Transforming internal business processes to deliver predictive maintenance recommendations to customers

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Abstract

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As technological progress continues to accelerate, industrial companies increasingly operate within the data-driven paradigm of Industry 4.0, where Artificial Intelligence (AI) plays a growing role. Maintenance services are one of the areas where emerging technologies can bring significant benefits by shifting from reactive or periodic to predictive maintenance approach. This shift can reduce production costs, improve operational efficiency and support sustainability by enabling early detection of maintenance needs.

The primary objective of this thesis was to investigate how equipment and maintenance service providers can transform their existing non-predictive maintenance processes to support AI-aided predictive maintenance. The thesis applied a Case Study approach, supported by a literature review, and investigation of the case company's internal processes, and semi-structured interviews with customers and internal stakeholders. The expected outcomes included: a literature-based overview of typical processes for delivering predictive maintenance services; an analysis of the case company's current maintenance processes; insights into customer expectations; and development proposals for transitioning to AI-aided predictive maintenance.

The focus of this thesis was on service provider's internal business processes, while an in-depth review of customers' internal processes and detailed technical solution analysis were outside the scope. The empirical context centered on aggregates customers in Finland.

The results showed that predictive maintenance processes typically include continuous monitoring, anomaly detection, criticality assessment, actionable recommendations and a feedback loop for continuous improvement. The internal process analysis confirmed that integrating predictive capabilities will require, in addition to the technical solution itself, also changes to process logic, roles, resourcing and customer-facing service practices. Two high-level future-state process options were developed to illustrate alternative levels of automation. Customer interviews indicated that predictive maintenance is perceived as valuable when recommendations are accurate, specific, verifiable, timely and easy to act upon. These combined insights enabled the development of a set of recommendations to support organizations transitioning towards predictive maintenance practices.

Future research could examine other customer segments and regions, compare practices and technical solutions across peers and competitors, and explore long-term implications of predictive maintenance for service providers and end customers.

Keywords
Predictive maintenance, artificial intelligence, business process transformation, maintenance services, customer value.

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1 Introduction

1.1 Thesis background

This thesis addresses the need to transform existing business processes to enable the effective delivery of AI-based predictive maintenance recommendations to end customers. The development task arises from the growing importance of predictive maintenance in industrial sectors, where timely and data-driven maintenance actions can significantly reduce unplanned downtime and improve operational efficiency.

The work is situated within the broader context of digital transformation and the adoption of artificial intelligence in industrial services. It focuses specifically on Metso's aggregates sector, where the AI-aided predictive maintenance solution is being currently piloted. Metso is a global provider of sustainable technologies, end-to-end solutions and services for aggregates, minerals processing and metals refining industries. With headquarters is in Espoo, Finland, Metso has over seventeen thousand employees in around 50 countries.

The Aggregates Business Area focuses on providing equipment, services, and digital solutions to produce aggregates used in construction and infrastructure projects. This includes crushers, screens, conveyors, and related services that help customers improve productivity, reduce downtime, and operate more sustainably. The business area plays a key role in Metso's digital transformation efforts, including the development and delivery of AI-based predictive maintenance solutions.

The thesis contributes to this larger transformation effort by exploring how internal business processes can be adapted to support the delivery of such AI-enabled services.

1.2 Objectives, Research Questions and Expected Outcomes

The primary objective of the thesis is to investigate current business processes and define how they should be transformed to support the delivery of predictive maintenance recommendations. This includes:

- Understanding the currently existing internal processes, that are involved in delivering maintenance services.
- Acquiring customers' perception of predictive maintenance services and automated maintenance recommendations from the angle of value and usefulness.

To achieve the objectives of this thesis, the following research questions (RQ) have been defined. These questions are intended to structure the development task in more detail and guide the research process:

RQ1: What are typical business processes for providing predictive maintenance services to industrial companies?

RQ2: How should non-predictive maintenance processes be transformed to effectively integrate automatic AI-based predictive maintenance recommendations?

RQ3: What would make AI-aided predictive maintenance services valuable to customers?

The expected outcomes of the thesis include:

- Consolidated information of potential/ typical business processes for providing predictive maintenance services to industrial companies, based on literature review. If feasible, a high-level logical model of such process. This supports addressing the Research Question #1.
- Analysis of service providers' typical business processes for providing non-predictive maintenance services to customers in industrial sector; if feasible, - a generic high-level business process map, on an example of Metso's current practices. This supports addressing the Research Question #2, as an outline of the to-be-transformed process.
- Insights into customer expectations from predictive maintenance services, with recommendations for Metso's service development. This addresses the Research Question #3 in full.
- Development proposals for transforming these processes to support AI-aided predictive maintenance delivery, specifically tailored to Metso.

The key concepts, relevant to this thesis, are predictive maintenance, perceived value and usefulness of services, business process modelling and transformation.

1.3 Delimitation of the Thesis

From the business process modelling and transformation perspective, the focus of this thesis is primarily internal, and to a limited extent, customer-facing processes. The study will explicitly exclude any in-depth technical analysis of the AI-aided predictive maintenance solution. While some technical details may be referenced to support understanding, they will be limited to a high-level overview. The business process investigation in this thesis is limited to a high-level mapping of the main steps and responsible roles involved in delivering predictive maintenance recommendations at Metso. The aim is to provide sufficient context for the development proposals, not to produce a comprehensive process manual. Detailed work instructions, technical system integrations, and exhaustive process variants are outside the scope of this study

Additionally, an in-depth study of customers' internal processes for purchasing predictive maintenance services is beyond the scope of this thesis. This decision is based on the breadth of the topic and the scale of research required, which could easily constitute a separate thesis. Although such insights could support process development, they are not essential for the core objectives of this study and are therefore excluded at this stage.

What comes to investigating customer insights on AI-aided predictive maintenance services, the work focuses on gathering general customer expectations and on understanding what aspects of the service would make it valuable to the selected customer groups. The research specifically excludes value selling-related investigations, detailed technical requirements gathering or recommendations or alike. The study focuses on the general, high-level expectations collected to the point of saturation, but also concrete enough to be of value to the commissioning company's service development team.

1.4 Structure of the Thesis

This thesis is organized into five main chapters. Chapter 1 introduces the background, objectives, research questions, and scope of the study. Chapter 2 presents the theoretical framework, reviewing the key concepts, models, and literature related to predictive maintenance, business process management, and customer value in industrial services. Chapter 3 describes the research approach, methods used for data collection and analysis, as well as the research implementation details. Chapter 4 presents the main findings from internal business process investigations and customer interviews, and well as outlines the proposed transformed (future) business process and considerations related to it. Finally, Chapter 5 discusses the results in relation to the research questions and theoretical framework, provides practical recommendations, and outlines suggestions for further research.

1.5 Abbreviations

This sub-chapter includes abbreviations used across the Thesis.

Abbreviation	Meaning
AI	Artificial Intelligence
AIoT	Artificial Intelligence of Things
BPM	Business Process Management
BPMN	Business Process Model and Notation

BPR	Business Process Reengineering
CMMS	Computerized Maintenance Management System
IC	Intelligent Control System (in Metso)
PdM	Predictive Maintenance
RUL	Remaining Useful Life (used in predictive models)
SAM	Sales/ Account Manager
TAM	Technology Acceptance Model
WO	Work Order
XAI	Explainable Artificial Intelligence
OEM	Original Equipment Manufacturer

1.6 A note on AI usage

The thesis has used:

- Keenious AI to search for thesis-relevant literature and sources.
- Copilot AI:
  - to help outline the thesis content into a logical structure,
  - to support with translation of customer interview questionnaire from English to Finnish, and to structure it in a logical way,
  - to transcribe the interviews conducted via Microsoft Teams,
  - to categorize interview answers into relevant topics,
  - to help refine the sections' contents and make sure all the relevant details have been included.

I made sure to cross-check and refine the AI-generated texts to make them free from errors, relevant, clear and understandable. The AI applications have been used responsibly, considering data protection and copyright. All sources cited in the report have been used correctly and are not AI-generated.

2 Theoretical framework

The theoretical framework provided in this Thesis is grounded in the following four complimentary key concepts: predictive maintenance enabled by AI, business process management and transformation, customers’ perceived value and usefulness of AI-aided maintenance recommendations and change management for digital transformation. Together, these perspectives ground the case study in Metso’s aggregates business context and guide analysis of how internal processes should evolve to consistently deliver predictive recommendations that customers actually value.

2.1 Predictive Maintenance (PdM) enabled by Artificial Intelligence (AI)

2.1.1 Maintenance and its types

In the industrial sector in general, and in the aggregates industry specifically, production is closely tied to the performance of various equipment. The condition of this equipment (its reliability, availability for operation, throughput capacity, and other operational parameters) is directly related to, and dependent on, not only the quality of the equipment itself and its fitness for purpose, but also on how well the equipment is maintained. (Ucar et al. 2024, 2; Abidi et al. 2022, 1). Maintenance practices can vary significantly depending on the type of equipment in question. In the aggregates industry, for example, mobile crushers and screens, as well as larger crushing-screening systems, are widely used. These types of equipment have many potential points of failure, ranging from motor issues to mechanical breakage of crushing parts due to unexpected objects or unnoticed wear. Each breakdown results in an unplanned production shutdown, which leads directly to a loss in production capacity and, consequently, profit for the operating company. (Duan et al. 2022, 293).

There are three major approaches to performing maintenance:

- Reactive.
- Periodic.
- Predictive.

Below, the three types are reviewed in more detail.

Reactive maintenance, also known as "run-to-failure" or "breakdown maintenance," is repairing equipment only after a failure has occurred. This approach is the most basic and is unplanned, so the maintenance happens only when operations have already been disrupted. Even though reactive maintenance requires no planning by definition and bares lower upfront costs, it often results in higher long-term expenses due to unplanned downtime, production losses, and potentially more extensive equipment damage. (Ucar et al. 2024, 2; Duan et al. 2022, 293). It is generally considered suitable only for non-critical assets where the cost of downtime is low.

Periodic maintenance is a planned, schedule-based approach where maintenance tasks are performed at predetermined intervals, regardless of the actual condition of the equipment. For simplicity, it can be compared to regular maintenance checks for a car: changing motor oil, checking condition of tires, etc., even though the car might be not giving out any warning signals just yet. The goal is to reduce the likelihood of failures by replacing parts or performing routine checks before breakdowns happen. Periodic maintenance can help extend equipment life and reduce unexpected downtime, but it may also lead to unnecessary maintenance actions and higher costs if interventions are performed too early or too frequently. (Ucar et al. 2024, 2; Abidi et al. 2022, 2).
This approach is a step ahead from reactive maintenance, however, it is not fully capable of predicting potential future failures, since it is not relying on real-time condition monitoring or assets usage patterns.

Predictive maintenance, in turn, is employing data analytics, sensor technologies and artificial intelligence to monitor actual condition of equipment and to predict potential failures and maintenance needs. By combining and analyzing real-time and historical data, such as vibration, temperature, operational logs, PdM aims to forecast failures before they occur, which allows to schedule maintenance only when it is necessary. (Carvalho et al. 2019, 1–2; Leukel, Gonzalez & Riekert 2021, 87–88). Therefore, this approach minimizes the unplanned downtime, reduces costs and prolongs equipment lifetime. (Ucar et al. 2024, 2; Duan et al. 2022, 293–294; Abidi et al. 2022, 1–2).

The table below summarizes the three maintenance approaches in a concise manner.

Table 1. Summary of maintenance types

Maintenance type	Short definition	Trigger	Data usage	Example
Reactive	Maintenance performed after equipment fails or breaks down.	Equipment failure or breakdown occurs.	No data used in advance.	Fixing a conveyor belt only after it snaps.
Periodic	Maintenance scheduled at regular intervals, regardless of equipment condition.	Calendar-based or usage-based schedule.	Uses historical averages, manuals.	Changing oil in a machine every 3 months.
Predictive	Maintenance based on real-time monitoring and prediction of equipment condition.	Data-driven prediction of impending failure.	Uses sensor data, analytics, AI.	Replacing a motor bearing when vibration analysis shows early signs of wear.

2.1.2 Predictive maintenance and AI (Artificial Intelligence)

PdM has developed in parallel with the emergence of Industry 4.0 and, more recently, Industry 5.0. With Industry 4.0, the world has witnessed the integration of cyber-physical systems, IoT (Internet of Things), and big data analytics, which made it possible to collect and analyze large volumes of operational data (Carvalho et al. 2019, 1–3). Industry 5.0 takes this further by placing greater emphasis on human-centricity, sustainability and resilience, and by encouraging collaboration between human expertise and intelligent automation (Bitam et al. 2025, 2–3; Maddikunta et al. 2022). In the light of the above, PdM is not just a more advanced maintenance approach and a technical tool, but rather a socio-technical system that brings together data, models, and human decision-making (Ramzan & Recupero 2025, 2–4).

The role of AI in PdM goes well beyond just making predictions. AI enables the automation of feature extraction, helps deal with noisy or incomplete data, and allows models to adapt as operational conditions change (Ucar et al. 2024, 2–4). When AI is combined with IoT, sometimes referred to as the Artificial Intelligence of Things (AIoT), PdM becomes even more powerful, as it can support real-time, distributed, and scalable analytics both at the edge and in the cloud (Bitam et al. 2025, 2–4).

Although the literature generally agrees that AI has transformative potential for PdM, there are still some important challenges and ongoing debates:

- *Data quality and scarcity:* several authors (Ramzan & Recupero 2025, 4–7; Carvalho et al. 2019, 8–9) point out that the effectiveness of AI models depends heavily on having access to high-quality, labeled data. In practice, failure events are rare in many industrial settings, which leads to imbalanced datasets and makes model training difficult. While there are promising advances in generative AI and synthetic data generation, these solutions are not yet widely used in real-world applications. (Ramzan & Recupero 2025, 16–18; Bitam et al. 2025, 18–20).

- *Model trustworthiness and explainability:* Ucar et al. (2024, 4–6) stress the importance of transparency, explainability, and ethical considerations in AI-based PdM. “Black box” models may be highly accurate, but if operators and engineers can’t understand or validate the results, it’s hard for them to trust and adopt these systems. This is why explainable AI (XAI) techniques and human-in-the-loop frameworks are becoming more important, especially in safety-critical industries. (Ucar et al. 2024, 23–25; Ramzan & Recupero 2025, 14–16).

- *Human–AI collaboration*: industry 5.0 shifts the focus from full automation to a more collaborative approach, where AI supports human judgment, ethical oversight, and contextual interpretation in PdM workflows (Ramzan & Recupero 2025, 2–4; Bitam et al. 2025, 3–4). Ucar et al. (2024, 6–7) also highlight that trustworthy AI should support, not replace, human decision-makers.

2.1.3 Relevance to the thesis

For this thesis, which looks at how business processes should be transformed to enable the effective delivery of AI-based predictive maintenance recommendations, these insights are highly relevant. The literature makes it clear that PdM is not just about deploying advanced algorithms to support maintenance activities, but also about integrating AI into the entire business process, from data collection and model development to decision-making and human involvement. Additionally, since PdM is in the essence of the thesis work, it is critical that this concept has been outlined in the first place.

2.2 Business process management and transformation

A business process can be defined as “a set of activities or logically related tasks that must be performed to accomplish a business objective” (Guha, Kettinger & Teng 1993, p. 15). In other words, business processes are structured sequences of work that deliver value to the organization or its customers, often spanning multiple departments, roles, or even organizations (Scheer & Nüttgens 2000, 1; Stjepić, Ivančić & Vugec 2020, 43).

Business process management (BPM) and transformation are at the heart of this thesis, as the research aims to understand and improve the internal processes involved in delivering predictive maintenance services at Metso’s aggregates sector. In the context of industrial maintenance services, well-defined and well-managed business processes are essential for ensuring reliability, efficiency, and the ability to adapt to new technologies such as AI-based predictive maintenance.

2.2.1 The role of business processes in predictive maintenance service delivery

As organizations grow and operations become more complex, it becomes increasingly important to move beyond informal routines and tacit knowledge. Clearly defined business processes help clarify roles, responsibilities, process steps, and touchpoints with related systems (Guha, Kettinger & Teng 1993, 15; Stjepić, Ivančić & Vugec 2020, 43). For Metso, this means mapping and understanding the internal processes that comprise the delivery of maintenance services, from the initial service request to the communication of potential recommendations and follow-up actions.

2.2.2 Key concepts in business process management

Business Process Management (BPM) is a holistic management approach that focuses on designing, analyzing, and continuously improving organizational processes to achieve strategic goals (Rosemann & de Bruin 2005; Dymora, Koryl & Mazurek 2019, 1). In the context of this thesis, BPM provides the framework for:

- Identifying and mapping current maintenance service processes (RQ1)
- Redesigning processes to support the integration of AI-based predictive maintenance recommendations (RQ2)

The BPM lifecycle typically includes phases such as process identification, analysis, redesign, implementation, and monitoring (Fettke & Di Francescomarino 2025, 69). For this thesis, the focus will be on the first three phases: mapping the current state, analyzing gaps, and proposing an updated process design. These steps will be informed by interviews with internal stakeholders and by reviewing existing process documentation where available.

2.2.3 Business process transformation and digitalization

Business process transformation refers to significant changes in how processes are structured and executed, often driven by new technologies or changing business requirements (Guha, Kettinger & Teng 1993, 14; Earl, Sampler & Short 1995, 32). In the context of predictive maintenance, transformation may involve:

- Introducing new data flows and decision points to support AI-generated recommendations and alerts.
- Clarifying touchpoints between customer-facing teams, operational teams and systems.
- Ensuring that process changes align with organizational strategy and support value delivery to customers, even if the customer interface itself is only lightly touched.

Recent literature highlights that traditional BPM logics, such as modelling of the processes as-is and strict adherence to the existing procedures, may not be sufficient in fast-changing, technology-driven environments (Baiyere, Salmela & Tapanainen 2020, 3). Instead, large industrial organizations like Metso may benefit from more flexible, adaptive processes and from empowering employees to make informed decisions in ambiguous situations.

2.2.4 Applicable standards and methodologies

Among many standards and methodologies that exist in the BPM field, the following two are the most relevant for mapping and transforming internal business processes for providing predictive maintenance services:

- Business Process Model and Notation (BPMN) for visualizing and communicating process flows. BPMN is a standardized way to describe nosiness processes in a clear, structured manner, designed to be understandable for anyone involved (Kocbek et al. 2015, 510).
- Business Process Reengineering (BPR) for considering more radical redesigns where needed (Guha, Kettinger & Teng 1993).

As for BPMN, the standardization is enabled by using typical elements to mark different parts of the process. For instance, Figure 1 illustrates the typical events; Figure 2 – typical connectors between the events (flows) and Figure 3 – swim lanes for further organizing the activities per process participant.

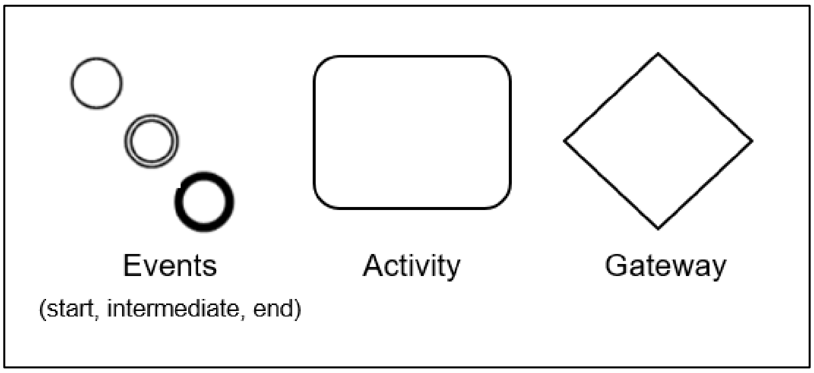

Figure 1. Typical BPMN event, activity and gateway elements (adapted from Aagesen and Krogstie 2010, 217)

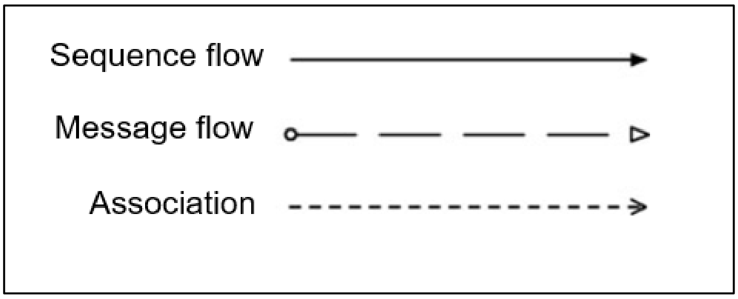

Figure 2. Typical BPMN connectors: sequence, message and association flows (adapted from Aagesen and Krogstie 2010, 217)

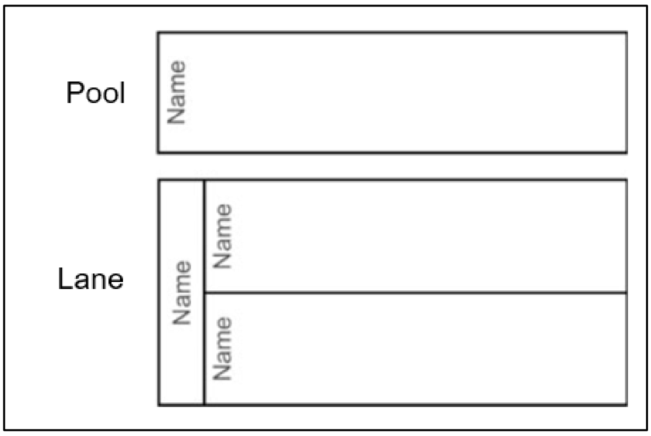

Figure 3. Typical BPMN swim lanes, pool and lane (adapted from Aagesen and Krogstie 2010, 217)

An example of a business process described using BPMN is shown in Figure 4. The sequence of actions and the responsible participants are displayed clearly. While this is undoubtedly one of the simplest possible processes (and the real-life examples are typically much more complex), the main purpose of using BPMN is to provide a concise overview of the entire process, ideally fitting it onto a single page. If the whole process does not fit, the remaining details can be described using business process instructions or by breaking them down into sub-processes (Gagné & Ringuette 2017).

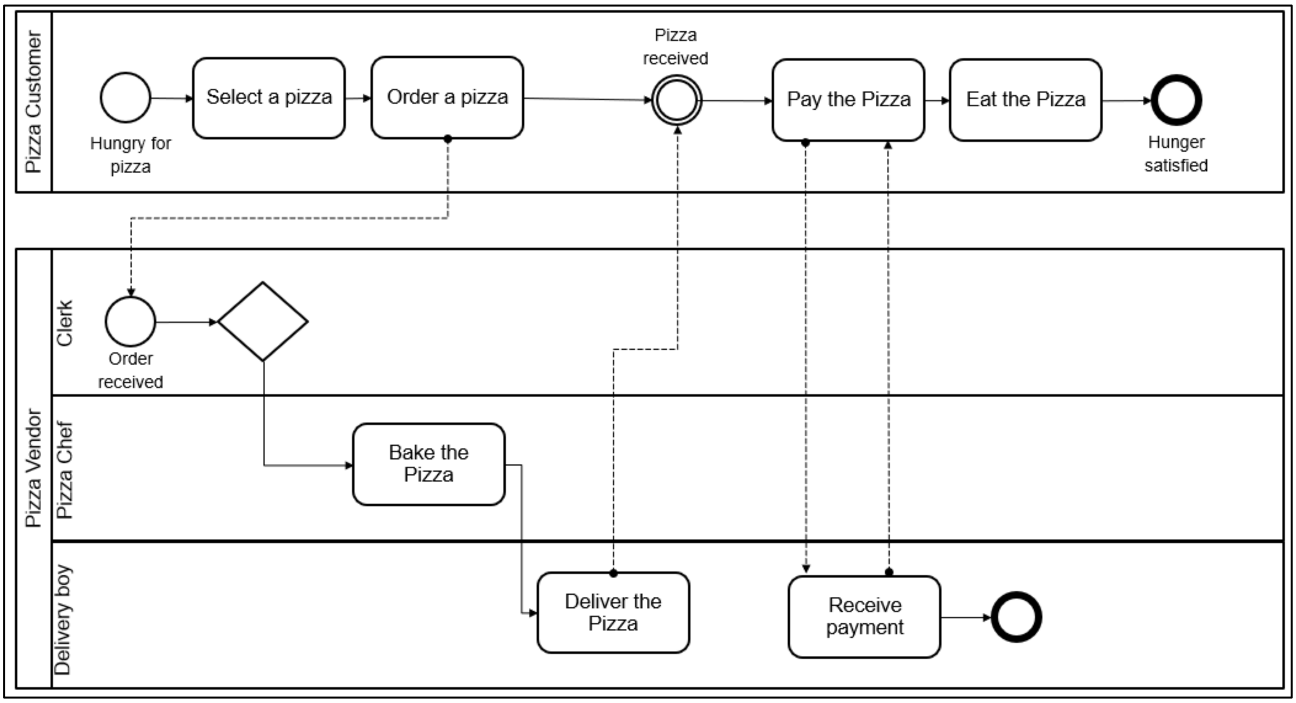

Figure 4. An example of a business process illustrated with BPMN (adapted from BPMN Quick Guide, 2nd Edition, 2017)

2.2.5 Relevance to the thesis

Business process management and transformation as a concept, applied to the field of internal business processes, provides the conceptual tools needed to:

- Map and analyze Metso's current maintenance service processes (RQ1).
- Identify and propose targeted process transformations to enable effective delivery of AI-based predictive maintenance recommendations (RQ2).

While the customer interface is not the primary focus, the ultimate aim is to ensure that internal process changes support the delivery of valuable, actionable, and trusted recommendations to customers (RQ3); moreover, customers will be represented as a critical touchpoint in the internal process map (RQ1 and RQ2).

2.3 Typical Business Processes in (Predictive) Maintenance Services

In industrial environments, the maintenance service delivery process has been evolving from reactive and schedule-based approaches toward more structured, data-driven practices enabled by predictive maintenance (PdM). A central difference is that PdM introduces continuous monitoring and algorithm-supported diagnosis, allowing maintenance decisions to be made before failures occur. The following process flow is constructed based on the recent relevant sources referenced below and describes a typical PdM-enabled maintenance workflow, starting from automated alert generation and extending through continuous improvement cycles. It reflects practices observed across manufacturing industries (Benhanifia, Ben Cheikh, Moura Oliveira, Valente & Lima 2025), multi-sector PdM deployments (Mallioris, Aivazidou & Bechtsis 2024), and mining operations (Robatto Simard, Gamache & Doyon-Poulin 2023), and aligns with implementation and process-design guidance from PdM implementation models such as PReMMa (Wagner & Hellingrath 2021) and Maintenance 4.0 frameworks (Werbińska-Wojciechowska & Winiarska 2023).

1. Continuous monitoring, alert generation, and automated maintenance suggestions

Predictive maintenance begins with continuous acquisition of asset condition data through sensors measuring parameters such as vibration, temperature, pressure, and electrical characteristics (Wagner & Hellingrath 2021). This data is processed using analytics and machine learning techniques to identify deviations from expected behavior (Achouch et al. 2022; Benhanifia et al. 2025). When anomalies are detected, the system generates alerts and may also provide machine-learning-driven recommendations on probable failure modes or remaining useful life. Several studies emphasize that this early identification capability differentiates PdM from condition-based monitoring and periodic maintenance, as it provides actionable predictions rather than simple threshold violations (Achouch et al. 2022; Mallioris, Aivazidou & Bechtsis 2024).

2. Alert reception and initial assessment

Once alerts are generated, they flow into centralized monitoring platforms, CMMS systems, OEM (original equipment manufacturer) portals, or shared dashboards depending on organizational structure. Studies show variability across industries: in mining, alerts typically reach internal maintenance personnel (Robatto et al. 2023); in manufacturing and mixed-sector environments, alerts may be shared between customers, OEMs, and service providers (Benhanifia et al. 2025; Mallioris, Aivazidou & Bechtsis 2024).

Maintenance engineers and reliability specialists perform an initial assessment to validate the alert by reviewing sensor data trends, environmental conditions, and past maintenance history (Achouch et al. 2022; Wagner & Hellingrath 2021). This stage ensures that false positives and sensor irregularities are filtered out, particularly in harsh operational conditions where noise and rapid load variations may affect measurements (Robatto et al. 2023).

3. Criticality-based decision: immediate action or predictive planning

A key decision point emerges after the initial assessment. The literature consistently highlights criticality as a decisive factor in determining the next steps:

- Critical issues: those posing safety risks, operational shutdowns, or imminent failure, trigger an expedited intervention. The criteria for classifying potential issues according to their criticality should be defined already at the stage of setting up the PdM system for a particular application (Wagner & Hellingrath 2021; Werbińska-Wojciechowska & Winiarska 2023). In mining operations, these correspond to the highest priority class (e.g., P1), requiring immediate attention and often bypassing routine planning cycles (Robatto et al. 2023).
- Non-critical issues follow a predictive planning logic, in which intervention timing aligns with estimated degradation rates, production schedules, and resource availability (Benhanifia et al. 2025; Mallioris, Aivazidou & Bechtsis 2024).

4. Work order creation and prioritization

Once the appropriate intervention path is chosen, a formal work order (WO) is created. The work order records asset details, failure indications, diagnostic insights, required competencies, spare parts, and safety considerations. Multiple studies confirm that structured documentation, whether through CMMS or standardized service report templates, is essential for linking predictive insights to operational execution (Sala, Pirola, Pezzotta, & Cavalieri 2022; Robatto et al. 2023). Work orders also serve as the mechanism for assigning priority, as observed clearly in mining operations where WO categories (e.g., P1–P3) regulate scheduling urgency (Robatto et al. 2023). Even in highly digital PdM environments, WO creation remains a necessary process step that ensures traceability, coordination, and data consistency (Sala at al. 2022).

5. Customer notification and coordination

For service providers operating externally or in hybrid service arrangements, customers must be informed about the alert outcome, recommended actions, and intervention timing. This communication step is crucial for ensuring access, safety compliance, and production alignment. In service delivery research, transparent communication with customers is identified as essential for coordinating resources and minimizing downtime (Sala et al. 2022). In mining operations, internal communication channels (e.g., between planners, supervisors, and operators) serve the same function, ensuring alignment across roles (Robatto et al. 2023).

6. Maintenance planning and scheduling

Planning integrates resource availability, technician competencies, spare parts, production schedules, and predicted failure timelines. PdM enhances this stage by enabling scheduling based on remaining useful life rather than fixed intervals (Benhanifia et al. 2025).

7. Execution of maintenance activities

Technicians execute the required tasks, such as inspections, repairs, component replacements or adjustments, based on the work order and available diagnostic information. Digital tools are often used to access historical machine data, alert details, and model outputs in real time. In PdM-enabled processes, technicians can perform more targeted interventions because diagnostic insights or automated recommendations identify likely root causes (Wagner & Hellingrath 2021). Environmental factors may influence execution complexity; for example, mining and aggregates environments impose challenges such as dust, humidity, and remote access requirements (Robatto et al. 2023). Execution concludes with verification that the asset is restored to functional condition.

8. Documentation and feedback

Upon completing the tasks, technicians document performed actions, parts used, measurements taken, and any additional findings. When the CMMS is present, the documentation is registered there. Multiple studies stress that structured documentation is vital for maintaining historical continuity and supporting future PdM model refinement (Sala et al. 2022; Benhanifia et al. 2025).

9. Data analysis and continuous improvement

The final step involves using operational and maintenance data to refine predictive models and maintenance policies. Studies highlight continuous improvement as a defining feature of PdM: model thresholds, feature sets, and decision rules are updated based on recent observations (Achouch et al. 2022; Mallioris, Aivazidou & Bechtsis 2024, Wagner & Hellingrath 2021). This iterative learning loop enhances predictive accuracy and supports strategic decisions such as improving component criticality rankings, optimizing spare parts management, and identifying systemic failure patterns (Sala et al. 2022; Benhanifia et al. 2025).

From the perspective of a maintenance service provider whose customers rely on external support for maintenance activities, the main touchpoints between the customer and the maintenance provider occur at several key stages of the process (Sala et al. 2022):

- Alert notification and initial context sharing, especially when alerts are visible on both the service provider’s and the customer’s dashboards, including a joint validation of the alert’s relevance.
- Coordination of intervention timing and site access, ensuring minimal disruption to production and alignment with operational or safety constraints.
- Feedback provision related to service quality, timing, communication, and the usability of digital tools, which supports iterative improvement processes.

These touchpoints help maintain transparency, align maintenance interventions with operational needs, and support continuous improvement in the service relationship.

Figure 5 (available in a bigger format in the Appendix 6) illustrates a logical BPMN representation of an example predictive maintenance service process, drafted based on the process summarized above. The diagram presents a high-level abstraction that is not grounded in any specific organizational or IT implementation, but instead focuses on decision logic, role responsibilities, and customer–service provider interaction. The process represents one alert life cycle and starts with automated condition monitoring and alert generation and continues through alert validation, criticality-based decision-making, customer coordination, maintenance execution, and continuous improvement through feedback into predictive models. The figure serves to visualize a typical predictive maintenance service process in a generalized form.

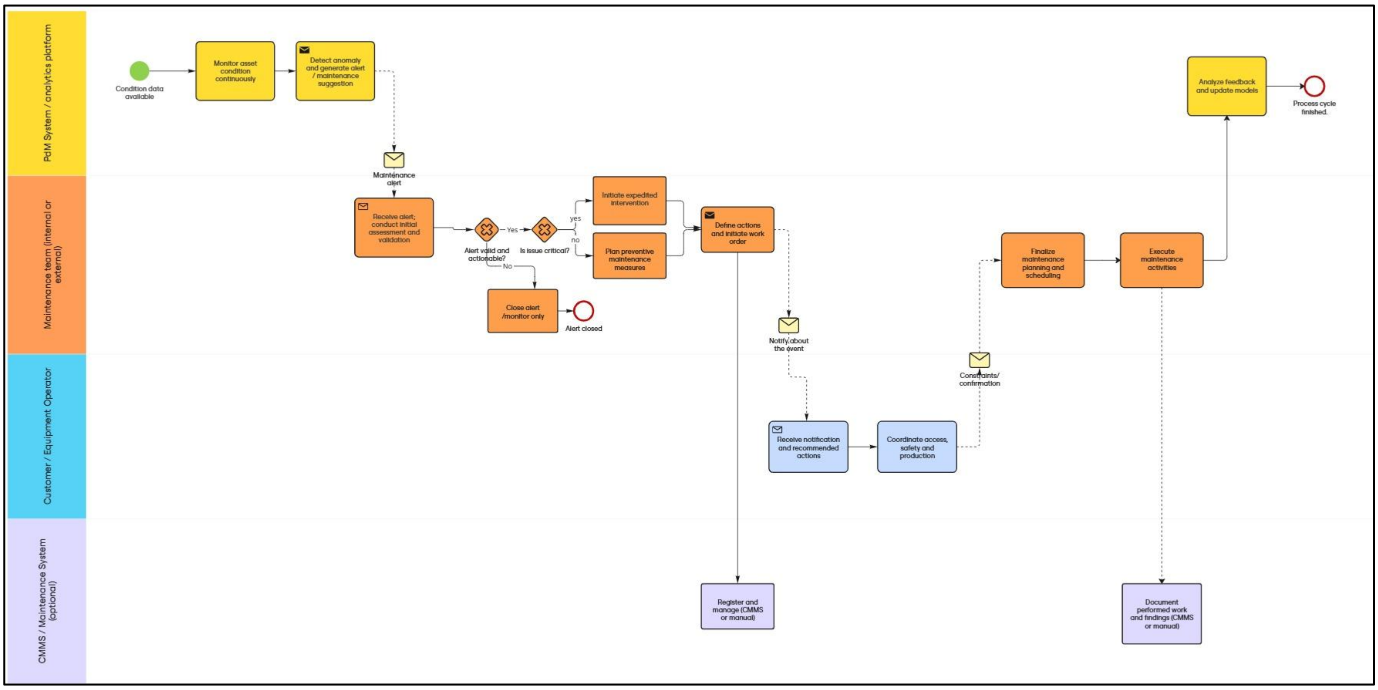

Figure 5. Logical BPMN model of a typical predictive maintenance service process

In summary, this section shows how predictive maintenance shifts the maintenance workflow from reactive responses to a proactive, data-driven process that begins at the moment an alert or automated recommendation is generated. These insights form the foundation for the implementation part of the Thesis, where the focus will be on identifying gaps in Metso's current processes and proposing concrete modifications needed to adopt similar PdM-enabled workflows.

2.4 Perceived value and usefulness of AI-aided Predictive Maintenance

2.4.1 Perceived value

The concept of *perceived value* is central for understanding what makes AI-aided predictive maintenance (PdM) services valuable to customers. In marketing and service research, perceived value is typically defined as the customer's overall assessment of the utility of a product or service, based on customer's perceptions of what is received and what is given away (Zeithaml 1988, 14; Sánchez-Fernández & Iniesta-Bonillo 2007, 428–429). Since stated by Zeithaml back in 1988, this definition has evolved from a simple price-quality "trade-off" to a multi-dimensional, context-dependent construct, comprising not only economic and functional benefits, such as costs optimization or production increase, but also risk reduction, trust, and user experience (Lapierre 2000; Sweeney & Soutar 2001; Ucar et al. 2024).

Recent meta-analysis by Blut et al. (2024) confirms that the most robust models of customer perceived value integrate both benefits, such as quality, convenience, and relational support, and sacrifices, such as price, effort, and risk (Blut et al. 2024). In B2B service settings (where AI-aided predictive maintenance services also belong), perceived value is mostly driven by the reliability and quality of the service, the efficiency and convenience it beings to customer operations, and the relationship strength between service provider and customer. At the same time, perceived value can be reduced by such factors as effort required from the customer, as well as any risks associated with the service. Even though the price component remains relevant, B2B customers tend to focus more on how the service impacts their overall business. Therefore, in this context, the maximum perceived value can be achieved by delivering high-quality, easy-to-use solutions, building strong and trust-base relationships and minimizing customer effort and risks (Blut et al. 2024, 520-521).

Grönroos & Voima (2013) further develop this concept by emphasizing that value is not created by the (service) provider alone but is co-created in use through interactions between the customer and the provider. From this perspective, perceived value emerges during the actual use of the service, rather than at the point of purchase (Grönroos & Voima 2013, 137–139). For AI-aided PdM, this means that value is realized when predictive recommendations are actually used to improve maintenance outcomes, and when the system fits the customer’s processes, needs, and environment.

2.4.2 Perceived usefulness

Perceived usefulness, a concept introduced in the Technology Acceptance Model (TAM), is also highly relevant for AI-aided PdM. It refers to the degree to which a user believes that using a system will enhance job performance (Davis 1989, 320). In PdM context, perceived usefulness is realized when predictive recommendations are not only accurate, but also actionable, timely, and well-integrated into existing workflows (Leukel et al. 2021, 93–94).

Recent research in AI-aided PdM highlights several key dimensions shaping perceived value and usefulness:

- Functional value refers to the expected operational benefits of PdM, such as improved reliability, reduced downtime, and optimized maintenance scheduling—objectives highlighted both in foundational PdM literature and recent AI-focused studies (Leukel et al. 2021, 87–88; Ucar et al. 2024, 2–4).
- Economic value: cost savings and resource efficiency remain important but are now complemented by the need for risk reduction and trustworthiness in AI recommendations (Ucar et al. 2024, 23–24; Bitam et al. 2025, 54–55).
- Transparency and explainability: the literature increasingly emphasize that explainability and transparency of AI models are essential for building user trust and acceptance, especially in industrial contexts where decisions can have significant operational consequences (Ucar et al. 2024, 23–24; Bitam et al. 2025, 54–55).
- Relational and experiential value: trust in the provider, ease of integration, and the ability for human operators to interact with and override AI recommendations are increasingly recognized as critical for realizing value in practice (Grönroos & Voima 2013, 139–140; Ucar et al. 2024, 28–29).

Additionally, human-centricity and stakeholder acceptance are critical for realizing the value of PdM in practice. Change management literature underscores the importance of clear communication, training, and participatory approaches to technology adoption (Long & Spurlock 2008, 2–3). Involving users in the design and rollout of PdM systems increases both perceived usefulness and overall acceptance, especially in environments where technical and non-technical stakeholders must collaborate.

2.4.3 Relevance to the Thesis

In summary, the perceived value and usefulness of AI-aided PdM are created by a combination of functional, economic, risk, and relational factors, as well as by the transparency, explainability, and integration of AI systems into existing process workflows.

The concepts directly support Research Question #3: *What would make AI-aided predictive maintenance services valuable to customers?* Understanding the concepts supports interpretation of customer expectations from PdM services, that I have collected through semi-structured interviews.

2.5 Summary of Theoretical Framework

This theoretical framework brings together the main concepts and research perspectives relevant to transforming business processes for AI-aided predictive maintenance in the industrial sector. The review started by outlining the evolution of maintenance approaches, highlighting how predictive maintenance leverages AI and data to improve equipment reliability and efficiency.

Next, the framework covered business process management (BPM) and transformation, emphasizing the importance of clear process mapping and the use of standards like BPMN for visualizing and improving workflows. The literature shows that concise, well-structured process models are essential for supporting digital transformation.

To complement these conceptual perspectives, typical business processes used in (predictive) maintenance services across industrial sectors were reviewed. The section described common stages such as continuous monitoring, alert validation, criticality-based decision-making, work order creation, customer coordination, and the feedback loops needed for continuous improvement. These process patterns illustrate how predictive maintenance is usually operationalized in practice and serve as a reference point for later comparison with Metso's current ways of working.

Finally, the section on perceived value and usefulness focused on what makes AI-aided predictive maintenance valuable to customers, especially in B2B service contexts. Recent research and meta-analyses underline that excellence (quality), convenience, and strong provider–customer relationships are key drivers of value, while excessive effort and perceived risks reduce it. The framework also highlighted the importance of transparency, explainability, and user involvement in the adoption of AI-based solutions.

Overall, these perspectives form a solid foundation for the empirical part of the thesis. They clarify the technical, organizational and customer-related factors that guide the analysis of Metso's current processes and support the development of recommendations for their future process design.

3 Methods and implementation

In this research, I focused on examining Metso’s current maintenance-related business processes and identifying how they should be adapted to enable the delivery of AI-aided predictive maintenance recommendations. In parallel, I examined how customers perceive such recommendations in terms of value, usefulness and practical applicability. Together, these two perspectives (internal processes and customer expectations) form the basis for developing proposals for a future process design that supports predictive maintenance delivery in a feasible and valuable way.

3.1 Research Approach

After reviewing the research approaches described in the book “Methods for Development Work” by Ojasalo, Moilanen, and Ritalahti (2022), the Case Study approach has been selected as the most suitable for this thesis.

The Case Study approach is appropriate because:

- The research aims to explore a real-world context: aggregates business area and its customers, in depth. Case Study enables a holistic examination of customer expectations, and process design within this bounded system.
- The research questions are primarily “what” and “how” questions, which align well with the exploratory and descriptive nature of Case Study research.
- Case Study supports the use of diverse data sources such as internal documentation and interviews with internal experts and customers, allowing triangulation and richer insights.
- The approach facilitates generating actionable recommendations grounded in real-world observations rather than hypothetical scenarios.

Comparison with other approaches:

- **Action research:** as per the approach definition, it is suitable for projects involving active implementation and iterative change cycles, whereas this thesis does not aim to implement changes during the research period. Therefore, Action Research is less relevant.
- **Constructive research:** this approach focuses on creating and validating a new construct (e.g., a tool or model) in practice. Although the thesis may propose a conceptual process model, the emphasis is on analysis and recommendations rather than full-scale implementation and validation.
- **Service design:** it emphasizes co-creation, iterative prototyping, and designing new service concepts. While valuable for innovative projects, this thesis prioritizes diagnostic

analysis and conceptual modeling rather than iterative design cycles, making Service Design less suitable for the defined objectives.

All in all, the Case Study approach is chosen because it enables an in-depth, context-specific analysis of technical requirements, customer value drivers, and process design considerations for AI-based predictive maintenance services. Compared to approaches such as Action Research, Constructive Research, and Service Design, Case Study provides the most appropriate framework for answering the research questions through qualitative methods and real-world data, ensuring findings are both credible and practically relevant.

3.2 Data Collection Methods

Data collection methods are generally categorized into qualitative and quantitative approaches.

Qualitative methods, commonly used in exploratory and explanatory research, help gain deep insights into complex phenomena (Flick 2014). The main techniques include:

- Interviews (structured, semi-structured, and unstructured): semi-structured interviews are especially valuable for their flexibility in following emerging themes.
- Observations: systematic observation of real-world settings allows researchers to understand contextual factors and interactions.
- Document analysis: reviewing existing documents supports triangulation and helps identify historical trends and patterns (Tuomi & Sarajärvi 2018, chapter 4).

Quantitative methods are used to collect and analyze numerical data to identify patterns, relationships, and causal effects (Saunders & Lewis 2023, chapter 12):

- Surveys: effective for gathering standardized data from larger populations.
- Statistical analysis: useful for testing hypotheses and drawing conclusions from empirical data.

In the context of my thesis, the following data sources were utilized:

- Existing literature related to current business processes.
- Internal experts with knowledge of the product and process areas.
- Customer representatives relevant to the offering under development.

The primary objectives of the data collection in the thesis were:

- To clarify the current business processes and understand how they compare with the processes required for the new customer offering. This comparison supported the identification of any necessary adjustments to existing processes.
- To assess the customers' overall attitude towards and expectations from AI-aided predictive maintenance services.

Based on these objectives, the main data collection methods in this thesis are qualitative. The following methods supported the research work within this thesis:

- Review of available literature related to the subject, and specifically to predictive maintenance and its business processes, to create a background for understanding the issue at hand, and to address the **research question #1.**
- Analysis of Metso's internal business process documentation on maintenance process (if exists), to address the research question #1.
- Semi-structured interviews with Metso's internal experts to support with mapping out the existing maintenance processes and obtaining general understanding of the requirements to turn it into a process that supports integrated AI-aided predictive maintenance services, to address the **research question #2.**
- Semi-structured and in-depth contextual interviews with customer representatives. This method was selected to allow for in-depth exploration of customer perceptions, which is essential for answering to address the **research question #3**. Moreover, this method facilitates natural, reflective conversation and to allows flexibility for new, unanticipated topics to emerge (Moilanen, Ojasalo & Ritalahti 2022, chapter. 4.2; Hirsjärvi & Hurme 2006, chapter 4.2.3). The number of interviews was limited by practical constraints, but the saturation principle was applied to ensure sufficient coverage.

3.3 Data Analysis Methods

3.3.1 Overview

This section describes how the collected data was analyzed to answer the research questions. The analytical approach was selected to ensure systematic, transparent and credible results, in line with qualitative research best practices (Flick 2014; Tuomi & Sarajärvi 2018). Because the thesis draws on two complementary data sources (customer interviews and internal process clarifications) two analytical methods were applied: thematic analysis for interview data and process-mapping analysis for internal business processes.

3.3.2 Thematic Analysis of Customer Interview Data

The customer interviews were analyzed using thematic analysis, which is well suited for identifying patterns in semi-structured qualitative data and synthesizing insights across participants. This method supports the exploratory nature of Research Question #3, which focuses on customer expectations and the perceived value of AI-aided predictive maintenance. Thematic analysis is also recommended in qualitative case studies where the aim is to collate perspectives and develop structured themes (Flick 2014).

The analysis process consisted of the following steps:

1. Transcript review.
   All interviews were recorded via Microsoft Teams and transcribed using Microsoft Copilot. Transcripts were checked and corrected manually to ensure accuracy.

2. Matching content to interview questions.
   Because the interviews were semi-structured, answers often appeared in varying order. To support comparison, responses were aligned back to the interview guide with the help of Copilot and validated manually.

3. Mapping answers into categories.
   Mapped answers were then categorized into meaningful units reflecting customer expectations, perceived value, trust drivers and adoption factors.

4. Manual review and synthesis.
   The final themes were reviewed manually to ensure completeness and consistency before being used in the Results chapter.

This process ensured a systematic and comparable interpretation of interview data while allowing new themes to emerge naturally.
A more detailed description of the interview data processing is provided in Section 3.5.3 Interview analysis steps.

3.3.3 Methods of Analysis of Metso’s Existing Processes

To analyze Metso’s existing business processes for providing maintenance services to end customers, I reviewed available internal documentation and conducted three informal, semi-structured interviews with internal stakeholders. The purpose of the analysis was to understand the current process logic, key steps, and system touchpoints, and to identify considerations relevant for integrating a predictive maintenance component.

The interview discussions with internal stakeholders were analyzed as follows:

1. **Transcript review.**
   Each discussion was recorded and automatically transcribed using Microsoft Copilot. The transcripts were then reviewed and corrected manually, following the same principles used in the analysis of customer interviews.

2. **Thematic grouping of responses.**
   The interview content was categorized into the following high-level themes:
   - description of the existing maintenance process,
   - considerations related to Metrics and the AI-aided predictive component,
   - views on what a future process could look like with predictive capabilities, and
   - other relevant remarks (limitations, challenges, and contextual information).
3. **Synthesis and validation.**
   Copilot was used to assist in grouping comments into topic areas, after which all outputs were manually checked for correctness and completeness. The resulting thematic summaries were used as the basis for drafting the as-is and to-be process descriptions.

Compared to customer interviews, the analysis of internal stakeholder discussions was more straightforward. As the participants were colleagues familiar with Metso's operations and terminology, discussions were more focused, and fewer clarifications were required. A more detailed description of the interview preparation and execution with internal stakeholders is provided in Section 3.4.

3.3.4 Data Management and Ethics

All data was handled in accordance with ethical research practices:

- Informed consent. All Customer interview participants received a research announcement (Appendix 2) and consent form (Appendix 3) and were informed of the study's purpose, voluntary participation and data-handling practices.
- Internal interview participants were informed in advance about the purpose of the discussion through a written message (email and calendar invite) and provided their consent to record the meeting for transcription purposes. A formal research announcement and consent form were not required, as these discussions were conducted as part of internal, work-related investigations between colleagues.
- Secure data storage. All collected data were stored in Metso's internal OneDrive with restricted access. Transcripts were anonymised to protect participant identities.
- Data retention and deletion. The data were used solely for this thesis. After the thesis is assessed and finalized, all personal and identifiable data, including recordings, will be deleted

unless otherwise agreed with participants and the commissioning organization. Anonymized material may be retained if required by Haaga-Helia.

- Use of AI tools. Microsoft Copilot was used for transcription, content structuring and coding assistance. All outputs were manually validated to ensure accuracy and avoid misinterpretation.

These practices comply with GDPR and Haaga-Helia's research ethics policies and support transparency, reliability and integrity in the research process.

3.4 Investigation of Metso's existing maintenance business processes in Aggregates

The investigation began with a review of Metso's internal business process portal to identify any existing process descriptions related to maintenance service provision for aggregates customers. This search revealed that no such processes had been formally documented in the portal. Discussions with relevant stakeholders confirmed the absence of an up-to-date company-level process description, although some colleagues shared older materials dating back to the period before the Metso–Outotec merger in 2020.

Given the lack of formal documentation, the primary source for understanding the current "as-s" maintenance process had to be discussions with internal stakeholders directly involved in customer maintenance services. The investigation therefore proceeded through the following steps.

1. **Identification of internal stakeholders**
   In consultation with my thesis commissioner, I identified three colleagues with complementary expertise:

    - **Sales/ Account Manager (SAM)** for Aggregates customers in Finland, responsible for customer relationships and day-to-day operations between Metso and its customers. The purpose of this discussion was to understand the practical workflow of maintenance-related interactions with customers and gather views on future process needs when a predictive component is added.
    - **Field Service Manager (FSM)** for Aggregates in Finland, responsible for coordinating maintenance and repair activities delivered by Metso's service experts. The aim was to gain first-hand insight into how maintenance services are currently organized operationally.
    - **Senior Digital Services Specialist (SDSS)**, responsible for digital service development in Aggregates, and subject matter expert on Metso Metrics and on the AI-

aided predictive maintenance pilot. This discussion focused on understanding current Metrics monitoring logic, alert flows, and what additional functionality the AI component introduces.

2. **Preparation for the discussions.**
   To ensure that all critical topics were covered consistently, I prepared a list of guiding questions related to:
   a. existing contractual arrangements concerning maintenance services,
   b. the current maintenance service process,
   c. condition monitoring and alerts, including Metrics workflows, and
   d. views on how a future process might look when a predictive component is integrated.
   e. The guiding list of questions is provided in Appendix 7.

   The final set of questions was tailored to each interviewee's role, so not all questions were asked in every discussion.

3. **Conducting the discussions**

The interviews were conducted via Microsoft Teams and lasted approximately one hour each:

- Sales/ Account Manager: 17.2.2026
- Field Service Manager: 19.2.2026
- Senior Digital Services Specialist: 25.2.2026

All discussions were informal, open, and collaborative. Participants were willing to share their knowledge, and they clarified when certain aspects fell outside their area of expertise. The semi-structured format also made it possible to explore relevant additional topics that emerged naturally during the conversations.

4. **Processing of the interview discussions**

The processing of internal discussions followed a streamlined version of the customer interview analysis:

- Transcripts were reviewed to correct recognition errors (e.g., misheard terminology or occasional incorrect substitutions).

- Answers were mapped to the guiding questions to support structured comparison. As the conversations were naturally flowing, this step helped align the insights with the intended thematic categories.

- Additional categories were created when discussions extended beyond the predefined question set.

- Copilot supported the structuring and summarization of content, after which all outputs were manually validated to ensure accuracy and preserve the original meaning.

The categorized summaries were consolidated into an Excel table for ease of reference and comparison across the interviewed stakeholders.

5. **Outlining the as-is and to-be maintenance business process maps**

Once the interview insights were synthesized, they formed the foundation for drafting the “as-is” process description and outlining potential “to-be” processes incorporating AI-aided predictive maintenance. The narrative descriptions from stakeholders were translated into structured BPMN-compliant process steps.

Draft process maps were then reviewed by the involved stakeholders via a shared Microsoft Teams space using live commenting. After minor refinements and clarifications, the high-level process descriptions were finalized. A simplified visual overview of the mapping workflow is presented in Figure 6.

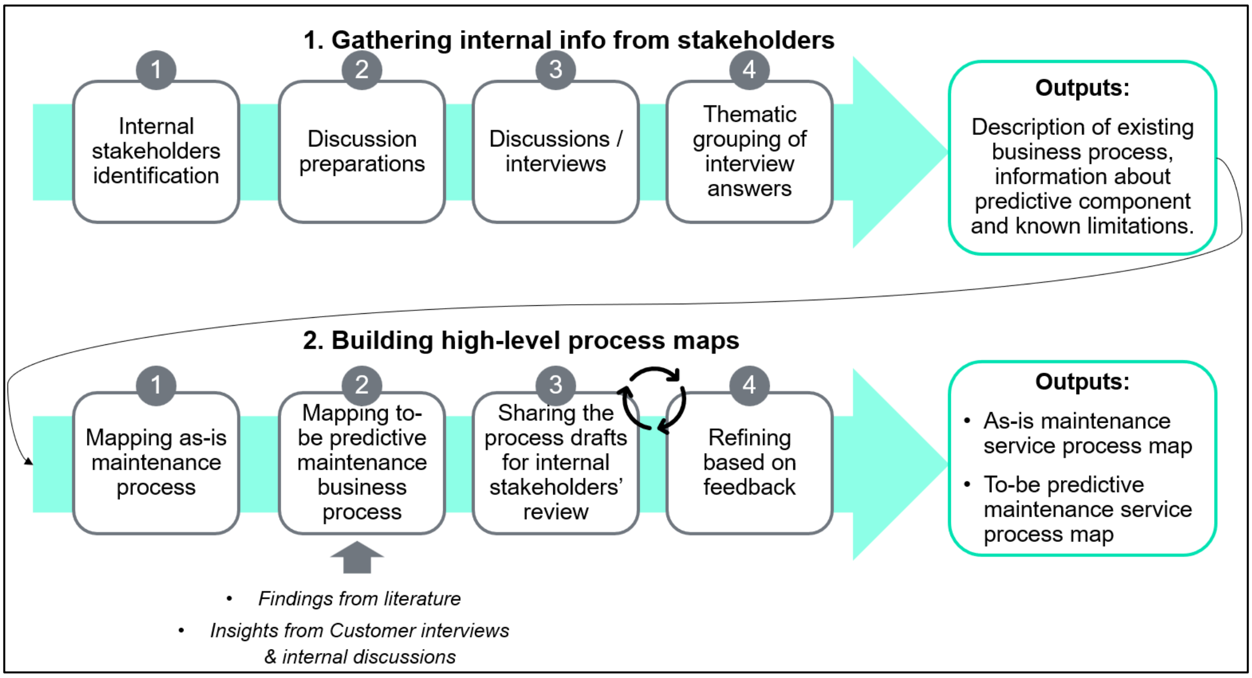

Figure 6. Business process map creation process.

3.5 Customer Interviews: preparation, execution and analysis

This section describes the steps I took to prepare for customer interviews, how I executed them, and how I analyzed the data and outcomes.

3.5.1 Preparation for interviews

At the preparation stage, I had to answer two major questions:
1) What do we need to find out from our customers (interview scope)?
2) Which customers should be interviewed?
The first question was critical for creating the interview questions and structure, while the second helped determine which customer groups would be most relevant for this study.

To develop these questions further, I had several discussions with the thesis commissioner (who also leads the team developing the AI-aided predictive maintenance solution) and one of the Sales/ Account Managers (SAM). For the interview scope ("What do we need to find out?"), the general line, discussed with the thesis commissioner, was to understand whether our customers are ready and willing to use AI-aided predictive maintenance services, specifically, whether they would apply automatic recommendations generated by the system to their own operations. Since willingness and readiness are quite subjective and broad concepts, we needed to develop a list of questions that would help us get relevant insights.

To do this, I used an initial set of questions discussed with my commissioner as a prompt to Copilot AI. After several iterations of prompting, analyzing, and refining, I had an initial interview question list ready for internal review. The list consisted of the following groups of questions:

- Introductory/opening questions: introducing ourselves and the research background.
- Interviewee's company background and maintenance context.
- Usage of Computerized Maintenance Management Systems (CMMS) and digital infrastructure (whether any digital solutions are used for planning and tracking maintenance work).
- Readiness to share production and equipment data, or any concerns related to it.
- Critical incident exploration: questions to discuss real-world maintenance incidents, aiming to set the scene for further discussion of potential AI-aided predictive maintenance solutions and to prompt the interviewee's imagination.
- Willingness to act on (AI-based) maintenance recommendations: questions to understand previous experience with similar solutions, what kinds of recommendations they would like

to receive, what would make them trust or distrust the recommendations, and preferred channels for receiving them.

- General questions about predictive maintenance solutions: what would make them valuable and stand out compared to others.
- General questions about customer expectations, challenges, and future outlook related to the topic, as well as openness to participating in a potential pilot project.
- Wrapping up.

I had the question list reviewed by colleagues with relevant knowledge and experience: my thesis commissioner, the SAM, and the Head of Technology and Digital Business. After a couple of minor tweaks, the final version of the interview questions was ready. We decided to keep the list open for changes, in case the first interviews revealed a need for adjustments. Indeed, after the first interview, we added a couple more questions to the "background and maintenance context" set, and the final list of questions was formed (see appendix 1).

As for the "Which customers should be interviewed?" question, it was multidimensional and required defining selection criteria:

- Customer type: whether to focus on end customers, distributors, or both.
- Customer segment: whether to focus on quarry operator customers (long-term, fixed-location sites with high-volume production), contractor customers (mobile-focused business, short-term projects), or both.
- Technical readiness: whether it is important that the customer is using Metrics (Metso's digital fleet and process monitoring solution that provides real-time data and analytics on crushing and screening equipment to optimize performance, maintenance and uptime) or has a CMMS.
- Location: whether to focus on the Nordics region, only Finland, or have no limits in this regard.

After reviewing the options with the thesis commissioner, and to keep the results relevant and the thesis scope manageable, the decision on the target audience was as follows:

- Customer type: end customers.
- Customer segment: both quarry and contractor customers.

- Technical readiness: customers already using Metrics (or those who have used it before), regardless of CMMS usage.
- Location: Finland, preferably close to the Capital Area.

Sales/ Account Managers were asked to choose customers for interviewing based on these criteria, as well as their general openness to discussions, according to the Account Managers’ experience.

As a result, the final list of customers for interviews was formed (table 2).

Table 2. Summary of selected customers for interview (description level)

	Description	Size	Segment
Customer 1	Large Nordic construction and civil engineering group operating across multiple countries; offers building, infrastructure, asphalt, concrete, and aggregates.	Large enterprise.	Quarry
Customer 2	Regional aggregates supplier with decades of history, providing crushed rock, gravel, and sand for construction; strong sustainability focus.	Mid-size.	Quarry
Customer 3	Leading producer of concrete products and rock-based building materials; covers aggregates, ready-mix concrete, and recycling; part of a global group.	Large enterprise.	Quarry
Customer 4	Specialist in rock blasting and crushing; supplies certified aggregates via crushing plants and contracting services.	Small.	Contractor
Customer 5	Mobile crushing contractor with long history; delivers aggregates and rock crushing services across multiple regions.	Small.	Contractor
Customer 6	Earthworks and site-preparation contractor performing groundworks and related services for infrastructure projects.	Small.	Contractor
Customer 7	Family-owned aggregates producer supplying rock aggregates, sand,	Small.	Contractor

	and special products across regional markets.		
Customer 8	Provider of aggregate sales, crushing, and transport services; supplies rock, gravel, sand, and soil for infrastructure and building projects.	Small.	Contractor

As it turned out in discussions with the SAM, the interviews were to be conducted in Finnish to enable a more natural and open dialogue. This posed a challenge for me, since my Finnish, although quite good, is not fully fluent for technical discussions.

To prepare for this, I took the following steps:

- Translated the list of questions from English into Finnish with the help of Copilot AI; the translation was then validated by my thesis commissioner.
- Created an English–Finnish vocabulary (Appendix 4) of relevant technical terms to better prepare for the interviews.
- Created a one-slide summary of the questions as an aid for the interviews.
- Filled out the research announcement and consent form (Haaga-Helia templates) and translated them into Finnish using Copilot AI; the translations were validated by my thesis commissioner.

The semi-structured interview setup was as follows:

- Language: Finnish.
- Duration: interviewees were informed that the interview would take approximately 60–90 minutes.
- Organizing interviews: arranged via Sales/ Account Managers responsible for the selected customers, with scheduling managed in a shared Excel table.
- Interview mode: face-to-face or via Microsoft Teams.
- Number of interviews: the plan was to conduct eight interviews and monitor for saturation.

3.5.2 Execution of interviews

The interviews were conducted between September 29th and November 12th, 2025. Initially, we preferred face-to-face interviews, but it turned out to be easier to arrange them via Teams. One planned face-to-face interview had to be cancelled twice due to unforeseen events with the customer and was eventually conducted via Teams. Interview conditions varied: some took place in offices, others in a fuel station café, a construction trailer, or even a car, as most interviews happened during the normal working day and interviewees participated during their work breaks.

In practice, the interviews lasted between 35 and 70 minutes (table 3), depending on how talkative the interviewees were. Some kept their answers short and to the point, while others wanted to share more ideas, side stories, or even give praise to Metso and its employees’ expertise. Even when answers were concise, the willingness to talk and openness were always present, and the interviews were conducted in a good spirit.

Thanks to the semi-structured format, the interviews often felt more like conversations than strict “question–answer” sessions, sometimes enlivened by a bit of humor. I adjusted the interview structure on the fly when I noticed that some topics were irrelevant for a particular customer, but I always made sure to get the most out of each conversation. In almost all eight interviews, my thesis commissioner and the SAM were present, which added a nice dynamic by allowing them to add questions or comments when appropriate, helping to steer the discussion in the right direction.

Regarding the number of interviews: as mentioned, we planned eight and agreed to monitor for saturation. After the first two or three interviews, we noticed that we were not getting much new or surprising information but decided to proceed with all eight to ensure we covered different customer types and validated the saturation point.

Table 3. Summary of conducted customer interviews

Customer #	Interview conducted date	Duration	Format
Customer 1	29.9.2025, 14:00	1 h 6 m	Face-to-face
Customer 2	30.9.2025, 12:00	55 m	MS Teams call
Customer 3	9.10.2025, 12:00	58 m	MS Teams call
Customer 4	14.10.2025, 13:00	42 m	MS Teams call
Customer 5	14.10.2025, 15:00	48 m	MS Teams call
Customer 6	14.10.2025, 17:00	40 m	MS Teams call
Customer 7	6.11.2025, 12:00	32 m	MS Teams call
Customer 8	12.11.2025, 12:00	42 m	MS Teams call

3.5.3 Interview analysis steps

After completing the interviews, I processed the data systematically to make the answers comparable and interpretable. The steps were as follows:

Step 1: transcription

Each interview was recorded using Microsoft Teams' transcription feature, including the face-to-face interview with Customer 1. After the interviews, I had meeting recordings, transcripts, and some notes on printed one-sliders with interview questions.

I checked and corrected transcriptions for wrongly recognized words by listening to the recordings while skimming the transcripts. Whenever errors occurred, I corrected them manually. For the first interview, I also manually assigned speakers to each line (two customers, thesis commissioner, and myself).

Step 2: text cleanup

I "brushed up" the transcribed content by turning raw speech into smooth sentences and removing filler words and repetitions. This was done with the help of Copilot AI within Metso's working environment using the following prompt:

"This is a customer interview for my master's thesis. Interview participants: from Metso – me (Marina) and [thesis commissioner's name]; from the customer's side: [customer name(s)]. Take this meeting recording transcript [link] and turn the live speech with its filler words and poor flow into a readable and understandable text. Don't imagine any meaning that is not there."

After Copilot processed the text, I validated the output to ensure the meaning and logic remained unchanged. The quality was high: filler words were removed, and answers were clear and concise while preserving the original meaning.

Step 3: matching answers to questions

Since the interviews were semi-structured, questions were often discussed in a different order or level of detail. To enable better comparison, I matched answers back to the original question list using Copilot AI with this prompt:

"Match the customer's answers given in the transcript [link] to the questions listed in this file [link]. If there was a suitable answer, provide it. If not, indicate that it was not mentioned. The interview is semi-structured, so we didn't always follow the logic of the questions. Also, if there is a good direct quote from the customer, take it from the original transcript [link]."

I then validated the mapping manually to ensure accuracy and corrected any misattributions. After validation, I copied the matched answers into a summary Excel table that consolidated responses from all customers.

Step 4: categorization of insights

Using the summary Excel, I created categorized themes with the help of Copilot AI. The categories included:

- User-friendliness.
- Alarms and notifications: content and delivery channels.
- Solution functionalities.
- Details on actionable recommendations, trust drivers, differentiating features, perceived value, ideal solution characteristics, adoption obstacles, and support/enablers.
- General comments: gratitude, praise, and improvement suggestions.

Step 5: manual review

Finally, I read through the Excel summary to cross-check any additional information or patterns that Copilot might have missed and added them manually. This ensured completeness and accuracy of the insights.

Anonymization:

For internal analysis, customer names were retained to understand the context and link responses to specific cases. However, before including any material in the thesis, all replies were anonymized to ensure confidentiality. The thesis only presents anonymized data, in compliance with ethical guidelines.

3.6 Process of recommendations development for transitioning to AI-aided PdM

The recommendations presented later in this thesis (Section 4.4.4.) were developed through a synthesis of three complementary data sources: (1) findings from relevant academic and professional literature on predictive maintenance processes, (2) insights gained from internal expert discussions about Metso's current and potential future maintenance processes, and (3) customer interview results. The goal was to create recommendations that are both grounded in established practices and informed by empirical evidence from the case context.

The development process followed the steps below.

1. Literature-based grounding

The starting point was the literature review presented in Section 2.3., which describes typical predictive maintenance workflows, key process components, and implementation considerations reported across industrial sectors. This provided a reference model for understanding what predictive maintenance typically requires and which process elements need to be in place before predictive recommendations can be delivered reliably.

2. Internal process insights

Next, the findings from the internal stakeholder discussions (Section 4.1.) were reviewed to identify gaps between Metso's existing reactive maintenance processes and typical predictive maintenance processes found in the literature. The internal insights helped clarify where the current workflow would need adjustments, particularly regarding alert handling, validation, resource requirements, and customer communication practices.

3. Customer-driven requirements

The third input came from the customer interview analysis (Section 4.2.). Customers' expectations, value drivers, trust factors, and adoption concerns were categorized and reviewed to understand what the predictive maintenance process must support from the end-user perspective. These insights ensured that the recommendations reflect not only internal feasibility, but also customer needs and practical constraints.

4. Integrative synthesis

After analyzing these three inputs separately, the findings were combined through integrative synthesis. The synthesis focused on identifying common themes across the sources and resolving differences between theoretical recommendations, internal operational views, and customer expectations. For example, literature emphasizes continuous improvement loops, internal stakeholders highlighted the need for validation and practical feasibility, while customers highlighted trust, usability, and correct timing of recommendations. The integrative step translated these perspectives into coherent, generalizable recommendations.

5. Structuring and final refinement

Finally, the emerging recommendations were organized into five thematic categories: (1) technical and system-level requirements, (2) process transformation requirements, (3) organizational capability requirements, (4) customer-facing and service design requirements, and (5) deployment and scalability considerations. These categories were chosen because they reflect the areas where changes are needed when moving from reactive to predictive maintenance. The recommendations were refined to avoid company-specific terminology when possible, making them applicable to both the commissioning organization and similar industrial service providers.

In summary, the recommendations in Section 4.4.4. represent a structured combination of theoretical insights, internal operational knowledge, and customer expectations. This process ensures that the proposed direction for transitioning to AI-aided predictive maintenance is both evidence-based and aligned with practical realities.

4 Results

In this chapter, I present the outcomes of the customer interviews, the outcomes of existing business processes investigation, and the suggestions on high-level business processes for delivering predictive maintenance services.

4.1 Findings from internal process investigations

As was briefly mentioned in the previous section 3.4, the investigation showed that there are currently no specific process descriptions registered in the company's official process portal, that would focus on delivering maintenance services to Metso's customers in Aggregates sector. Therefore, the source of truth, as far as the current processes are concerned, were discussions with the internal subject matter experts – Sales/ Account Manager (SAM) and Field Service Manager (FSM), as well as Senior Digital Services Specialist (SDSS) for specifics of Metso Metrics and potential of AI-aided solution.

The findings are categorized into four groups:

1) existing contractual agreements related to maintenance,
2) current maintenance service process,
3) condition monitoring and alerts as of today, and
4) views on a future process with an integrated predictive component.

It is worth mentioning that, due to the research scope limitations, the investigations have been narrowed down to Nordics/ Finland region when it comes to the existing maintenance processes with end customers. Despite this limitation, it is a valid format, because it allows to outline the matter-of-fact processes as the starting point (since they are on such a high level that keeps them scalable to other regions).

Below, I have outlined summarized findings per each topic.

4.1.1 Existing contractual agreements related to maintenance

Across all three interviews, it became evident that Metso's Aggregates business does not typically operate through formal maintenance contracts with end customers. Both the SAM and the FSM emphasized that maintenance support for Aggregates equipment is generally provided on a case-by-case basis. The main exceptions relate to warranty coverage and the Extended Protection Service (EPS) available for new equipment, including several scheduled inspections at certain operating intervals, during which Metso proactively identifies issues that fall under the warranty scope.

Outside warranty or EPS, all maintenance work is typically handled reactively and invoiced individually.

4.1.2 Current maintenance process

All three interviewees described the current maintenance service process as predominantly reactive, initiated when a customer reports a problem. The FSM characterized daily operations metaphorically as “*being like a fire station*”, referring to the immediate response required when customers call.

Below is a step-by-step description of the existing maintenance process, as described by the internal stakeholders.

1. **Customer initiation**
   The process normally starts when a customer contacts Field Service through a dedicated phone number or directly reaches out to a known technician due to long-standing personal connections. Customers usually contact Metso’s Field Service department for support with electrical and automation faults, while mechanical maintenance is typically carried out by customers themselves or with third-party services.
2. **Initial triage and remote support**
   Technicians or the FSM provide remote assistance by phone. While no remote-control actions can be executed, technicians can offer immediate recommendations, including temporarily disabling non-critical functions to keep production running. This ensures continuity until a full repair can be completed later.

   When the machine is connected to Metso Metrics, technicians check Metrics indicators, which often helps pinpoint the issue.
   Sometimes the issue is resolved after remote assistance. If not, the workflow continues to the next point.
3. **Decision on site visit**
   If an on-site assessment is necessary, the visiting practicalities are agreed with the customer, and technician(s) typically depart at earliest convenience.
4. **Work order creation**
   Service Order is created into the Enterprise Resource Planning and Field Service Management systems.
5. **On-site repair**
   Commissioned technician(s) perform the required repair works.

The typical process workflow for the existing maintenance process described above is depicted on the diagram below (Figure 7, available in a bigger size in Appendix 8).

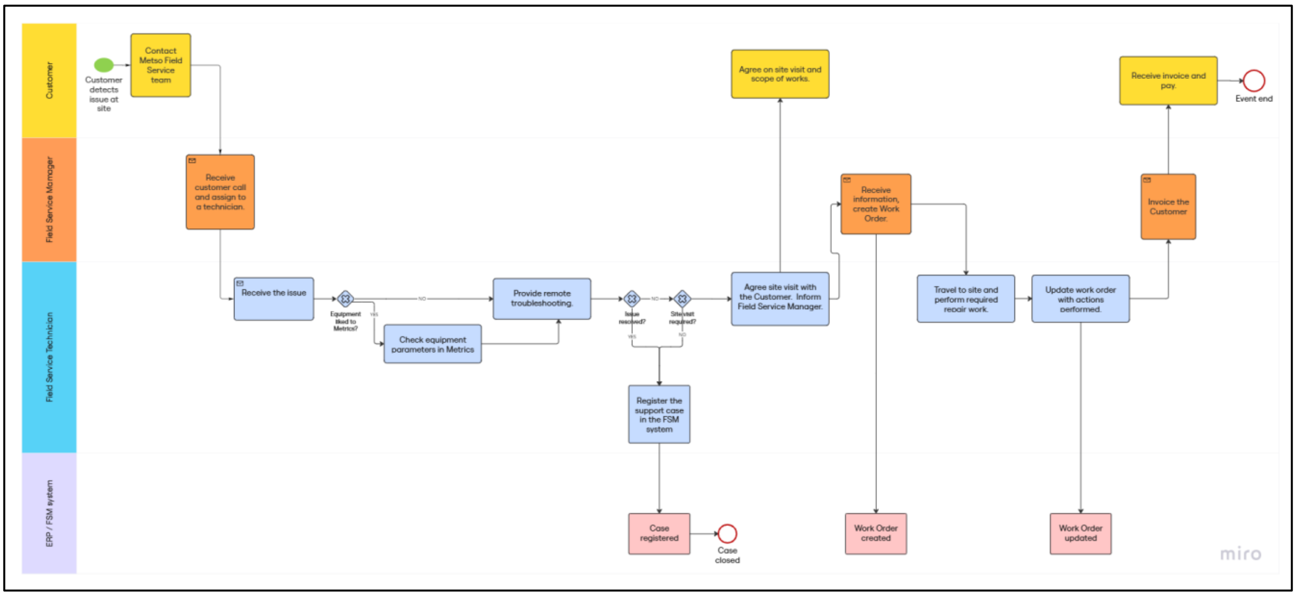

Figure 7. Current process for maintenance services provision in Metso Aggregates, Finland

4.1.3 Condition monitoring and alerts, as-is today

The Senior Digital Services Specialist (SDSS) provided a detailed overview of Metrics functionalities. Operational data (e.g., pressures, revolutions per minute, power consumption, oil temperatures, engine load, fuel consumption, and various control parameters) is collected via the IC automation system and transmitted through an onboard modem to the Metrics cloud platform. Both Metso personnel and customers see essentially the same user interface, example of which is displayed on Figure 8.

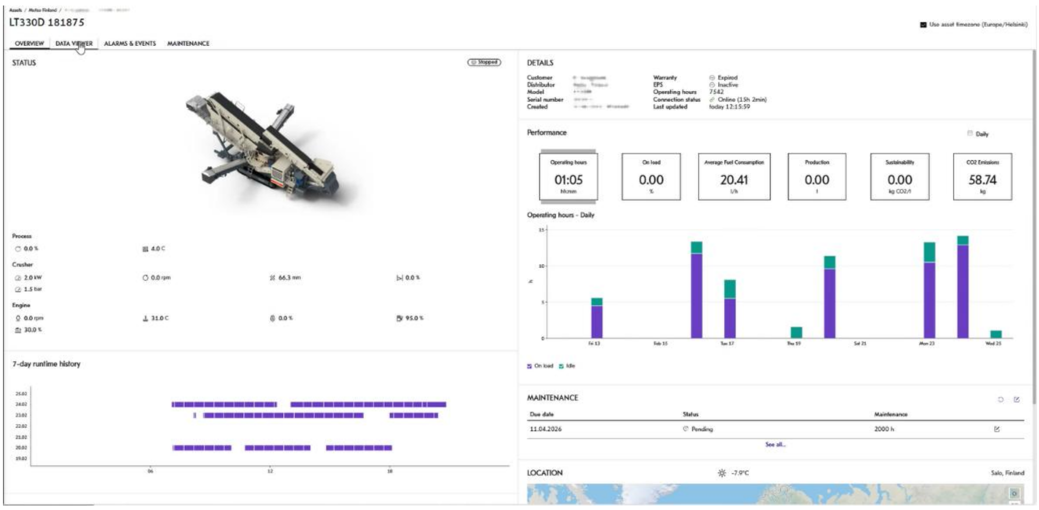

Figure 8. A screenshot of Metso Metrics interface

Metrics also contains maintenance schedules derived from official machine manuals. While customers can manually log additional maintenance events, the SDSS noted this feature is “not so much used.”

Alerts displayed in Metrics originate exclusively from the machine’s automation system. Metrics does not generate or interpret alerts; it only presents them.

There is no classification logic to suppress repetitive alarms or distinguish between active machine operation and downtime. Furthermore, Metrics does not offer mechanisms to validate or close alerts following troubleshooting. Although email or SMS notifications exist, their adoption among users remains limited.

All interviewees agreed that Metrics is currently used reactively. None of the teams continuously monitor alerts. The SAM explicitly stated, *“we are not following Metrics… we don’t have any specific personnel who’d be following Metrics.”*

The FSM highlighted several operational limitations:

- Many false or benign alerts occur (e.g., during cold starts or voltage drops), requiring interpretation by experienced technicians.
- If not all equipment in a process chain is connected to Metrics, it reduces visibility into root-cause relationships.
- “Machine cards” and configuration documentation are often inaccurate or outdated, hindering reliable analysis.

4.1.4 Views on a future process with an integrated predictive component

At the moment, Metso is piloting an AI-aided predictive maintenance solution, *Palantir*, which is designed to complement Metso Metrics and enable condition-based monitoring. Metrics provides raw operational data, while Palantir analyzes this data using expert-defined logic. These algorithms are developed jointly with Field Service technicians and Technical Support to identify anomalies such as hydraulic leaks or abnormal pressure cycles.

Alerts generated by Palantir are enriched with recommended maintenance actions and lists of related spare parts. They can also be forwarded to Salesforce and displayed to end customers through the new digital portal. Currently, all Palantir-generated alerts undergo manual validation by Metso experts before being shown to customers. As the SDSS noted, *“we are only sending valid* *alerts to the portal."* Technicians have also validated several alerts directly with customers during the ongoing pilot activities.

Palantir includes a feedback mechanism that allows validators, and later, customers, to classify alerts as valid, invalid, or irrelevant. Interviewees emphasized that, for the solution to operate effectively and deliver benefits to both end customers and Metso, a dedicated role or team would eventually be needed to:

- review predictive alerts,
- contact customers proactively,
- coordinate corrective actions with Field Service, and, optionally,
- forward parts-related leads to Sales.

The SDSS highlighted a longer-term ambition to reach a fully automated ("autopilot") state where alerts no longer require human validation once their accuracy is sufficiently proven.

According to the internal stakeholders, a future maintenance process with an embedded predictive component could follow the sequence below:

1. Continuous data flow from equipment → Metrics → Palantir, where AI analyzes patterns.
2. Palantir identifies anomalies and determines criticality levels.
3. An alert is created in Palantir.
4. The alert is validated by a Metso technician or, in the future, automatically.
    - **If valid:** the alert is pushed to the customer portal and communicated via the appropriate notification channels. Metso may also:
      • Contact the customer to schedule Field Service or provide phone assistance,
      • Forward a lead to spare parts sales (manually or automatically).
    - **If invalid:** the alert is closed, and feedback is returned to the system for learning.
5. The customer reviews the alert and examines the recommended actions and required spare parts.
6. The customer may:
   • Order parts directly through the portal,

- Schedule maintenance, or
- Provide feedback to further refine predictive logic.

This envisioned process closely follows the high-level AI-aided predictive maintenance model introduced in Section 2.3 and reinforced by topic-specific literature. The FSM identified several constraints that affect the feasibility of such a solution in Aggregates operations:

- **Lead time for wear parts:** in some cases, predictive alerts must be issued months in advance to be actionable, as repairs may depend on long-lead components.
- **High process variability:** frequent changes in material characteristics, process configurations, and operating modes make pattern learning more challenging than in Mining applications.
- **Incomplete connectivity:** gaps in equipment coverage can limit the reliability of predictive insights.

These insights provide a strong foundation for mapping a realistic future business process with an integrated AI-aided predictive maintenance component. They also highlight potential challenges and considerations, including resource requirements and technical constraints, which must be addressed during development. When combined with customer interview findings presented in Section 4.2, the internal perspectives help ensure that both operational feasibility and customer expectations inform the redesign of processes and the evaluation of future technical solutions.

4.2 Insights from Customer Interviews

The customer interviews provided a nuanced understanding of how maintenance is organized across different aggregates operators, and how AI-aided predictive maintenance could fit into their daily work. Although the companies interviewed varied in size, technical maturity and operational context, the discussions revealed several consistent patterns that create a meaningful background for interpreting customer expectations later in this chapter. Throughout all eight interviews the participants represented roles with direct responsibility for equipment condition, from operational- and maintenance managers to site-level supervisors and owner-operators. Their inputs bring in practical day-to-day experience particularly with crushers and screens, as well as responsibility for planning and executing maintenance activities.

I have categorized the results of the interviews into the following groups:

1. Background information, such as roles of interviewees, customer company's size of the fleet related to our scope of work (crushers, screens), usage of a CMMS or other digital tools for maintenance.
2. Features of a PdM solution
3. Value-driving features and customers' vision of an ideal PdM solution
4. Factors impacting trust (and distrust) towards PdM solutions
5. Factors impacting adoption of PdM solutions
6. Summary of customer expectations and value drivers.

4.2.1 Background information

Most interviewees reported using Metso equipment to some extent, though machine fleets were typically mixed. Digitalization levels also varied: some organizations used formal CMMS solutions or integrated fleet-monitoring tools, while others relied mainly on manual tracking methods and experiential knowledge. Together, these interviews provide a good overview of maintenance practices in the aggregates sector and help contextualize what customers value, expect and require from potential AI-aided predictive maintenance recommendation services.

The summary of the interviewee roles, number of crushing/screening equipment in use and Metso's share in it (sometimes approximate, we need these only for understanding the context of the scale of the firm), as well as whether a CMMS (Computerized Maintenance Management System) is in use, is represented in the table below.

Table 4. Summary of customers' background

Interviewee	Roles represented (as stated by interviewees)	Metso equipment in use?	CMMS / digital tools for maintenance
Customer 1	Person in charge of assets & maintenance for the aggregates business; regional maintenance manager who also oversees mechanical design needs and supervises electricians.	Yes	Yes: Dynamics 365 (earlier was SAP); also uses OEM telematics (incl. Metrics) and PowerBI for reporting.
Customer 2	Production director (crushing); maintenance manager (runs own workshop); person responsible for electrical maintenance.	Yes	Yes, CMMS in use (Arrow Novi).
Customer 3	Decides on maintenance & spare parts purchases; approves larger procurements.	Yes	No CMMS.

Customer 4	Site foreman responsible for maintenance; plans major overhauls/maintenance windows and spares.	Yes	Yes, a CMMS by SKF.
Customer 5	Works/operations manager handling purchases (esp. spares).	Yes	No CMMS.
Customer 6	Receives worksite maintenance/repair requests; orders service; entrepreneur involved in larger repairs.	Yes	No CMMS.
Customer 7	Multi-role across company; performs repairs; participates in operations.	Yes	No CMMS.
Customer 8	Co-owner running the crushing site; making all decisions; on site daily.	Yes	No digital tools.

4.2.2 Features of a PdM solution

The interviews revealed a consistent set of expectations regarding the essential features of a potential predictive maintenance (PdM) solution. Although customers differed in their digital maturity and operational conditions, several themes were repeatedly highlighted across discussions. These insights can be grouped into five main categories (illustrated in Figure 10): monitoring and alert objects, automatic maintenance reminders, notification logic and channels, and spare-parts-related features.

Customers emphasized, above all, the importance of receiving timely alerts about the condition of critical components – mentioned by seven out of eight respondents. These include bearings, motors, and consumables such as filters, as well as anomalies such as unusual vibration patterns or temperature spikes. Interviewees consistently linked these capabilities to the prevention of costly breakdowns and unplanned downtime:

> "If there was temperature monitoring or vibration measurement, for example, a rise in bearing temperature would show a fault is coming." (Customer 7)
>
> "For example, [the solution could provide] bearing failure prediction in advance." (Customer 2)
>
> "It would be valuable if the system could identify abnormal events, vibrations, and give concrete alerts." (Customer 1)
>
> "I've always wished for oil quality monitoring. That would be extremely important." (Customer 3)

In addition to these critical alerts, five interviewees expressed a desire for routine operational notifications that support ongoing maintenance planning. These include automated reminders based on predefined operational criteria, such as usage hours. Such reminders were described as practical tools for ensuring timely maintenance tasks and avoiding situations where work is forgotten in the midst of daily operations.

A significant part of the discussion concerned the logic and channels through which notifications should be delivered. Across all eight interviews, two consistent expectations emerged:

1) alerts must reach the right person, and
2) the notification channel should depend on the criticality of the event.

Customers stressed that critical alerts must be communicated quickly and decisively, typically via mobile phone, SMS, or a similar immediate-attention channel, while non-critical notifications could be directed to email or an integrated dashboard to avoid unnecessary overload. This approach reflects a pragmatic need to balance operational urgency with information manageability (refer to the principal logic for alarms and notifications routing on Figure 9). As one customer explained,

> "Alerts should be immediately visible in our system. It would be good if an external party, like Metso, could also see the alerts and contact us if needed. SMS or phone alerts would be useful." (Customer 4)

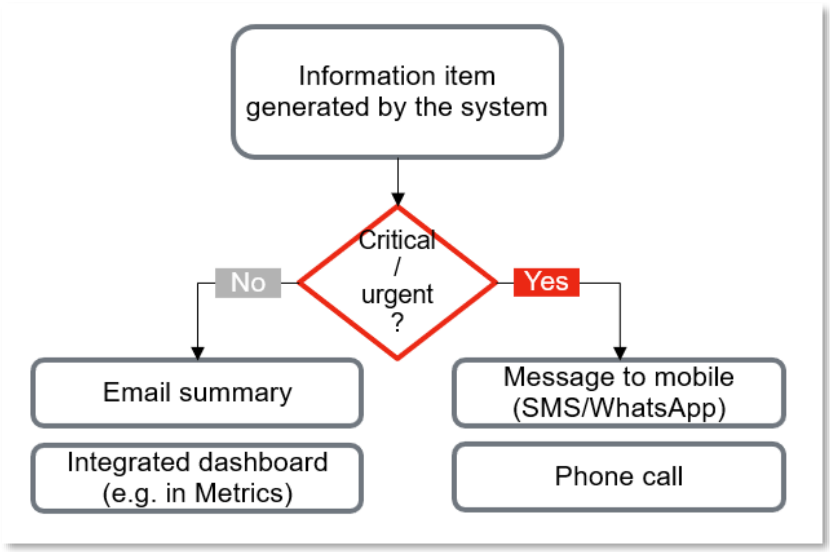

Figure 9. Principal logic for notifications routing

Customers also shared their preferences for complementary channels such as WhatsApp groups or CMMS dashboards used on worksites:

> "Email always gets through. WhatsApp is also good, because we have a WhatsApp group at the site for sharing info and pictures." (Customer 5)

> "Email, Metrics alert or a dedicated window in the system would be good. Critical alerts could come by text message." (Customer 8)

Finally, three customers highlighted the value of integrating spare-parts-related information and ordering capabilities directly into the PdM interface. This feature was described as especially helpful when linked to alerts, making it easier to identify the correct part, check its availability and delivery times, and initiate ordering without delay. As customers noted:

> "It would be great if the message included a direct link to order spare parts. For example, 'this clutch should be replaced; click here to order.' Same for oil changes: order filters here.'" (Customer 1)

> "[I'd like to see] Integrated spare parts ordering from the alert/dashboard." (Customer 4)

These expectations reflect customers' desire not only for early warnings but also for smoother workflows around maintenance preparation, parts procurement, and response actions.

Figure 10. Mind-map of PdM solution features mentioned in customer interviews

Overall, the features described in this section outline the functional expectations customers have for a PdM solution and reflect the practical needs that arise in their day-to-day maintenance work.

The next sub-section is dedicated to the aspects of a PdM solution that would add value for the interviewed customers.

4.2.3 Value-driving features and customers' vision of an ideal PdM solution

This part of the analysis focuses on what customers said would truly make a predictive maintenance solution valuable in their day-to-day work. While Section 4.2.2 described which features customers expect to see in a PdM solution, this section shifts the perspective to why these elements matter and how they shape customers' perceptions of usefulness and value.

Across the interviews, value-adding elements clustered consistently around three broader themes: (1) operational value, (2) economic value, and (3) experiential value. The value-related part of the survey is the most critical for answering the research question #3; summarized answers in a table form are available in Appendix 5.

1. Operational value: preventing failures, improving decision-making, and acting at the right time

The strongest pattern across the interviews was that customers expect a PdM solution to support timely and accurate maintenance decisions. Seven out of eight customers emphasized value in preventing unexpected failures, minimizing downtime, and recognizing issues early enough to react. Customers linked this directly to their operational environment: equipment failures are both costly and stressful, especially when they cause complete production stops.

What customers considered most helpful included:

- clear early detection of anomalies (e.g., unusual vibration, temperature increases, or oil contamination),
- visibility into how critical the issue is,
- approximate time-to-failure estimates,
- actionable recommendations instead of raw data,
- clarity on where the problem is occurring and what to check first.

Customers also noted that this level of guidance prevents unnecessary work by distinguishing between "needs attention now" and "can wait".

As one customer explained:

> "The system should tell us the fault location and give instructions on how to start troubleshooting. It's like when a car mechanic connects a diagnostic device — you're told the order of things to check." (Customer 6)

Another highlighted the added value of timing:

> "I would like the system to say, for example, 'The screen bearing will last about 40 more hours,' and show the spare part availability and price." (Customer 1)

2. Economic value: avoiding unnecessary costs and optimizing maintenance resources

Economic value is reflected in customers' desire to avoid unplanned downtime, plan maintenance windows better, and make cost-effective decisions. This was mentioned by most interviewees, although expressed differently depending on their digital maturity.

Customers associated economic value with:

- avoiding catastrophic failures that require expensive repairs,
- avoiding the not-so-necessary maintenance that wastes time or materials,
- receiving spare parts information early enough to order on time (as described also in chapter 4.2.2.),
- reducing the need to keep large spare parts stocks "just in case".

Three customers specifically mentioned the added benefit of seeing correct spare parts, availability, delivery times, and, ideally, the ability to order them directly through the system.

3. User experience value: ease of use, trust, and seamless integration into existing ways of working

The third category relates to how customers experience the solution. All eight interviewees emphasized the importance of user-friendliness, clear interfaces, and simple visualizations such as color-coded indicators and clean status panels.

Customers described value in:

- intuitive interfaces ("like a smartphone")
- alerts routed to the right people through the right channels
- clear and simple data visualization (color coding, concise summaries)
- integration with existing systems

- the possibility for operators (not only managers) to receive relevant information at the machine

One customer summarized the experiential requirement concisely:

> "Ease of use is the most important. Crushing plant workers are not IT professionals. The system must be simple." (Customer 4)

Another added:

> "…Large display showing motor hours and maintenance needs, visual oil quality monitoring, option to order spare parts directly." (Customer 8)

Additionally, two customers mentioned the importance of fast support from the service provider in urgent cases, especially when the system detects a critical issue.

All the value-driving factors described above are summarized on Figure 11.

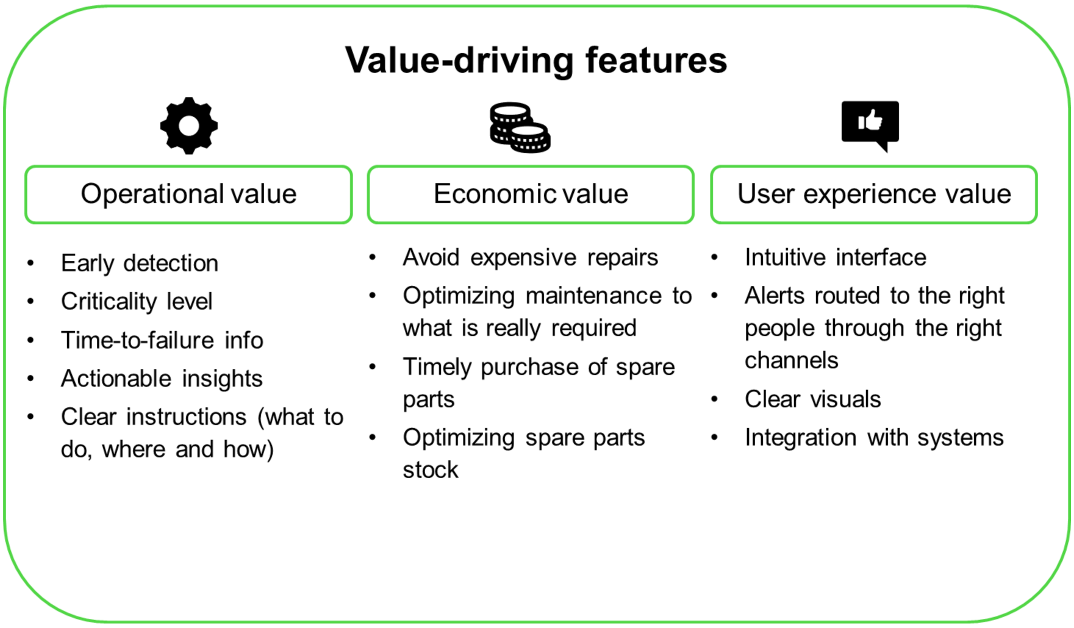

Figure 11. Value-driving features of a PdM solution, based on customers' answers

What is an ideal PdM solution would look like for customers

When bringing these perspectives together, an "ideal" PdM solution, as described across interviews, would be one that:

- predicts issues early, with information that is both clear and actionable,
- supports better maintenance planning and avoids unnecessary interventions,
- provides clarity on criticality levels,

- offers integrated spare parts identification and ordering,
- routes alerts to through the right channels to the right recipients (matching the criticality level),
- presents information visually and intuitively,
- is simple enough for anyone to use, regardless of digital skill level,
- and includes support from the service provider when needed.

In other words, customers expect the solution to meaningfully support their maintenance decisions, reduce operational risks, and fit seamlessly into existing work practices. This understanding will support feature prioritization when developing the solution, to make sure the solution aligns with customer needs in the best possible way.

4.2.4 Factors impacting trust (and distrust) towards PdM solutions

The previous section outlined features that customers value in a potential PdM solution. To complement this, the interview data also revealed several factors that influence how much customers would trust (or distrust) automated recommendations. The factors are tightly connected to the day-to-day operations reality and reflect practical, experience-based view of what makes recommendations reliable and actionable. In total, five distinct trust-related themes emerged, outlined below.

1. Accuracy, concreteness and practical usefulness (mentioned by seven customers).

According to our customers, trust increases when recommendations are accurate, concrete and bring clear added value. At the same time, generic or obvious suggestions were seen as reducing credibility:

> "It must provide a concrete benefit and be tested in practice. The information has to be accurate and up-to-date, not 'nonsense'. Trust is built when the recommendation gives more than just a basic maintenance reminder." (Customer 1)
>
> "Not something generic like 'check lubrication'. Of course we check that." (Customer 6)

Several customers noted that the number of notifications itself can have an impact: over-alerting, including too many low-priority or nonactionable messages, was seen as creating 'noise' that reduces trust in the system. As one customer noted, 'you can't react to every small defect', and another emphasized that email alerts should be avoided because 'we get too many already'.

2. Correct timing of recommendations (mentioned by six customers)

Customers emphasized that timing strongly affects trust: a recommendation that arrives too early is seen as wasteful, while one arriving too late is considered dangerous or useless:

> "Recommendations must be timely. If everything is done too early, costs rise unnecessarily. Too-late maintenance can cause major damage." (Customer 2)

3. Verifiability of recommendations (mentioned by five customers)

Customers trust recommendations when the alert matches what they see, hear, or measure, and when the system's sensors and software behave reliably. Conversely, trust is weakened when a sensor reports an issue that cannot be confirmed, or when the alert contradicts operator experience. This includes:

- the ability to verify the anomaly manually,
- consistent and correct behavior of sensors,
- alignment with operator's experience and knowledge.

> "Recommendations must be verifiable by measurement." (Customer 7)
>
> "If a sensor reports a fault and nothing is found, then you don't trust it." (Customer 4)
>
> "If the alert doesn't match what we see, then we start doubting it." (Customer 1

4. Clear and actionable guidance (mentioned by seven customers)

This factor directly connects with the previous one: customers said they would trust a recommendation more if it tells them clearly where the issue is, what likely caused it and what should be checked first. Lack of such detail reduces trust.

> "The system should tell us where the fault is and what to check first – like a car diagnostics tool." (Customer 6)

5. Explainability, or understanding the cause of the alert (mentioned by three customers).

Understanding the reason behind a recommendation increases trust. Customers specifically mentioned wanting to see what measurement changed and how it deviated from normal conditions.

> "It would be helpful to see what caused the alert — whether temperature rose quickly or vibration changed." (Customer 1)

Together, these factors highlight that customers assess predictive recommendations through a combination of technical reliability, practical usefulness, and alignment with real operational experience. The next section (4.2.5) adds to these themes by examining the factors that influence the adoption of PdM solutions more broadly, including organizational readiness, digital maturity, and practical constraints identified in the interviews.

4.2.5 Factors impacting adoption of PdM solutions

Several practical considerations that influence whether customers would actually adopt a PdM system were discussed during the interviews. These adoption factors relate to customers' operational environments, digital capabilities, and internal practices. In total, six themes emerged, summarized below.

1. Connectivity and network limitations (mentioned by three customers).

Unreliable mobile or internet connectivity was mentioned as a potential limitation, particularly for sites located in remote areas. For these customers, unreliable connections make it difficult to rely on any solution that depends on continuous data transfer. As summarized by one of the customers:

> "In Finland, network connections are very poor, especially in remote areas. You wouldn't believe it if you live in the city, but out here in the periphery, phones don't even work." (Customer 3)

2. Varied digital skills (all customers)

The already mentioned factor in the section about value-adding features, user-friendliness was consistently highlighted as a prerequisite for adoption. Many aggregates industry sites employ operators with limited experience in digital tools, and multiple customers noted that older employees in particular may find new systems difficult to use. Customers stressed that any PdM system must be intuitive, require minimal training, and fit naturally into daily workflows to be widely adopted.

> "The challenge is staff skills. Older employees have no experience with computers, and not everyone has a smartphone." (Customer 3)

> "User-friendliness is key, because crushing plant workers are not IT professionals. The system must be simple to use." (Customer 4)

3. Cautious attitudes toward digitalization (mentioned by three customers).

Adoption is also influenced by organizational mindset. Some customers explained that certain managers or operators are cautious about digitalization, either due to unfamiliarity or because previous digital tools have not delivered expected benefits.

> "Older management is cautious about digitalization, but I see a lot of benefits in it." (Customer 7)

4**. Data quality and sensor/system reliability concerns** (mentioned by six customers)

Several customers emphasized that adoption depends on the PdM system producing reliable data. Concerns related to incomplete data, incorrect sensor behavior, or system malfunctions were frequently mentioned. Customers noted that adding more sensors can itself introduce additional failure points.

> "Challenges are data entry, incomplete starting data, adding sensors brings new failure points, technical availability, reliability, and costs." (Customer 1)

Without confidence in data quality and signal reliability, willingness to rely on automated recommendations decreases significantly.

5. **Cost and resource constraints** (mentioned by five customers)

Cost considerations were an important adoption factor. Customers highlighted that predictive systems must provide clear economic benefit, e.g. reducing downtime or lowering operational risks. High upfront investment or overly frequent recommended interventions were seen as potential barriers.

> "Finding the right timing is difficult. Fully predictive maintenance can be expensive, and unexpected failures can still occur." (Customer 2)

> "Balance between inventory and maintenance is important. You can't keep everything in stock, and getting parts quickly isn't always possible." (Customer 8)

6. **Strong reliance on experience-based, reactive practices** (mentioned by five customers)

Finally, adoption is influenced by existing work practices. Several customers openly acknowledged that their maintenance culture is still largely reactive, driven by operator observations or sudden changes in machine performance. This mindset can slow down the shift toward predictive approaches.

> "Our daily life should be more predictive, but operations are largely reactive repairs. We react when someone signals a problem or efficiency drops." (Customer 1)

In summary, these factors demonstrate that the adoption of PdM solutions depends not only on system functionality but also on practical constraints such as site connectivity, staff skills, organizational attitudes, and the reliability of underlying data. These insights also highlight that successful implementation requires careful attention to customer context and support needs.

4.2.6 Summary of customer expectations and value drivers

The eight customer interviews provided a broad and detailed view of how maintenance is currently organized in the aggregates sector and what customers expect from a potential shift toward predictive maintenance. Despite differences in company size, digital maturity, and operating environments, seven out of eight interviewees expressed clear interest in automated recommendations, provided that such recommendations are accurate, timely, and practical. Customers also shared constraints and concerns, such as trust in system outputs, data reliability, and varying levels of digital skills, which are essential to consider when designing and deploying a PdM solution. Notably, all eight customers indicated willingness to participate in piloting the solution once available, suggesting strong engagement potential for validating and iterating the concept in real operating environments.

Based on the interview findings across all customers, the value-driving, trust-creating and adoption-supporting factors can be prioritized into three groups: high-priority, useful, and nice-to-have. The prioritization reflects (1) how frequently a factor appeared across interviews, (2) its perceived link to operational continuity or risk reduction, and (3) whether it is essential for the baseline functioning of a predictive maintenance solution.

High-priority factors

These elements collectively form the minimum viable foundation for any PdM solution. Without them, customers would struggle to trust, adopt, or benefit from predictive recommendations.

- **Early detection of anomalies and operationally critical warnings** (7/8 customers). Customers expect the system to provide timely, reliable alerts on bearings, motors, oil condition and other critical components.
- **Accuracy, specificity and practical usefulness of recommendations** (7/8 customers). Recommendations must be concrete, correct and relevant. Generic suggestions do not add value.
- **Clear, actionable guidance** (7/8 customers). Customers want guidance similar to “car diagnostics”: identifying the issue, its location, likely cause, and steps for verification.
- **Correct timing of recommendations** (6/8 customers). Recommendations that arrive too early are seen as wasteful, while too-late alerts undermine trust and value.
- **Verifiability and sensor/system reliability** (5/8 customers). Alerts must be verifiable by observations or measurements; false alarms or unconfirmable anomalies impact negatively.
- **User-friendliness and low cognitive effort** (all customers). The system must be intuitive and usable by operators with varying digital skill levels.
- **Right alert routing** (all customers). Customers emphasized the need for critical alerts to be sent via phone/SMS and non-critical information via email or dashboard.

Two design considerations follow directly from this:

- how “critical” and “non-critical” events are defined for each customer context, and

- who should receive each type of alert and through which channel.

  These elements must be configurable to fit customer-specific operating practices.

- **Adequate connectivity or tolerance for poor connectivity** (3/8 customers). While not universal, network limitations in remote sites mean that PdM solutions must either accommodate intermittent connectivity or clearly define technical preconditions for deployment.

Useful factors

These features enhance usability, efficiency and planning, but customers would still adopt a PdM solution without them if the core features above perform well.

- **Integrated spare parts identification and ordering** (3/8 customers). Considered helpful for speeding up maintenance preparation.
- **Visualization and status dashboards** (4/8 customers). Supports faster interpretation, reduces cognitive load.
- **Explainability of alerts** (3/8 customers). Understanding why an alert was triggered increases trust.
- **Balanced inventory and maintenance planning support** (4/8 customers). Helps align predictive recommendations with parts availability and production schedules.

Nice-to-have features

These elements were mentioned infrequently, tend to be company- or context-specific, or serve more as convenience than necessity.

- **Fully integrated multi-OEM fleet view** (2/8 customers). Useful for larger mixed fleets but not essential.
- **Advanced explanatory graphs or trend analytics** (2-3 customers). Mainly valued by customers who already use digital tools; this would not be a practical need for smaller contractor customers.
- Automated links to documentation or manuals (1 customer). Helpful, but not critical.
- **Proactive outreach from Metso** (2 customers). Appreciated, but not part of the PdM system itself and dependent on the chosen service model.

In summary, customers see the most value in a PdM solution when its recommendations are accurate, verifiable and timed appropriately, alerts reach the right people through the right channels, and the system itself is simple to use and fits naturally into their existing workflows. Addressing these priorities will be essential for building trust and supporting adoption as the solution is developed and piloted.

4.3 Proposed Updated Business Process Maps for Metso

Based on the internal stakeholder discussions (Section 4.1), the insights from customer interviews (Section 4.2), and relevant findings from the theoretical framework, I developed two potential future-state business process options for delivering AI-aided predictive maintenance services to customers. These options reflect two different levels of automation:

1) a process where Metso reviews automatically generated alerts before they are sent to customers, and
2) a fully automated process in which alerts are delivered without prior human validation.

4.3.1 Future process option 1: Metso validates alerts before sending

In the first option, the process logic would be as follows:

- The PdM solution continuously evaluates operational data from equipment and detects anomalies. Based on these anomalies, it generates predictive alerts that include criticality levels, recommended actions, and spare parts information where relevant.
- Metso's PdM team receives these alerts and recommendations and validates them. Depending on the validation outcome, feedback is returned to the system to support continuous learning, and only validated recommendations are released to customers.
- Customers receive confirmed alerts or recommendations and plan and execute the necessary maintenance activities, involving Metso's Field Service team when needed.

The full flow is illustrated in Figure 12 (also available in Appendix 9).

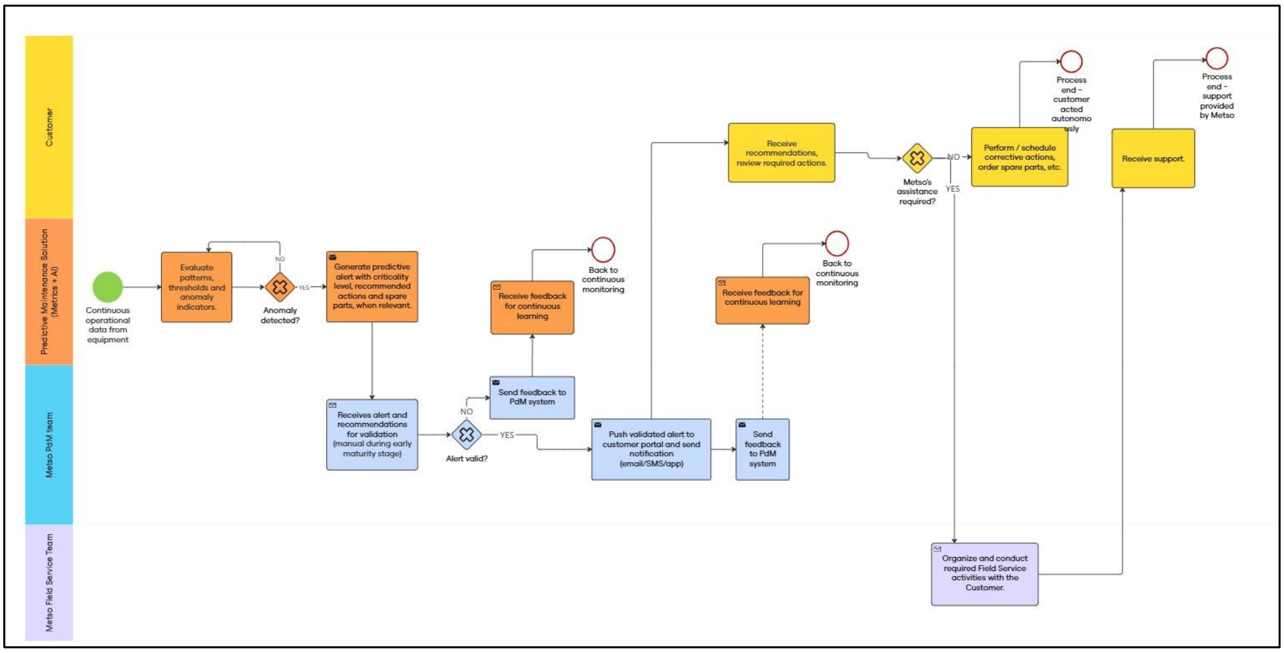

Figure 12. Future process for AI-aided PdM service provision, Metso validates alerts

This version is particularly relevant during the initial deployment phases, where predictive accuracy and operational stability are still developing. The threshold for shifting to a more automated model must be jointly defined by relevant subject-matter experts, including PdM solution developers, Field Service, and equipment Product Managers.

4.3.2 Future process option 2: Fully automated alerts

The second option, illustrated in Figure 13 (and in Appendix 10), represents a fully automated predictive maintenance workflow:

- As in the previous option, the PdM solution continuously evaluates operational data, identifies anomalies, and generates predictive alerts with related recommendations.
- Unlike the first option, the alerts are sent directly to customers without prior manual validation by Metso.
- Customers can then validate alerts from their side (for example, marking them as valid, invalid, or irrelevant), and this feedback is returned to the PdM system for continuous improvement. Customers then perform the required maintenance activities and involve Metso if necessary.
- Metso's PdM team monitors the feedback trends and focuses on maintaining the overall performance and accuracy of the predictive solution.

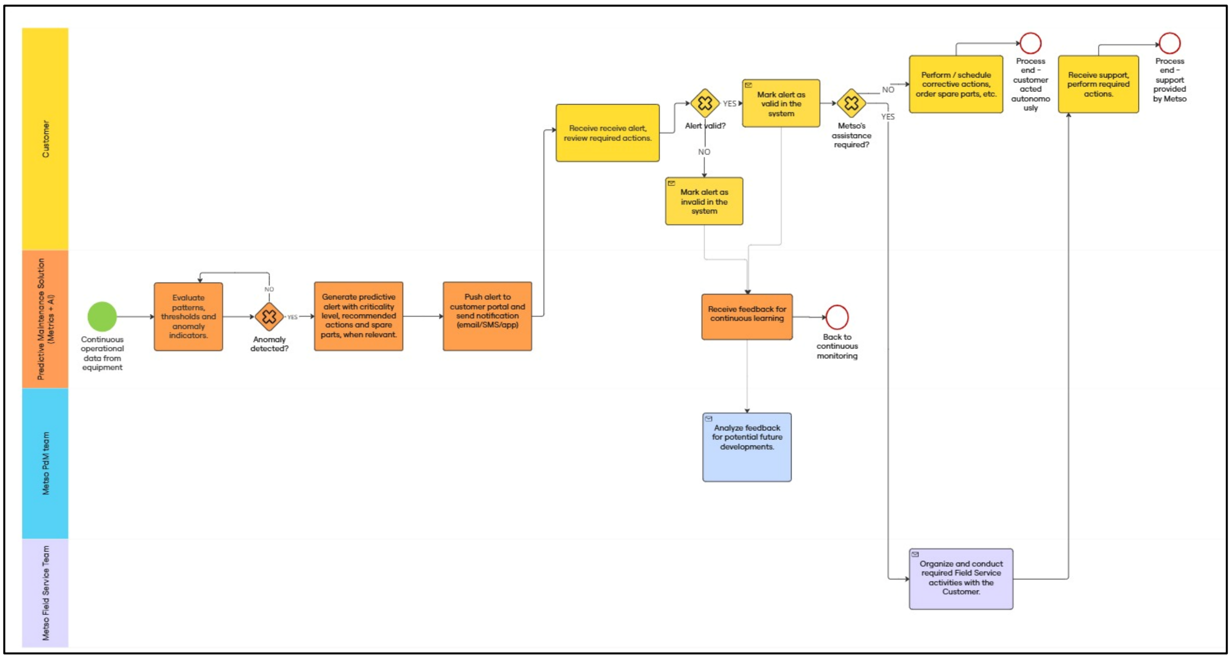

Figure 13. Future process for AI-aided PdM service provision, fully automated

4.3.3 Comparison of the two future-state workflows

Table 5 summarizes the practical differences between the two potential workflows.

Table 5. Comparison of features of the two future process flows

Aspect	#1 Metso validates alerts before sending	#2 Fully automated (no prior Metso validation)
Primary purpose / when to use	Early deployment, while model accuracy and operational coverage are still maturing.	Mature stage, when alert precision, routing, and feedback loops are sufficiently proven.
Validation step	Metso PdM team reviews alerts, returns feedback to the system; only valid alerts reach customers.	System pushes alerts directly to customers; customers can validate/provide feedback; Metso monitors feedback trends.
Customer experience	Customers receive **manually validated** alerts with higher initial trust; manual latency possible.	Customers receive **fully automated** alerts; trust depends on sustained accuracy and explainability; faster loop.
Operational load on Metso	Higher (validation effort, potential outreach on critical cases).	Lower day-to-day validation load; higher need for monitoring model quality and feedback analytics.
Risk profile	Lower risk of false positives reaching customers; risk is slower response on time-critical events if validation queues build up.	Higher risk exposure to false/low-quality alerts if model drifts; mitigated by robust monitoring and clear customer feedback mechanisms.

Data quality tolerance	Can compensate for imperfect signal quality via human review.	Requires consistently high data and model quality (to avoid noise and alert fatigue).
Spare parts & sales triggers	Validated alerts may include actions/leads to parts sales or Field Service scheduling.	Customer-validated alerts can directly trigger customer actions; Metso analyzes aggregated feedback and demand signals.

Optional enhancement: proactive outreach

In both future-state processes, proactive outreach to customers could be considered for specific types of critical alerts. Interviewees noted that for severe cases, a direct phone call from Metso would be appreciated. Proactive outreach could help ensure that customers are aware of urgent issues and understand the required actions to avoid major failures.
This approach, however, requires further investigation: the underlying rules, logic, and customer agreements must be clearly defined, and the activity would require dedicated resources and consistent internal guidelines.

4.3.4 Shift from reactive to predictive service delivery

Compared to the current reactive process (Figure 7), where customers identify issues and initiate contact, both future-state options represent a fundamental shift toward predictive service delivery. Instead of reacting to failures, the technical solution would identify potential issues early and guide the maintenance flow before disruptions occur.

To enable either of the proposed future-state processes, several prerequisites must be met:

- **Technical readiness:** the AI-aided PdM solution must be sufficiently developed and reliable. This includes accuracy and explainability of alerts and recommendations, appropriate criticality classification, alert-routing logic, addressing potential issues with connectivity, a user-friendly interface, and the presence of a feedback loop to support continuous learning.
- **Operational business model:** the business model for predictive maintenance service delivery requires further detailing and internal approval.
- **Internal resourcing:** adequate internal capacity must be ensured to validate alerts (for option 1), support customers, and conduct proactive outreach where relevant. Workload estimates should be conducted to determine the required resourcing, which may include new roles. The example of potential internal process roles is outlined in Table 6. The roles are exactly process roles; one employee can handle one or several roles, depending on the scale of the service deployment and related workload.

- **Customer agreements:** service frameworks and related contractual details must be formalized with customers to clarify expectations, responsibilities, and communication practices.

Table 6. Potential roles in service provider's organization to support PdM process

Role / capability (Service provider)	Option 1: Service provider validates before sending	Option 2: Fully automated alerts
PdM Process / Service Owner	Owns end-to-end PdM alert handling process; defines validation flow & operating rules. Maintains rules/thresholds/quality checks.	Owns end-to-end automated PdM service; defines automation guardrails & operating rules. Maintains rules/thresholds/quality checks.
PdM Alert Validator (Human-in-the-loop)	Reviews AI alerts, confirms criticality & actions; sends feedback to system; releases only validated alerts to customers.	Not required as a core step (may exist only as exception handling for critical or disputed cases)
PdM Feedback & Quality Monitor	Tracks validation outcomes and patterns; uses feedback to improve quality of automated notifications quality (in addition to validation work)	Monitors customer feedback trends; focuses on overall performance and accuracy of the predictive solution.
PdM Customer Support / Service Specialist	Explains validated alerts; supports customer actions; supports proactive outreach where relevant.	Supports customers reacting to automated alerts; handles questions/escalations when needed.
Field Service Coordination (PdM ↔ Field Service)	Coordinates follow-up when validated alerts require service involvement	Coordinates follow-up when customers request service provider's support after receiving automated alerts

In summary, the two proposed future maintenance processes translate the findings from internal stakeholder discussions, customer interviews, and the theoretical framework into concrete options for organizing predictive maintenance service delivery at Metso. The first option emphasizes reliability through human validation, while the second represents a more automated and scalable model that becomes feasible once accuracy and operating conditions are sufficiently mature. Together, these options illustrate the shift required to move from the current reactive maintenance process toward a more proactive, data-driven service.

4.4 Summary of key findings and recommendations

This section provides a consolidated summary of the main findings and development outcomes produced in this Thesis. Together, these findings answer all three research questions and provide a basis for business process transformation towards AI-aided predictive maintenance service.

Although the findings are based on the Metso case study, the recommendations below are generalizable to other organizations seeking to transition from reactive to predictive maintenance service provision.

4.4.1 Summary of findings related to Research Question 1: typical processes for predictive maintenance

The analysis of existing literature sources provided in chapter 2.3. showed that predictive maintenance processes typically follow a structured, data-driven flow that includes condition monitoring, anomaly detection, criticality assessment, relevant notifications, maintenance planning, execution and a closed-loop feedback mechanism (Appendix 6). The essential elements of the PdM workflows are early detection of issues, actionable recommendations, integration with existing maintenance management systems, and iterative model improvement based on the feedback generated by real cases.

These insights form a reference model against which maintenance service providers' existing processes can be assessed, and that can serve as a guiding principle for designing the provider's future processes, incorporating the predictive component.

4.4.2 Summary of findings related to Research Question 2: transformation needs for reactive maintenance processes towards predictive maintenance (on Metso's example)

The investigation of Metso's current practices in Aggregates sector showed that maintenance services are reactive, initiated when customers contact Metso about a problem (Appendix 8). Metso Metrics is used primarily as a descriptive monitoring tool rather than a proactive one. The currently piloted AI-aided PdM solution generates predictive alerts, that need to be reviewed manually by experts before reaching customers.

To integrate AI-aided predictive maintenance, Metso would need to introduce several process changes (described in the section 4.3.4), including, first and foremost, ensuring technical readiness of the PdM solution, defining internal operational business model to support the predictiveness capabilities, define and secure the required internal resources, and outlining the new customer service models as official offerings.

Two future-state high-level AI-aided PdM maintenance process options were designed: 1) a process where Metso validates alerts before sending them to customers (Appendix 9), and 2) a fully automated process where validated alerts are sent directly to customers (Appendix 10). Once the prerequisites for reaching the predictive maintenance service model are achieved, these process options can be adopted, provided that the system maturity and operational feasibility are at place. These transformation needs align directly with what customers expressed in the interviews, summarized next.

4.4.3 Summary of findings related to Research Question 3: customer expectations and value drivers

Customer interviews, results of which are detailed out in section 4.2., showed clear interest in AI-aided predictive maintenance, provided that the solution offers:

- specific, verifiable, accurate and timely alerts,
- clear and actionable recommendations (what to check and where, how to act upon the recommendation; possibility to plan services or purchase spare parts through the solution),
- alters notification logic and delivery channels matching operational urgency,
- integration with existing systems and flows (when possible),
- additional value of being more than just a digital maintenance log,
- simple and intuitive user interface, overall user-friendliness.

Additionally, customers highlighted constraints such as varying levels of digital skills, connectivity limitations in remote sites, reliance on experiential knowledge in existing practices, and cost considerations. These insights are important to consider when designing the future PdM service.

4.4.4 Summary of recommendations derived from the findings

The recommendations presented in this chapter build on findings from sections 4.4.1-4.4.3 and highlight several practical considerations for organizations moving from reactive maintenance practices toward AI-aided predictive maintenance. These recommendations bring together the key points from internal process investigation, customer interviews, and the reviewed literature, and are focused on what is needed to make predictive maintenance work in practice.

Technical and system-level requirements

The first and most important requirement is that the predictive maintenance solution itself must be technically ready. This includes reliable data collection, stable connectivity, and predictive models that perform well enough to support real decisions. The solution should provide clear, explainable alerts and must integrate smoothly with the organization’s existing tools (for example, monitoring platforms, maintenance systems or customer-facing portals). Continuous monitoring of alert quality and model behavior is needed to keep the system trustworthy and up to date.

Process transformation requirements

When a technically functioning predictive solution is available, organizations need to define how predictive alerts will be handled in daily work. This includes creating a clear process for alert validation (manual or automated), criticality assessment, and notification routing. A feedback mechanism, allowing experts and later customers to validate alerts, is important for both improving the models and keeping the recommendations meaningful over time. As model accuracy improves, organizations should also outline when and how they will move from manual validation to a more automated flow.

Organizational capability requirements

Introducing predictive maintenance also requires people and roles to support it. Organizations should define responsibilities for handling alerts, contacting customers when needed, coordinating with field service teams, and monitoring overall service performance. Resource needs should be estimated in advance, as predictive maintenance often brings new tasks that do not exist in reactive workflows. Governance for maintaining rules, thresholds and quality checks is also necessary.

Customer-facing and service design requirements

From the customer’s perspective, the recommendations must be practical and easy to use. Alerts should be specific, verifiable and timed appropriately. Notification channels should match the urgency of the situation: critical alerts should reach the right person quickly, while routine information can be delivered through less urgent channels, like emails. Interfaces should be simple enough for users with different digital skill levels. Customers also benefit from early visibility into spare parts and planning options, as this helps them prepare and avoid unnecessary downtime.

Deployment and scalability considerations

Finally, a phased deployment approach is recommended. Organizations may start with selected customer segments or equipment types and expand once the processes and the technical solution are proven in real use. Clear communication practices and service-level expectations should be defined early, especially when predictive alerts trigger actions that involve both the provider and the customer. Pilot projects can help validate the technical solution, confirm the process design, and gather customer feedback before scaling more broadly.

Together, these results form a coherent basis for designing and evaluating future maintenance process models, which are further interpreted in the Discussion chapter.

5 Discussion

This chapter discusses the results of the thesis in relation to the research questions, the theoretical framework, and the expected outcomes of the study. It also reflects on the practical significance of the findings, the reliability and limitations of the research, and potential directions for future studies.

5.1 Summary of the Results

The main purpose of this thesis was to investigate what is required to transform internal business processes to enable delivery of predictive maintenance recommendations to customers. In the course of the work, I examined both equipment and service provider's (Metso's) internal processes and customer expectations, in addition to investigating available literature on the subject.

The main results can be summarized as follows. First, the literature review revealed clear patterns in how predictive maintenance processes are typically structured: continuous monitoring, anomaly detection, criticality assessment, actionable recommendations, and a feedback loop for continuous improvement. Second, the internal analysis of Metso's current processes, as part of the case study, confirmed that the existing maintenance workflow is reactive, and that integrating a predictive component will require updates to process logic, roles, resourcing, and customer-facing service practices. Two alternative future-state processes were developed to illustrate how predictive alerts could be delivered in practice, depending on system and service offering maturity. Third, customer interviews demonstrated that customers value predictive maintenance when recommendations are accurate, specific, verifiable, timely, and easy to act upon, and when the system is simple to use in everyday operations. Together, these findings enabled the development of a set of recommendations that organizations can use when transitioning from reactive to predictive maintenance practices.

5.2 Interpretation of Results in Relation to Research Questions

RQ1: What are typical business processes for providing predictive maintenance services to industrial companies?

Literature on PdM workflows emphasizes early detection, data-driven decision-making, criticality-based routing, and continuous improvement cycles. The logical BPMN model derived in the thesis aligns closely with widely accepted PdM frameworks, such as those described by Wagner & Hellingrath (2021), Achouch et al. (2022), and Industry 4.0 frameworks (Werbińska-Wojciechowska & Winiarska 2023). This alignment reinforces the validity of the high-level process model produced in the Results chapter. The outcome of RQ1 therefore not only reflects established best practices but also provides a clear benchmark for evaluating the readiness of an organization transitioning toward predictive maintenance.

RQ2: How should nonpredictive maintenance processes be transformed to effectively integrate automatic AI-based predictive maintenance recommendations?

The interpretation of findings related to RQ2 points to several areas where transformation is needed. The shift from reactive to predictive maintenance requires more than adding an AI model to an existing workflow: it also requires aligning roles, responsibilities, and core process steps with the logic of predictive operation. This is consistent with business process transformation literature (e.g., Guha, Kettinger & Teng 1993, Baiyere, Salmela & Tapanainen 2020), which emphasizes that technology-driven change often triggers the need to rethink workflows, information flows, decision-making structures, and resourcing.

The thesis results suggest that transformation should occur in at least four dimensions:

1. **Technical readiness** – the predictive solution must be reliable, explainable, and integrated with existing tools before any process changes can be effectively implemented.

2. **Process redesign** – automated predictive recommendations need clear entry points in the process, along with validation, routing, and feedback mechanisms.

3. **Organizational capabilities** – new or adjusted roles are needed to manage alert validation, customer outreach, and continuous monitoring and assessment of the PdM solution's performance.

4. **Customer agreements and service models** – predictive alerts and recommendations change the nature of customer interaction, which requires formalizing responsibilities and communication practices.

The two proposed future-state process versions reflect early- and late-stage predictive maturity and provide concrete operational templates for organizations at different stages of PdM development. The interpretation of RQ2 therefore reveals that transformation is both technical and organizational, and that predictive maintenance cannot be applied to a reactive maintenance workflow without foundational changes.

RQ3: What would make AI-aided predictive maintenance services valuable to customers?

The findings related to RQ3 confirm the importance of perceived value and perceived usefulness in the adoption of predictive maintenance solutions, as discussed in the concept of Technology

Acceptance Model (Davis 1989) and perceived value-related literature (Zeithaml 1988; Lapierre 2000; Blut et al. 2024). The customer interviews showed that value is created when predictive recommendations support practical maintenance decisions: by identifying issues early, clarifying criticality, and making it easier to plan or act. Customers also emphasized ease of use, information clarity, the right notification channels, and trustworthy system behavior.

The practical interpretation is that predictive maintenance will only be adopted if the solution reduces cognitive load rather than adds to it (Blut et al. 2024). This aligns strongly with earlier studies showing that complexity, lack of clarity, or excessive noise can hinder adoption of digital maintenance tools. The results of this thesis therefore contribute context-specific evidence from the aggregates sector that reinforces these broader theoretical concepts.

5.3 Comparison with Theoretical Framework

Across all research questions, the results align well with existing literature in predictive maintenance, business process transformation, and customer value perception.

- **PdM literature** emphasizes early detection, actionable guidance, human-in-the-loop validation, and continuous improvement. The findings from both customer interviews and internal stakeholder discussions support these principles, confirming that PdM cannot be reduced to anomaly detection alone; actionable insights and contextualization are essential for value creation.

- **BPM and process transformation literature** highlights that digital transformations often challenge existing routines and require rethinking the entire process logic. This was reflected clearly in the internal findings: shifting to predictive maintenance requires reconfiguring responsibilities, defining new roles, and aligning workflows with the logic of predictive operation rather than waiting for customer phone calls.

- **Customer value and acceptance literature (especially, concepts of perceived usefulness and perceived value)** emphasizes the importance of clarity, ease of use, fit to user context, and trust in system outputs. Customer interviews strongly echoed these themes and provided detailed examples from real operations in aggregates sites, illustrating how these theoretical concepts play out in practice.

An attempt to find comparable Master’s theses focusing specifically on business process transformation for AI-aided predictive maintenance did not yield any direct matches. This suggests that while predictive maintenance is widely researched from a technical perspective, its implications for internal business process redesign remain an emerging and relatively unexplored topic in academic literature.

Together, these interpretations highlight several practical implications for organizations considering the adoption of predictive maintenance, both generally and in the context of the Metso case study.

5.4 Implications for Organizations Transitioning Toward Predictive Maintenance

The recommendations provided in Chapter 4.4.4 are generalizable to other industrial service providers moving from reactive to predictive maintenance. The key implication is that predictive maintenance is not only a technical problem but also an organizational one. Organisations need to:

- ensure technical maturity before redesigning workflows,
- define clear decision logic for how predictive alerts and recommendations enter the process,
- build capabilities for validation and customer coordination,
- design customer-facing interfaces and communication practices that support adoption,
- and approach predictive maintenance deployment in phases.

These implications underline that successful PdM adoption depends on building both technological and organizational readiness.

For Metso specifically, the results provide concrete input for the ongoing pilot activities and future service model development. The two proposed future-state processes offer a practical foundation for defining how predictive alerts will be validated and delivered to customers as the solution matures. The findings also highlight where additional internal resources or new roles may eventually be required. Moreover, customer interview insights can directly support feature prioritization and user interface design as the predictive maintenance solution evolves.

5.5 Reliability, Ethics, and Limitations

The reliability of the research was supported by triangulating multiple data sources, including literature, internal stakeholder interviews, and eight customer interviews. All interview transcripts were checked manually, and anonymization was applied prior to including insights in the thesis.

However, the research approach has several limitations. The internal process investigation was limited to the Aggregates business area in the Nordic region, which may not fully represent processes in other regions or business units. Similarly, customer interviews focused on Finnish end customers, while the distributor's network has not been part of the investigation. Although saturation was reached, additional interviews from other markets or customer segments could provide further nuance. The thesis also does not include deep technical analysis of the predictive model or its configuration, as this was outside the defined scope.

These limitations do not diminish the validity of the findings but highlight areas where additional research could complement this work.

Finally, on a personal note, the thesis process also deepened my understanding of how technical, organizational and customer-related perspectives must be considered together when designing data-driven industrial services.

5.6 Suggestions for Further Research

Based on the limitations above, several opportunities for further research emerge:

- extending the customer insights study to other geographic regions, customer types, or digital maturity levels,
- investigating how predictive maintenance processes function when distributors are involved,
- analyzing predictive maintenance maturity levels across different OEMs or industries to benchmark readiness and adoption patterns,
- conducting a more detailed technical study on model performance, explainability, or integration with operational systems,
- studying long-term organizational impacts when predictive maintenance becomes part of daily operations.

These topics would provide deeper understanding and help organizations refine their predictive maintenance strategies over time.

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Appendices

Appendix 1. Interview research questions (in English and Finnish)

Customer interview questions / Asiakashaastattelukysymykset

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1. Introduction

- Brief introduction of myself and the purpose of the interview.
- Emphasize that the discussion is part of academic research and not tied to any commercial offering.
- Confirm consent to record the interview and remind the participant of their rights (voluntary participation, confidentiality, right to withdraw).

</td><td>

1. Esittely

- Lyhyt esittely itsestäni ja haastattelun tarkoituksesta.
- Korosta, että keskustelu **on osa akateemista tutkimusta** eikä liity kaupalliseen tarjontaan.
- Varmista lupa nauhoittaa haastattelu ja muistuta osallistujaa heidän oikeuksistaan (vapaaehtoisuus, luottamuksellisuus, oikeus vetäytyä).

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2. Background and maintenance context

- Can you describe your role and responsibilities in relation to maintenance?
- What types of equipment are you currently using in your operations?
- How is maintenance typically managed at your site (e.g., in-house, outsourced, hybrid)?
- How do you nowadays decide, when to do the maintenance?
- What do you check or take into account when planning maintenance?
- When (or how much in advance) do you plan maintenance works?

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2. Tausta ja kunnossapidon konteksti

- Voisitko kuvailla roolisi ja vastuusi kunnossapitoon liittyen?
- Minkä tyyppisiä laitteita käytät tällä hetkellä toiminnassasi?
- Miten kunnossapito yleensä hoidetaan teillä (esim. omana työnä, ulkoistettuna, hybridi)?
- Miten päätätte tällä hetkellä, milloin kunnossapitoa tehdään?
- Mitä tarkistatte tai huomioitte huoltoa suunnitellessa?
- Milloin (tai miten paljon aikaisemmin) suunnittelette huollot?

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3. CMMS usage and digital infrastructure

Do you currently use a CMMS (Computerized Maintenance Management System)?
If yes:

Which system do you use and how?
What are its main strengths and limitations in your view?
How well does it support your daily maintenance operations?

If no:

How do you track and manage maintenance activities?

What other digital tools or platforms are used in your maintenance processes?
How would you describe your site's overall digital maturity in maintenance?

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3. Kunnossapidon järjestelmän (CMMS) käyttö ja digitaalinen infrastruktuuri

Käytättekö tällä hetkellä CMMS-järjestelmää (Computerized Maintenance Management System)?
Jos kyllä:

Mitä järjestelmää käytätte ja miten?
Mitkä ovat sen tärkeimmät vahvuudet ja rajoitukset mielestäsi?
Kuinka hyvin järjestelmä tukee päivittäistä kunnossapitoa?

Jos ei: Miten seuraatte ja hallinnoitte kunnossapitotoimia?
Mitä muita digitaalisia työkaluja tai alustoja käytetään kunnossapitoprosesseissa?
Miten kuvailisit kunnossapidon digitaalista kypsyyttä teillä?

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4. Readiness to share production and equipment data

What assets are currently connected and for what purpose?
In addition to Metrics, are you using any other systems for production data collection?

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4. Valmius jakaa tuotanto- ja laitetietoja

Mitkä laitteet ovat tällä hetkellä yhdistettynä ja mihin tarkoitukseen?
Käytättekö Metricsin lisäksi muita järjestelmiä tuotantodatan keräämiseen?
Mitä huolia sinulla voisi olla operatiivisen datan jakamisesta (esim. tietoturva, omistajuus, hyödyllisyys)?

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• What concerns might you have about sharing operational data (e.g., security, ownership, usefulness)?	
5. Critical incident exploration The aim of this technique is to uncover real-world examples that reveal deeper insights into readiness and willingness. *Can you describe a recent maintenance event that went particularly well or poorly?* • What happened? • Who was involved? • What tools or systems were used? • What was the outcome? • What would you do differently next time? • What lessons did you take away from that experience?	**5. Kriittisten tapausten tarkastelu** Tämän tekniikan tavoitteena on löytää tosielämän esimerkkejä, jotka paljastavat syvällisempiä näkemyksiä valmiudesta ja halukkuudesta. *Voisitko kuvailla viimeaikaisen kunnossapitotapahtuman, joka meni erityisen hyvin tai huonosti?* • Mitä tapahtui? • Kuka (ketkä) oli(vat) mukana, rooleina? Sekä teiltä, että Metsolta, jos päti silloin. • Mitä työkaluja tai järjestelmiä käytettiin? • Mikä oli lopputulos? • Mitä tekisit seuraavalla kerralla toisin? • Mitä opit kokemuksesta?
6. Willingness to act on AI-based maintenance recommendations • Have you ever received automated maintenance recommendations (from any system)? What kinds of recommendations were they? What did you do with them? • What kinds of recommendations would you like to receive automatically?	**6. Halukkuus toimia tekoälypohjaisten kunnossapitosuositusten perusteella** • Oletteko koskaan saaneet automaattisia kunnossapitosuosituksia (mistä tahansa järjestelmästä)? Millaisia suosituksia ne olivat? Mitä teitte niiden kanssa? • Millaisia suosituksia haluaisitte saada automaattisesti?

• Would you consider adjusting your maintenance plans based on AI-generated insights? Why or why not? • What would make you trust or distrust such recommendations? • How would you prefer to receive these recommendations (e.g., email, dashboard, mobile app)? • How would you process and act on them internally?	• Harkitsisitteko kunnossapitosuunnitelmien muuttamista tekoälyn tuottamien oivallusten perusteella? Miksi tai miksi ei? • Mikä saisi teidät luottamaan tai olemaan luottamatta tällaisiin suosituksiin? • Miten haluaisitte vastaanottaa nämä suositukset (esim. sähköposti, dashboard, mobiilisovellus)? • Miten käsittelisitte ja toteuttaisitte suositukset sisäisesti?
7. Generally, about predictive maintenance solutions • Have you evaluated or used any **predictive** maintenance solutions before? If yes, what did you like or dislike? • What would make a predictive maintenance solution stand out to you compared to others? • What would make this solution valuable to you personally or to your team?	**7. Yleisesti ennakoivista kunnossapitoratkaisuista** • Oletteko arvioineet tai käyttäneet ennakoivia kunnossapitoratkaisuja aiemmin? Jos kyllä, mistä piditte tai ette pitäneet? • Mikä saisi ennakoivan kunnossapitoratkaisun erottumaan muista? • Mikä tekisi ratkaisusta arvokkaan sinulle henkilökohtaisesti tai tiimillesi?
8. Expectations and future outlook • What do you think are the biggest challenges in moving toward predictive maintenance? • What would an ideal predictive maintenance solution look like for you?	**8. Odotukset ja tulevaisuuden näkymät** • Mitkä ovat mielestäsi suurimmat haasteet siirryttäessä ennakoivaan kunnossapitoon? • Miltä ihanteellinen ennakoivan kunnossapidon ratkaisu näyttäisi sinulle?

• What kind of support or features would make such a solution more useful or easier to adopt? • What do you think your organization needs to be better prepared for AI-based maintenance? • Would you be open to piloting a predictive maintenance solution?	• Millainen tuki tai ominaisuudet tekisivät ratkaisusta hyödyllisemmän tai helpommin omaksuttavan? • Mitä organisaatiosi mielestäsi tarvitsee ollakseen paremmin valmistautunut tekoälypohjaiseen kunnossapitoon? • Olisitko avoin pilotoimaan ennakoivan kunnossapidon ratkaisua?
9. Wrap-up • Is there anything else you'd like to share about your experience with maintenance or digital tools? • Would you be open to a follow-up if needed?	**9. Yhteenveto** • Onko jotain muuta, mitä haluaisit jakaa kokemuksistasi kunnossapidon tai digitaalisten työkalujen parissa? • Olisitko avoin jatkohaastattelulle tarvittaessa?

Appendix 2. Interview Research Announcement (translated into Finnish)

Tutkimustiedote

- **Opinnäytetyön nimi:**
  Transforming business processes to deliver predictive maintenance recommendations (Liiketoimintaprosessien kehittäminen ennakoivan kunnossapidon suositusten toimittamiseksi)
- **Opiskelijan nimi ja yhteystiedot:** Marina Manvelian. *********@*****.com
  +358 401 *** ***
- **Ohjaavan opettajan nimi ja sähköpostiosoite:** Lili Aunimo, *******@******.fi
- **Toimeksiantaja:** Metso Finland Oy
- **Aineiston keruun tavoite:**
  Aineiston keruun tavoitteena on arvioida asiakkaiden valmiutta ja halukkuutta ottaa käyttöön tekoälypohjaisia ennakoivan kunnossapidon ratkaisuja.
- **Aineiston keruun toteuttamistapa ja vaiheet:**
  Tutkimus toteutetaan laadullisin menetelmin, kuten dokumenttianalyysin ja puolistrukturoitujen haastattelujen avulla. Haastattelut nauhoitetaan Microsoft Teamsin kautta ja litteroidaan Microsoft Copilotin avulla.
- **Osallistumisen kesto:**
  Haastatteluun osallistuminen kestää arviolta 60–90 minuuttia keskustelun syvyydestä riippuen.
- **Etukäteisvalmistautuminen:**
  Osallistujien ei tarvitse valmistautua laajasti. He voivat halutessaan tutustua sisäisiin dokumentteihin tai pohtia kokemuksiaan kunnossapitoprosesseista ja ennakoivasta kunnossapidosta ennen haastattelua.
- **Osallistumisen hyöty tutkittavalle tai hänen edustamalleen organisaatiolle:**
  Tutkimuksen tulokset voivat tukea ennakoivan kunnossapidon käytäntöjen kehittämistä ja käyttöönottoa osallistujien organisaatioissa.
- **Aineiston käsittely, säilytys, luovutustahot, mahdollinen hävittäminen ja jatkokäyttö:**
  Kaikki aineisto tallennetaan turvallisesti Metson ja Haaga-Helian suojattuihin tallennuspalveluihin kuten OneDrive tai SharePoint, joihin on rajattu pääsy. Henkilötietoja ei tallenneta ulkoisille laitteille. Haastattelunauhoitukset poistetaan litteroinnin jälkeen. Tutkittavan tai yrityksen nimeä ei mainita opinnäytetyössä eikä julkaista missään.

Anonymisoitua aineistoa käytetään vain opinnäytetyöhön ja käsitellään EU:n yleisen tietosuoja-asetuksen (GDPR 679/2016) ja kansallisen lainsäädännön mukaisesti.

- **Tuloksista tiedottaminen:**
  Opinnäytetyöraportti julkaistaan Theseus-verkkokirjastossa.
- **Rahoitus ja mahdolliset intressiristiriidat:**
  Opinnäytetyö tehdään osana opiskelijan työtä Metso-yhtiössä. Ulkopuolista rahoitusta ei ole, eikä tiedossa ole intressiristiriitoja.
- **Lisätiedot:**
  Marina Manvelian (*****@******.com)

Appendix 3. Interview Consent Form (translated into Finnish)

Suostumuslomake

Annan suostumukseni osallistua tutkimukseen *"Liiketoimintaprosessien kehittäminen ennakoivan kunnossapidon suositusten toimittamiseksi"* liitteenä olevan tutkimustiedotteen mukaisesti.

Edellä mainitun tutkimustiedotteen sisältö on kerrottu minulle ja ymmärrän mitä tutkimus koskee, mitä osallistuminen tarkoittaa minulle, mihin antamaani dataa käytetään ja miten sitä säilytetään. Minulla on ollut mahdollisuus esittää kysymyksiä ja olen saanut riittävän vastauksen kaikkiin kysymyksiini.

Ymmärrän, että osallistuminen tutkimukseen on vapaaehtoista. Olen selvillä siitä, että voin peruuttaa tämän suostumukseni koska tahansa syytä ilmoittamatta ja esimerkiksi keskeyttää haastattelun niin halutessani.

Suostumuksen voi peruuttaa ottamalla yhteyttä opinnäytetyön tekijään sähköpostitse. Huomaa, että kun tutkimustulokset on analysoitu, yksittäisen osallistujan osuutta ei voida enää jälkikäteen poistaa.

Lisätietoja tutkimuksesta antaa opinnäytetyön tekijä **Marina Manvelian**, sähköposti: *******@******.com.

Allekirjoituksellani vahvistan, että annan suostumukseni tutkimukseen osallistumisesta.

____

Suostumuksen antajan nimi

______________________________ ______________________________

Päiväys Allekirjoitus

Appendix 4. Finnish-English vocabulary to support customer interviews

Maintenance & Equipment

Finnish	English
Kunnossapito	Maintenance
Ennakoiva kunnossapito	Predictive maintenance
Kunnossapito-ohjelma	Maintenance program
Huoltokirja	Maintenance logbook
Laitteisto	Equipment
Murskain	Crusher
Seula	Screen
Siirtohihna	Conveyor
Tuotantolaitos	Production plant
Käyttökatko	Downtime
Vika	Fault / Failure
Varaosa	Spare part

Digital Tools & Data

Finnish	English
Tuotantodata	Production data
Käyttötieto	Usage data
Digitaalinen järjestelmä	Digital system
Tiedonkeruu	Data collection
Etävalvonta	Remote monitoring
Anturi	Sensor
Internet-yhteys	Internet connection
Tietoturva	Data security
Tiedon jakaminen	Data sharing

Finnish	English
Tiedon omistajuus	Data ownership

IC System Sensors – Finnish-English Vocabulary

Finnish Term	English Term	Explanation
Kunnossapidon (hallinta)järjestelmä	CMMS	Computerized maintenance management sys-tem
IC-järjestelmä	IC system (Intelligent Control system)	Automaattinen ohjausjärjestelmä, jota käytetään murskaus- ja seulontalaitteiden valvontaan ja säätöön.
IC-anturi	IC sensor	Anturi, joka on osa IC-järjestelmää ja mittaa esimerkiksi tärinää, lämpötilaa, painetta tai tuotantomäärää.
Tärinäanturi	Vibration sensor	Havaitsee laitteiston epänormaalin tärinän, joka voi viitata vikaantumiseen.
Lämpötila-anturi	Temperature sensor	Mittaa komponenttien lämpötilaa ylikuumenemisen estämiseksi.
Paineanturi	Pressure sensor	Valvoo hydraulisten tai pneumaattisten järjestelmien painetta.
Tuotantomittaus	Production measurement	Anturit mittaavat tuotantomääriä, kuten murskatun materiaalin tonnimäärää.
Etävalvonta	Remote monitoring	Anturien keräämä tieto siirretään etäjärjestelmään, kuten Metricsiin, analysointia varten.
Ennakoiva kunnossapito	Predictive maintenance	Antureiden avulla havaitaan poikkeamia, jotka voivat ennakoida vikoja.
Tiedonkeruu	Data collection	Anturit keräävät reaaliaikaista tietoa laitteiston toiminnasta.
Automaattinen säätö	Automatic adjustment	IC-järjestelmä voi säätää laitteiston asetuksia automaattisesti anturitiedon perusteella.

Appendix 5. Summary of value-related interview answers

1. OPERATIONAL VALUE (early detection, clear diagnosis, timing, criticality, actionable recommendations)

Value driver	*Customer(s)*	*Representative quote*
Early detection of anomalies / failure prediction	C2, C4, C5, C7, C8	"It would be valuable if the system could identify abnormal events, vibrations, and give concrete alerts." – C1 "If there was temperature monitoring or vibration measurement, a rise in bearing temperature would show a fault coming." – C7
Clear criticality indication	C1, C4, C7, C8	"The system should tell us how critical the issue is so we know whether to act now or later." – (paraphrased; expressed across 4 interviews)
Concrete action steps / troubleshooting guidance	C2, C4, C6, C7	"The system should tell us the fault location and give instructions on how to start troubleshooting — like a car diagnostic tool." – C6
Time-to-failure estimate	C1, C8	"I'd like the system to say, for example: 'The screen bearing will last about 40 more hours,' and show spare-part availability and price." – C1
Accurate, trustworthy recommendations	C1, C2, C3, C4, C6, C7	"Recommendations must be something you can verify: the sensor has to measure correctly, and you must be able to confirm the fault." – C8
Preventing unnecessary maintenance	C1, C2, C7	"It helps avoid unnecessary costs; you don't want to fix something too early without reason." – C2 (summarized)

2. ECONOMIC VALUE (avoiding breakdowns, reducing downtime, optimizing costs & spare-parts handling)

Value driver	*Customer(s)*	*Representative quote*
Preventing expensive failures and downtime	C1, C2, C4, C7, C8	"If the system catches an issue early, we avoid the big breakdowns, that's where the money goes." – C2 (summarized)

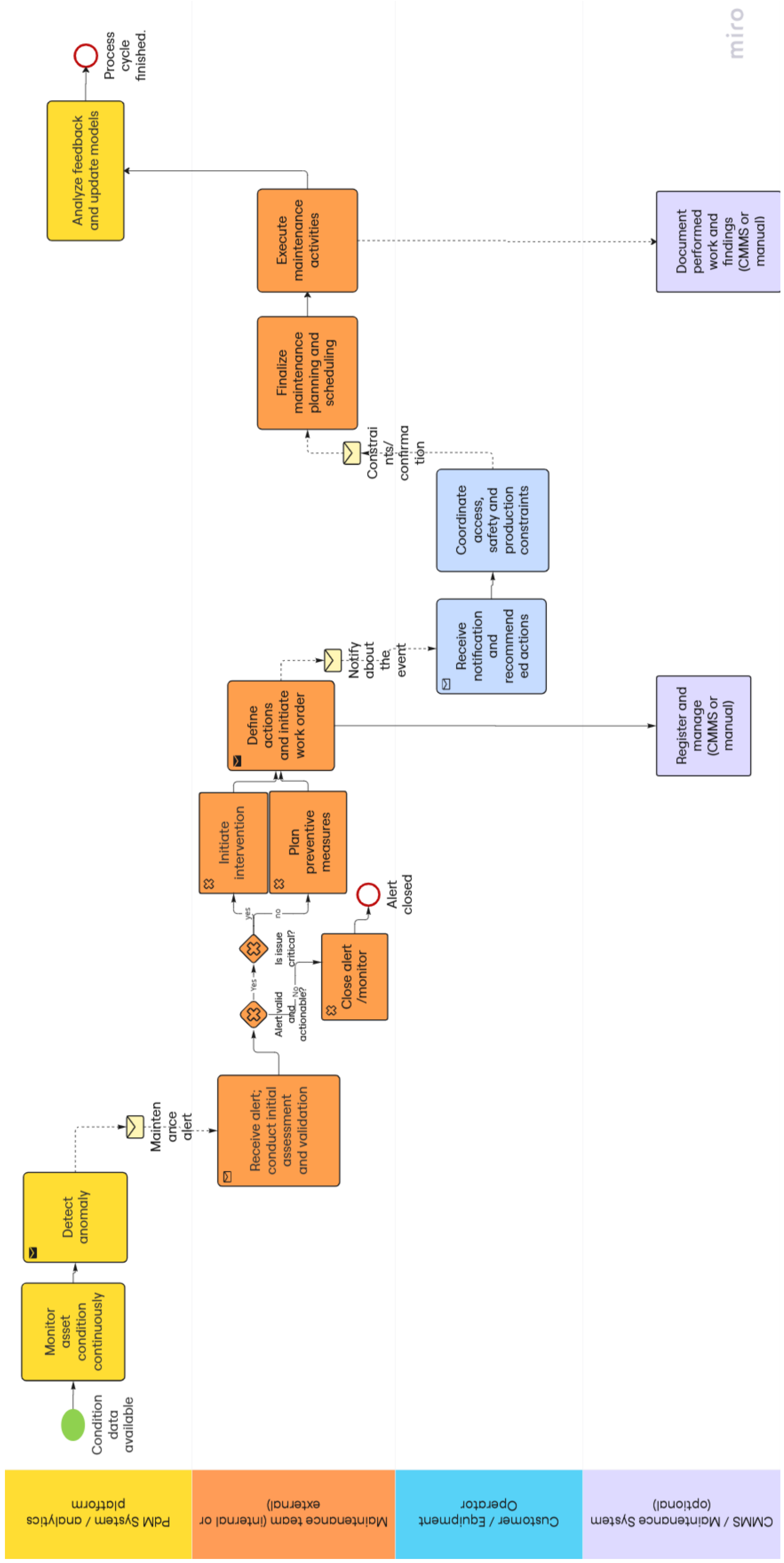
Better planning of maintenance windows	C1, C2, C4, C5, C7	"Predictive information helps schedule maintenance without interrupting production unnecessarily." – C4 (summarized)
Spare-parts identification + ordering integration	C1, C4, C3	"It would be great if the message included a direct link to order spare parts." – C1 "Integrated spare-parts ordering from the alert/dashboard would be useful." – C4
Avoiding over-stocking / optimizing inventory	C1, C4, C7	"We keep a big stock because we don't know what will break. If the system could predict issues, we wouldn't need to store so much." – C4 (summarized)
Avoiding unnecessary early maintenance	C2, C7	"You can't react to every small defect — sometimes you run until it's worth fixing." – C7

3. EXPERIENTIAL VALUE (ease of use, clarity, visualization, right channeling of alerts, trust, integration)

Value driver	*Customer(s)*	*Representative quote*
User-friendliness / intuitive interface	All 8 customers	"Ease of use is the most important. The system must be simple enough for non-technical staff." – C4 "User-friendliness — like a smartphone." – C8
Clear data visualization (dashboards, color coding, large display)	C1, C3, C7, C8	"…Large display showing hours and maintenance needs, visual oil quality monitoring, option to order spare parts directly." – C8 "Clear reports with color codes would help anticipate repairs." – C3
Correct alert routing (critical vs. non-critical)	All 8 customers	"Critical alerts should not come by email — phone or SMS is needed. Non-critical ones can come to email." – C2 "Operator-side alerts on the machine are important because the driver must see the warning immediately." – C1
Integration with existing systems	C1, C2, C4, C7	"Alerts should be visible directly in our system. It would help if Metso can also see them and contact us if needed." – C4

Trust in the system & service provider	C1, C2, C4, C7	"I trust recommendations when they are concrete and based on real need." – C3 (summarized)
Support from Metso during critical events	C4, C6	"In critical cases, fast support from Metso is important." – C6 (summarized)

Appendix 6. Logical BPMN model of a typical predictive maintenance service process



Appendix 7. Guiding questions for discussions on maintenance services with internal stakeholders

1. **Contractual background**

   How is Metso currently involved in Maintenance services with Aggregates end-customers?

   Are there maintenance agreements?

2. **Maintenance process**
   Could you walk me through how maintenance processes typically run today in Aggregates services, from the moment an issue arises to the completion of maintenance work?

   a. Where does the process start?

   b. What happens next?

3. **Proactive or reactive maintenance services**

   Does Metso proactively reach out to end-customers for maintenance recommendations/ activities planning, or is it mainly reactive maintenance (customer initiates)?

4. Condition monitoring, alerts & detection

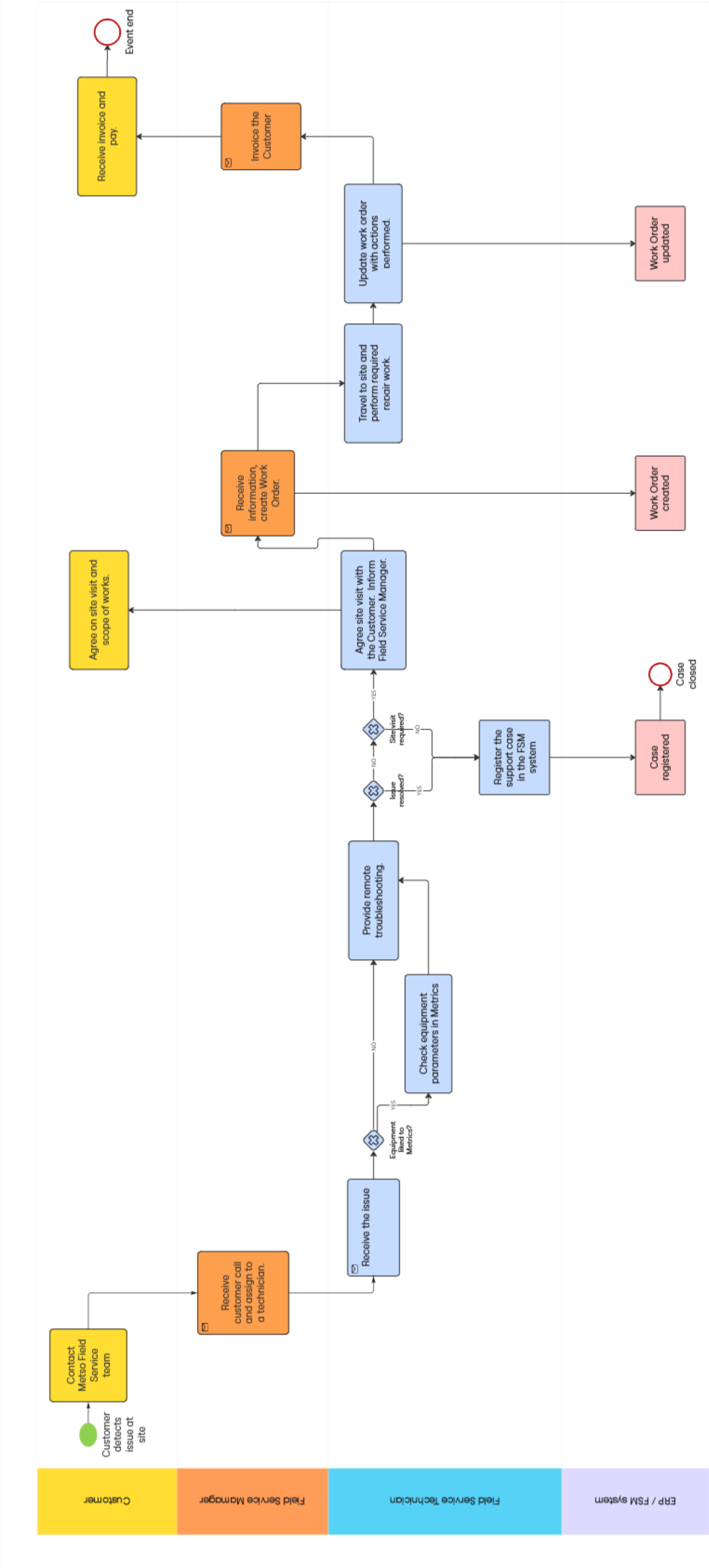
- How is equipment condition currently monitored?
- When an anomaly or issue is detected (via Metrics or by other means), what happens next?

5. Metrics-specific data and workflows
   - What exactly does Metrics monitor today?
   - What kind of alerts does Metrics generate?
   - How are Metrics alerts currently processed (internally and with the customer)
   - What would be required to support more predictive logic (vs. descriptive/monitoring logic)?
   - And the piloted AI-aided predictive maintenance feature: what does it do on top of Metrics?

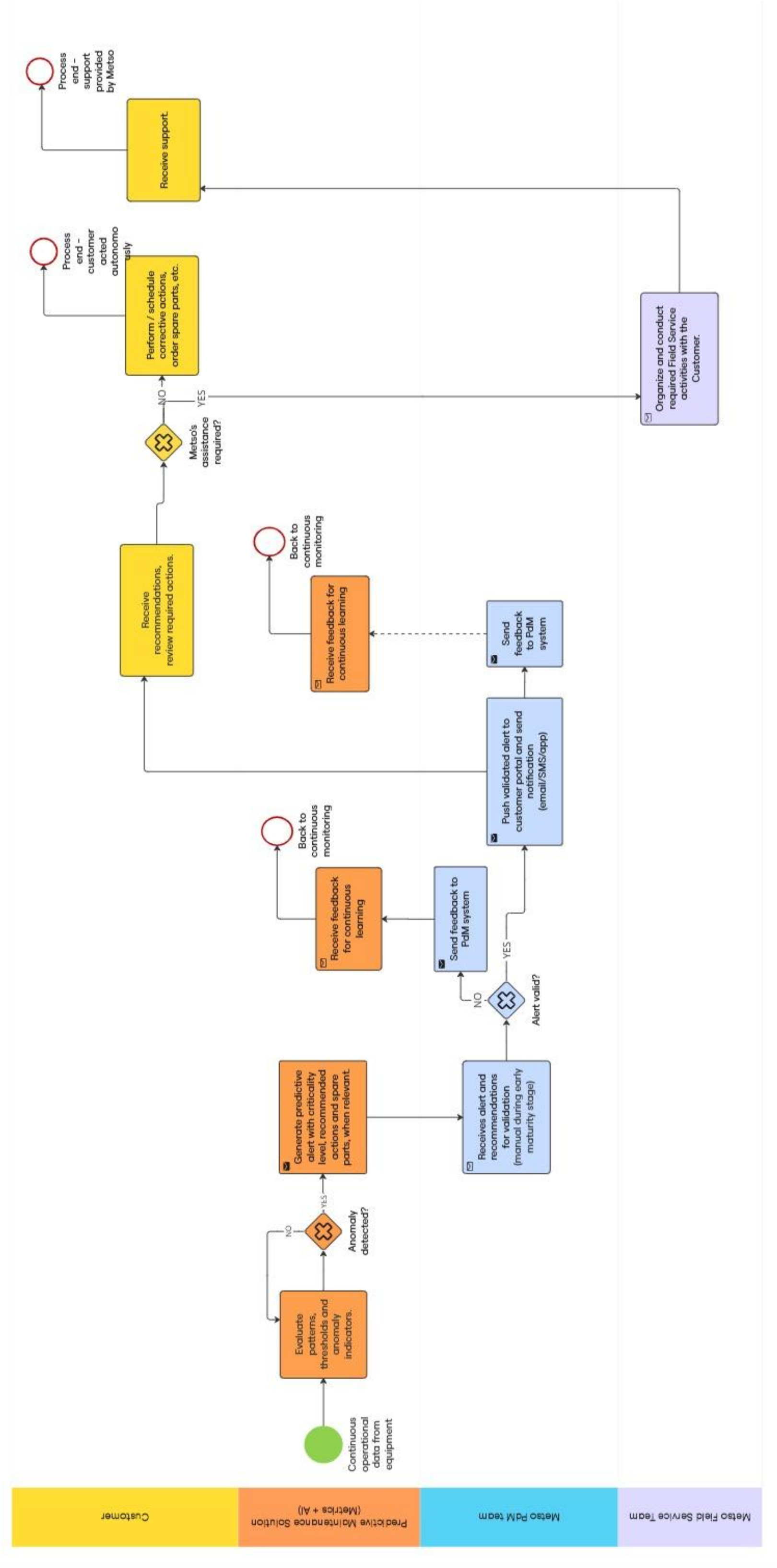
6. **Future process**

   When a predictive component would be integrated, how would a process look like then?

Appendix 8. Current process for maintenance services in Metso Aggregates, Finland



Appendix 9. Future process for AI-aided PdM service provision, Metso validates alerts



Appendix 10. Future process for AI-aided PdM service provision, fully automated