	0	0	0	0	0	0	0	0	0	0	0
BR4	1	0	0	0	0	0	0	0	0	0	0	0
BR5	0	1	0	0	0	1	0	1	0	0	0	0
BR6	0	1	0	0	1	0	1	0	0	1	0	0
BR7	1	0	0	1	1	0	0	0	1	0	0	0
BR8	0	1	0	0	0	0	0	0	0	0	0	0
BR9	0	1	0	0	1	0	0	1	0	0	0	0
BR10	0	1	0	0	0	0	0	0	0	0	0	0
BR11	0	0	1	0	0	0	0	0	0	0	0	0
BR12	0	0	1	0	0	0	0	0	0	0	0	0

Table 3.7: The final binary direct reachability matrix using thresholds.

3.3.4. Level partition

The intersection of the antecedent set (= set of other variables that reach that specific variable) and the reachability set (= set of different variables that that variable reaches) determines the level that a given variable occupies. These sets are represented in Table 3.8 for the barriers. The variable in question won't reach any "new" variables if the intersection set equals the reachability set. Table 3.8 shows that BR1 has reachability set (1), which indicates that it does not affect other barriers, and antecedent set (1, 4, 7), which suggests that BR1 is influenced by barriers 1, 4, and 7. BR1 is, therefore, categorized as level 1 and does not reach any additional variables. The same principle applies to BR2, BR3, BR10, and BR12. As a result, we eliminate BR1, BR2, BR3, BR10, and BR12 from every set and begin the process over. With level 1 eliminated, the reachability set equals the intersection of the reachability set and the antecedent set in the second iteration for BR4, BR8, and BR11. As a result, these are assigned to level 2 and do not reach any additional variables in the system without them. Until the last variable, in this case, BR6 is assigned, the process is repeated.

Variable	Reachability Set	Antecedent Set	Intersection Set	Level
BR1	{1}	{1, 4, 7}	{1}	1
BR2	{2, 10}	{2, 5, 6, 8, 9, 10}	{2, 10}	1
BR3	{3}	{3, 11}	{3}	1
BR4	{1, 4}	{4, 7}	{4}	2
BR5	{2, 5, 6, 8}	{5, 6, 7, 9}	{5, 6}	3
BR6	{2, 5, 6, 7, 10}	{5, 6}	{5, 6}	5
BR7	{1, 4, 5, 7, 9}	{6, 7}	{7}	4
BR8	{2, 8}	{5, 8, 9}	{8}	2
BR9	{2, 5, 8, 9}	{7, 9}	{9}	3
BR10	{2, 10}	{2, 6, 10}	{2, 10}	1
BR11	{3, 11}	{11}	{11}	2
BR12	{3, 12}	{12}	{12}	1

Table 3.8: Summary of level partitions of barriers.

3.3.5. Visualization

The variables are arranged using the level partition from the previous phase to get the final graph. Arrows are positioned per their directional relationship based on the binary direct relations after the variables have been structured hierarchically (table 3.7). Figure 3.2 displays the results for the barriers.

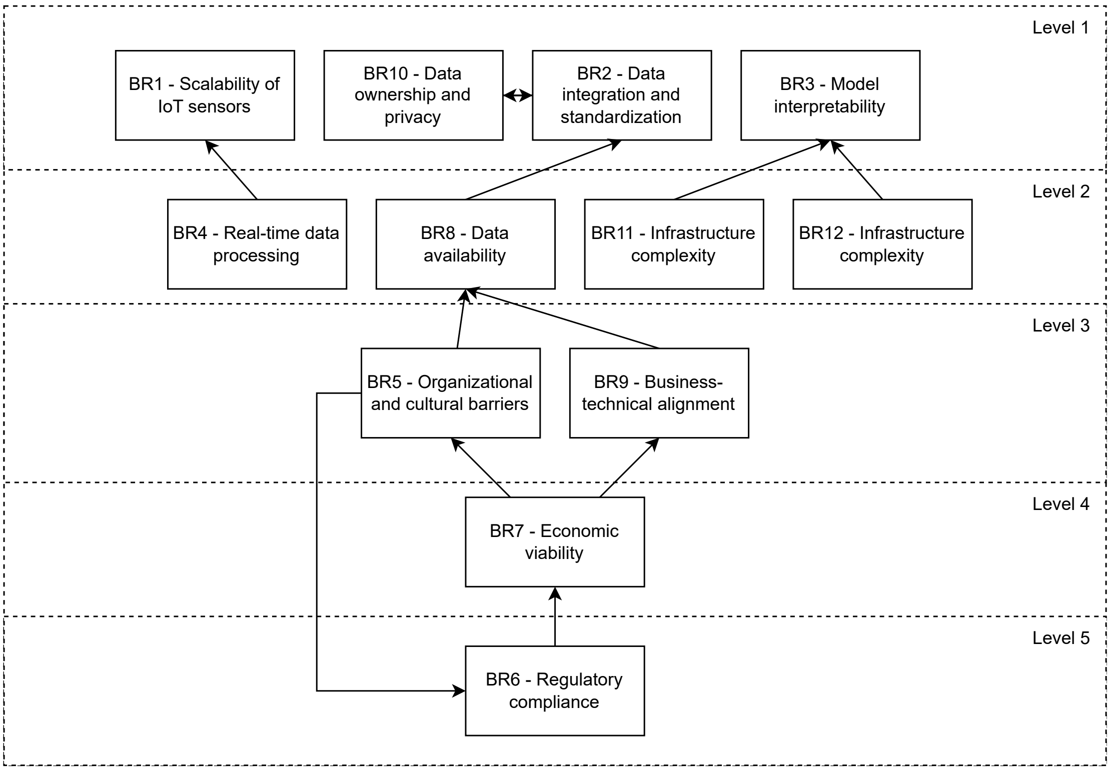

Figure 3.2: Final directed graph barriers.

3.3.6. Fuzzy MICMAC

The fuzzy direct reachability matrix was calculated by overlaying the numerical representation of strength, presented in Table 3.1, onto the BDRM presented in Table 3.7. The relationship with the highest frequency is then used to generate the aggregated multiplied fuzzy direct reachability matrix. Therefore, it was calculated by taking the strength factor of each particular fuzzy direct reachability matrix recognized by the greatest number of experts presented in Table 3.6. Table 3.9 displays the multiplied fuzzy matrix aggregate. As discussed in Kamble et al. (2018) [33] and Khatwani et al. (2015) [36], the diagonal is set to 1.

Table 3.9: Aggregated multiplied fuzzy direct reachability matrix barriers with driving power and dependency.

	BR1	BR2	BR3	BR4	BR5	BR6	BR7	BR8	BR9	BR10	BR11	BR12	Driving Power
BR1	1.00	0.00	0.00	0.75	0.00	0.00	0.00	0.70	0.00	0.00	0.00	0.00	2.45
BR2	0.00	1.00	0.00	0.90	0.00	0.00	0.00	1.00	0.00	0.95	0.00	0.00	3.85
BR3	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
BR4	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
BR5	0.00	0.70	0.00	0.00	1.00	0.65	0.00	0.60	0.00	0.00	0.00	0.00	2.95
BR6	0.00	0.65	0.00	0.00	0.65	1.00	0.85	0.00	0.00	0.75	0.00	0.00	3.90
BR7	0.55	0.00	0.00	0.55	0.55	0.85	1.00	0.60	0.75	0.00	0.00	0.00	4.85
BR8	0.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.80	0.00	0.00	0.00	2.80
BR9	0.00	0.55	0.00	0.00	0.50	0.75	0.75	0.80	1.00	0.70	0.00	0.50	5.55
BR10	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.70	1.00	0.00	0.00	2.65
BR11	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.60	2.20
BR12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Dependency	1.55	4.85	1.60	3.20	2.70	3.25	2.60	4.70	3.25	3.40	1.00	2.10	

Cluster classification

The factors are grouped into four clusters according to their driver-dependence power after generating the fuzzy MICMAC stabilized matrix.

The outcomes for the barriers were:

- **The autonomous cluster**, or the driving forces and factors with little reliance. Variables BR1, BR3, BR11, and BR12 are prevalent in this cluster. As a result, other variables do not significantly impact these barriers and do not generally have much capacity to affect other variables.
- **The dependent cluster**, which consists of variables with great dependence power but poor driving. BR4 and BR10 are the variables that make up this cluster. As a result, these barriers have a shallow ability to influence other factors within the system; other variables have a relatively high capacity to influence them.
- **The linkage cluster**, which contains variables with a high degree of reliance and driving force. A network of interdependencies is created by the components in this cluster, which both influence and are influenced by several other variables in the system. This cluster contains the variables BR2, BR6, BR8, and BR9. Since modifications to these variables have the potential to have repercussions across the entire network of barriers, they are essential to the system. These factors are crucial for system stability and control because of their significant driving force and reciprocal dependence, which means that changes in one could drastically change the behavior of other clusters. Variables in the Linkage Cluster indicate areas that require close observation and management to preserve system equilibrium.
- **The independent cluster**, which consists of variables with solid driving and weak dependent power. Variables BR5 and BR7 fill this cluster. These factors have a powerful ability to impact others, but they are the ones least affected by them. The system's strongest motivator is BR7, representing the economic viability of predictive maintenance technology.

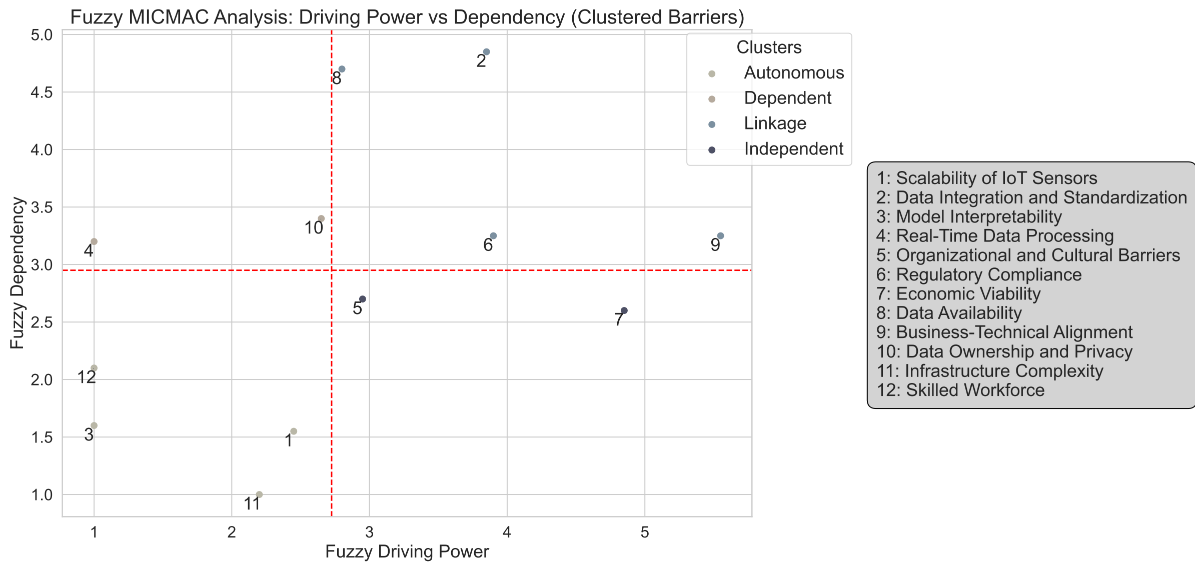

Figure 3.3: Driving and dependence power of the barriers

3.4. Discussion

In this section, the key findings from the analyses in Chapter 3 are discussed, aiming to identify and categorize the barriers to implementing PdM technology in the cargo rail industry based on their driving power and dependency. These findings are discussed in the context of answering subquestion 3:

"What are the driving entrance barriers to implementing predictive maintenance technology on trains for freight rail operators?"

A combination of ISM and fuzzy MICMAC analyses classified the entrance barriers into several categories based on their driving and dependence power, providing a structured view of the obstacles that inhibit PdM adoption in railways. The driving barriers identified include economic viability, regulatory compliance, and business-technical alignment, each with substantial implications for the PdM adoption process.

Economic viability

The analysis underscored economic viability as a high-driving power and independent barrier. This barrier reflects the substantial initial investments required for PdM technology, particularly in sensor installation, data integration, and workforce training. The economic feasibility of PdM hinges on demonstrating long-term cost savings, such as reduced downtime and optimized maintenance schedules, which can justify the upfront costs. The freight rail sector must, therefore, quantify these benefits to build a compelling business case for PdM. Such an approach is essential to gain stakeholder commitment and overcome financial resistance, a critical barrier to PdM adoption.

Regulatory compliance

Regulatory compliance emerged as another significant barrier, reflecting the railway sector's stringent safety and operational standards. The lack of standardized legal frameworks and safety certification processes for predictive technologies complicates PdM's deployment at scale. This regulatory uncertainty discourages investment in PdM, as operators may face delays or financial risks associated with non-compliance. Addressing this barrier requires collaborative efforts between industry stakeholders and regulatory bodies to establish consistent standards that facilitate PdM's safe and effective implementation.

Business-technical alignment

The findings highlight the importance of aligning PdM technology with the broader business objectives of railway operators, a barrier with both high dependence and driving power. Effective PdM implementation requires integration with existing maintenance workflows, cross-departmental collaboration, and a clear understanding among stakeholders of PdM's value in enhancing operational efficiency and safety. Without such alignment, PdM may be perceived as a costly technical add-on rather than a strategic asset, limiting its acceptance and impact. This barrier's significance emphasizes the need for a holistic implementation strategy that includes technical, managerial, and cultural considerations.

Distinction fundamental and non-fundamental barriers

This chapter aims to identify the driving barriers to implementing PdM technology on freight trains. These barriers are of particular interest because they drive or influence other obstacles. To fully understand the challenges to adoption, it is essential to differentiate between fundamental and non-fundamental barriers.

Fundamental barriers are those that make the implementation of PdM technology entirely unfeasible. In contrast, non-fundamental barriers do not directly prevent the technology from being introduced. Looking at these identified driving barriers, economic viability and regulatory compliance are fundamental barriers because PdM technology cannot reach the market without them. Other relevant fundamental barriers in this study include real-time data processing and a skilled workforce, data availability, data integration and standardization, and data ownership and privacy are identified as potential fundamental barriers. These are critical to the functionality and feasibility of PdM systems because unresolved challenges in these areas could entirely prevent their operation or deployment.

On the other hand, barriers such as business-technical alignment, scalability of IoT sensors, model interpretability, organizational and cultural barriers, and infrastructure complexity are considered non-fundamental barriers. These barriers, while impactful, do not make the implementation infeasible but instead influence its optimization and adoption.

The goal should be strategically addressing these driving barriers to resolve the fundamental challenges first, paving the way for successful implementation while also minimizing the impact of non-fundamental barriers to enhance effectiveness and efficiency.

Implications for PdM implementation

These barriers collectively highlight that successful PdM adoption in the railway sector requires more than just technological advancement. A multi-faceted approach addressing economic, regulatory, and organizational challenges is critical. The railway industry can create a favorable environment for PdM's sustainable deployment by prioritizing a straightforward economic analysis and advocating for regulatory support. Additionally, fostering alignment between technical innovations and strategic business goals will ensure that PdM technology is integrated as a core component of railway operations rather than an isolated initiative.

Future research should focus on developing frameworks to quantify PdM's financial and operational benefits, establishing industry-wide standards, and exploring ways to foster organizational acceptance. Collaborative efforts between technology providers, operators, and regulators will be essential to overcome these barriers and achieve PdM's full potential in the railway industry.

3.5. Conclusion

This chapter presents a comprehensive analysis of the barriers to implementing PdM in the railway sector, utilizing ISM and fuzzy MICMAC to unravel their interdependencies. The analysis highlights the interconnected nature of these barriers, emphasizing their roles in shaping the feasibility and success of PdM deployment.

Economic viability stands out as a central challenge, as the significant upfront investments in technology, infrastructure, and workforce require a compelling financial case to secure stakeholder commitment. Demonstrating tangible benefits, such as reduced maintenance costs and minimized downtime, is crucial for justifying these expenditures and overcoming resistance.

Regulatory compliance further complicates the adoption process due to the railway industry's stringent safety standards and the lack of clear certification protocols for predictive technologies. This regulatory ambiguity creates uncertainty and risks for operators, underscoring the need for collaborative efforts between industry players and regulatory bodies to establish consistent and supportive frameworks.

The integration of PdM into existing business and technical systems is another critical barrier. Misalignment between predictive technologies and organizational objectives can hinder acceptance, reducing PdM's impact on operational efficiency and safety. Effective implementation requires a holistic approach that bridges technical innovation with strategic business goals, ensuring cross-departmental collaboration and shared understanding of PdM's value.

Addressing these barriers requires a multifaceted strategy that prioritizes fundamental challenges while fostering organizational readiness. Economic and regulatory issues must be resolved to create a viable foundation for implementation, enabling the railway sector to realize PdM's potential for transforming maintenance practices. By fostering alignment across technical, regulatory, and organizational dimensions, stakeholders can pave the way for sustainable and impactful adoption of PdM technologies.

4 Cost-benefit analysis

The introduction of this chapter focuses on assessing the economic viability of PdM implementation within the railway industry. Building on insights from previous chapters, it emphasizes the critical role of economic factors as key determinants for the adoption and long-term success of PdM. The analysis highlights that understanding and demonstrating PdM's financial benefits, such as cost reduction and improved reliability, are crucial for gaining stakeholder buy-in. Additionally, the introduction notes that the inherent uncertainties in data, including variable costs and equipment life spans, require careful consideration. A Monte Carlo simulation approach is introduced to account for these uncertainties, making the cost-benefit analysis more robust and adaptable to real-world variability.

4.1. Introduction

Building on the findings from chapter 3, it is clear that the barrier of economic viability stands as a significant independent variable that shapes the feasibility and success of predictive maintenance implementation in the railway sector. In this context, economic viability dictates the pace of technological adoption and indicates long-term sustainability and profitability for railway operators. Understanding this viability, therefore, is essential for informed decision-making and the effective deployment of predictive maintenance technologies.

Given the restricted timeframe of this study, it is essential to acknowledge the uncertainties inherent in the data gathered. Variability in costs, equipment longevity, and external factors such as market conditions introduce a degree of unpredictability that could impact financial outcomes. To manage these uncertainties, this analysis employs Monte Carlo simulations, which offer a probabilistic approach to estimate outcomes across a range of potential scenarios. The analysis becomes more robust by incorporating uncertainty intervals, allowing stakeholders to anticipate and plan for variability in implementation costs and benefits.

This cost-benefit analysis focuses explicitly on Deutsche Bahn Cargo as a case study. As a public entity, Deutsche Bahn provides ample data for analysis, and its large-scale operations make it an ideal example for understanding predictive maintenance in freight rail. The study further narrows its focus to wheel monitoring, with sensors positioned on bogies to capture critical performance data. Monitoring wheels is integral to maintaining safety and efficiency in freight operations.

By assessing the cost implications and potential gains from predictive maintenance, this chapter provides a practical framework to support railway operators, policymakers, and stakeholders in making data-informed decisions.

4.2. Methodology

This section focuses on the cost-benefit analysis framework used to evaluate PdM for cargo rail wheel maintenance compared to traditional maintenance. It includes an in-depth examination of various cost components, such as implementation, operational, and maintenance costs, alongside revenue benefits from PdM improvements. The analysis incorporates Monte Carlo simulations to address uncertainty in cost estimations, which provides probabilistic insights into potential financial outcomes. Additionally, inflation correction is applied over the 20-year analysis period to reflect future costs accurately.

4.2.1. Cost-benefit analysis

This cost-benefit analysis evaluates the financial impact of implementing PdM technology for cargo rail wheel maintenance compared to traditional maintenance (TM). The study incorporates wheel maintenance and replacement costs, operational downtime, increased revenue from reduced downtime, sensor and cybersecurity expenses, and improved safety and energy efficiency benefits. Monte Carlo simulations account for uncertainty, and inflation adjustments are applied over a 20-year period.

Predictive maintenance vs. traditional maintenance

Costs for the PdM scenario are compared to traditional maintenance costs, which are also simulated using Monte Carlo methods. Traditional maintenance involves higher material loss, frequent maintenance events, and operational disruption costs. By contrast, the PdM scenario benefits from reduced material loss and less frequent maintenance but incurs additional costs from implementing and maintaining the predictive sensors.

4.2.2. Cost components

The analysis considers several cost components, as Figure 4.1 illustrates. This diagram highlights the implementation costs associated with PdM technology in gray, covering aspects like education for maintenance crews and installation expenses. The yearly costs and benefits—depicted in beige—include significant factors such as wheel lifecycle costs, downtime impacts, sensor upkeep, and potential efficiency improvements. Furthermore, individual cost or benefit components linked to these categories are detailed in taupe, specifying elements like corrective maintenance, energy efficiency gains, cybersecurity expenses, and accident risks. The following section will delve into the primary cost and benefit components, explaining how they are integrated into the cost-benefit analysis model.

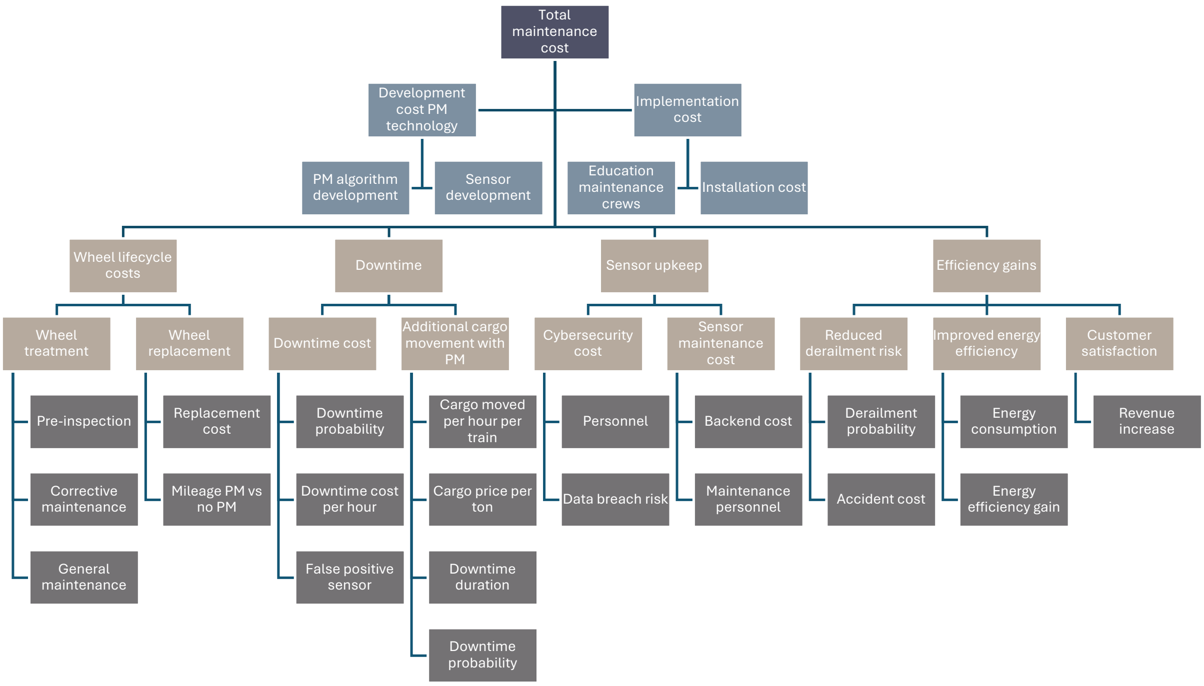

Figure 4.1: Overview of the cost and benefit components for PdM in wheel maintenance.

Wheel lifecycle costs

The lifecycle costs of a wheel can be categorized into two main components: wheel treatment costs and wheel replacement costs. Both play a significant role in determining the overall cost of maintaining a rail fleet and are highly dependent on whether PdM or conventional maintenance (no-PdM) is used. The following sections explain these costs in detail.

Wheel treatment costs

Wheel treatment costs encompass the regular maintenance actions required to keep the wheels in optimal condition. These actions are split into three main components: pre-inspection, corrective maintenance, and scheduled maintenance.

Pre-inspection
Pre-inspection is the first step in conventional wheel maintenance. It involves manually inspecting the wheelset during scheduled maintenance to determine whether further treatment is necessary. With PdM, this component is entirely automated by sensors, removing the need for manual pre-inspections. The yearly pre-inspection costs are calculated as follows:

$$C_{\text{pi,PdM}} = 0, \quad C_{\text{pi,no-PdM}} = C_{\text{pi}} \times \Delta T_{\text{M}} \times n_{\text{trains}}$$

Where C_{pi} represents the pre-inspection cost, ΔT_{M} is the maintenance interval, and n_{trains} is the number of trains.

Corrective maintenance
Corrective maintenance refers to unscheduled repairs after a field inspection reveals a fault. PdM systems reduce the likelihood of such events by detecting potential issues early. The probability of requiring corrective maintenance differs between PdM and no-PdM systems, and the associated yearly costs are as follows:

$$C_{\text{cm,PdM}} = P_{\text{c, PdM}} \times C_{\text{cm}} \times n_{\text{trains}}, \quad C_{\text{cm,no-PdM}} = P_{\text{c, no-PdM}} \times C_{\text{cm}} \times n_{\text{trains}}$$

Here, $P_{\text{c, PdM}}$ and $P_{\text{c, no-PdM}}$ are the probabilities of corrective maintenance with and without PdM, respectively. C_{cm} is the corrective maintenance cost per event.

Scheduled maintenance
Scheduled maintenance is the periodic servicing of the wheelset based on pre-inspection results or PdM recommendations. With PdM, maintenance is performed as determined by the sensors, meaning it cannot be postponed. In contrast, conventional maintenance may result in fewer interventions, as not every pre-inspection results in immediate action. The costs for scheduled maintenance are composed of labor and wheelset treatment, as shown in the following equations:

$$C_{\text{wm,PdM}} = (C_{\text{wm, labor PdM}} + C_{\text{p,wheel}}) \times P_{\text{maintenance, PdM}} \times (1 - \Delta\eta_{\text{maintenance}}) \times \Delta T_{\text{M}} \times n_{\text{wheels}} \times n_{\text{wagon}}$$

$$C_{\text{wm,no-PdM}} = (C_{\text{wm, labor no-PdM}} + C_{\text{p,wheel}}) \times P_{\text{maintenance, no-PdM}} \times \Delta T_{\text{M}} \times n_{\text{wheels}} \times n_{\text{wagon}}$$

Where:

- $C_{\text{wm, labor PdM}}$ and $C_{\text{wm, labor no-PdM}}$ are the labor costs for wheel treatment with and without PdM, respectively,
- $C_{\text{p,wheel}}$ is the price of wheel placement,
- $P_{\text{maintenance, PdM}}$ and $P_{\text{maintenance, no-PdM}}$ are the probabilities of requiring scheduled maintenance with and without PdM,
- $\Delta\eta_{\text{maintenance}}$ is the improvement in maintenance efficiency with PdM.

The total yearly treatment costs for PdM and no-PdM are calculated as:

$$TC_{\text{treatment, PdM}} = (C_{\text{pi,PdM}} + C_{\text{cm,PdM}} + C_{\text{wm, PdM}})$$

$$TC_{\text{treatment, no-PdM}} = (C_{\text{pi,no-PdM}} + C_{\text{cm,no-PdM}} + C_{\text{wm, no-PdM}})$$

Wheel replacement costs
Wheel replacement occurs after the wheels reach a certain mileage, which varies depending on the maintenance strategy employed. With PdM, wheel defects are generally detected earlier and are

less severe, leading to a longer lifespan than conventional maintenance strategies. The yearly wheel replacement costs are calculated as follows:

$$RC_{\text{wheels, PdM}} = \frac{d_{\text{year}}}{L_{\text{PdM}}} \times n_{\text{wheels}} \times C_{\text{wr}}, \quad RC_{\text{wheels, no-PdM}} = \frac{d_{\text{year}}}{L_{\text{no-PdM}}} \times n_{\text{wheels}} \times C_{\text{wr}}$$

Where:

- d_{year} is the yearly mileage of the fleet,
- L_{PdM} is the lifespan of the wheels under predictive maintenance (PdM),
- $L_{\text{no-PdM}}$ is the lifespan of the wheels under conventional maintenance (no PdM),
- n_{wheels} is the total number of wheels in the fleet.
- C_{wr} is the price to for replacing a wheel.

Downtime events

Wheel flats account for 31.8% of total downtime in European railways [25], causing major operational disruptions. Maintenance activities like re-profiling are crucial to avoid further damage to both rolling stock and infrastructure [2]. PdM aims to reduce the frequency and severity of downtime by detecting wheel defects early, leading to quicker and less costly repairs.

Downtime costs include storage fees for out-of-service trains and personnel costs as maintenance teams remain on standby. During downtime, trains are unable to transport cargo, leading to direct revenue loss. By reducing and shortening downtime events, PdM enables trains to stay operational longer, generating more revenue.

The probability of downtime with PdM can be modeled as:

$$P_{\text{downtime, PdM}} = P_{\text{downtime, no-PdM}} \times (1 - \Delta\eta_{\text{PdM}})$$

The downtime costs for both scenarios, with and without PdM, are:

$$C_{\text{downtime, PdM}} = P_{\text{downtime, PdM}} \times n_{\text{trains}} \times C_{\text{downtime\_event}} \times (T_{\text{downtime}} - T_{\text{downtime\_saved}})$$

$$C_{\text{downtime, no-PdM}} = P_{\text{downtime, no-PdM}} \times n_{\text{trains}} \times C_{\text{downtime\_event}} \times T_{\text{downtime}}$$

Where:

- $P_{\text{downtime, PdM}}$ and $P_{\text{downtime, no-PdM}}$ are the probabilities of downtime with and without PdM,
- $\Delta\eta_{\text{PdM}}$ is the efficiency gain from PdM,
- n_{trains} is the number of trains,
- $C_{\text{downtime\_event}}$ is the cost per hour of downtime,
- T_{downtime} is the downtime duration,
- $T_{\text{downtime\_saved}}$ is the downtime saved with PdM.

False positives in predictive maintenance

Predictive maintenance can also result in false positives, where defects are wrongly identified, causing unnecessary maintenance and downtime costs. These are calculated as:

$$C_{\text{false\_positive\_maintenance}} = P_{\text{false\_positive}} \times P_{\text{PdM, corrective}} \times C_{\text{cm}} \times n_{\text{trains}}$$

$$C_{\text{false\_positive\_downtime}} = P_{\text{false\_positive}} \times C_{\text{downtime\_event}} \times T_{\text{downtime}} \times n_{\text{trains}}$$

Where:

- $P_{\text{false\_positive}}$ is the false positive rate,
- $P_{\text{PdM, corrective}}$ is the probability of corrective maintenance under PdM,
- $C_{\text{corrective\_maintenance}}$ is the cost of corrective maintenance,
- $C_{\text{downtime\_event}}$ is the downtime cost per hour,
- T_{downtime} is the downtime duration,
- n_{trains} is the number of trains.

The total cost for both scenarios, including false positives, is:

$$C_{\text{PdM,falsepositive}} = C_{\text{false\_positive\_maintenance}} + C_{\text{false\_positive\_downtime}}$$

$$C_{\text{no-PdM,falsepositive}} = 0$$

Revenue increase from reduced downtime
The increase in revenue due to reduced downtime through PdM can be calculated by first determining the total downtime hours saved:

$$H_{\text{downtime, saved}} = (P_{\text{downtime, no-PdM}} - P_{\text{downtime, PdM}}) \times T_{\text{downtime}} + T_{\text{downtime\_saved}} \times P_{\text{downtime, PdM}} - T_{\text{downtime}} * P_{\text{false\_positive}}$$

Where:

- $P_{\text{downtime, PdM}}$ is the annual downtime probability with predictive maintenance,
- $P_{\text{downtime, no-PdM}}$ is the annual downtime probability without predictive maintenance,
- T_{downtime} is the total downtime duration per event,
- $T_{\text{downtime\_saved}}$ is the downtime saved per event under PdM,
- $P_{\text{false\_positive}}$ is the false positive rate of the PdM sensors.

Next, the additional cargo that can be transported due to the saved downtime is computed as:

$$C_{\text{additional\_cargo}} = H_{\text{downtime, saved}} \times C_{\text{cargo\_capacity}} \times n_{\text{trains}}$$

Finally, the additional revenue generated from transporting this extra cargo is:

$$R_{\text{additional, PdM}} = C_{\text{additional\_cargo}} \times R_{\text{revenue\_per\_ton}}$$

Where:

- $C_{\text{cargo\_capacity}}$ is the cargo capacity transported per hour per train,
- $R_{\text{revenue\_per\_ton}}$ is the revenue generated per ton of cargo transported,
- n_{trains} is the number of trains in the fleet.

Operational costs

In this section, the operational costs associated with cybersecurity and sensor maintenance, as well as two critical components of maintaining the integrity and functionality of predictive maintenance systems, are detailed. Each cost component is divided into its constituent parts, and formulas for calculating total expenses are provided.

Cybersecurity costs
Maintaining cybersecurity for predictive maintenance systems is essential to protect data and systems. Cybersecurity costs can be divided into two main categories: personnel costs for cybersecurity-specific maintenance and the costs of maintaining cybersecurity systems. The total cybersecurity costs are calculated as follows:

$$C_{\text{cyber}} = C_{\text{maintenance, personnel, cyber}} + C_{\text{cybersecurity, maintenance}}$$

Where:

- C_{cyber} is the total cybersecurity cost,
- $C_{\text{maintenance, personnel, cyber}}$ is the cost of personnel dedicated to maintaining cybersecurity,
- $C_{\text{cybersecurity, maintenance}}$ is the cost associated with maintaining the cybersecurity systems themselves (e.g., software updates and infrastructure maintenance).

This ensures that both human and system resources are accounted for in protecting the predictive maintenance framework from potential cyber threats.

Sensor maintenance costs
Another significant operational cost comes from maintaining the sensor infrastructure. These sensors are critical for the functioning of the predictive maintenance system as they collect the necessary data. The cost of sensor maintenance is broken down into service costs and backend maintenance costs.

The total service cost for the sensors is calculated based on the number of wagons and wheels, the service interval, and the cost per service:

$$C_{\text{service}} = \frac{C_{\text{per\_service}} \times n_{\text{wagon}} \times n_{\text{wheels}}}{S_{\text{interval}}} / 4$$

Where:

- C_{service} is the total service cost for maintaining the sensors,
- $C_{\text{per\_service}}$ is the cost of servicing each sensor,
- n_{wagon} is the number of wagons in the trainset,
- n_{wheels} is the number of wheels in each wagon (with one sensor assumed per bogie, i.e., 4 wheels per bogie),
- S_{interval} is the service interval, indicating the frequency of sensor servicing (per year).

In addition to the sensor service costs, backend maintenance costs include system maintenance and data analysis. These costs are calculated as follows:

$$C_{\text{backend}} = C_{\text{backend\_maintenance}} + \frac{C_{\text{analyst}}}{5000} \times n_{\text{wagon}} \times n_{\text{wheels}} / 4$$

Where:

- C_{backend} is the total backend maintenance cost,
- $C_{\text{backend\_maintenance}}$ is the cost associated with maintaining the backend systems (e.g., data servers, software infrastructure),
- C_{analyst} is the cost of hiring analysts to process and interpret sensor data, with an assumption of 1 analyst per 5000 sensors.

Finally, the total maintenance cost for the sensors is the sum of the service and backend costs:

$$C_{\text{maintenance}} = C_{\text{service}} + C_{\text{backend}}$$

By accounting for both the direct service costs and the backend infrastructure, this formula ensures a comprehensive understanding of the total operational costs for sensor maintenance.

Improved efficiency

In this section, we discuss the potential improvements in operational efficiency due to predictive maintenance (PdM), focusing on accident risk reduction and energy efficiency improvement. Each area is analyzed with respect to its cost impact, both in the scenario where PdM is implemented and when it is not.

Accident risk reduction
One key area of improvement with PdM is the reduction in accident risk. Predictive maintenance helps identify potential failures before they lead to accidents, thus lowering the probability of accidents. The expected annual costs of accidents are calculated for both scenarios: with and without PdM.

Without PdM, the expected annual cost of accidents is given by:

$$C_{\text{a, no-PdM}} = P_{\text{accident, no-PdM}} \times C_{\text{per\_accident}} \times n_{\text{trains}}$$

With PdM, the expected annual cost of accidents is reduced:

$$C_{\text{a, PdM}} = P_{\text{accident, PdM}} \times C_{\text{per\_accident}} \times n_{\text{trains}}$$

Where:

- $C_{\text{a, no-PdM}}$ is the expected annual cost of accidents without predictive maintenance,
- $C_{\text{a, PdM}}$ is the expected annual cost of accidents with predictive maintenance,
- $P_{\text{accident, no-PdM}}$ is the annual accident probability when no predictive maintenance is performed,
- $P_{\text{accident, PdM}}$ is the annual accident probability when predictive maintenance is performed,
- $C_{\text{per\_accident}}$ is the cost incurred per accident (including damage to rolling stock, infrastructure, and potential legal and medical expenses),
- n_{trains} is the number of trains in the fleet.

By comparing these two values, the cost savings from reducing accident risks due to PdM can be calculated, providing a clear financial justification for implementing PdM.

Energy efficiency improvement
Predictive maintenance can also improve energy efficiency by optimizing train operations and reducing energy wastage due to mechanical faults or inefficiencies in the system. The total energy costs, which include electricity and other energy sources, are calculated as follows:

$$C_{\text{energy}} = E_{\text{consumption, electricity}} \times n_{\text{wagon}} + E_{\text{consumption, other}} \times n_{\text{wagon}}$$

Where:

- C_{energy} is the total energy cost for operating the fleet,
- $E_{\text{consumption, electricity}}$ is the energy consumption cost from electricity per wagon,
- $E_{\text{consumption, other}}$ is the energy consumption cost from other sources (e.g., fuel) per wagon,
- n_{wagon} is the number of wagons in the fleet.

Predictive maintenance leads to more efficient train operations, which reduces energy consumption. The savings from reduced energy consumption due to PdM are calculated as follows:

$$C_{\text{E, reduced}} = C_{\text{energy}} \times \Delta\eta_{\text{E}}$$

Where:

- $C_{\text{E, reduced}}$ is the reduced energy cost per train due to improved efficiency,
- $\Delta\eta_{\text{E}}$ is the percentage of efficiency improvement in energy consumption from implementing predictive maintenance.

By implementing PdM, the fleet can operate with lower energy costs, contributing to overall savings and a reduced environmental impact.

Customer satisfaction The reduced downtime and increased safety due to PdM technology directly leads to higher customer service, directly impacting revenue. The following formula calculates the additional revenue generated from enhancing service standards. It assumes that the improvement in customer service leads to a proportional increase in revenue based on the baseline:

$$R_{\text{additional}} = R_{\text{baseline}} \times \text{CSI}$$

where:

- $R_{\text{additional}}$ is the additional revenue from service improvement,
- R_{baseline} is the baseline revenue per wagon per year,
- CSI is the customer service improvement.

Implementation costs

Implementing predictive maintenance systems incurs crew education and sensor installation costs. These costs are not one-time expenditures; sensors must be replaced every few years, and crews must continually update their knowledge to keep pace with technological advancements. Therefore, these costs recur periodically over the lifetime of the system.

Crew costs
To ensure the effective implementation and operation of the predictive maintenance system, the crews must be properly trained. This training cost depends on the number of crews involved and the number of wagons in the fleet. The total crew cost is calculated as follows:

$$C_{\text{crew}} = C_{\text{education}} \times n_{\text{crews}} \times n_{\text{wagon}}$$

Where:

- C_{crew} is the total cost of educating the crew,
- $C_{\text{education}}$ is the cost of education per crew member,
- n_{crews} is the number of crews involved in the system's implementation,
- n_{wagon} is the number of wagons in the fleet.

Since crew knowledge must stay current with the latest technology and practices, these education costs will recur every few years to ensure the teams remain up to date.

Sensor installation costs
The sensor installation cost accounts for both the physical sensors and the labor required to install them. Each wagon in the fleet is equipped with sensors, typically one per bogie (four wheels per bogie). The total sensor installation cost is calculated as follows:

$$C_{\text{installation}} = (C_{\text{sensor, installation}} + C_{\text{sensor}}) \times n_{\text{wagon}} \times n_{\text{wheels}}/4$$

Where:

- $C_{\text{installation}}$ is the total cost of installing the sensors,
- $C_{\text{sensor, installation}}$ is the installation cost per sensor,
- C_{sensor} is the cost of each sensor,
- n_{wagon} is the number of wagons in the fleet,
- n_{wheels} is the number of wheels per wagon (with one sensor assumed per bogie, i.e., four wheels per bogie).

Since sensors must be replaced every few years due to wear or technological advancements, this cost also recurs periodically.

Total implementation costs
The total implementation cost is the sum of the crew education and sensor installation costs:

$$C_{\text{implementation}} = C_{\text{crew}} + C_{\text{installation}}$$

This formula provides a comprehensive view of the initial and recurring costs of implementing and maintaining a predictive maintenance system. It ensures that both the human and hardware elements of the system are accounted for and highlights the need for periodic reinvestment in sensor replacement and crew training to ensure long-term efficiency. The variable list can be found in Appendix E.

4.2.3. Inflation correction

The model accounts for the impact of inflation over time. A 3% annual inflation rate is assumed, and costs are adjusted accordingly for the 20-year analysis period. The inflation correction is applied to both recurring and one-time costs. Recurring costs, such as sensor replacements, are adjusted regularly, reflecting their projected future costs.

4.2.4. Monte Carlo simulation

Monte Carlo simulation is a statistical technique that uses random sampling and probabilistic modeling to understand the behavior of systems influenced by uncertainty. In this cost-benefit analysis, Monte Carlo simulation is essential for capturing the inherent variability in the inputs (such as maintenance costs, downtime, and energy efficiency improvements) and for generating a range of possible outcomes rather than a single deterministic result.

Fundamentals of Monte Carlo simulation

Monte Carlo simulations rely on repeated random sampling from probability distributions of uncertain variables. By simulating many possible outcomes, the method quantifies the range of possible results and the probability of different outcomes.

The key steps in a Monte Carlo simulation are:

- **Define the input variables and their distributions:** Each uncertain variable (e.g., cost per maintenance event, downtime duration, sensor replacement costs) is modeled using an appropriate probability distribution, such as normal, uniform, or triangular.
- **Random sampling:** For each simulation, random samples are drawn from the defined probability distributions. Each sample represents one possible realization of the variable.
- **Repetition of simulations:** This process is repeated for a large number of iterations (40,000 in this analysis), and in each iteration, a set of input samples is used to calculate the outputs, such as total costs, net benefits, or savings.
- **Analysis of results:** The simulated results are aggregated to estimate the output variables' mean, variance, and confidence intervals. This gives a probabilistic view of the expected outcomes and helps understand the risks and uncertainties involved.

Relevance of Monte Carlo Simulation

Monte Carlo simulations are used in this cost-benefit analysis for two main reasons:

- **Uncertainty Management:** Since many input variables (e.g., maintenance costs, downtime costs, and accident risk reduction) are uncertain, Monte Carlo simulation helps capture this uncertainty. It provides a more robust analysis compared to a single deterministic scenario [22].
- **Decision-Making Support:** By simulating multiple possible future outcomes, the simulation offers insights into the probability of different cost and benefit scenarios. This helps decision-makers understand the likelihood of achieving a positive net benefit from predictive maintenance and assess the associated financial risks [22, 43].

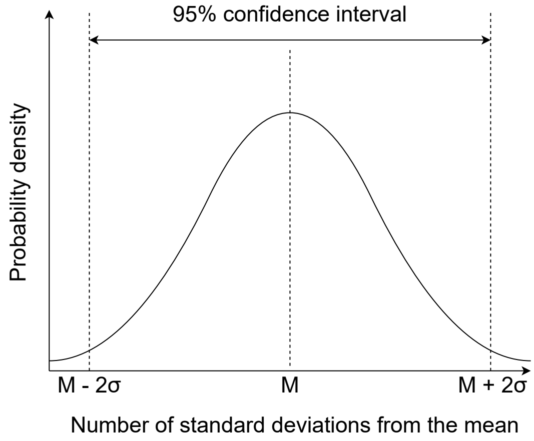

Figure 4.2: Probability distribution of net benefits with a 95% confidence interval.

Monte Carlo Simulation Implementation

A Monte Carlo simulation was conducted to account for uncertainty in the variables affecting the costs and benefits of PdM versus TM. This method incorporated randomness to simulate a wide range of scenarios, providing robust estimates of the expected outcomes under varying conditions [43, 55, 22].

The simulation framework incorporates a diverse set of variables to capture the complexity of the decision-making process [58]:

Decision variables represent the strategic choices to be evaluated within the simulation. These include whether to adopt PdM or continue with TM and the frequency of scheduled maintenance interventions. These variables reflect the potential levers that stakeholders can adjust to optimize costs and benefits.

State variables describe the current and evolving conditions of the system being analyzed. Key state variables include the lifespan of wheelsets under both PdM and TM, the current probability of downtime events disrupting operations for TM, and the likelihood of accidents occurring for TM. These variables dynamically influence the performance of maintenance strategies and serve as inputs to other parts of the model.

Objective variables define the outcomes that the simulation seeks to measure and optimize. In the case of this study, these are the total maintenance costs. This variable provides the key criteria for evaluating the financial success of PdM compared to TM.

Stochastic variables capture uncertainties inherent in the system. Examples include the cost variability of maintenance events (e.g., corrective and replacement costs), the duration and costs associated with downtime events, and the probability of false positives in PdM systems. Stochastic variables are modeled using probabilistic distributions, such as normal distributions, to reflect their variability and provide a realistic basis for the simulation. A summary of the state and stochastic variables used in this model can be found in Appendix E.

The simulation is conducted over 40,000 iterations to ensure a comprehensive exploration of possible outcomes. Confidence intervals for the cost differences are constructed to illustrate the range of likely outcomes, capturing the variability inherent in the stochastic variables. The cost intervals follow a normal distribution as illustrated in Figure 4.2.

The results of the Monte Carlo simulation highlight several critical aspects of the PdM implementation. The analysis provides an estimate of the likelihood of PdM achieving cost savings over TM, along with evaluating the risks associated with different cost components. This probabilistic approach provides a robust framework for decision-making, enabling stakeholders to evaluate the trade-offs between PdM and TM under uncertainty.

4.2.5. Financial bandwidth for predictive maintenance development

In this cost-benefit model, the costs associated with developing the predictive maintenance technology have been excluded. This choice allows for an analysis of the financial bandwidth available for the investment in the development phase, providing insight into the maximum allowable budget for technology advancement. To assess this, the financial gains resulting from the predictive maintenance system will be examined to determine the potential ROI over a time horizon of 20 years.

For each iteration of the Monte Carlo simulation, random samples are drawn from these probability distributions to compute the total costs and benefits associated with PdM and TM. These calculations incorporate cost components discussed in subsection 4.2.2. The difference in total costs between PdM and TM (ΔC) is calculated for each iteration as:

$$\Delta C = C_{\text{total},PdM} - C_{\text{total},TM},$$

where positive values ($\Delta C > 0$) indicated that PdM was more expensive, while negative values ($\Delta C < 0$) suggested cost savings. The aggregated results provide insights into the likelihood of PdM being more cost-effective than TM, quantified by the probability $P(\Delta C > 0)$.

Discount rate investment

The analysis assumes that any initial development costs must be recovered within this 20-year period. To account for the time value of money, a discount rate will be applied based on the weighted average cost of capital (WACC) [27]. The WACC is calculated as follows:

$$\text{WACC} = \frac{E}{V} \times C_e + \frac{D}{V} \times C_d \times (1 - T) \tag{4.1}$$

where:

- E is the value of equity,
- D is the value of debt,
- C_e is the cost of equity,
- C_d is the cost of debt,
- V represents the total value, calculated as $V = D + E$,
- T is the corporate tax rate.

The WACC reflects the minimum return required by investors and creditors to fund the project, considering both equity and debt financing options. By applying this discount rate, the analysis will identify the level of development investment that can be supported by the anticipated returns from the predictive maintenance system, ensuring financial feasibility over the specified time frame. A discount rate of 7.39% is found using data from NYU (2024) [50].

Furthermore, by using the Monte Carlo intervals, the model allows for an assessment of the probability that predictive maintenance technology may end up being more costly than traditional maintenance methods across a range of development costs. This probabilistic approach provides insights into the risks associated with different investment levels, helping to define an optimal investment threshold that maximizes the likelihood of cost-effectiveness in implementing predictive maintenance.

4.3. Results

This section presents a detailed comparison between implementing PdM and continuing with traditional wheel maintenance practices on cargo trains. The analysis focuses on total maintenance costs over time and a detailed breakdown of key cost components.

4.3.1. Total maintenance costs over time

As shown in Figure 4.3, the analysis of total maintenance costs over a 20-year period, adjusted for inflation, reveals significant cost savings with the adoption of PdM compared to TM. The PdM scenario exhibits a more controlled and predictable cost growth with a flatter cumulative cost curve. In contrast, the TM scenario shows a steeper increase, indicating higher and accelerating costs over time.

To quantify the cost-effectiveness of PdM, a Monte Carlo simulation was conducted, running 40,000 iterations to capture a wide range of potential cost scenarios. The simulation estimates that PdM results in a cost reduction of approximately 39.5% on average over TM, with a 95% confidence interval suggesting savings between 31.3% and 47.8%. This high confidence level supports the reliability of PdM as a cost-saving strategy over the long term.

The probability that PdM is more cost-effective than TM was calculated across various scenarios. In 100% of the simulations, PdM yielded lower cumulative costs than TM, underscoring the high likelihood that PdM is a financially beneficial choice for maintenance.

The model excludes the initial development costs of PdM technology, focusing on operational cost differences over time. The consistent reduction in maintenance costs with PdM is attributed to proactive interventions, which prevent the escalation of issues that lead to more costly repairs and unplanned downtime in TM.

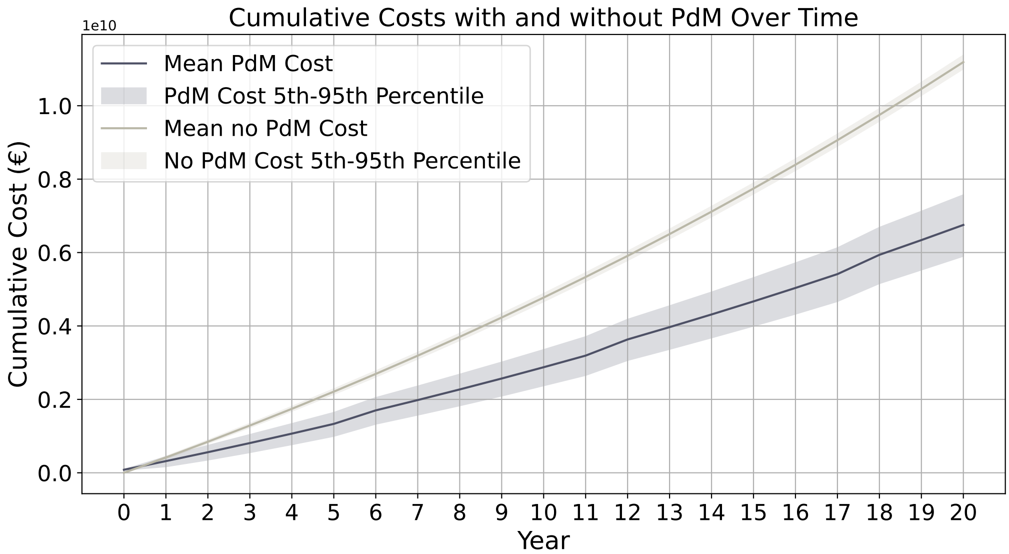

Figure 4.3: Total maintenance costs over time (inflation-adjusted): with and without predictive Maintenance

4.3.2. Detailed financial metrics

Figure 4.4 presents a comparative view of the mean annual operating costs across multiple categories for both maintenance strategies. Key cost areas—such as accident-related expenses, downtime, and wheel treatments—are markedly lower under PdM due to its proactive, data-driven approach. However, PdM also introduces additional costs, notably for sensor implementation and cybersecurity, which are integral to establishing a reliable predictive framework. This distribution of costs highlights PdM's potential to shift expenses from reactive repairs toward investments in technology and preventive measures.

Table 4.1 quantifies these financial changes, presenting the exact values associated with each cost category. Notably, PdM achieves significant savings by reducing accident-related costs from €47.4 million to €1.88 million and downtime expenses from €59.4 million to €23.8 million. These savings underscore PdM's effectiveness in minimizing disruptions and enhancing operational safety. Conversely, new expenses associated with PdM—such as sensor installation (€83 million) and ongoing service costs (€9.6 million)—represent an upfront investment in infrastructure and technology. Despite these added costs, the total annual expenses with PdM amount to €197 million, compared to €386 million without PdM, thereby demonstrating a notable 49% reduction in yearly overall operating costs. Because the sensor replacements do not happen yearly but every 6 years, the 20-year cost reduction is less.

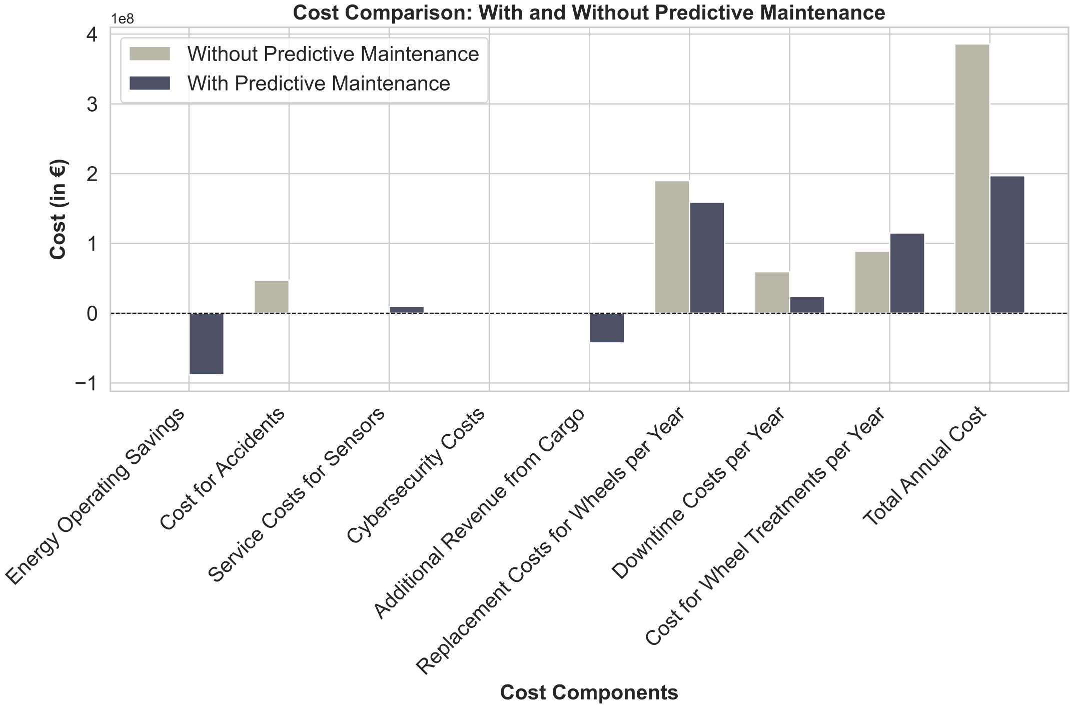

Figure 4.4: Mean yearly operating costs split over the different categories.

Table 4.1: Cost comparison: with and without predictive maintenance

Metric	**With Predictive Maintenance**	**Without Predictive Maintenance**
Energy Operating Savings	€8.84×10^7	€0.00
Cost for Accidents	€1.88×10^6	€4.74×10^7
Implementation Costs for Sensors	€8.3×10^7	€0.00
Service Costs for Sensors	€9.60×10^6	€0.00
Cybersecurity Costs	€1.10×10^5	€0.00
Additional Revenue from Cargo	€4.27×10^7	€0.00
Replacement Costs for Wheels per Year	€1.59×10^8	€1.90×10^8
Downtime Costs per Year	€2.38×10^7	€5.94×10^7
Cost for Wheel Treatments per Year	€1.15×10^8	€8.89×10^7
Total Annual Cost	**€1.97×10^8**	**€3.86×10^8**

4.3.3. Probability of predictive maintenance cost-effectiveness based on development cost

The results of the cost-benefit analysis model, as shown in Figure 4.5, indicate the probability that PdM technology will be more expensive than traditional maintenance methods across a range of initial development costs. The Monte Carlo simulation reveals a clear trend: as the initial development cost for PdM increases, the probability that PdM will surpass the cost of traditional maintenance also rises.

For development costs below € 0.8 billion, the probability that PdM is more expensive remains under 10%, suggesting a relatively high likelihood of achieving cost savings with PdM. However, as development costs approach € 1.0 billion, this probability begins to exceed 50%, indicating a substantial risk that PdM could become cost-prohibitive at higher investment levels. When the development cost reaches € 1.4 billion, the probability of PdM being more costly approaches 100%, making it almost certain that PdM would not be cost-effective compared to traditional maintenance at this level of investment.

This analysis underscores the importance of controlling initial development costs to ensure the financial viability of the PdM technology. By setting a target investment threshold, such as below € 1.0 billion, stakeholders can maximize the probability of achieving cost-effective outcomes with PdM over the 20-year analysis period.

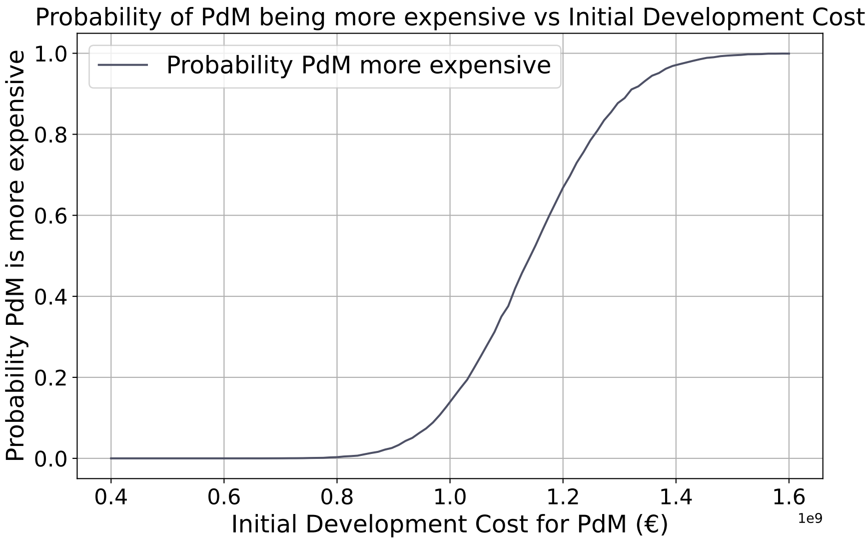

Figure 4.5: Development costs of PdM technology plotted against the probability of the case with PdM being more expensive over a 20-year time period than the case without PdM.

4.4. Discussion

This section assesses the financial and operational impacts of implementing PdM technology on trains, focusing on the costs and benefits of PdM for wheel monitoring. The discussion also addresses subquestion 4.

Subquestion 4: What costs and benefits are associated with implementing predictive maintenance technology for wheel maintenance on trains for freight rail operators?

Implementing PdM offers a substantial reduction in cargo rail operators' average operating costs, decreasing by 39.5% over a 20-year period (from €1.1 billion without PdM to €0.7 billion with PdM). This reduction underscores PdM's economic appeal, particularly for operators like DB Cargo, whose discounted financial capacity for PdM investment stands at €0.6 billion (see Figure 4.5). Given these figures, PdM investment is a financially sound choice for train operators.

The findings in Table 4.1 highlight the nuanced impact of different cost components in a predictive maintenance PdM versus TM setup. An observation is that while PdM implementation incurs substantial service costs, these costs are relatively negligible compared to the broader financial savings achieved. The cybersecurity costs, while necessary to support PdM, are an order of magnitude lower than other components and contribute minimally to the total annual cost, emphasizing that investments in these areas are minor compared to the broader cost reductions enabled by PdM.

One key area where PdM presents an apparent disadvantage is in wheel treatment costs. PdM's proactive approach brings trains in for wheel servicing earlier, increasing the frequency of wheel treatments and costs. Consequently, when isolating wheel treatment costs, TM may appear more economical due to less frequent interventions. However, the increased cost from more frequent wheel treatments in PdM is offset by the overall reduction in replacement costs and the broader cost savings.

Furthermore, while components such as energy operating savings, accident-related costs, additional cargo revenue, wheel replacement costs, and downtime costs contribute incrementally when evaluated separately, their combined impact drives a substantial reduction in the total annual cost. The cumulative effect of these marginal savings reveals the economic advantage of PdM, leading to a nearly 50% reduction in total annual costs compared to TM. Thus, while PdM involves additional investments in certain areas, the overall cost savings justify the approach, with benefits that extend across energy, safety, and operational downtime dimensions.

Indirect benefits from PdM technology

- **Impact on bearing wear**
  PdM implementation for wheel monitoring indirectly influences wheel bearing costs by minimizing wear on the wheel bearing. By enabling early detection of wheel damage, PdM reduces shocks transferred to bearings, thereby decreasing bearing degradation. This preventative effect on bearing wear represents one of the major indirect benefits of PdM, although the precise extent of this impact remains unclear. Future research could investigate these effects further to provide a more comprehensive cost-benefit analysis.
- **Reduction in track damage**
  The use of PdM is anticipated to reduce indirect damage to rail tracks by diminishing the shock impact of damaged wheels. Although this benefit positively affects both train operators and infrastructure owners, accurately quantifying track damage reduction proves challenging and has not been fully addressed here. To enhance the understanding of PdM's full value, additional studies are recommended to establish metrics for track damage reduction, which could support broader motivation for PdM implementation across railway networks.
- **Indirect benefits for infrastructure owners and maintenance contractors**
  PdM technology also yields significant indirect benefits for infrastructure owners and maintenance contractors. Reduced track wear and lowered derailment probabilities mean fewer track maintenance requirements, benefiting infrastructure owners. For maintenance contractors, PdM creates a more consistent workload by scheduling most maintenance tasks in advance, reducing the occurrence of emergency repairs. Additionally, track maintenance contractors, often paid per track kilometer under their care, benefit financially from lower track damage, which in turn reduces their operating costs.
- **Investment responsibility and benefit distribution**
  While PdM provides economic advantages across different stakeholders, it also raises questions regarding the distribution of investment responsibility. The financial benefits from PdM vary among maintenance contractors, infrastructure owners, and train operators. Determining an equitable investment strategy may require assessing the relative gains of each stakeholder to foster collaborative funding and development of PdM.

In summary, this analysis provides a preliminary understanding of the financial and operational benefits associated with PdM for cargo train maintenance. To better quantify PdM's impact, further research into unmeasured benefits, such as reduced bearing and track wear, is recommended. A clearer picture of each stakeholder's financial gains from PdM will help identify those best positioned to invest in its development and deployment, potentially leading to a shared investment model that supports the widespread adoption of PdM technology.

4.5. Conclusion

This chapter establishes the financial viability of PdM in the railway sector, supported by a detailed cost-benefit analysis. PdM offers clear, long-term financial and operational advantages over TM, especially in reducing expenses linked to unscheduled repairs, accidents, and operational downtime. While the initial costs of implementing PdM—including sensor deployment and infrastructure investments—are considerable, Monte Carlo simulations reveal that projected annual savings offset these upfront expenses. This results in an estimated 39.5% reduction in total maintenance costs over a 20-year period, creating a substantial opportunity for continued development of PdM technologies specifically suited to wheel monitoring on freight trains.

Moreover, the indirect benefits of PdM, such as enhanced wheel monitoring, are valuable to various stakeholders, which can play a pivotal role in facilitating PdM's broader adoption. If all stakeholders realize tangible benefits from PdM, the technology's implementation across the railway sector could accelerate significantly. However, if certain stakeholders perceive PdM as a cost-only investment without clear returns, this could delay its widespread adoption.

5 Discussion and recommendations

This chapter centers on synthesizing the findings from previous chapters to guide the railway industry's adoption of PdM technologies. It addresses key challenges, such as regulatory compliance and sector-specific barriers, and suggests that lessons from sectors like aviation and infrastructure could help overcome these obstacles. The chapter also emphasizes the importance of aligning business and technical strategies, noting that a cohesive approach can strengthen PdM's role in advancing digital transformation within the railway sector.

5.1. Discussion

This section focuses on discussing and providing recommendations based on the analysis conducted in the preceding chapters. This chapter highlights regulatory compliance as both a barrier and a potential opportunity, especially considering the railway sector's complex safety and regulatory standards. Additionally, it explores industry-specific challenges and potential cross-industry learning, underscoring how insights from sectors like aviation and infrastructure could benefit the railway industry. The chapter further examines the alignment of business and technical strategies, suggesting that a coherent approach could enhance the impact of PdM on digital transformation efforts in the railway industry.

5.1.1. Regulatory compliance as a barrier and opportunity

Regulatory compliance remains one of the primary barriers to PdM implementation, with government agencies often focused more on societal benefits than on the operational gains PdM offers railway operators. Current regulations may be cautious or slow in accommodating new technologies, partly due to limited evidence of their broader societal impact and the challenges of updating regulatory frameworks to support such advancements. This regulatory conservatism, while protecting public interests, can inadvertently slow the adoption of PdM. Therefore, framing PdM's value in terms that align with public policy objectives can help shift regulatory perspectives. Specifically, by highlighting PdM's environmental, workforce, and safety benefits, stakeholders can encourage regulatory bodies to view PdM as an investment in societal progress rather than a mere operational enhancement.

Environmental benefits of PdM

Environmental sustainability is a top priority in public policy, especially with the EU's current nitrogen emission limits and heightened environmental regulations. PdM offers several clear environmental advantages that align with these priorities:

1. **Energy conservation through optimized components:** chapter 4 discusses how PdM contributes to reduced energy consumption, mainly by maintaining rounder wheels, which create less friction and thus require less energy to operate. By ensuring components are maintained before deterioration impacts energy efficiency, PdM reduces the railway's carbon footprint—a significant consideration for environmentally focused regulators.
2. **Reduction in emergency maintenance interventions:** PdM decreases the need for unplanned or emergency repairs, which often require additional resources, personnel, and logistics that increase fuel use and emissions. Fewer unscheduled interventions mean a more predictable maintenance schedule that minimizes these environmental impacts.

3. **Extended lifecycle of components:** By detecting and addressing wheel damage early, PdM helps prolong the lifecycle of wheels and other components. This reduces the frequency of replacements, conserving resources and limiting the environmental impact associated with the production, transportation, and disposal of replacement parts. Such lifecycle extension aligns with circular economy principles and could resonate strongly with environmental agencies and policymakers.

Workforce efficiency and the current labor market

The shortage of skilled labor in the job market, particularly in technical and industrial sectors, poses challenges for the railway industry and public transportation infrastructure planning. PdM can contribute to addressing this shortage by optimizing workforce deployment:

1. **Elimination of redundant pre-inspections:** Traditional maintenance often includes regular visual inspections to determine whether a train needs repair. PdM bypasses this preliminary inspection step by providing real-time data on component health, ensuring that maintenance personnel are engaged only when repairs are required. This increases efficiency and reduces the strain on the workforce.
2. **Streamlining maintenance resources:** The ability of PdM to detect issues early reduces the need for emergency repair teams, freeing up these skilled personnel for other essential tasks. This redistribution of workforce resources helps alleviate the pressure on a limited workforce and enables personnel to focus on more impactful projects within the railway system.
3. **Indirect reduction of maintenance on rail tracks:** By reducing damage to train wheels through proactive intervention, PdM also lowers the likelihood of wear and tear on rail tracks. This enhances train performance and indirectly reduces the need for track maintenance, further relieving workforce demands and aligning with government goals of minimizing resource constraints in public infrastructure.

Enhanced safety and public confidence

Safety remains one of the strongest arguments for PdM adoption, particularly from a regulatory perspective. PdM technology enhances railway safety by continuously monitoring key train components, notably wheelsets. This proactive approach supports early detection of faults that could potentially lead to accidents:

1. **Real-time condition monitoring:** PdM systems offer nearly live insights into the status of essential components like wheels, allowing maintenance teams to intervene as soon as signs of damage appear. By addressing issues at the earliest stage, PdM helps prevent severe problems such as extensive wheel flats, which can lead to unsafe operating conditions. This preemptive maintenance is essential to reducing risks and preventing disruptions to service.
2. **Reduction of safety-related incidents:** Implementing PdM could lead to fewer safety-related incidents and reduced risk of service delays caused by component failures. Improved safety records align with public transportation goals, as government bodies aim to uphold and enhance public confidence in the safety and reliability of railway systems.
3. **Support for regulatory safety goals:** As safety is often a key focus in regulatory frameworks for public transportation, PdM's safety benefits align well with governmental goals. Real-time monitoring and early fault detection demonstrate a proactive maintenance approach that enhances operational efficiency and directly supports regulatory objectives to ensure public safety.

Convincing governmental bodies to support PdM

To encourage regulatory bodies to prioritize PdM, stakeholders must comprehensively view its societal benefits. Environmental, workforce, and safety benefits provide a narrative beyond operational efficiency to underscore PdM as a responsible, sustainable, and forward-looking solution for the railway sector. By building coalitions with environmental, labor, and safety advocacy groups, the railway industry can further support a case for regulatory support. Additionally, providing clear metrics on reduced energy use, workforce efficiency, and safety improvements can demonstrate PdM's value as a public good, paving the way for regulatory frameworks that actively encourage its adoption.

In conclusion, the alignment of PdM with public policy priorities makes it a promising candidate for regulatory support. While regulatory compliance presents challenges, these can be mitigated by emphasizing PdM's alignment with societal goals in environmental sustainability, workforce optimization, and safety—three areas that resonate strongly with government bodies and the public alike. By framing PdM within these values, industry advocates can make a compelling case for its wider adoption and the regulatory adaptations needed to facilitate its integration into the railway sector.

5.1.2. Sector-specific barriers and cross-industry learning

Data integration and standardization

Data integration and standardization are barriers to high driving power in the railway industry. Similar challenges are evident in the infrastructure and aviation sectors. In aviation, data standardization enables PdM by harmonizing the vast datasets from various sensors and subsystems, which supports real-time fault prediction and maintenance scheduling. Similarly, infrastructure sectors, like Rijkswaterstaat in the Netherlands, face data integration issues due to decentralized asset management, where consistent data formats and quality across regions are crucial for effective PdM.

In both sectors, overcoming data integration and standardization barriers required substantial investments in data infrastructure and adopting uniform data standards. For the railway industry, a similar approach could be beneficial. Implementing PdM effectively would involve establishing consistent data formats across all assets and systems, facilitating the integration of predictive analytics and real-time monitoring capabilities.

Organizational and cultural barriers

The barrier of organizational and cultural resistance is another independent challenge in PdM implementation, notably affecting the railway and infrastructure sectors. Organizational reluctance often stems from resistance to change, concerns over job displacement, and the need for substantial training. In infrastructure, Rijkswaterstaat's experience showed that fostering a culture of data-driven decision-making and incremental PdM adoption helped mitigate this resistance. Involving stakeholders early and providing clear communication about the benefits of PdM was key to a successful rollout.

Learning from sector-specific challenges

The railway industry can draw valuable lessons from the challenges faced by other sectors, particularly by emphasizing strategies that foster cultural readiness for PdM adoption. Key practices include implementing structured training programs, adopting phased rollouts, and engaging stakeholders early to mitigate resistance. By leveraging these experiences, the railway sector can proactively address issues such as data standardization and cultivate an organizational culture that supports the adoption of PdM and its sustainable long-term use.

These cross-sector insights underscore that, while each industry has unique challenges, the strategies employed by aviation and infrastructure sectors to overcome barriers offer a robust foundation for PdM implementation in railways. Future research could explore additional industries with comparable dynamics, such as the maritime sector, which shares a heavy-duty operational environment and stringent safety requirements, or the energy distribution sector, characterized by capital-intensive infrastructure, regulatory frameworks, and complex maintenance subcontracting.

5.1.3. Business-technical alignment and its impact on digital transformation

Importance of business-technical alignment as a linkage barrier

The alignment between business strategy and technical capabilities emerges as a critical linkage barrier in the digital transformation landscape. Despite business-technical alignment not being identified as a fundamental barrier, this barrier has even higher driving power than economic viability, highlighting the essential role of business-technical alignment in successful digital transitions. Organizations may experience resource allocation, priority-setting, and expectation management gaps when business objectives are not closely aligned with technical capabilities. In the railway industry, where PdM technology depends on such alignment, misaligned priorities can significantly hinder PdM's implementation and effectiveness.

Challenges of transitioning to digital services

One of the most prevalent challenges when transitioning to digital services is the misalignment of business and technical expectations. Often, business leaders may not fully understand the technical aspects of the associated risks of PdM, leading to oversights in budgeting, unrealistic performance expectations, and underestimated maintenance requirements [10]. In high-tech industries, achieving alignment requires a balance between understanding technical risks and leveraging business opportunities

[1]. The infrastructure and aviation sectors have demonstrated that digital projects risk overestimating technical capabilities and underestimating the support needed for a smooth transition without precise alignment.

Strategies to overcome alignment barriers

To overcome alignment challenges, it is recommended that organizations adopt strategies such as:

- **Increasing technical literacy for business leaders**: Training initiatives can help business leaders gain a foundational understanding of PdM technologies, reducing misalignment risks [1, 11].
- **Implementing enhanced communication channels**: Establishing consistent communication between business and technical teams can set realistic goals and align priorities for digital transformation efforts [1, 11].
- **Developing joint key performance indicators (KPIs)**: Shared KPIs, which reflect both business objectives and technical achievements, effectively maintain focus on mutual goals, helping ensure long-term PdM success in railway operations [1, 11].

When managed effectively, business-technical alignment is a non-fundamental linkage barrier that accelerates PdM adoption by influencing other fundamental barriers and contributing to a more sustainable and efficient railway maintenance system.

5.1.4. Equitable investment strategy

An equitable investment strategy for PdM in the railway sector should center on distributing costs according to the benefits each stakeholder receives. PdM offers clear advantages to train operators, infrastructure owners, and maintenance contractors; however, these benefits' direct and indirect nature varies significantly across each group. This complexity necessitates a nuanced approach to investment responsibility, ensuring fair contribution by aligning investment levels with the degree of benefit each stakeholder derives. Relevant principles and potential structures for equitable investment in PdM can be drawn from multi-stakeholder partnership (MSP) frameworks and collaborative models in other sectors.

Principles of an equitable investment strategy

1. **Proportional contribution based on benefits:** A core principle for equitable investment is the alignment of financial contributions with the degree of benefit each stakeholder gains. Train operators who experience substantial direct savings—such as a 37% reduction in operating costs over 20 years—would logically carry a larger share of the PdM investment. On the other hand, infrastructure owners and maintenance contractors benefit indirectly through reduced track wear and lower emergency repair costs, might contribute proportionally less but still meaningfully participate in funding the technology.
2. **Incentivizing indirect beneficiaries:** For stakeholders like infrastructure owners and maintenance contractors, whose benefits are substantial yet indirect, incentives can play a critical role in securing investment. Governments or industry regulators could offer incentives or subsidies to encourage infrastructure owners to support PdM deployment, given its societal benefits, such as increased safety and reduced derailment risks. This approach can balance the financial load and reduce barriers for stakeholders who are less immediately motivated by direct economic gains.
3. **Long-term, sustainable partnership frameworks:** Drawing on insights from MSP literature, effective long-term collaborations are often achieved by creating partnership frameworks that balance accountability, shared governance, and flexibility [26, 5, 67]. These frameworks encourage transparency in roles, responsibilities, and benefits while ensuring adaptability to changing circumstances. For PdM, this might mean establishing a consortium or public-private partnership (PPP) where contributions are revisited periodically based on evolving benefit metrics and technological advancements.

Implementing an equitable investment model: strategies and structures

Building on the principles above, various models from different sectors can offer guidance on implementing an equitable investment approach. Viable structures include:

Consortium-based investment model - In the telecom industry, companies invested in 5G technology through consortiums, which allowed them to pool resources and share risks for the common benefit of accessing next-generation networks. A similar consortium could be created for PdM investment, involving train operators, infrastructure owners, and maintenance contractors as stakeholders.

Each stakeholder would contribute based on an initial assessment of expected benefits, with regular reassessments to reflect updated performance and cost savings data [5]. Such a model would foster collective accountability, encourage collaboration on technology improvements, and ensure all parties have a stake in PdM's success [67]. This approach requires an accurate cost-benefit analysis across all stakeholders. Key metrics could include reductions in bearing wear, track damage, and maintenance workload distribution. A recurring evaluation period, such as every five years, could adjust each stakeholder's investment proportion based on realized benefits, ensuring ongoing equity as the technology matures and benefits evolve.

Public-Private Partnership (PPP) model - Given PdM's societal benefits—such as improved safety, reliability, and efficiency in public transport infrastructure—a PPP could be an ideal model. In PPPs, the public sector typically offers initial funding or incentives to lower the investment threshold for private stakeholders, especially for infrastructure improvements benefiting the public.

For PdM, governments or rail authorities could subsidize initial technology adoption for track monitoring systems, while train operators and contractors are responsible for implementing and maintaining the systems. This model would spread initial investment risks while motivating private stakeholders to invest further as they realize cost savings.

Challenges and considerations

1. **Accurate measurement of indirect benefits:** One of the main challenges is quantifying the indirect benefits, such as reduced track wear and bearing degradation. While train operators can measure their savings more directly, infrastructure owners and maintenance contractors need more comprehensive data on PdM's impact on their assets. Further studies to develop reliable metrics for indirect benefits, such as reduced track damage and maintenance consistency, would help justify proportional contributions.
2. **Governance and accountability:** For a consortium or PPP to succeed, it must include clear governance structures that define each stakeholder's role, responsibilities, and financial commitments. Drawing from MSP frameworks, incorporating regular reviews, transparent decision-making processes, and accountability mechanisms (such as independent audits) can strengthen trust and collaboration [5].
3. **Adjusting to evolving technology and benefits:** The value of PdM may increase over time as technology improves and additional benefits emerge. To accommodate these shifts, an equitable investment model should include provisions for periodically revising contributions, potentially based on new performance indicators or cost savings. This flexibility would ensure that investment responsibilities remain fair as the PdM technology evolves and the benefits become more universally measurable.

An equitable investment strategy for PdM in railways requires a collaborative approach that aligns each stakeholder's financial responsibility with the specific benefits they gain. Consortium-based models, public-private partnerships, and benefit-proportional investments offer viable frameworks tailored to the unique benefit distribution among train operators, infrastructure owners, and maintenance contractors. By adopting an MSP approach with transparent, flexible, and accountable structures, stakeholders can collectively fund PdM that optimizes investment equity, maximizes returns, and supports the widespread adoption of this technology.

5.2. Strengths and weaknesses

Strengths

1. **Comprehensive scope of analysis:** The thesis thoroughly examines the challenges and opportunities associated with implementing PdM in the railway industry. It effectively identifies technical, organizational, and financial barriers while considering cross-industry best practices for overcoming them. This multifaceted approach ensures a well-rounded understanding of the subject.
2. **Application of methodologies:** ISM and Fuzzy MICMAC demonstrate a solid commitment to methodological rigor. These tools help clarify the complex relationships between barriers and offer a systematic way to prioritize interventions, making the findings valuable for academic and practical applications.
3. **Cross-industry comparisons:** Drawing lessons from aviation and public infrastructure sectors enhances the thesis's relevance by incorporating proven strategies from industries with similar

challenges. This comparative lens adds depth to the analysis and strengthens the credibility of the proposed recommendations.

4. **Economic insight:** The inclusion of a cost-benefit analysis provides a quantitative dimension to the study, offering compelling evidence of the financial feasibility of PdM. By calculating potential long-term savings (up to 39.5% over two decades), the thesis equips stakeholders with a persuasive case for investment.
5. **Structured recommendations:** The study offers well-defined and actionable recommendations, such as phased implementation strategies, stakeholder alignment, regulatory clarity, and workforce training. These insights directly address identified barriers and provide a practical roadmap for implementation.
6. **Integration of stakeholder perspectives:** By recognizing the roles of operators, manufacturers, regulators, and policymakers, the thesis acknowledges the complex, multi-stakeholder environment of the railway sector, which is crucial for a successful PdM rollout

Weaknesses

1. **Limited empirical validation:** While the thesis employs robust analytical frameworks, its reliance on secondary data and theoretical insights limits real-world applicability. Future research could address this by incorporating empirical validation through case studies, pilot programs, or field experiments within the railway sector. This would provide evidence of PdM's impact and enhance the study's credibility.
2. **Focus on freight trains:** The narrow focus on freight trains reduces the generalizability of the findings. Further studies could explore the applicability of PdM in passenger and high-speed rail systems to provide a more comprehensive understanding of its potential across diverse railway operations. Expanding the scope would also uncover unique challenges faced by these segments.
3. **Regulatory framework analysis:** While the thesis highlights the importance of regulatory compliance, it could benefit from a deeper exploration of specific national and international standards affecting PdM adoption. Future research should conduct detailed analyses of regulatory frameworks to identify enablers and constraints, offering actionable guidance for policymakers and industry stakeholders.
4. **Stakeholder diversity:** The current study underrepresents the perspectives of frontline maintenance workers and smaller operators, who are integral to the practical implementation of PdM. Future research could involve a more diverse range of stakeholders through structured surveys or focus groups, capturing insights from all levels of the industry to ensure a more inclusive understanding of challenges and solutions.
5. **Dynamic nature of PdM technology:** Rapid advancements in PdM technologies, such as machine learning and IoT, might render some findings outdated. To address this, future research could adopt a dynamic modeling approach incorporating scenario planning to account for technological evolution and emerging trends. Regular updates to cost-benefit analyses could also ensure their continued relevance.
6. **Implementation challenges in fragmented systems:** The thesis highlights stakeholder collaboration but does not fully address the technical and operational complexities of integrating PdM across fragmented railway networks. Further research should delve into standardization efforts, interoperability challenges, and change management strategies to facilitate smoother adoption.
7. **Dependence on unstructured interviews:** The reliance on unstructured interviews introduces variability in data collection and potential biases, impacting the consistency of insights. Future studies could use semi-structured or structured interviews with predefined questions to ensure systematic coverage of key topics.

By addressing these limitations, future research can build on the strengths of this thesis while improving the empirical foundation, stakeholder inclusivity, and methodological robustness. This will ensure that findings remain relevant and actionable in the rapidly evolving context of PdM adoption in the railway industry.

6
Conclusions and reflection

This chapter summarizes the thesis conclusions and reflections on the study's findings. This chapter provides key recommendations for stakeholders in the railway industry and outlines directions for future research. It emphasizes the importance of aligning PdM efforts with business goals, regulatory requirements, and operational frameworks to ensure PdM's effective integration. Additionally, the chapter discusses lessons learned and the strategic implications of PdM adoption, especially in addressing industry-specific challenges and fostering organizational change. The focus is creating a sustainable roadmap for PdM implementation that supports the industry's long-term digital transformation goals.

6.1. Conclusion

This thesis explores PdM in the railway sector, identifying and analyzing barriers to its implementation and assessing its financial feasibility. The findings show that economic viability, regulatory compliance, and business-technical alignment are the critical barriers. Economic viability is a primary factor, as stakeholders need assurance of cost-effectiveness through demonstrated long-term savings. Regulatory compliance presents another challenge due to stringent safety standards and limited legal frameworks for predictive technologies. Business-technical alignment, crucial for integrating PdM seamlessly into operations, emphasizes the need for multi-stakeholder commitment and strategic alignment.

A cost-benefit analysis validates PdM's potential to reduce long-term maintenance costs by 39.5% over 20 years for DB Cargo. This includes direct savings from optimized maintenance and indirect benefits like extended component life and reduced emergency repairs. The analysis indicates that while PdM implementation might incur significant initial costs, future operational efficiencies offset these.

The study concludes that a collaborative, industry-wide approach is essential for successful PdM adoption, addressing economic, regulatory, and organizational alignment. Recommendations include industry collaboration to create supportive regulatory frameworks, further research on unmeasured benefits like reduced track damage, and equitable investment models for stakeholders. Embracing these strategies can help drive PdM's widespread adoption, benefiting both railway operators and the industry.

6.2. Recommendations for the stakeholders

The research question of this study is:

What critical actions can enable the effective implementation of predictive maintenance technology in the freight rail industry?

The answer to this question can be broken down into several concrete recommendations to the stakeholders of PdM technology in the freight rail industry. These consist of:

- **Regulatory collaboration and compliance**: Work with regulatory bodies to develop a framework that aligns PdM technology with safety and environmental standards. Present the societal benefits of PdM, such as enhanced safety and reduced emissions, to gain regulatory support and enable a smoother compliance process.

  - **Quantify environmental and societal benefits to gain regulatory support**: Frame PdM as a technology aligned with societal priorities like sustainability, public safety, and workforce efficiency enhancements. For example, emphasize PdM's potential to reduce emissions and optimize energy usage, which can make a compelling case for regulatory bodies to provide the necessary policy adjustments and incentives.
- **Develop industry standards for data management**: Implement standardized data management protocols across the railway industry to enable seamless data sharing, integration, and predictive analysis. By learning from sectors like aviation, which rely heavily on standardized data, the railway sector can improve data interoperability, reduce redundant processes, and simplify PdM model deployment.
- **Invest in workforce training and development**: Address organizational and cultural barriers by training maintenance staff and management on PdM's benefits and operational processes. Not only is a skilled workforce earmarked as a fundamental barrier, but building a skilled workforce also can improve adoption rates and ensure long-term success.
  - **Foster a culture of data-driven decision-making**: To address cultural resistance, invest in programs that promote a data-informed approach within the workforce. Training sessions, incentives, and case studies demonstrating PdM's success in other industries can encourage railway personnel to adopt and integrate PdM processes with greater enthusiasm.
  - **Pilot testing and gradual scaling**: Start with pilot PdM projects on specific components or infrastructure areas, such as wheelset or track monitoring. Gradually scale up based on results to manage risks and ensure the technology's reliability before broader adoption. This phased approach can increase stakeholder confidence and provide valuable data to refine PdM strategies.
- **Explore multi-stakeholder investment models**: Given the high initial costs, consider collaborative investment strategies where costs and benefits are shared across stakeholders. This approach can help mitigate financial barriers and make PdM a viable option for all parties involved.
  - **Regularly update investment contributions based on performance**: PdM technologies will improve over time, as will their cost savings and operational impact. Stakeholders should periodically re-evaluate their financial contributions to ensure fair distribution aligned with evolving benefits and cost savings.
  - **Develop metrics for unquantified benefits**: Create measurable indicators for indirect PdM benefits, like reduced track damage and improved reliability, to provide a complete picture of its financial and operational value. This can further justify investments and encourage adoption among stakeholders.
- **Leverage cross-industry insights**: Adapt best practices from sectors like aviation and public infrastructure, which have successfully implemented PdM. Learning from these industries can provide insights into overcoming similar barriers, such as high upfront costs and complex data integration challenges.

6.3. Recommendations for further research

This section outlines directions for future studies to build on the findings of this thesis, enhancing the understanding and implementation of PdM in the railway industry:

1. **Empirical validation of barriers and benefits**
   Future studies should include pilot programs or real-world case studies within railway systems to validate the identified technological barriers and quantified benefits empirically. This would provide stronger evidence for the economic, technical, and operational feasibility of PdM, addressing current limitations in data reliability and contextual variability.
2. **Extension to passenger and high-speed rail**
   Expanding the scope of research to include passenger and high-speed rail systems could offer a broader perspective on the unique challenges and benefits of PdM in diverse railway contexts. This would enhance the generalizability of findings and reveal opportunities for cross-segment innovations.

3. **Dynamic modeling approaches**
   Given the rapid evolution of PdM technologies, such as machine learning and IoT, future research should adopt dynamic modeling techniques. Scenario planning could be used to anticipate technological advancements, operational trends, and changing cost-benefit landscapes.
4. **Stakeholder diversity and inclusivity**
   Engaging a more diverse range of stakeholders, including track owners, OEMs, and smaller railway operators, through structured surveys or focus groups can provide richer insights into practical challenges and solutions. This inclusivity will improve the practical applicability of PdM strategies.
5. **Development of new metrics for indirect benefits**
   Establishing standardized, measurable indicators for currently unquantified benefits, such as reduced track damage or improved reliability, is necessary. These metrics would help assess PdM's impact comprehensively and provide stronger investment justifications.
6. **Enhanced regulatory analysis**
   Further studies could provide in-depth analyses of national and international regulatory frameworks to identify specific enablers and constraints for PdM adoption. This would inform policy-making and guide railway operators in aligning with legal requirements.
7. **Explore other similar industries**
   While this thesis has focused on the airline and infrastructure sectors, further exploration of other industries, such as energy transport and maritime, could yield additional valuable insights. These industries face unique challenges and employ distinct strategies that may provide innovative solutions and complementary perspectives for addressing barriers in the railway industry.

By pursuing these avenues, future research can address existing knowledge gaps and contribute to a more robust and actionable understanding of PdM technology in railways, supporting its sustainable adoption and operational success.

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A

Reference list quantitative part of literature review

This appendix provides a comprehensive list of the 100 academic articles referenced in the quantitative analysis of PdM implementation within the railway industry. These sources span a range of topics, including technical advancements, managerial strategies, and combined approaches, and form the foundation for the study's exploration of barriers, challenges, and opportunities in PdM adoption. The curated selection includes peer-reviewed papers, industry reports, and case studies published between 2018 and 2024, ensuring relevance to the current state of PdM technology and practices. This reference list supports the findings discussed in the thesis and offers a resource for further exploration into PdM applications across various sectors.

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B

Driving power analysis

B.1. Standard driving power plot

Driving power analysis is critical for identifying the most influential barriers to implementing Predictive Maintenance (PdM) in the railway industry. By examining the extent to which each barrier impacts others within the system, driving power analysis provides a structured understanding of which obstacles hold the greatest potential to drive change if addressed effectively. Barriers with high driving power often serve as root causes, influencing multiple dependent barriers. Addressing these high-impact barriers can create cascading improvements, reducing the complexity of implementing PdM by simultaneously mitigating related challenges.

For example, in Figure B.1, barriers like ”economic viability” or ”data standardization” emerge as key drivers due to their foundational role in shaping the feasibility and scalability of PdM systems. Recognizing their significance enables policymakers, operators, and other stakeholders to prioritize resources and efforts strategically, focusing on resolving these root barriers to maximize impact.

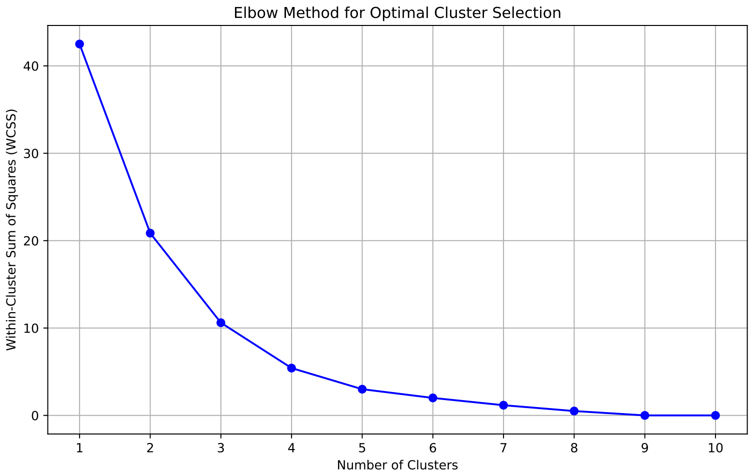

Figure B.1: Elbow method identifying 3 cluster groups.

B.1.1. Using the elbow method to group barriers

The elbow method is a statistical technique used in clustering analysis to determine the optimal number of groups or clusters within a dataset. In the context of driving power analysis, it can be applied to group barriers based on their influence levels, helping to categorize them into distinct clusters such as high-impact, moderate-impact, and low-impact barriers.

To apply the elbow method:

1. **Calculate Driving Powers:** For each barrier, calculate its driving power as the sum of its direct and indirect impacts on other barriers, as derived from the structural reachability matrix.
2. **Run Clustering Analysis:** Use a clustering algorithm (e.g., k-means) to assign each barrier to a cluster based on its driving power score. Run this analysis iteratively for different numbers of clusters (e.g., 2 to 10).
3. **Determine Total Within-Cluster Variance (WCV):** Measure the WCV for each clustering iteration. Figure B.2 presents a plot of the WCV. WCV decreases as the number of clusters increases but diminishes significantly after a certain point.
4. **Identify the Elbow Point:** Plot the WCV against the number of clusters. The ”elbow point” is the inflection point where adding more clusters results in minimal additional variance reduction. This point indicates the optimal number of groups for classifying the barriers.
5. **Interpret the Clusters:** Based on the clustering results, categorize the barriers. For example, barriers in the highest-driving-power cluster represent primary targets for strategic interventions.

By leveraging the elbow method, stakeholders can efficiently group barriers and focus on clusters representing the most significant obstacles to PdM adoption, ensuring a systematic and impactful approach to overcoming these challenges.

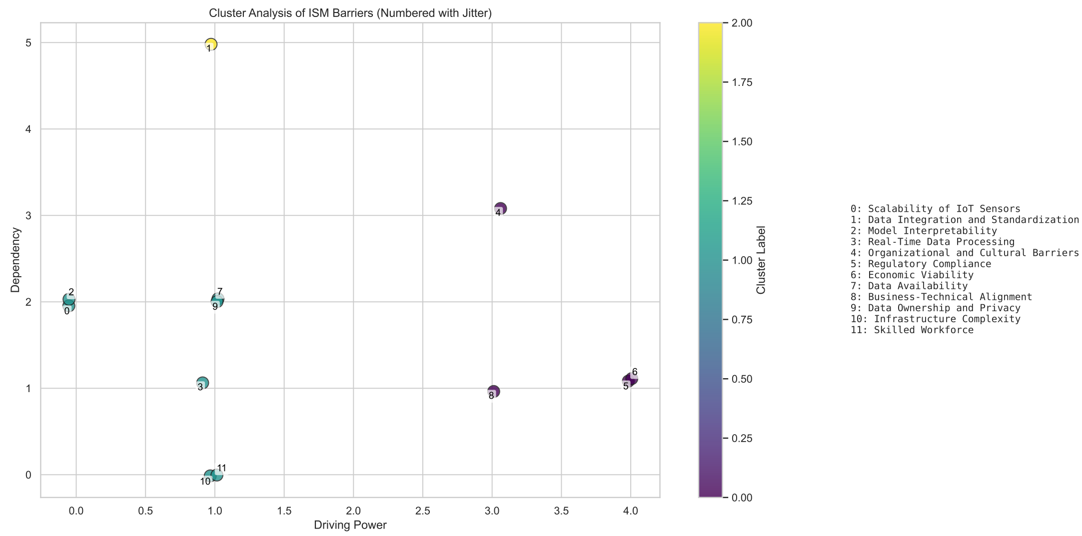

Figure B.2: Standard driving power using the ISM method.

B.2. Fuzzy MICMAC plot after one multiplication and the importance of multiple multiplications

The Fuzzy MICMAC plot after one multiplication provides an initial view of the distribution of barriers based on their driving and dependence power. In this stage, each barrier’s influence and dependency are calculated using the direct relationships derived from the reachability matrix. These values are then normalized to create a two-dimensional scatter plot that categorizes barriers into four quadrants: autonomous, dependent, linkage, and independent variables.

After the first multiplication, the plot reveals the barriers’ immediate or direct impacts as presented in Figure B.3. For instance, barriers with high driving power but low dependence are placed in the independent quadrant, identifying them as key drivers. Conversely, barriers with high dependence but low driving power are categorized as dependent, reflecting their reliance on other factors for resolution. The linkage and autonomous quadrants represent barriers with mixed or negligible influence patterns.

B.2.1. Importance of multiple multiplications

While the plot after one multiplication highlights the direct relationships among barriers, it does not account for indirect or cascading influences that emerge over time. These indirect effects are crucial for understanding the system’s complexity and effectively prioritizing interventions. Multiple multiplications of the reachability matrix allow the analysis to incorporate these secondary and tertiary relationships, progressively refining each barrier's driving and dependence powers.

As multiplications continue, the influence of higher-order interactions becomes apparent, and the positions of barriers in the MICMAC plot stabilize. This iterative process helps identify systemic barriers that exert significant indirect influence across the system and distinguishes them from localized challenges. For example, a barrier like economic viability may initially appear moderately influential. Still, it could emerge as a key driver after considering its cascading effects on other barriers, such as data standardization or regulatory compliance.

Without multiple multiplications, the analysis risks oversimplifying the interdependencies, leading to suboptimal prioritization of barriers. Therefore, iterative multiplications are essential for a comprehensive understanding of the systemic dynamics that underpin the successful implementation of Predictive Maintenance (PdM) in the railway industry.

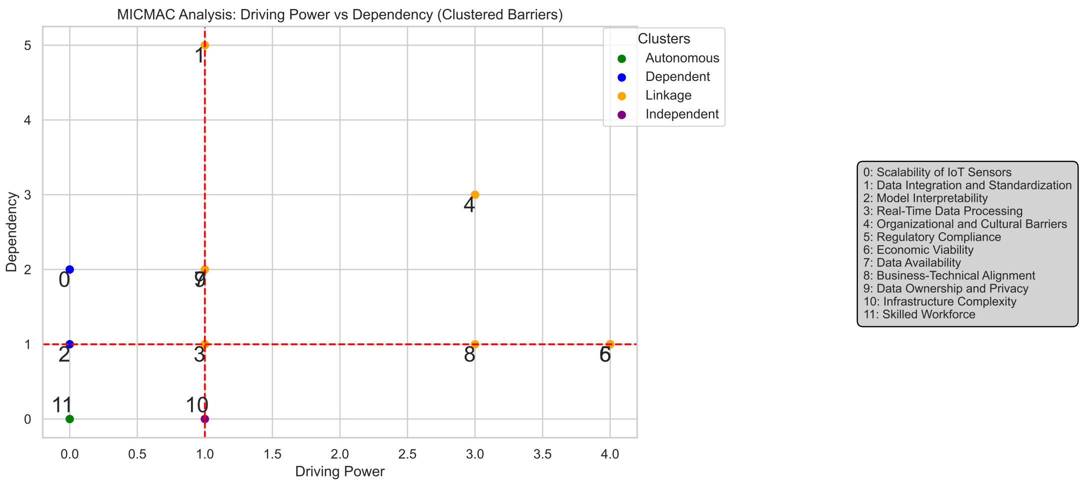

Figure B.3: Fuzzy MICMAC plot after single multiplication.

C

Fuzzy MICMAC code

```python
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
"""
Fuzzy MICMAC Analysis
"""

import numpy as np
import matplotlib.pyplot as plt
from adjustText import adjust_text

# Define the barriers and data
barriers = [
    "Scalability␣of␣IoT␣Sensors", "Data␣Integration␣and␣Standardization", "Model␣Interpretability",
    "Real-Time␣Data␣Processing", "Organizational␣and␣Cultural␣Barriers", "Regulatory␣Compliance",
    "Economic␣Viability", "Data␣Availability", "Business-Technical␣Alignment",
    "Data␣Ownership␣and␣Privacy", "Infrastructure␣Complexity", "Skilled␣Workforce"
]

# Tally Matrix as a list of lists
tally_matrix = [
    ["-", 13, 9, 15, 7, 5, 11, 14, 8, 6, 10, 12],
    [13, "-", 16, 18, 14, 13, 17, 20, 11, 19, 10, 7],
    [9, 16, "-", 13, 8, 5, 9, 15, 6, 7, 12, 14],
    [15, 18, 13, "-", 7, 5, 11, 14, 8, 6, 10, 12],
    [7, 14, 8, 7, "-", 13, 11, 12, 10, 9, 11, 8],
    [5, 13, 5, 5, 13, "-", 17, 10, 10, 15, 6, 9],
    [11, 10, 9, 11, 11, 17, "-", 12, 15, 8, 7, 9],
    [14, 20, 15, 14, 12, 10, 12, "-", 16, 9, 10, 11],
    [8, 11, 6, 8, 10, 15, 15, 16, "-", 14, 8, 10],
    [6, 19, 7, 6, 9, 8, 7, 9, 14, "-", 11, 10],
    [10, 10, 12, 10, 11, 6, 7, 10, 8, 11, "-", 12],
    [12, 7, 14, 12, 8, 9, 9, 11, 10, 10, 12, "-"]
]

literature_mentions = [22, 30, 27, 35, 19, 18, 18, 26, 15, 23, 20, 24]
individual_thresholds = [0.6 * mentions for mentions in literature_mentions]

# Step 1: Normalize tally_matrix to create fuzzy influence matrix
max_value = max([val for row in tally_matrix for val in row if val != "-"])
fuzzy_matrix = np.zeros((len(barriers), len(barriers)))

for i in range(len(barriers)):
    for j in range(len(barriers)):
        if i != j and tally_matrix[i][j] != "-":
            if tally_matrix[i][j] >= individual_thresholds[i]:  # Apply threshold
                fuzzy_matrix[i][j] = tally_matrix[i][j] / max_value
            else:
                fuzzy_matrix[i][j] = 0  # Below threshold

# Add identity matrix (self-influence is assumed)
```

```python
fuzzy_matrix += np.identity(len(barriers))

# Max-Min Composition Function
def max_min_composition(matrix1, matrix2):
    """
    Perform max-min composition of two matrices.
    """
    size = matrix1.shape[0]
    result = np.zeros_like(matrix1)
    for i in range(size):
        for j in range(size):
            result[i, j] = np.max(np.minimum(matrix1[i, :], matrix2[:, j]))
    return result

# Step 2: Iterative max-min matrix multiplication to account for indirect influences
stabilized = False
indirect_matrix = fuzzy_matrix.copy()
max_iterations = 1000  # Set a limit for maximum iterations

for iteration in range(max_iterations):
    new_matrix = max_min_composition(indirect_matrix, fuzzy_matrix)

    # Check for stabilization
    if np.allclose(new_matrix, indirect_matrix, atol=1):
        stabilized = True
        break
    indirect_matrix = new_matrix

if not stabilized:
    print("Warning: The matrix did not converge after maximum iterations.")

# Results
print(f"Converged in {iteration + 1} iterations.")


# Step 3: Calculate fuzzy driving power and fuzzy dependency
fuzzy_driving_power = indirect_matrix.sum(axis=1)
fuzzy_dependency = indirect_matrix.sum(axis=0)

# Step 4: Clustering and visualization
median_driving_power = np.median(fuzzy_driving_power)
median_dependency = np.median(fuzzy_dependency)

# Define cluster colors
cluster_colors = {
    "Autonomous": "#B9B7A7",
    "Dependent": "#B5AA9D",
    "Linkage": "#7C90A0",
    "Independent": "#4E5166"
}

# Assign colors to barriers
colors = []
for i in range(len(barriers)):
    if fuzzy_driving_power[i] < median_driving_power and fuzzy_dependency[i] <
        median_dependency:
        colors.append(cluster_colors["Autonomous"])
    elif fuzzy_driving_power[i] < median_driving_power and fuzzy_dependency[i] >=
        median_dependency:
        colors.append(cluster_colors["Dependent"])
    elif fuzzy_driving_power[i] >= median_driving_power and fuzzy_dependency[i] >=
        median_dependency:
        colors.append(cluster_colors["Linkage"])
    else:
        colors.append(cluster_colors["Independent"])

# Plot Fuzzy MICMAC Clusters in 2D plot with numbered barriers and colored clusters
plt.figure(figsize=(12, 8))  # Increase the figure size
scatter = plt.scatter(fuzzy_driving_power, fuzzy_dependency, color=colors)

# Annotate each point with its barrier index, starting from 1
texts = []
for i in range(len(barriers)):
```

```python
    texts.append(plt.text(fuzzy_driving_power[i], fuzzy_dependency[i], str(i + 1), ha='center', va='center', fontsize=18))

# Adjust text to avoid overlap
adjust_text(texts, arrowprops=dict(arrowstyle='->', color='gray', lw=0.5))

# Add quadrant dividers at the median driving power and dependency
plt.axhline(y=median_dependency, color='red', linestyle='--')
plt.axvline(x=median_driving_power, color='red', linestyle='--')

# Labels and title with larger font size
plt.xlabel('Fuzzy Driving Power', fontsize=18)
plt.ylabel('Fuzzy Dependency', fontsize=18)
plt.title('Fuzzy MICMAC Analysis: Driving Power vs Dependency (Clustered Barriers)', fontsize=20)
plt.grid(True)
# Increase font size for tick numbers on both axes
plt.tick_params(axis='both', labelsize=16)  # Increase font size for both x and y axis tick numbers


# Custom legend for numbered barriers on the side, starting from 1
legend_labels = [f"{i + 1}: {barrier}" for i, barrier in enumerate(barriers)]
legend_text = "\n".join(legend_labels)
plt.figtext(1.02, 0.5, legend_text, ha="left", va="center", fontsize=18, bbox=dict(facecolor="lightgrey", edgecolor="black", boxstyle="round,pad=0.5"))

# Cluster legend closer to the plot
for cluster, color in cluster_colors.items():
    plt.scatter([], [], color=color, label=cluster)
plt.legend(title="Clusters", loc="upper right", bbox_to_anchor=(1.15, 1), borderaxespad=0.2, fontsize=18, title_fontsize=18)

plt.tight_layout(rect=[0, 0, 1.0, 1.0])  # Adjust layout to fit the legend on the side
plt.savefig('Fuzzy_MICMAC2.pdf', bbox_inches='tight')
plt.show()
```

D Cost-benefit analysis code

```python
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
"""
Created on Thu Dec  5 11:36:51 2024

@author: kietfoeken
"""

import numpy as np
import matplotlib.pyplot as plt

#%%
# Number of Monte Carlo simulations
num_simulations = 40000
timepath = 20 #years
inflation_rate = 0.03  # Assuming a 3% annual inflation rate
initial_cost_interval = 6 #lifetime sensors

# Constants
wagon = 80000
wheels_trainset = 4
years = 1 # for calculation costs per year
num_trains = wagon/40 # Number of trains
baseline_revenue = 4.177e9*1.03**6/80000*wagon

def clip_negative(arr, min_value=0):
    return np.clip(arr, a_min=min_value, a_max=None)

cost_per_treatment_pm = 2216 # Cost per treatment (mean=5000, std=200)
downtime_event_cost_pm = 10000 # average downtime event cost
PM_efficiency_gain = clip_negative(np.random.normal(loc=0.3, scale=0.03, size=num_simulations))
PM_efficiency_gain_m = clip_negative(np.random.normal(loc=0.5, scale=0.03, size=num_simulations))
lifespan_with_PM = clip_negative(np.random.normal(loc=1440000, scale=100000, size=num_simulations))
yearly_maintenance_cost_cyber = clip_negative(np.random.normal(loc=50000, scale=3000, size=num_simulations)) # Existing cost of maintenance
cybersecurity_maintenance_cost = 10000 # Yearly cost for cybersecurity
maintenance_personnel_cost_cyber = 100000 # Yearly cost for maintenance personnel
downtime_saved_per_event = clip_negative(np.random.normal(loc=12, scale=2, size=num_simulations))  # hours saved per downtime event
annual_accident_probability_pm = clip_negative(np.random.normal(loc=0.001, scale=0.001, size=num_simulations))
false_positive_rate = clip_negative(np.random.normal(loc=0.05, scale=0.01, size=num_simulations))  # Assuming a 5% false positive rate with a small variation
customer_service_improvement = clip_negative(np.random.normal(loc=0.005, scale=0.005, size=num_simulations))
lifespan_no_PM = 1200000
annual_accident_probability_no_pm = clip_negative(np.random.normal(loc=0.0252, scale=0.002, size=num_simulations)) # 10% chance of an accident without predictive maintenance
downtime_event_cost_hour = 1667
```

```
wheel_replacement_cost = 4000 # Cost of replacing a single wheel in Euros
yearly_mileage = 178500 # km per year
cargo_capacity_per_hour = 90.3 # tons of cargo transported per hour
revenue_per_ton = 16.5 # revenue in Euros per ton of cargo
downtime_time = 60 #hours needed for wheel treatment
cost_per_service = clip_negative(np.random.normal(loc=300, scale=100, size=num_simulations))# average costs in euros of servicing/replacing a single sensor
service_interval = 5 #years
sensor_installation_cost = 100 #installation personnel cost per sensor
sensor_cost = 200 #manufacturing cost per sensor
education_cost = clip_negative(np.random.normal(loc=1000000, scale=100000, size=num_simulations))#cost for reschooling one maintenance crews
crews = 1/2300 #one crew for every 20 wagon
backend_cost = 100 # cost per sensor per year for cloud services etc
analyst_cost = 100000 # cost per analyst. assume 1 analyst for every 5000 sensors
cost_per_accident = 940092  # Cost per accident in euros
efficiency_improvement = clip_negative(np.random.normal(loc=0.02,scale=0.02, size=num_simulations))
energy_consumption_electricity = 2680191281
energy_consumption_other = 1742124333
annual_downtime_probability_nopm = clip_negative(np.random.normal(loc=0.297,scale=0.05, size=num_simulations))
pre_inspection_cost = clip_negative(np.random.normal(loc=100,scale=10, size=num_simulations))
maintenance_interval = 115/30
PM_corrective_odds = clip_negative(np.random.normal(loc=0.07,scale=0.03, size=num_simulations))
NoPM_corrective_odds = clip_negative(np.random.normal(loc=0.15,scale=0.05, size=num_simulations))
corrective_maintenance_price = 2000
PM_maintenance_labor = 70
NoPM_maintenance_labor =100
PM_placement_wheel = 140
NoPM_placement_wheel = 140
PM_maint_odds = 1
NoPM_maint_odds = clip_negative(np.random.normal(loc=0.4,scale=0.05, size=num_simulations))

#%% Wheel treatment costs
# Total material loss in 1 year for both scenarios
PM_pre_inspection = 0
NoPM_pre_inspection = pre_inspection_cost * maintenance_interval * num_trains

PM_corrective_maintenance = PM_corrective_odds * corrective_maintenance_price * num_trains
NoPM_corrective_maintenance = NoPM_corrective_odds * corrective_maintenance_price * num_trains

PMmaintenance = (PM_maintenance_labor+PM_placement_wheel) * PM_maint_odds * (1-PM_efficiency_gain_m) * maintenance_interval * wheels_trainset * wagon
NoPMmaintenance = (NoPM_maintenance_labor+NoPM_placement_wheel) * NoPM_maint_odds * maintenance_interval * wheels_trainset * wagon

# Define the costs of handling a false positive
false_positive_maintenance_cost = false_positive_rate * (PM_corrective_odds * corrective_maintenance_price * num_trains)
false_positive_downtime_cost = false_positive_rate * (downtime_event_cost_hour * downtime_time * num_trains)

# Total cost for both scenarios
PM_treatment_cost_samples = PM_pre_inspection + PM_corrective_maintenance + PMmaintenance + false_positive_maintenance_cost + false_positive_downtime_cost
No_PM_treatment_cost_samples = NoPM_pre_inspection + NoPM_corrective_maintenance + NoPMmaintenance

#%% Downtime costs
# Calculate total downtime costs for both scenarios
annual_downtime_probability_pm = annual_downtime_probability_nopm * (1-PM_efficiency_gain)
PM_downtime_cost = annual_downtime_probability_pm * num_trains * downtime_event_cost_hour * (downtime_time - downtime_saved_per_event)
No_PM_downtime_cost = annual_downtime_probability_nopm * num_trains * downtime_event_cost_hour * downtime_time

#%% Replacement costs
total_mileage = yearly_mileage

# Calculate the number of replacements over n years for both scenarios
```

```
replacements_with_PM = total_mileage / lifespan_with_PM
replacements_without_PM = total_mileage / lifespan_no_PM

# Calculate total replacement costs for both scenarios over time
total_replacement_cost_with_PM = replacements_with_PM * wheel_replacement_cost * wagon *
    wheels_trainset
total_replacement_cost_without_PM = replacements_without_PM * wheel_replacement_cost * wagon *
     wheels_trainset

#%% Increased revenue PM with lower downtime
downtime_events_PM = annual_downtime_probability_pm
downtime_events_no_PM = annual_downtime_probability_nopm

# Calculate downtime caused by false positives
false_positive_downtime_hours = false_positive_rate * downtime_time

downtime_hours_saved = (downtime_events_no_PM - downtime_events_PM) * downtime_time +
    downtime_saved_per_event * downtime_events_PM - false_positive_downtime_hours
# Calculate the additional tons of cargo transported due to saved downtime
additional_cargo_tons = downtime_hours_saved * cargo_capacity_per_hour * num_trains
# Calculate the additional revenue generated from transporting more cargo
additional_revenue_PM = additional_cargo_tons * revenue_per_ton
#%% Costs cybersecurity
cyber_cost = (maintenance_personnel_cost_cyber + cybersecurity_maintenance_cost)

#%% Sensor maintenance -> assuming 1 sensor per wheelset
service_cost = cost_per_service * wagon * wheels_trainset / service_interval
backend_cost = (backend_cost + analyst_cost/5000) * wagon * wheels_trainset / 2
maintenance_cost = service_cost + backend_cost

#%% Implementation cost
crew_cost = education_cost * crews * wagon

installation_cost = (sensor_installation_cost + sensor_cost) * wagon * wheels_trainset / 2 #
    total installation cost of sensors on fleet

implementation_cost = crew_cost + installation_cost

#%% Accident risk reduction
# Calculate the expected annual cost of accidents without predictive maintenance (no_pm)
expected_cost_no_pm = annual_accident_probability_no_pm * cost_per_accident * num_trains

# Calculate the expected annual cost of accidents with predictive maintenance (pm)
expected_cost_pm = annual_accident_probability_pm * cost_per_accident * num_trains

#%% Improved efficiency
energy_cost =  energy_consumption_electricity/80000* wagon + energy_consumption_other/80000*
    wagon

# Calculate the reduced energy consumption per train due to efficiency improvement
reduced_energy_consumption = energy_cost * (efficiency_improvement)
saved_energy = reduced_energy_consumption

#%% customer satisfaction
# Calculate the additional revenue due to higher service standards
additional_revenue_service_improvement = baseline_revenue * customer_service_improvement

#%% yearly cost
yearly_cost_samples_pm = PM_treatment_cost_samples + PM_downtime_cost +
    total_replacement_cost_with_PM - additional_revenue_PM + cyber_cost + maintenance_cost +
    expected_cost_pm - saved_energy - additional_revenue_service_improvement
yearly_cost_samples_no_pm = No_PM_treatment_cost_samples + No_PM_downtime_cost +
    total_replacement_cost_without_PM + expected_cost_no_pm

#%% Initial costs
initial_cost = implementation_cost

#%% total cost PM
initial_development_costs = 0
inflation_factors = (1 + inflation_rate) ** np.arange(timepath)
discount_rate = 0.0739
discount_factors = (1 / (1 + discount_rate)) ** np.arange(timepath)

```

```
def total_cost_pm(yearly_cost_samples_pm,initial_cost,initial_development_cost):
    yearly_costs_matrix_pm = np.random.choice(yearly_cost_samples_pm, (num_simulations, timepath))
    inflation_adjusted_costs_pm = yearly_costs_matrix_pm * inflation_factors
    recurring_cost_matrix = np.zeros((num_simulations, timepath))

    # Apply inflation and discounting
    inflation_adjusted_costs_pm = yearly_costs_matrix_pm * inflation_factors
    recurring_cost_matrix = np.zeros((num_simulations, timepath))

    for i in range(initial_cost_interval - 1, timepath, initial_cost_interval):
        recurring_cost_matrix[:, i] = initial_cost * inflation_factors[i]
    # Calculate the total cost matrix
    total_cost_matrix = inflation_adjusted_costs_pm + recurring_cost_matrix

    # Discount initial development cost
    cumulative_cost_matrix_pm_initial = np.zeros((total_cost_matrix.shape[0], timepath + 1))
    cumulative_cost_matrix_pm_initial[:, 0] += initial_development_cost / discount_factors[19] + initial_cost
    cumulative_cost_matrix_pm_initial[:, 1:] = total_cost_matrix
    cumulative_cost_matrix_pm = np.cumsum(cumulative_cost_matrix_pm_initial, axis=1)

    return cumulative_cost_matrix_pm

#%% total cost noPM

def total_cost_no_pm(yearly_cost_samples_no_pm):
    yearly_costs_matrix_no_pm = np.random.choice(yearly_cost_samples_no_pm, (num_simulations, timepath))
    inflation_adjusted_costs_no_pm = yearly_costs_matrix_no_pm * inflation_factors

    cumulative_cost_matrix_no_pm_initial = np.zeros((inflation_adjusted_costs_no_pm.shape[0], timepath + 1))
    cumulative_cost_matrix_no_pm_initial[:, 0] += 0
    cumulative_cost_matrix_no_pm_initial[:, 1:] = inflation_adjusted_costs_no_pm
    cumulative_cost_matrix_no_pm = np.cumsum(cumulative_cost_matrix_no_pm_initial, axis=1)

    return cumulative_cost_matrix_no_pm

#%% analytics
cumulative_cost_matrix_pm_initial = total_cost_pm(yearly_cost_samples_pm,initial_cost, initial_development_costs)
total_cost_pm_20_years = cumulative_cost_matrix_pm_initial[:, 20]

cumulative_cost_matrix_no_pm_initial = total_cost_no_pm(yearly_cost_samples_no_pm)
total_cost_no_pm_20_years = cumulative_cost_matrix_no_pm_initial[:, 20]

probability_pm_higher = np.mean(total_cost_pm_20_years > total_cost_no_pm_20_years)

print(f"Probability that cost with PdM is higher than cost without PdM after 20 years: {probability_pm_higher:.4f}")

development_costs = np.linspace(0.4e9, 0.16e10, 100)
probabilities = []

for dev_cost in development_costs:
    costs_pm = total_cost_pm(yearly_cost_samples_pm,initial_cost,dev_cost)
    costs_no_pm = total_cost_no_pm(yearly_cost_samples_no_pm)
    probabilities.append(np.mean(costs_pm[:, 20] > costs_no_pm[:, 20]))

# Plot the results
plt.figure(figsize=(10, 6))
plt.plot(development_costs, probabilities, label='Probability PdM more expensive', color='#4E5166')
plt.xlabel('Initial Development Cost for PdM €()', fontsize=18)
plt.ylabel('Probability PdM is more expensive', fontsize=18)
plt.title('Probability of PdM being more expensive vs Initial Development Cost', fontsize=18)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.grid(True)
plt.legend(fontsize=18)
plt.savefig('CBA-developmentcost.pdf')
plt.show()
```

```python

#%% visualization
n_years = cumulative_cost_matrix_pm_initial.shape[1]

# Initialize arrays to store the mean, lower bound, and upper bound for each year
mean_pm = np.zeros(n_years)
lower_bound_pm = np.zeros(n_years)
upper_bound_pm = np.zeros(n_years)

mean_no_pm = np.zeros(n_years)
lower_bound_no_pm = np.zeros(n_years)
upper_bound_no_pm = np.zeros(n_years)

# Compute statistics for each year
for year in range(n_years):
    mean_pm[year] = np.mean(cumulative_cost_matrix_pm_initial[:, year])
    lower_bound_pm[year] = np.percentile(cumulative_cost_matrix_pm_initial[:, year], 5)  # 5th percentile
    upper_bound_pm[year] = np.percentile(cumulative_cost_matrix_pm_initial[:, year], 95)  # 95th percentile

    mean_no_pm[year] = np.mean(cumulative_cost_matrix_no_pm_initial[:, year])
    lower_bound_no_pm[year] = np.percentile(cumulative_cost_matrix_no_pm_initial[:, year], 5)  # 5th percentile
    upper_bound_no_pm[year] = np.percentile(cumulative_cost_matrix_no_pm_initial[:, year], 95)  # 95th percentile

years = np.arange(0, n_years)  # Year indices (1 to n_years)

# Plotting PM costs
plt.figure(figsize=(12, 6))
plt.plot(years, mean_pm, label='Mean PdM Cost', color='#4E5166')
plt.fill_between(years, lower_bound_pm, upper_bound_pm, color='#4E5166', alpha=0.2, label='PdM Cost 5th-95th Percentile')

# Plotting No PM costs
plt.plot(years, mean_no_pm, label='Mean no PdM Cost', color='#B9B7A7')
plt.fill_between(years, lower_bound_no_pm, upper_bound_no_pm, color='#B9B7A7', alpha=0.2, label='No PdM Cost 5th-95th Percentile')

# Formatting the plot
plt.title('Cumulative Costs with and without PdM Over Time', fontsize=18)
plt.xlabel('Year', fontsize=18)
plt.ylabel('Cumulative Cost €()', fontsize=18)
plt.legend(fontsize=16)
plt.xticks(years, fontsize=16)
plt.grid(True)
plt.yticks(fontsize=16)  # Show each year on the x-axis
plt.savefig('CBA.pdf')
plt.show()
```

E

Cost-benefit analysis variable list

Table E.1: Overview of variables, their values/distributions, and references

Variable	Value/Distribution	References
C_{analyst}	$\sim N(\mu = 100000, \sigma = 10000)$	internal
C_{backend}	$\sim N(\mu = 100, \sigma = 50)$	internal
$C_{\text{cargo\_capacity}}$	$\sim N(\mu = 90.3, \sigma = 10)$	[17]
C_{cm}	$\sim N(\mu = 2000, \sigma = 200)$	[12]
$C_{\text{cybersecurity, maintenance}}$	$\sim N(\mu = 10000, \sigma = 1000)$	internal
C_{dpm}	$\sim N(\mu = 10,000, \sigma = 1,000)$	[12]
$C_{\text{downtime\_event}}$	$\sim N(\mu = 1667, \sigma = 100)$	[40]
$C_{\text{education}}$	$\sim N(\mu = 100000, \sigma = 10000)$	estimate
$C_{\text{maintenance, personnel, cyber}}$	$\sim N(\mu = 100000, \sigma = 10000)$	internal
$C_{\text{per\_accident}}$	$\sim N(\mu = 940092, \sigma = 100000)$	[32]
$C_{\text{per\_service}}$	$\sim N(\mu = 300, \sigma = 30)$	estimate
C_{pi}	$\sim N(\mu = 100, \sigma = 10)$	[12]
$C_{\text{sensor, installation}}$	$\sim N(\mu = 100, \sigma = 10)$	internal
C_{sensor}	$\sim N(\mu = 200, \sigma = 20)$	internal
C_{tpm}	$\sim N(\mu = 2216, \sigma = 500)$	[12]
$C_{\text{wm, labor no-PM}}$	$\sim N(\mu = 100, \sigma = 10)$	internal
$C_{\text{wm, labor PM}}$	$\sim N(\mu = 100, \sigma = 10)$	internal
CSI	$\sim N(\mu = 0.005, \sigma = 0.001)$	estimate
$\Delta\eta_{\text{maintenance}}$	$\sim N(\mu = 100, \sigma = 10)$	estimate
$\Delta\eta_{\text{PM}}$	$\sim N(\mu = 0.3, \sigma = 0.03)$	[44]
ΔT_{M}	$\sim N(\mu = 3.8, \sigma = 0.3)$	[12]
d_{year}	$\sim N(\mu = 178500, \sigma = 10000)$	[46]
$E_{\text{consumption, electricity}}$	$\sim N(\mu = 33502, \sigma = 3000)$	[17]

Continued on next page

Variable	Value/Distribution	References
$E_{\text{consumption, other}}$	$\sim N(\mu = 21776, \sigma = 2000)$	[17]
$L_{\text{no-PM}}$	$\sim N(\mu = 1200000, \sigma = 100000)$	[46]
L_{PM}	$\sim N(\mu = 1440000, \sigma = 100000)$	[46, 44]
n_{crews}	$\sim N(\mu = 1/2300, \sigma = 1/20000)$	[19]
n_{trains}	2000	[17]
n_{wheels}	4 per wagon	[56]
$P_{\text{accident, no-PM}}$	$\sim N(\mu = 0.0252, \sigma = 0.001)$	[38]
$P_{\text{accident, PM}}$	$\sim N(\mu = 0.001, \sigma = 0.001)$	[38]
$P_{\text{c, no-PM}}$	$\sim N(\mu = 0.15, \sigma = 0.05)$	[12]
$P_{\text{c, PM}}$	$\sim N(\mu = 0.07, \sigma = 0.03)$	[12]
$P_{\text{downtime, no-PM}}$	$\sim N(\mu = 0.297, \sigma = 0.05)$	[12]
$P_{\text{false\_positive}}$	$\sim N(\mu = 0.05, \sigma = 0.01)$	estimate
$P_{\text{maintenance, no-PM}}$	$\sim N(\mu = 100, \sigma = 10)$	internal
$P_{\text{maintenance, PM}}$	$\sim N(\mu = 100, \sigma = 10)$	internal
R_{baseline}	63000	[17]
$R_{\text{revenue\_per\_ton}}$	$\sim N(\mu = 16.5, \sigma = 2)$	[17, 46]
S_{interval}	$\sim N(\mu = 5, \sigma = 0.5)$	internal
T_{downtime}	$\sim N(\mu = 60, \sigma = 40)$	[40]
$T_{\text{downtime\_saved}}$	$\sim N(\mu = 12, \sigma = 2)$	estimate
TF_{pm}	$\sim N(\mu = 4.49, \sigma = 0.5)$	[12]

Table E.2: Overview of variables, their values/distributions, references, and descriptions

Variable	Value/Distribution	References	Description
C_{analyst}	100000	internal	Cost of hiring an analyst to process and interpret sensor data.
C_{backend}	100	internal	Backend maintenance costs for systems supporting predictive maintenance.
$C_{\text{cargo\_capacity}}$	90.3	[17]	Cargo capacity transported per hour per train.
C_{cm}	2000	[12]	Cost per corrective maintenance event.
$C_{\text{cybersecurity, maintenance}}$	10000	internal	Costs associated with maintaining cybersecurity systems.
C_{dpm}	$10,000$	[12]	Cost per downtime event.
$C_{\text{downtime\_event}}$	1667	[40]	Cost incurred per hour of downtime.
$C_{\text{education}}$	$\sim N(\mu = 100000, \sigma = 10000)$	estimate	Education costs for training crews on predictive maintenance technologies.
$C_{\text{maintenance, personnel, cyber}}$	100000	internal	Cost for personnel specifically involved in cybersecurity maintenance.
$C_{\text{per\_accident}}$	940092	[32]	Average cost incurred per accident.
$C_{\text{per\_service}}$	$\sim N(\mu = 300, \sigma = 100)$	estimate	Cost of servicing each sensor.
$C_{\text{p,wheel}}$	140	[12]	Cost for placement wheel.
$C_{\text{sensor, installation}}$	100	internal	Labor cost associated with sensor installation.
C_{sensor}	200	internal	Cost of each individual sensor.
C_{tpm}	2216	[12]	Cost per treatment under predictive maintenance.
$C_{\text{wm, labor no-PM}}$	100	internal	Labor costs for wheel maintenance under traditional maintenance.
$C_{\text{wm, labor PM}}$	70	internal	Labor costs for wheel maintenance under predictive maintenance.
C_{wr}	4000	[12]	Replacement costs per wheel.
CSI	$\sim N(\mu = 0.005, \sigma = 0.001)$	estimate	Customer service improvement factor, proportional to revenue increase.

Continued on next page

Variable	Value/Distribution	References	Description
$\Delta\eta_{\text{maintenance}}$	$\sim N(\mu = 100, \sigma = 10)$	estimate	Efficiency improvement in maintenance activities.
$\Delta\eta_{\text{PM}}$	$\sim N(\mu = 0.3, \sigma = 0.03)$	[44]	Efficiency improvement from predictive maintenance.
ΔT_{M}	3.8	[12]	Average maintenance interval in years.
d_{year}	178500	[46]	Total yearly mileage of the fleet.
$E_{\text{consumption, electricity}}$	33502	[17]	Energy consumption cost (electricity) per wagon.
$E_{\text{consumption, other}}$	21776	[17]	Energy consumption cost (other sources, e.g., fuel) per wagon.
$L_{\text{no-PM}}$	1200000	[46]	Lifespan of wheels under traditional maintenance (in km).
L_{PM}	$\sim N(\mu = 1440000, \sigma = 100000)$	[46, 44]	Lifespan of wheels under predictive maintenance (in km).
n_{crews}	$1/2300$	[19]	Number of maintenance crews required per wagon.
n_{trains}	2000	[17]	Total number of trains in the fleet.
n_{wheels}	4 per wagon	[56]	Number of wheels per wagon.
$P_{\text{accident, no-PM}}$	$\sim N(\mu = 0.0252, \sigma = 0.001)$	[38]	Probability of an accident under traditional maintenance.
$P_{\text{accident, PM}}$	$\sim N(\mu = 0.001, \sigma = 0.001)$	[38]	Probability of an accident under predictive maintenance.
$P_{\text{c, no-PM}}$	$\sim N(\mu = 0.15, \sigma = 0.05)$	[12]	Probability of corrective maintenance under traditional maintenance.
$P_{\text{c, PM}}$	$\sim N(\mu = 0.07, \sigma = 0.03)$	[12]	Probability of corrective maintenance under predictive maintenance.
$P_{\text{downtime, no-PM}}$	$\sim N(\mu = 0.297, \sigma = 0.05)$	[12]	Probability of downtime under traditional maintenance.
$P_{\text{false\_positive}}$	$\sim N(\mu = 0.05, \sigma = 0.01)$	estimate	Probability of false-positive maintenance events under predictive maintenance.
$P_{\text{maintenance, no-PM}}$	$\sim N(\mu = 100, \sigma = 10)$	internal	Maintenance probability under traditional maintenance.
$P_{\text{maintenance, PM}}$	$\sim N(\mu = 100, \sigma = 10)$	internal	Maintenance probability under predictive maintenance.
R_{baseline}	63000	[17]	Baseline revenue per wagon per year.

Continued on next page

Variable	Value/Distribution	References	Description
$R_{\text{revenue\_per\_ton}}$	16.5	[17, 46]	Revenue generated per ton of cargo transported.
S_{interval}	5	internal	Service interval for sensor maintenance (in years).
T_{downtime}	60	[40]	Duration of downtime per event.
$T_{\text{downtime\_saved}}$	$\sim N(\mu = 12, \sigma = 2)$	estimate	Downtime saved per event with predictive maintenance.