



Digital Technologies 4.0 and Green Transition Impacts on Predictive Maintenance

WP3 – Observatory - D3.2 - M36 - Digital Technologies 4.0 and Green Transition Impacts on Predictive Maintenance



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Document summary

Document type:	Public Report
Title	Digital technologies 4.0 and green transition impacts on predictive maintenance
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Reviewer	Hervé Danton
Date	Mai 2025
Document status	1.0
Document description	This document describes the main impacts of new technologies in the field of predictive maintenance and their consequences for the adaptation of organisations and skills.
Cite this deliverable as:	Pichoutou et al., 2025. - D3.2 - M36 - Digital Technologies 4.0 and Green Transition Impacts on Predictive Maintenance
Document level	Public



GLOSSARY AND/OR ACRONYMS

AFDET - French Association for the Development of Technical Education
AFM - Asociación de Fabricantes de Máquina Herramienta- Machine Tool Manufacturers Association
AFNOR - French association for standardisation
AI - Artificial Intelligence
AR - Augmented Reality
CAGR - Compound Annual Growth Rate
CAM - Computer-Aided Manufacturing
CMMS - Computerized Maintenance Management System
CNC - Computer Numerical Control
CoVE - Centres of Vocational Excellence
EaaS - Equipment-as-a-Service.
EQF - European Qualification Framework
ESCO - European Skills, Competences, Qualifications and Occupations
HVET - Higher Vocational Education and Training
IoT - Internet of Things
IT - Information Technology
IUT - University Institute of Technology
LCAMP - Learner-Centric Advanced Manufacturing Platform
LLM - Large Language Model
MV - Mecanic Vallée
PdM - Predictive Maintenance
PLC - Programmable Logic Controller
SLMs - Task-Specific Language Models
SME - Small and Medium-sized Enterprises
TKNIKA - Centre for Applied Research in Vocational Training in the Basque Country.
TPM - Total Productive Maintenance
VR - Virtual Reality
WP - Work Package



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EXECUTIVE SUMMARY

The LCAMP (Learner-Centric Advanced Manufacturing Platform) project, under the CoVE initiative, aims to strengthen regional skill ecosystems in Advanced Manufacturing through collaboration, resilience, and innovation.

This report, developed by the LCAMP Observatory and led by the French cluster Mecanic Vallée and the Campus des Métiers et des Qualifications Industrie du Futur, with the support of partners located in Sweden, Germany, Italy and Slovenia examines how Industry 4.0 technologies and sustainability trends influence Predictive Maintenance and workforce adaptation, emphasizing the alignment of VET programs with the skills and training needs in manufacturing.

This report, based on **literature review, interviews, and surveys with VET Centres and industrial companies**, highlights the **current state of PdM adoption, key challenges, and future trends** shaping its development. Main findings are:

In SMEs side:

- **Implementing Predictive Maintenance (PdM) offers substantial added value for SMEs** by increasing machine uptime, extending equipment lifespan, and reducing unplanned downtime and maintenance costs. By **leveraging emerging technologies - especially Machine Learning, Generative AI, and IoT** - PdM enables real-time monitoring and predictive analytics, which allow for **early failure detection, improved operational efficiency, and reduced repair expenses**.
- In a world increasingly focused on sustainability, **Predictive Maintenance (PdM) provides concrete solutions by helping companies reduce energy consumption, minimize waste, and lower their carbon footprint**.
- However, **despite these clear advantages**, many **SMEs face significant barriers** to adoption, including high costs, technical integration issues, and a shortage of skilled professionals in AI, IoT, data analytics, and cybersecurity.
- Solutions like Maintenance-as-a-Service (MaaS) and PdM-as-a-Service (PdMaaS) allow SMEs to benefit from advanced technologies without heavy upfront investment, offering scalable, flexible, cost-effective alternatives to traditional infrastructure-heavy approaches.

In VET Centres side:

- **VET institutions need to align curricula with Industry 4.0 needs**, ensuring that maintenance operators acquire **complementary skills beyond their core expertise**. As well as traditional maintenance knowledge, workers need to develop skills in IoT integration, AI-driven analytics, cyber security and the ability to manage internal collaborations and external partnerships. These expanded competencies will enable them to effectively implement PdM solutions and navigate the increasing digitalization of industrial maintenance
- **Nevertheless, updating maintenance training remains difficult**, as VET institutions must quickly adapt programs to include dual qualifications and hybrid delivery methods, integrating both traditional maintenance expertise and Industry 4.0 digital competencies (e.g., AI, IoT, cybersecurity, external partnership management).

By addressing these challenges through **investment in skills, financial support, and new service models**, SMEs can **enhance efficiency, reduce maintenance costs, and strengthen their competitive edge in a changing, greener and more digital industrial landscape**.



1. INTRODUCTION

1.1. COMPANY TESTIMONIAL

From Total Productive Maintenance (TPM) deployment to Predictive Maintenance solutions (PdM).

A South German automotive supplier specializing in plastics faced major challenges: competition, production discontinuation, a 50% turnover drop, workforce reduction, and facility closures. To maintain efficient small-series production, the company introduced TPM in 2012, focusing on proactive maintenance strategies.

TPM, developed by Seiichi Nakajima (Seiichi Nakajima, 2023), aims to maximize machine efficiency and minimize downtime. It involves all employees in maintenance, particularly through 'autonomous maintenance,' where operators handle simple tasks. TPM optimizes Overall Equipment Effectiveness (OEE) by reducing six key losses: unplanned downtime, changeover times, minor breakdowns, speed losses, quality defects, and start-up failures. Built on eight pillars, including planned maintenance, efficiency improvements, training, quality assurance, leadership, and safety, TPM seeks 'zero downtime' and 'zero defects.'

The company moved from reactive to preventive maintenance by documenting machine failures, using a Computerized Maintenance Management System (CMMS), and training teams in preventive techniques. Sensor-based data collection set the stage for Predictive Maintenance (PdM), which aimed to improve operational safety and reduce costs.

However, early PdM efforts faced challenges. Machines lacked standardized interfaces, making data collection difficult. Initial analysis relied on manual CSV exports and Excel calculations, limiting accuracy. High-quality, real-time data was essential for reliable predictions, but infrastructure and expertise gaps slowed progress. Cultural resistance to data-driven decision-making also posed hurdles. Despite these challenges, the plant introduced OEE tracking, optimized spare parts inventory, and conducted risk management to refine PdM strategies.

The rise of Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) has since transformed the PdM. Advanced sensors enable continuous monitoring, cloud computing facilitates real-time data processing, and AI-driven analytics improve failure predictions. These technologies overcome previous limitations by automating data collection, enhancing forecasting accuracy, and reducing human intervention. However, successful adoption still requires skilled personnel and cultural shifts toward data-driven maintenance.

For SMEs, PdM remains an underutilized opportunity. Embracing IoT, AI, and ML can significantly enhance competitiveness, provided expertise gaps are addressed. The journey toward intelligent maintenance is ongoing, technology now offers the tools to make 'zero downtime' a reality.

Ralf Steck – former Head Of Injection Moulding & Metallization / odeloD



1.2. PURPOSE OF THE REPORT

As industrial systems grow increasingly complex, ensuring machine reliability, minimizing downtime, and optimizing maintenance costs have become critical challenges for companies. Traditional maintenance strategies - **reactive and preventive approaches** - often lead to inefficiencies, unexpected failures, and excessive operational costs. In response, **Predictive Maintenance (PdM) is revolutionizing industrial maintenance**, shifting companies from reactive interventions to **data-driven, proactive decision-making**.

The emergence of **Industry 4.0 technologies** - including **Artificial Intelligence (AI), the Internet of Things (IoT), Digital Twins, and Big Data analytics** - is accelerating this transformation. At the same time, **the green transition** is imposing new sustainability and efficiency requirements on industries. In this evolving landscape, **PdM is not just a technological upgrade; it is a strategic necessity** for optimizing asset performance, reducing operational risks, and driving cost efficiency.

For **Small and Medium-sized Enterprises (SMEs)**, PdM offers a competitive advantage by improving equipment uptime and reducing maintenance costs. However, widespread adoption remains **hindered by key barriers** such as **high implementation costs, lack of skilled personnel, and technological integration challenges**.

In parallel, **Vocational Education and Training (VET) institutions** play a crucial role in preparing the future workforce for these changes. As maintenance shifts toward **AI-powered diagnostics and predictive analytics**, **training programs must evolve** to equip professionals with the **technical, digital, and data-driven decision-making skills** required in modern industry.

This report examines how **PdM is reshaping industrial maintenance**, explores the **technological, economic, and workforce implications**, and provides **strategic insights** for both **SMEs and VET institutions** to navigate this transition effectively.

Purpose of This Report

The main question is: How emerging digital technologies 4.0 and green transition trends impact predictive maintenance, affects maintenance activities within industries, market and jobs, VET Centres and learning pathway?

This report aims to provide actionable benchmarks and strategic insights for two key audiences:

- For SMEs: It offers a clear roadmap for adopting PdM, addressing challenges, and leveraging emerging digital technologies to enhance maintenance efficiency.
- For VET Institutions: It outlines how training programs can align with industry needs, ensuring that workers are equipped with PdM-related competencies that support Industry 4.0 and green transition goals.

Scope and Key Questions Addressed

This study, conducted as part of the LCAMP Observatory, **by LCAMP partners from France, Sweden, Germany, Italy and Slovenia** explore the intersection of emerging digital technologies 4.0, green transition trends, and predictive maintenance, with a specific focus on their impacts on industry, workforce, and training programs. The key questions addressed include:

- Why PdM can be a lever for transformation within maintenance organisations and for competitiveness within companies?
- What are the main drivers and barriers to PdM adoption in SMEs?
- How do digital and green transition trends impact maintenance activities and job roles?
- What organizational and workforce transformations are required to implement PdM effectively?
- How can VET institutions align training programs with industry needs to bridge skills gaps?



- What strategic recommendations can support SMEs and VET institutions in this transformation?

The term “**emerging**” here does not imply the novelty of technologies, but rather the emergence in industrial adoption and implementation.

Methodology

The insights presented in this report are based on a **comprehensive analysis**, combining:

- **Literature review** of PdM trends, technologies, and market data
- **Survey data** from SMEs and VET institutions across multiple European regions.

This structured approach ensures that the report provides **both strategic insights and practical guidance**, making it a **valuable resource for decision-makers in SMEs and the VET sector**.



1.3. METHODOLOGY

The LCAMP Observatory methodology is described in the Observatory, process cycle chapter included in (D3-1-Observatory-Methodology-Final-Version-1-1.Pdf, n.d.) document.

It includes:

- The methodology to select jobs to analyse
- The methodology to analyse the impacts
- The methodology to validate the Sub-Report

This year, an additional criterion has been added to justify the selection of the field of observation:

- Relevance of the “Field to Observe” based on the 6 criteria previously described in the methodology (existing jobs, trends impacts, employability, strategic topic, education level, training courses Impact).
- Added value for industrial processes: the subject is included in at least one of the 7 transformations analysed in WP7 initiative which is about ADVanced MANufacturing scans: LCAMP initiative supporting the transformation of SMEs (‘SME - VET Connection’, n.d.).

In order to clarify the objectives of each stage and to control the planning and the main deadlines of the process, the methodology has been clarified compared to previous years. As shown in this diagram, stages 3 and 4 have been divided into 4 distinct phases:

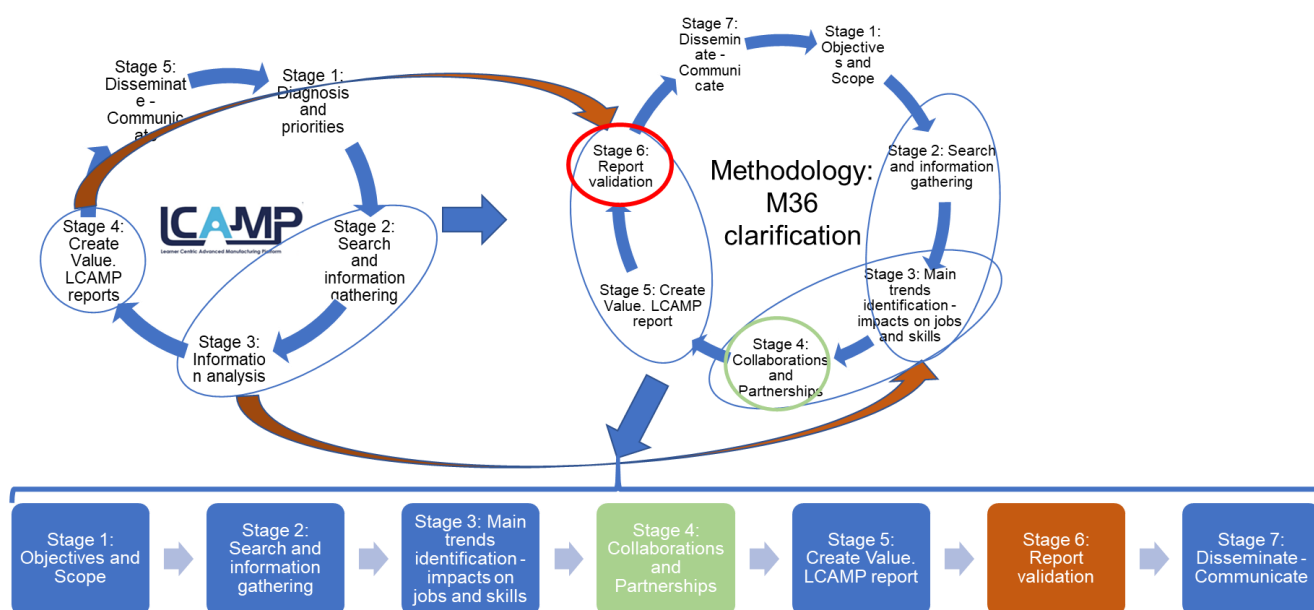


Figure 1. LCAMP Observatory methodology

Stage 4: In addition to the literature review and discussions with experts in the field, it was decided to carry out surveys of SMEs and VET centres to reinforce the conclusions drawn from the literature review.



1.3.1. STAGE 1 - JUSTIFICATION OF PDM TOPIC

A first joint analysis carried out with the French, Swedish, German, Italian and Slovenian partners identified the main reasons for selecting this theme; the present report provides precise information and confirms these initial statements.

Relevance:

- Existing jobs: PdM and Maintenance operators are operating within Industrial companies.

Table 1. Example of ESCO Occupation list involved in maintenance activities (Professions, n.d.).

Esco code	Esco Occupation Code	Esco Occupation Description
2152.1.13	Predictive maintenance expert	Predictive maintenance experts analyse data collected from sensors located in factories, machineries, cars, railroads and others to monitor their conditions in order to keep users informed and eventually notify the need to perform maintenance".
3515.1.6	Mechanical maintenance supervisor	Industrial maintenance supervisors organise and supervise the activities and maintenance operations of machines, systems and equipment. They ensure inspections are done according to health, safety and environmental standards, and productivity and quality requirements.
7212.3.2	Laser welding robot operator programming + production and maintenance monitoring	Laser beam welders set up and tend laser beam welding machines designed to join separate metal workpieces together through the use of a laser beam radiating a concentrated heat source that allows for precise welding. Optional Skills and Competences involve "maintain mechanical equipment"
7411.1	Electrical maintenance operator	Electricians fit and repair electrical circuits and wiring systems. They also install and maintain electrical equipment and machinery. This work can be performed indoors as well as outdoors, in nearly every type of facility.

- Trends impacts: Driven by numerous Emerging Digital Technologies 4.0 such as IoT, AI, machine learning, Cloud-Based computing and Big Data analytics are transforming traditional maintenance approaches.
- Employability: Wide range of demand in aerospace, automotive, energy, and Industry 4.0.

Table 2. Maintenance employability

COUNTRY	SOURCE	KEY WORD	NUMBER OF OFFERS
France	France Travail	"Maintenance"	72 084
	APEC. "Job Search - Maintenance".	"Maintenance"	37 187
	lindustrie-recrute	"Maintenance"	1 290
Germany	Statistics of the Federal Employment Agency	Job Vacancies in "Technical service staff in Maintenance and repair-skilled tasks"	+1500



	Statistics of the Federal Employment Agency	Unemployed Persons in "Technical service staff in Maintenance and repair-skilled task"	+1000
Slovenia	Deloglasnik.si	Filters: level of education: EQF: 4,5,6 Whole country Field of work: maintenance and repair	38
Italy	Randstad.it	Key word: "Maintenance"	803
	Indeed.com	Key word: "Maintenance"	+10000

- Relevance for the Smart Specialisation Strategy: 11 regions among the 21 French regions consider the maintenance activities among the priorities.
- Education level: Maintenance training identified from EQF 4 to 6

Table 3. Maintenance training examples (extract of the full details available in Annex 4)

Country	Source	Training course description	EQF Level
France	IUT Rodez	Professional Bachelor's Degree in Maintenance for the Industry of the Future (Industry 4.0).	EQF 6
	UIMM / CFAI-AFPI	Higher National Diploma in Systems Maintenance, Production System Option.	EQF 5
	Lycée Alexis Monteil	Professional Baccalaureate in Maintenance of Connected Production Systems.	EQF 4
Slovenia	Maintenance Association of Slovenia (DVS)	Basics of Vibration Diagnostics and Bearing Selection, Installation, and Lubrication Provider: Maintenance Association of Slovenia (DVS)	SOK/ EQF 5-6
	Secondary Education Centre Ljubljana (SIC Ljubljana)	Mechanic Training Program Provider: Secondary Education Centre Ljubljana (SIC Ljubljana).	SOK/ EQF 4
Germany	Vdi-wissensforum	Seminars "Condition-/ Prozessmonitoring & Predictive Maintenance" Condition Monitoring and Process Monitoring.	EQF 6
	bbw-seminare	Predictive Maintenance in Training.	EQF 4
Italy	Formazione Michelangelo	"Maintenance Specialist Course" The Maintenance Specialist Course was created with the aim of certifying maintenance technicians and ensuring high-quality standards in the management of company assets.	EQF 4-5
	Festo C.T.E	"Maintenance Specialist Course" Autonomy and efficiency in operational maintenance for the improvement of maintenance department KPIs. Meets the mandatory training requirements for access to Level 1 Maintenance Competency Certification	EQF 4-5

- Training courses impacts:
 - Emerging Digital Technologies 4.0 are transforming traditional maintenance approaches and must therefore be included in training programs.



- Dual qualifications (e.g., combining industrial mechatronics with digitalization) are becoming more relevant.
- Added Value for Industrial Processes:
 - Predictive Maintenance addresses at least one criterion in ADMA methodology: Transformation 2: Digital Factory, Digital capabilities, Transparent view on shop floor status, evaluation 4.0
 - Additional challenges in implementing the PdM and organisational changes: a turning point has been identified in Industrial Services, with Maintenance as a Service (MaaS) actors being developed, potentially impacting the internal organisation of SMEs
 - **Modulation:** the topic of PdM is seen as interesting but in the future, not a priority, as currently many SMEs are far from it; maintenance organisations are often focused on curative maintenance.

1.3.2. STAGE 2 & 3 - SEARCH AND INFORMATION GATHERING

Stages 2 and 3 involved conducting the literature review and analysis of the field of observation, enabling us to identify the most recent and relevant sources, including scientific and academic papers, industry reports and white papers, standards and regulations, patents and technical documentation, case studies and real-world applications, as well as online articles, blogs, and open-source projects.

All of these sources are indicated in chapters “References”.

1.3.3. ADJUSTMENT & VALIDATION OF THE FIELD OF OBSERVATION

The revised methodology thus applied enabled us to refine and validate the final description of the field of observation: **How emerging digital 4.0 technologies and green transition trends impact predictive maintenance, affect maintenance activities within industries, the market and jobs, VET Centres and learning pathways?**

The term “**emerging**” here does not imply the novelty of technologies, but rather the emergence in industrial adoption and implementation.

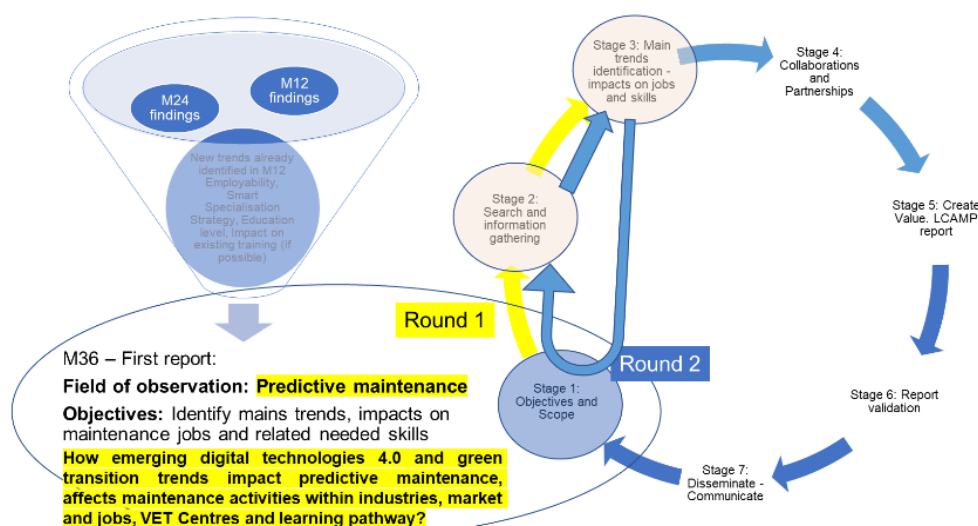


Figure 2. Methodology applied to Predictive Maintenance field of observation



1.3.4. STAGE 4 - COLLABORATIONS AND PARTNERSHIPS

During stages 1 to 3, the main findings were identified, enabling us to validate the scope of the study, move on to stage 4 - collaborations and partnerships - and build two surveys to SMEs and VET Centres.

1.3.4.1. SURVEY ELABORATION

The content of the surveys was reviewed and validated by face-to-face interviews with SME managers and VET centre trainers, and finally by all the LCAMP internal partners involved. The guide lines to build the surveys was to address following points.

Trend Identification and Tracking

- **Objective:** Track the adoption rate of Predictive Maintenance practices within SMEs and understand the urgency or lag in adopting these technologies.
- **Insight for SMEs:** Provides information on where they stand relative to peers in adopting Predictive Maintenance, helping them identify gaps and opportunities.
- **Insight for VETs:** Reveals trending technologies and processes in demand, enabling curriculum adjustments that align with industry needs.

Technology and Process Adoption Levels

- **Objective:** Gauge the level of implementation of key technologies and methods in Predictive Maintenance, such as sensors & IoT, Data analytics and big data, Deep Learning Models, Anomaly Detection and Fault Diagnosis, Natural Language Processing (NLP), Prescriptive maintenance...
- **Insight for SMEs:** Enables them to benchmark their progress in adopting new technologies and identify where additional investment may be needed.
- **Insight for VETs:** Informs on technology adoption trends, helping to integrate these technologies into hands-on training programs and simulations.

Market Shifts and Competitive Positioning

- **Objective:** Understand how Predictive Maintenance is influencing market dynamics, including customer demand, regulatory pressure, and competitive landscape.
- **Insight for SMEs:** Offers perspective on market opportunities in Maintenance domain, encouraging strategies to meet new demands or niche markets + adapt Maintenance Organisation within SMEs
- **Insight for VETs:** Allows VETs to focus on training for competencies linked to emerging market needs, preparing students for areas with high potential.

Challenges and Barriers in Transition

- **Objective:** Identify the primary barriers SMEs face in adopting Predictive Maintenance, such as cost, lack of expertise, or regulatory challenges.
- **Insight for SMEs:** Highlights specific areas where external support (e.g., funding, consulting) could accelerate their transition.
- **Insight for VETs:** Informs where additional educational support might be required, such as training on regulatory compliance or funding application processes.

Assessment of Impact on Jobs and Skills



- **Objective:** Assess how Predictive Maintenance impacts existing roles and the emergence of new job functions within manufacturing.
- **Insight for SMEs:** Helps identify which roles will become obsolete or evolve, supporting workforce planning and reskilling efforts.
- **Insight for VETs:** Informs on emerging job profiles, allowing them to update course offerings and training programs to match current job market requirements.

Skills and Competencies Gap Analysis

- **Objective:** Identify the specific skills and competencies that are lacking in the current workforce, both technically and in terms of people, and that are needed to support the development of predictive maintenance.
- **Insight for SMEs:** Provides a clear understanding of training needs within the organization and industry, facilitating targeted upskilling initiatives.
- **Insight for VETs:** Supports curriculum development with a focus on priority skills, whether technical (e.g., data analysis, energy management) or non-technical (e.g., sustainability literacy, problem-solving).

Training Needs and Preferred Learning Modalities

- **Objective:** Discover the types of training SMEs need and the preferred delivery formats, such as online, in-person, or hybrid training options.
- **Insight for SMEs:** Ensures that training options are accessible and practical, supporting their workforce's development in a flexible manner.
- **Insight for VETs:** Allows VET institutions to adjust training formats to the preferences and constraints of SMEs, making programs more accessible and impactful.

Anticipated Future Needs and Emerging Trends

- **Objective:** Gather insights on the future outlook of SMEs regarding Predictive Maintenance, including planned investments, expected technologies, and skill requirements.
- **Insight for SMEs:** Helps businesses align future workforce planning and investment decisions with anticipated market and technological changes.
- **Insight for VETs:** Guides the future evolution of training programs to stay ahead of the industry's needs, ensuring students are trained in the latest competencies and emerging practices.

1.3.4.2. SURVEY EXECUTION

Sample of SMEs and VET Centres consulted the surveys have been addressed to:

- SMEs: our contacts in the organisation (responsible of Maintenance services or responsible of the company)
- VETs: our contacts in the organisation responsible of learning pathways.

Table 4. Organisations consulted

TARGET AUDIENCE	COUNTRY	NUMBER OF ORGANISATIONS CONSULTED
SMEs	FR	11
	GER	60
	SI	11
	SWE	20
	IT	1



Total SMEs		103
VET	FR	11
	GER	14
	SI	16
	SWE	10
	IT	1
Total VET		52
Overall total		155

1.3.4.3. ANALYSIS AND RELIABILITY OF THE SURVEY RESULTS

Survey Quality Analysis

- **Aim of the survey:** The survey aims to gather data to understand the current state, challenges and trends in predictive maintenance (PdM) for SMEs. It asks specific questions about technologies, implementation strategies, barriers and future developments.
- **Sample selection:** The survey targets companies and VET centres in different sectors and countries (including France, Germany, Sweden, Italy and Slovenia). A non-probability method called 'convenience sampling' (Suen Lee-Jen Wu et al., 2014) is used, as the sample is targeted and focused.
- **Methodology:** The survey is based on an extensive literature review on state of the art in PdM. It is designed as a cross-sectional study, collecting data at a specific point in time. The survey contains mostly closed questions (e.g. multiple choice, Likert scales) and only a few open questions.

Results and findings:

- **Technologies and implementation strategies:** The survey documents the current state of PdM technologies and their implementation in various industries.
- **Challenges:** Identifies key challenges in implementing PdM.
- **Future developments:** The survey provides insights into future developments and training needs to address the expected skills gaps.

Categorisation:

- **Descriptive survey** (Silva, 2008): Documents trends, challenges and status quo in PdM.
- Non-probability method: Convenience sampling, no evidence of random or stratified sampling.
- **Cross-sectional study** (Hemmerich, n.d.): One-time data collection without iterative processes or long observation periods.
- **Quantitative:** Closed-ended questions with structured, numerically evaluable data.

Recommendations:

- To improve the validity of the survey and minimise bias, adjustments could be made, such as the introduction of probabilistic sampling methods.

Survey Representativeness Analysis

Assumption:

- Selected companies with a direct link to the topic, who are professionally and factually recognised, support us without reservation in providing high quality responses to our surveys. This also applies to the training centres.

Reality:



- However, reality has shown that it is very difficult to get responses to surveys. In the end, cold calling had to be used to obtain survey results. This supportive behaviour of industry and training centres extended to many European partner countries.

Evaluation of the results:

- The response rate to a survey varies according to a number of factors, including the target population, the distribution channel and the design of the questionnaire. For internal surveys, such as those carried out among a company's employees, the average response rate is generally between 30% and 40%. On the other hand, external surveys, aimed at external audiences, have lower average response rates, often between 10% and 13%. (Bhat, 2018; hubspot, 2023)
- In the specific context of manufacturers and training centres, response rates can vary depending on the commitment of respondents and the perceived relevance of the survey. For example, one study showed that customer satisfaction surveys generally achieve a response rate of 33%, although this figure varies according to the perceived value to the respondent. (Bhat, 2018)
- It is important to note that the length and complexity of the questionnaire also influences the response rate. Surveys with fewer than 12 questions have an average response rate of 83%, while longer surveys may have a lower response rate.(Le Sphinx, 2024)

1.3.5. STAGE 6 - REPORT VALIDATION

The report has been validated by experts during a collaboration meeting.



2. EVOLUTION OF MAINTENANCE STRATEGIES

Modern industrial equipment has become increasingly complex, leading to a growing interest in more flexible maintenance strategies to ensure high reliability and sustainability. These strategies are categorized into three main types: reactive (or corrective), preventive, and predictive maintenance.

Effective maintenance management for any asset requires selecting the most suitable strategy based on the specific needs of the equipment. Each approach has its own advantages and limitations, making it essential to understand their impact on asset performance and work schedules to make an informed decision.

Equipment failures can be costly, so a predictive maintenance strategy that is designed to predict failures before they happen allowing time for remedial action to be undertaken may seem to be the most obvious approach to follow. However, some non-essential items can run to failure without causing any real problems and can also be quick and inexpensive to replace. In such cases, a maintenance team may be willing to accept a corrective maintenance procedure. Run to failure may also be adopted in situations where remedial action is not feasible – for example certain space crafts/ satellites may be designed based on no-maintenance assumptions and may be allowed to run to failure (and then abandoned).

A third type of strategy, preventive maintenance, is also widely used by industry. This approach, like predictive maintenance, seeks to prevent a failure before it occurs, but there is a slight difference between preventive maintenance and predictive maintenance.

2.1. MAINTENANCE - DEFINITIONS

For a better understanding of the subject, here are the definitions of the three Maintenance's strategies and the optimum maintenance strategy description. (TWI, n.d.) completed by (arxiv, 2024).

2.1.1. REACTIVE (CORRECTIVE) MAINTENANCE - RM

Definition of **Corrective Maintenance**: Maintenance carried out **after a fault is detected**, aimed at restoring an asset to a condition in which it can perform its intended function (*NF EN 13306*, 2018).

Despite the inherent advantages of preventive and predictive techniques, Reactive (or Corrective) Maintenance can be the best solution in some cases. Where the cost of part failure and repair is less than the preventive or predictive maintenance costs, corrective maintenance is often the best solution.

So, for example, in the case of a light bulb, corrective is certainly the best option as the cost and time taken to replace the bulb is unlikely to dramatically impact budgets or work schedules. However, this changes as the part becomes more imperative to operations such as with, for example, a wind turbine blade or ship's engine.

Corrective maintenance can be particularly damaging when it has not actually been decided upon as a plan of action, letting something unwittingly run to failure can be costly in time, money and safety.



2.1.2. PREVENTIVE MAINTENANCE - PM

Definition of **Preventive Maintenance**: Maintenance carried out **at predetermined intervals** or according to prescribed criteria to **reduce the probability of failure** or degradation of the asset (NF EN 13306, 2018).

Definition of **Condition-Based Maintenance**: Preventive maintenance based on **monitoring or inspecting the condition** or performance of an asset to determine the need for maintenance (NF EN 13306, 2018).

Preventive monitoring is used where the cost of letting something keep running until it breaks is too high, the part is too critical, is difficult to replace or repair, or could have serious implications for employee safety or work schedules.

This approach is not necessary for all items, but allows for those that are more important to be maintained.

Preventive maintenance, also known as planned maintenance, involves scheduling routine maintenance activities for specific equipment to reduce the risk of failures. This approach ensures that maintenance is performed while the machine is still operational and functioning normally, preventing unexpected breakdowns and minimizing associated downtime and costs.

It involves scheduled maintenance activities such as cleaning, lubricating, inspecting, and repairing equipment before failures occur. By reducing unplanned repairs, PM enhances efficiency and extends asset lifespan; an optimal maintenance policies that maximize the system reliability/availability and safety performance at the lowest maintenance costs is described in the paper (arxiv, 2024).

Preventive maintenance programs encompass five distinct strategies, all based on planned maintenance principles. Each strategy is structured and scheduled differently to align with specific business.(IBM Business operations, 2023)

Types of Preventive Maintenance:

1. Usage-based maintenance (UBM): Scheduled based on asset usage (e.g., oil changes after a certain mileage).
2. Time-based maintenance: Conducted at fixed intervals (e.g., weekly inspections per manufacturer guidelines).
3. Condition-based maintenance (CBM): Uses real-time monitoring tools to assess equipment health and schedule maintenance as needed.
4. Predictive maintenance (PdM): Leverages data analytics and Artificial Intelligence (AI) to anticipate failures before they happen.
5. Prescriptive maintenance: Goes beyond predictive maintenance by recommending corrective actions to prevent failures.

2.1.3. PREDICTIVE MAINTENANCE - PDM

Definition of **Predictive Maintenance**: A form of condition-based maintenance carried out following a prediction derived from **analysis and evaluation of significant parameters** of the item's degradation, often using **IoT, sensors, and AI** (NF EN 13306, 2018).

As defined previously one of the 5 strategies of Preventive Maintenance, Predictive maintenance (PdM) is a proactive maintenance approach that uses data-driven insights and real-time monitoring to predict and address equipment issues before they cause failure. By collecting data from sensors and applying advanced analytics and machine learning, PdM detects patterns and potential faults, allowing maintenance teams to intervene only when necessary. This minimizes unplanned downtime, reduces maintenance costs, and optimizes equipment performance by addressing issues based on actual conditions rather than fixed schedules. (IBM Business operations, 2023)



Predictive maintenance clearly marks a turning point in the world of industrial services. Unlike previous approaches, such as reactive service models, preventive maintenance, and condition-based maintenance, predictive maintenance adds a critical edge to the use of sensors and measuring machine data. PdM builds on the four cornerstones of digitalization: interconnectivity, digital data, automation, and value creation. (Berger, 2018)

This type of maintenance is becoming more accessible thanks to improvements in emerging digital 4.0 technologies for monitoring, data collection and analysis, as well as reduced costs.

2.2. OPTIMUM MAINTENANCE STRATEGY

The optimum maintenance strategy is determined by optimising the cost of quality, the cost of repair, the cost of maintenance, the cost of downtime and human safety.

- Cost Comparison:
 - RM has the lowest prevention cost but high repair costs due to its run-to-failure approach.
 - PM minimizes repair costs by scheduling maintenance in advance.
 - PdM balances both repair and prevention costs, reducing unplanned failures while avoiding excessive preventive maintenance.
- Key Insights:
 - RM is cost-effective initially but leads to higher downtime and emergency repairs.
 - PM ensures scheduled interventions, avoiding unexpected failures but potentially leading to unnecessary maintenance.
 - PdM leverages data and analytics to optimize maintenance, providing the best cost-performance trade-off.
- Suitability:
 - RM is best for non-critical assets where failure has minimal impact.
 - PM is ideal for machines with predictable wear and available downtime windows.
 - PdM is most effective for high-value, critical assets where predictive insights can maximize uptime and reduce costs.

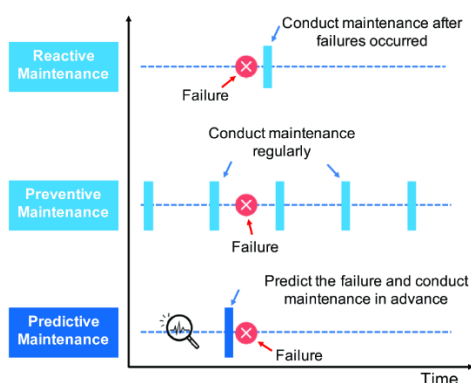


Figure 3. Maintenance plans of RM, PM and PdM

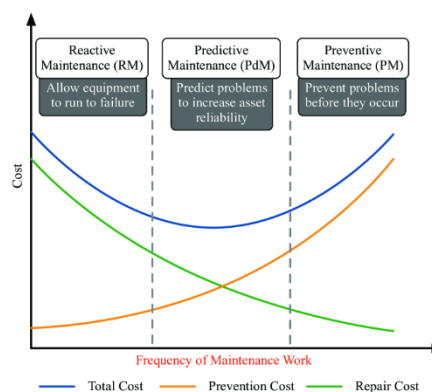


Figure 4. Comparison of RM, PM and PdM on the cost and frequency of maintenance work

Source: (arxiv, 2024)



Table 5. Benefits, challenges and applications of RM, PM and PdM - Sources (A Survey of Predictive Maintenance: Systems, Purposes and Approaches, n.d.)

	Benefits	Challenges	Suitable applications	Unsuitable applications
RM	• Maximum utilization and production value • Lower prevention cost	• Unplanned downtime • High spare parts inventory cost • Potential further damage for the equipment • Higher repair cost	• Redundant, or non-critical equipment • Repairing equipment with low cost after breakdown	• Equipment failure creates a safety risk • 24/7 equipment availability is necessary
PM	• Lower repair cost • Less equipment malfunction and unplanned downtime	• Need for inventory • Increased planned downtime • Maintenance on seemingly perfect equipment	• Have a likelihood of failure that increases with time or use	• Have random failures that are unrelated to maintenance
PdM	• A holistic view of equipment health • Improved analytics options • Avoid running to failure • Avoid replacing a component with useful life	• Increased upfront infrastructure cost and setup (e.g., sensors) • More complex system	• Have failure modes that can be cost-effectively predicted with regular monitoring	• Do not have a failure mode that can be cost-effective

The comparison highlights that PdM offers the most efficient long-term solution, balancing costs and reliability, but requires advanced technology and data management.

2.3. PREDICTIVE MAINTENANCE - A STEP BEFORE PRESCRIPTIVE MAINTENANCE

Definition of **Predictive Maintenance**: Prescriptive maintenance goes a step beyond predictive maintenance by not only anticipating failures but also recommending or automatically initiating corrective actions.

Prescriptive maintenance technology is transforming asset performance management with the premise why simply predict production issues when you can prescribe fixes for them and act on the prescriptions. Predictive maintenance models have advanced to the stage where they are able to consider the articulated production and resource usage goals of an enterprise or organization. Prescriptive maintenance is the asset maintenance strategy that uses machine learning to adjust operating conditions for desired outcomes, as well as intelligently schedule and plan asset maintenance (aspentech, n.d.; upkeep, n.d.).

Here's how we can summarize the goals of each strategy:



- **Reactive:** “Fix it when it breaks.”
- **Preventive:** “Fix it before it breaks.”
- **Predictive:** “Fix it when data says it's about to break.”
- **Prescriptive:** “Fix it this way, at this time, to avoid problems, optimize performance and operating constraints”.

While Prescriptive maintenance is becoming the next frontier beyond predictive maintenance, the following chapters are focused on Predictive Maintenance:

- The context
- Market Outlook & Growth Projections
- Technological Evolution & Adoption
- Predictive Maintenance as a Service (PdMaaS): A Cost-Effective and Scalable Solution
- PdM principles and impacts of emerging digital technologies 4.0
- PdM Impact in maintenance activities in SMEs
- Emerging digital technologies 4.0: Impact on maintenance training in VET Centres.

3. PDM - CONTEXT

Given the acceleration in the adoption of emerging 4.0 technologies in the PdM field over the past 10 years, an analysis of the expected outlook over two time periods seems appropriate.

Here, we draw on a study presented in 2018 (Berger, 2018), and two more recent publications, the first published in 2024 (Allied Market Research, 2024) and the second one with a last update in January 2025 (Fortune Business Insights, 2025).

In 2018 Roland Berger predicted that predictive maintenance (PdM) would revolutionise industrial services by using algorithms and sensor data to anticipate failures before they occur, thereby optimising asset performance and reducing costs. This evolution was to lead to a transformation of service and business models, moving from reactive maintenance to proactive, data-driven strategies.

The recent publications confirm and even exceeds the 2018 forecasts, with two main events: the COVID-19 pandemic and the emergence, in the meantime, of generative AI.

Here are the key trends, market changes and technological advances expected in 2018, the current situation and forecasts to 2033, confirmed by other publications.

3.1. MARKET OUTLOOK & GROWTH PROJECTIONS

3.1.1. PERSPECTIVE PUBLISHED IN 2018

The following Forecast global PdM market development to 2022 has been built from the following sources: (Berger, 2018), (IoT Analytics, 2017), (persistencemarketresearch, 2025). (Scope of Forecast global PdM market development described in Annex 2).



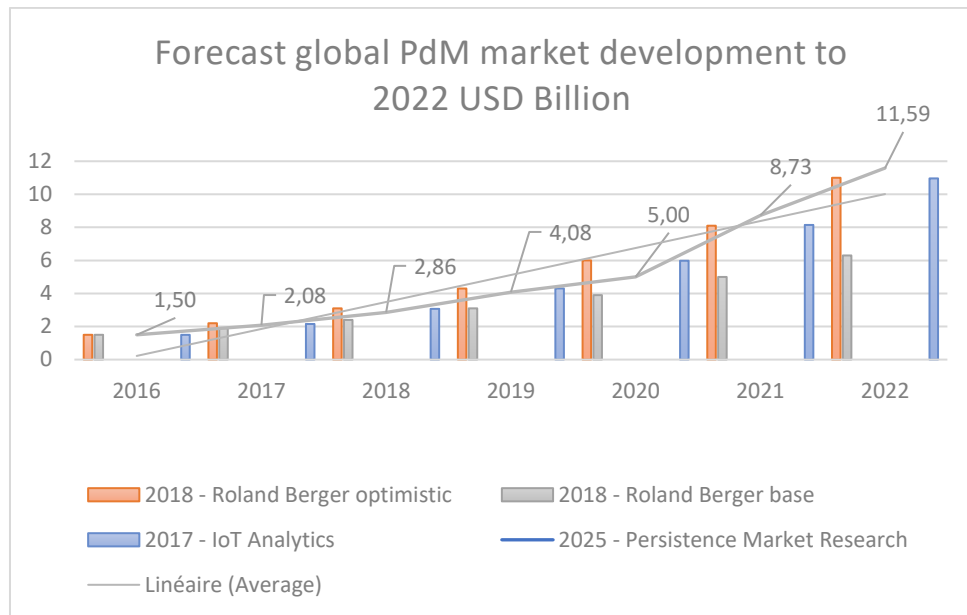


Figure 5. Forecast global PdM market development to 2022

- The **PdM market was projected to reach USD 11 billion by 2022**, particularly in Europe.
- At that time, **81% of businesses were investing in PdM**, with 40% believing it would be crucial for future business success.
- The global PdM market was **expected to grow between 20% and 40% annually across industries**.
- Key sectors expected to adopt PdM included **automotive, aerospace, and industrial manufacturing**.

3.1.2. PERSPECTIVES PUBLISHED SINCE 2023

The following Forecast global PdM market development to 2033 has been built from the following sources: (*Predictive Maintenance Market Share, Global Industry Size Forecast*, 2024), (*Fortune Business Insights*, 2025), (*Fortune Business Insights*, 2025), (*Predictive Maintenance Market Size, Share, Report 2025-33*, 2024), (<https://www.polarismarketresearch.com>, 2024), (*Allied Market Research*, 2024), (<https://www.marketresearchfuture.com>, 2022), (*Grand View Research*, 2022), (*persistencemarketresearch*, 2025)

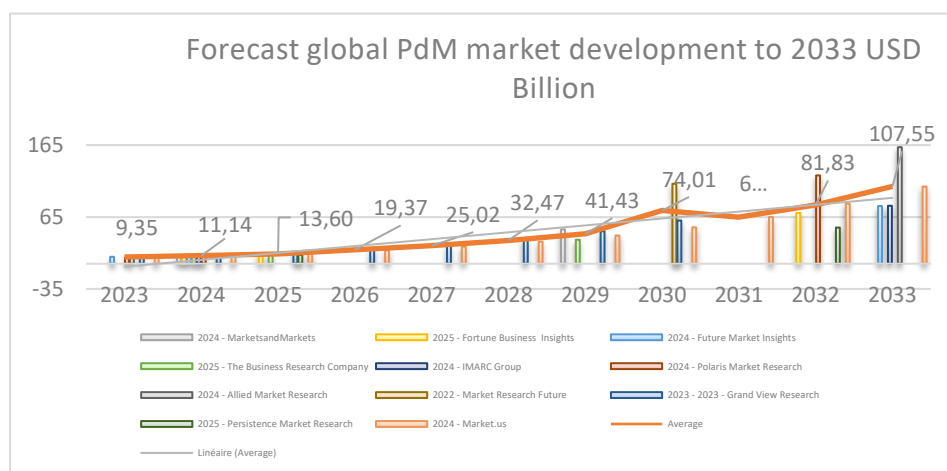


Figure 6. Forecast global PdM market development to 2033



- The global predictive maintenance (PdM) market was valued at USD 10.93 billion in 2024 and is expected to reach USD 70.73 billion by 2032, growing at a CAGR of 26.5% (Fortune Business Insights, 2025). (Scope of Forecast global PdM market development described in Annex 2).
- Some projections estimate the market could reach **USD 107 billion by 2033** (CAGR of 32.2%) (*Predictive Maintenance Market*, n.d.)
- The shift towards **automated, cloud-based PdM solutions** continues to drive market growth.

3.1.3. KEY DIFFERENCES BETWEEN 2018 AND 2024

- In 2018, PdM was still considered an **emerging trend**, while by 2024, it had become a **necessary standard** for industrial competitiveness.
- While **market growth projections** have followed the average of those estimated in 2018 through to 2020, they have exceeded expectations since 2021.
- **COVID-19 acted as a catalyst** for adoption, as companies sought **remote monitoring solutions** due to travel restrictions and labor shortages, pushing industries toward **data-driven and AI-powered** PdM solutions.
- **Generative AI** introduces a new era in PdM.

3.1.4. REGIONAL VARIATIONS

The article (Allied Market Research, 2024) mentions regional variations influenced by industrial demand, technological progress, and government policies.

- North America leads in PdM adoption due to early technological integration, strong investments in IoT, AI, and machine learning, and a concentration of major tech firms. Government support and Industry 4.0 initiatives further drive growth, particularly in manufacturing and aerospace.
- Europe prioritizes sustainability and efficiency, with EU regulations and industry standards accelerating PdM adoption. Countries like Germany, known for their manufacturing strength, are actively implementing smart factory initiatives to enhance industrial performance.
- Asia-Pacific is witnessing rapid PdM expansion, driven by industrial growth in China, Japan, and India. Increased digital transformation investments and smart manufacturing advancements fuel market momentum, though adoption levels vary, with Japan and South Korea leading the way.
- Latin America and the Middle East are increasingly recognizing PdM's benefits in cost reduction and efficiency improvements. However, limited infrastructure and lower investment levels present challenges, slowing adoption in some areas.

3.1.5. GLOBAL PDM MARKET SHARE BY END-USE ANALYSIS, 2024

Large companies are the primary adopters, contributing to **over 75%** of the market in 2023

Among PdM techniques, vibration monitoring was the most widely used, representing 28% of the market in 2023.

The **manufacturing sector** emerged as the largest industry adopter, holding **over 29%** of the market share in 2023

(*Predictive Maintenance Market*, n.d.)



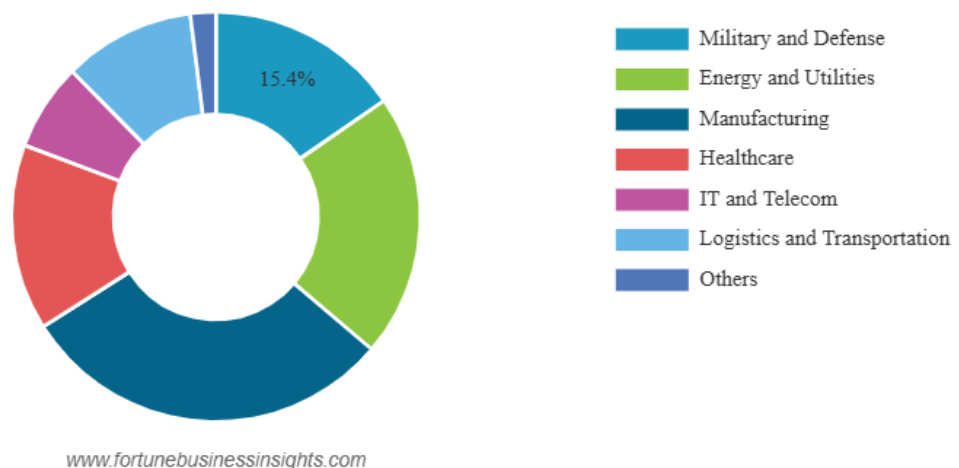


Figure 7. Global PdM Market Share by End-Use Analysis, 2024

3.2. TECHNOLOGICAL EVOLUTION & ADOPTION

3.2.1. SITUATION IN 2018

- PdM was **primarily driven by sensor technology, data analytics, and cloud-based solutions.**
- Companies relied on **structured data and pre-programmed algorithms** to detect failures.
- **Predictive ability was still limited**, and **machine learning models were not fully integrated** into maintenance workflows.
- The focus was on **data collection rather than real-time decision-making.**

3.2.2. SITUATION SINCE 2023

3.2.3. SIGNIFICANT TECHNOLOGICAL IMPROVEMENTS:

The last 3 years have seen a revolution in the adoption of new solutions based on generative AI,

- **AI, machine learning, and digital twins** have become the **core enablers** of PdM.
- **Generative AI is revolutionizing PdM**, making maintenance **proactive, cost-effective, and highly automated:**
- It enhances PdM by anticipating machine failures, auto-generating repair plans, and providing personalized repair guidance. It simplifies predictive model development, reducing the reliance on large data science teams while improving accuracy and efficiency.
- In manufacturing, generative AI-powered PdM systems are proving effective. For instance, an automotive company implemented such a system, achieving a 30% reduction in downtime and 20% lower maintenance costs.
- **Cloud-based PdM solutions and digital twins** now enable continuous monitoring and virtual simulations for equipment forecasting.



Sample of recent Developments:

- June 2024: IBM Corporation launched Maximo Application Suite (MAS) version 9.0, featuring an enhanced AI-driven predictive maintenance solution, a more intuitive user interface, and expanded IoT integration for real-time data analytics and asset monitoring
- July 2024: Sensit, a key player in predictive maintenance technologies for heavy-duty industries, unveiled Sensit Pro, a cutting-edge diagnostics solution tailored for fleet managers.
- July 2024: ManWinWin Software expanded its predictive maintenance solutions, introducing proactive tools to anticipate and prevent equipment failures before they occur.

3.2.4. COMPETITIVE LANDSCAPE

Companies are launching **industry-specific PdM solutions** to **increase efficiency and market share**.

Major players like **IBM, Siemens, GE, and C3.ai** are expanding through **partnerships, acquisitions, and R&D investments**.

- July 2024: I-care Group finalized an agreement with Sensirion Connected Solutions GmbH to acquire the assets and licenses of its predictive maintenance product line.
- In September 2024, COMPREDICT and Renault Group announced a partnership focused on predictive maintenance technology using virtual sensors. COMPREDICT's software-based virtual sensors provide real-time data without requiring additional hardware, significantly reducing the total cost of ownership for OEMs (Original Equipment Manufacturer). (Fortune Business Insights, 2025)
- The articles (Allied Market Research, 2024) and (Fortune Business Insights, 2025) mentioned these additional initiatives:
- Amazon Web Services (AWS) launched 'Amazon Lookout for Equipment', a predictive maintenance solution that leverages machine learning and sensors to optimize maintenance scheduling and detect potential equipment failures (2021).
- Siemens acquired Senseye to enhance PdM capabilities (2022).
- Accenture acquired Nextira to expand AI-driven Predictive solutions (2023).
- General Electric plans to support the aerospace business by providing artificial intelligence and machine learning technology in predictive maintenance services and automated inspection processes. (2024)

3.2.5. KEY DIFFERENCES BETWEEN 2018 AND 2024

- In 2018, PdM was focused on data collection, while in 2024, it has evolved to real-time, AI-driven predictive analytics.
- The integration of generative AI has significantly improved predictive accuracy and decision-making.
- Digital twins have enabled virtual maintenance simulations, something not widely adopted in 2018.
- Companies in 2024 are leveraging software-based PdM rather than relying solely on hardware-heavy solutions.
- Major companies invest heavily in the sector.
- Testimonial from Fives group:
 - The evolution of the industrial context where projects can no longer be exploratory but must demonstrate their value, we have moved from POC (Proof of concept) to POV (Proof of value).



- We have moved from a wave of 'Big Data' to more 'Smart Data' projects.
- From their point of view, and depending on the machine, they're now more interested in setting up models capable of detecting an anomaly than in qualifying it.

3.3. PDM AS A SERVICE (PDMAAS): A COST-EFFECTIVE AND SCALABLE SOLUTION

While MaaS (Maintenance-as-a-Service) was not widely discussed **as an alternative business model** in 2018, the rise of Maintenance-as-a-Service (MaaS) in 2024 allows SMEs to access PdM solutions without requiring full infrastructure ownership.

PdMaaS provides **manufacturing plants** with **affordable** and **on-demand access** to predictive maintenance solutions. Many **startups** are leveraging this model to help businesses **reduce infrastructure costs** while **maximizing asset utilization**.

Key benefits of **PdMaaS** include:

- **Eliminating infrastructure and development costs**
- **Enhancing scalability** through cloud-based access
- **Extending asset lifespan** and optimizing **remaining useful life**
- **Increasing machine uptime and reliability** by **detecting issues before failure**

This approach enables businesses to **shift from reactive to proactive maintenance**, ensuring **greater operational efficiency** with minimal investment.

Maintenance as a Service (MaaS) is developed as "Services 4.0" by companies that consolidate their experience and expertise in the field and seek to leverage them.

In parallel the traditional model of selling industrial equipment is evolving towards a service-oriented approach known as Equipment-as-a-Service (EaaS). In this model, manufacturers retain ownership of their machinery and offer customers access based on usage metrics, such as operational hours. This shift obliges providers to deliver efficient supervision and maintenance services to ensure optimal performance and customer satisfaction.

EaaS allows customers to utilize advanced equipment without significant upfront investments, paying instead for the actual usage. This arrangement transfers the responsibility of maintenance, repairs, and upgrades to the equipment provider, ensuring that the machinery operates efficiently and reducing downtime for the customer. For instance, the airline industry has long employed a similar model, where jet engine manufacturers charge airlines based on engine flight hours, encompassing maintenance and performance guarantees. (Christiansen, 2022)

This service-based model benefits both providers and customers. Providers gain a steady revenue stream and closer customer relationships, while customers enjoy access to the latest technology with reduced financial risk and operational responsibilities. As a result, EaaS is becoming an increasingly attractive business model in various industries, promoting sustainability and efficiency. (Jean-Philippe Richard-Charman, 2023)

Here are some notable examples:

Equipment as a Service

- **CHG-MERIDIAN** is one of the world's leading **technology2use companies**, developing, financing, and managing customised business models for technology in the IT, industrial and healthcare sectors. The company offers integrated, end-to-end management of all assets based on the principles of the circular economy. (chg-meridian, n.d.)



- **Trumpf – Equipment-as-a-Service (EaaS) for Laser Cutting Machines:** Trumpf offers a pay-per-use model for laser cutting machines, where customers use the machines and only pay for the actual operation. Maintenance and service are included in the model. (*Pay per Part* | TRUMPF, n.d.)

Maintenance as a Service

- **Siemens** offers a range of predictive maintenance solutions across industries such as manufacturing, energy, and healthcare. Their technologies enable businesses to detect anomalies, predict equipment failures, and strategically schedule maintenance activities (Marcus Law, 2023).
- **MachineMetrics** connects to numerous machine tools, collecting extensive data on machine health and performance. This data allows for the identification of indicators leading to machine failures, enabling the implementation of condition-based maintenance programs (machinemetrics, n.d.).
- With 20 years' experience in PdM, **I-Care** offers a global approach designed to maximise asset reliability, improve maintenance efficiency and minimise unexpected failures (I-care, 2025).

Equipment and Maintenance as a Service

- **Festo and FlexFactory** have joined forces to provide flexible and cost-effective manufacturing solutions as part of 'as a service' business models. The partnership aims to enable the manufacture of a wide range of product variants while minimising business and operational risks. Key components include models such as '**Maintenance as a Service**' and '**Equipment as a Service**', which reduce financial risks through '**Pay per Part**' or '**Pay per Use**'. Festo contributes its expertise in production automation and AI-based software solutions, while FlexFactory acts as a business enabler and orchestrator. (Festo, 2021)
- **Fives Group:** Fives' data science and technical experts have designed a proven nine-step methodology to implement a comprehensive predictive maintenance program across various industries. This process begins with the connection to CNC or PLC or strategic sensor and the deployment of an application to gather critical data. These solutions now enable us to offer advanced maintenance services with a high degree of commitment or machine performance improvement (fivesgroup, n.d.).



4. PDM - TECHNOLOGICAL FOUNDATIONS

In November 2023, Fernando Brügge wrote in the (Fernando Brügge, 2023) article, in sum-up:

- For Vendors: The PdM market is maturing, but challenges remain. Vendors must focus on industry-specific solutions, better data integration, and improving prediction accuracy to gain market trust.
- For End Users: PdM solutions help companies save hundreds of thousands of dollars by reducing unplanned downtime and optimizing asset utilization. Investing in PdM can pay off with the first correct failure prediction.

Despite its benefits, PdM accuracy remains an issue, with many solutions achieving less than 50% accuracy, leading to false alarms that reduce trust in the technology. However, advances in AI-driven analysis and improved data sources are boosting reliability.

- 95% of PdM adopters report a positive ROI, with 27% achieving amortization within a year.
- Search interest in PdM has tripled since 2017, surpassing other maintenance-related searches, indicating its growing importance as a must-have industrial solution.

Given these observations, it seems necessary to take a step back and highlight the technical and industrial revolution that has been taking place since 2017, accelerating since 2023 with the availability of promising AI-based solutions.

The following comparative analysis, based on (Fernando Brügge, 2023; FMI - Future Market Insights, n.d.; Knud Lasse Lueth, 2017, 2019; Research, 2024) highlights the significant transformations in the Predictive Maintenance (PdM) landscape since 2017. These changes are driven by **evolving supplier strategies, technological advancements, integration practices, and emerging challenges.**

Vendor Landscape and Specialization

- 2017: Approximately 110 technology firms were active in PdM, spanning segments like condition monitoring hardware, industrial automation hardware, connectivity, storage & platforms, and analytics.
- 2019: The number of PdM-focused vendors doubled to over 180, with the analytics segment becoming the most crowded, accounting for 35% of vendors.
- 2023: Successful PdM vendors began specializing in specific industries and assets, integrating their solutions into Asset Performance Management (APM) and Computerized Maintenance Management Systems (CMMS) to enhance value propositions.
- 2024: The trend towards specialization intensified, with vendors focusing on niche markets to offer tailored solutions. This approach allowed for deeper domain expertise and more effective predictive models, addressing unique challenges within specific sectors.

Technological Advancements

- 2017: PdM strategies combined traditional condition monitoring with analytics algorithms, enabling failure predictions before occurrences.
- 2019: The analytics segment diversified into nine types, including data visualization, machine learning, predictive analytics, and anomaly detection, highlighting a trend towards more specialized analytical approaches.
- 2023: Three primary types of PdM were identified, with anomaly detection gaining prominence. PdM software tools commonly featured data collection, analytics, visualization, and prescriptive actions, emphasizing comprehensive solutions.



- 2024: Integration of Artificial Intelligence (AI) and Machine Learning (ML) became more pronounced, enhancing the accuracy of predictive models. The adoption of cloud computing and IoT technologies facilitated real-time data processing and remote monitoring capabilities

Integration and Workflow

- 2017: PdM solutions were primarily standalone, focusing on predictive capabilities without deep integration into existing maintenance workflows.
- 2019: There was a gradual shift towards integrating PdM solutions with existing systems, but many implementations remained siloed.
- 2023: Integration of PdM into maintenance workflows became crucial, with solutions increasingly embedded within APM and CMMS platforms, facilitating seamless operations and data flow.
- 2024: The emphasis on integration deepened, with PdM solutions becoming integral components of enterprise asset management systems. This seamless integration enabled automated maintenance scheduling and real-time decision-making, reducing operational disruptions.

Challenges and Opportunities

- 2017: The focus was on demonstrating the potential efficiency gains of PdM, with users reporting 25%-30% improvements.
- 2019: Challenges included data quality issues and the need for skilled personnel to interpret complex data outputs.
- 2023: Despite advancements, challenges persisted, notably the accuracy of PdM solutions, with many achieving less than 50% accuracy, leading to trust issues. However, 95% of adopters reported a positive ROI, with 27% seeing amortization within a year, underscoring the financial benefits of effective PdM implementations.
- 2024: Data management complexities and integration challenges remained significant. The emergence of Industrial DataOps aimed to address these issues by streamlining data workflows and improving data quality, thereby enhancing the reliability of PdM systems.

Despite challenges in data management and system integration, advancements in AI, IoT, and analytics continue to enhance PdM's accuracy and adoption.

Let's now focus on understanding how Pdm works, what its pillars are, and how generative AI is providing answers to improving prediction models and analysing and understanding its results.

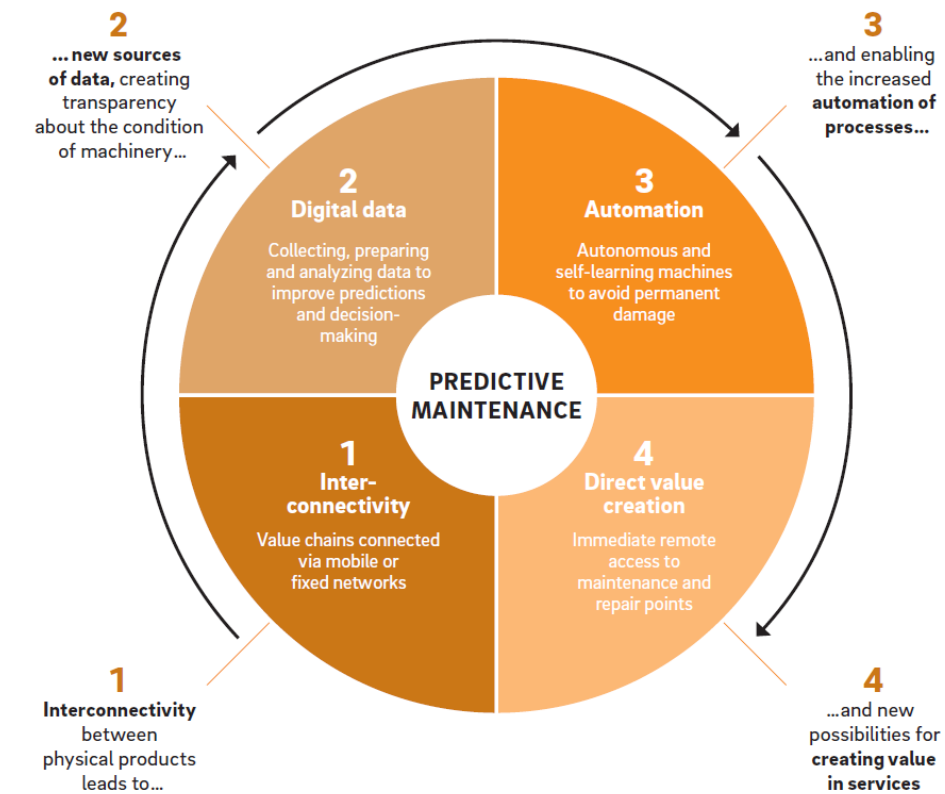
4.1. HOW PDM WORKS

Predictive Maintenance (PdM) has evolved into a cornerstone of industrial efficiency, transitioning from traditional reactive and preventive strategies to a proactive, data-driven approach. At its core, PdM is built upon four fundamental pillars of digitalization: interconnectivity, data-driven insights, automation, and value generation (Berger, 2018). These principles enable the seamless collection, analysis, and utilization of sensor data, allowing industries to anticipate equipment failures, optimize maintenance schedules, and enhance service quality.

- **Interconnectivity:** Seamless integration of devices and systems, enabled by IoT, ensures real-time data exchange and improved operational visibility, forming the foundation of smart manufacturing (IBM Business operations, 2023).
- **Digital Data:** Continuous collection and processing of operational metrics facilitate actionable insights, fostering a culture of data-driven decision-making (Google Cloud, 2025).



- **Automation:** The deployment of AI-driven algorithms and robotics minimizes human intervention, optimizing maintenance actions and improving overall efficiency (IBM Business operations, 2023).
- **Value Creation:** Digital transformation enhances service models, improves customer satisfaction, and drives sustainable business growth (SSON Editor, Barbara Hodge, 2019).



Source: Roland Berger

Figure 8. The four cornerstones of digitalization - Roland Berger

While traditional predictive maintenance relied on rule-based systems and statistical models, advances in IoT, AI and generative AI have revolutionised its capabilities.

This chapter examines the PdM framework, which leverages IoT, AI and Large Multimodal Models (LMMs) to address predictive maintenance challenges. In addition, it highlights the transformative role of generative AI in overcoming limitations faced by traditional approaches.



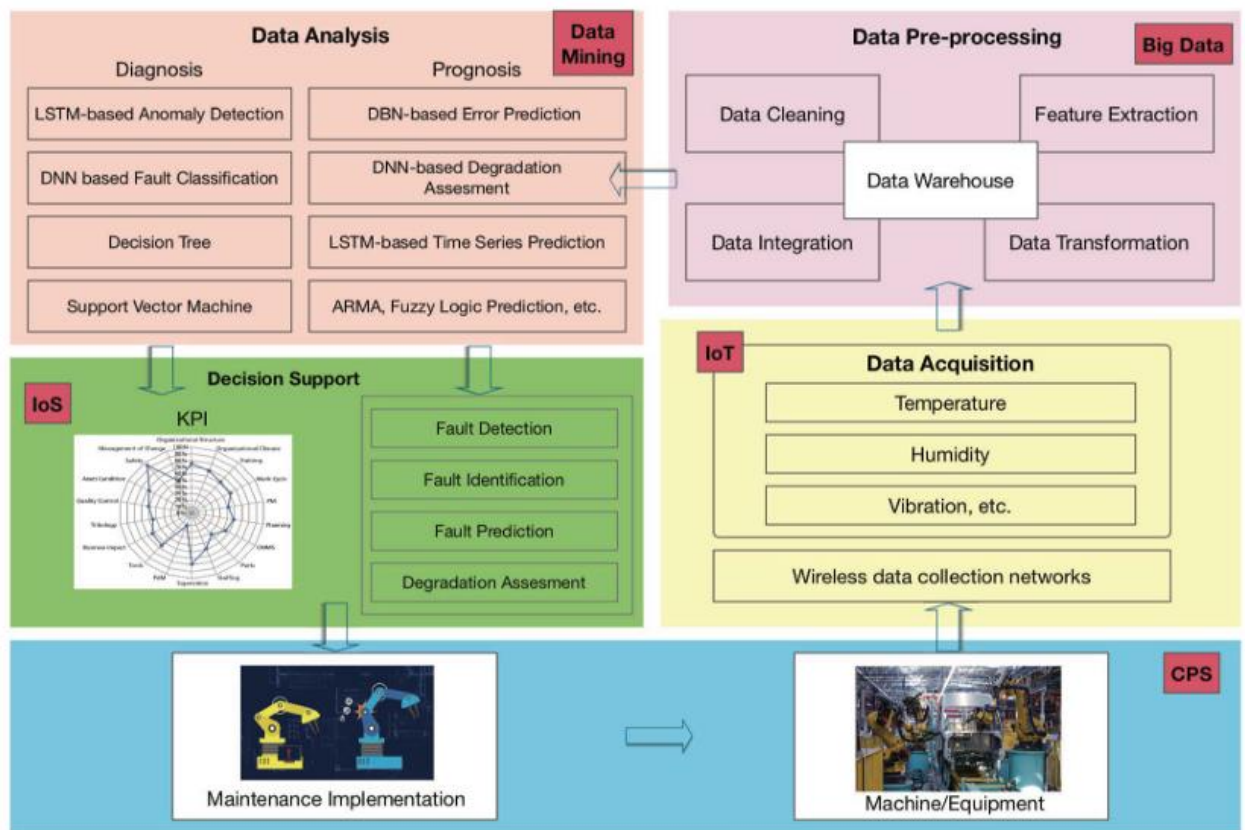


Figure 9. System architecture for the intelligent and PdM 4.0.

([1912.07383] A Survey of Predictive Maintenance: Systems, Purposes and Approaches, 2019)

The architecture and processes described align with the structure defined in **IEC 63270-1 (not already published)**, which outlines functional blocks, data interfaces, and life cycle perspectives for predictive maintenance in industrial automation (FprEN IEC 63270-1, 2025).

4.1.1. IOT AS THE FOUNDATION

Data Acquisition Through IoT Devices.

IoT sensors are the backbone of PdM, providing real-time data on machine health, including temperature, vibration, pressure, energy consumption, etc. These sensors, Installed directly on critical components, enable continuous monitoring and data collection, which is essential for predictive analytics (IBM Business operations, 2023). For example:

- **Vibration sensors** detect anomalies in rotating machinery.
- **Thermal sensors** identify overheating components.
- **Acoustic sensors** capture sound patterns indicative of wear and tear.
- **Humidity Sensors** help detect corrosion risk or moisture-induced failures in electrical components.
- **Gas Sensors** can detect leakages in industrial environments, particularly for hazardous gases.
- **Current & Voltage Sensors** monitor electrical fluctuations, which may indicate motor degradation or wiring faults.
- **Strain Sensors** measure mechanical stress and strain to predict potential structural failures in machinery.



- **Oil Quality & Particle Sensors** analyse lubricant health, detecting metal particles that indicate gear or bearing wear.
- **Ultrasonic Sensors** identify fluid leaks, cracks, or improper lubrication through high-frequency sound waves.

Data Transmission & Edge Computing: Data is transmitted through cloud-based or edge computing systems for real-time processing, minimizing latency and optimizing bandwidth (Thomaz Cortes, Guillaume Decaix, Thomas Hansmann, Khoon Tee Tan, and Yi Zhou, 2021).

Connectivity: The collected data is transmitted to central systems using IoT connectivity solutions. This ensures that data from various parts of an operation are aggregated for comprehensive analysis.

Impact of 5G on Predictive Maintenance

The introduction of 5G technology enables faster and more reliable data transmission. With higher bandwidths and lower latency times, 5G significantly improves communication between IoT sensors and central data platforms. This leads to more efficient data processing and enables real-time analyses that further increase the efficiency of predictive maintenance systems. 5G also supports the integration and use of augmented reality and other advanced technologies in maintenance processes. (Predictive Maintenance, 2024)

4.1.2. DATA STORAGE AND PROCESSING

- **Cloud Storage:** IoT data is often stored in cloud-based systems to enable scalable storage solutions and accessibility for further processing (IBM Business operations, 2023).
- **Data Preprocessing:** Before analysis, data undergoes preprocessing steps to clean and normalize the data, addressing issues such as missing values and noise (Riccio et al., 2024).

4.1.3. AI-POWERED PREDICTIVE ANALYTICS

4.1.3.1. CHALLENGES IN TRADITIONAL PREDICTIVE MAINTENANCE METHODS

Although traditional predictive maintenance methods remain useful in certain situations, they face several challenges that reduce their effectiveness in today's complex, data-intensive industrial environments (Takyar, 2023). Key limitations include:

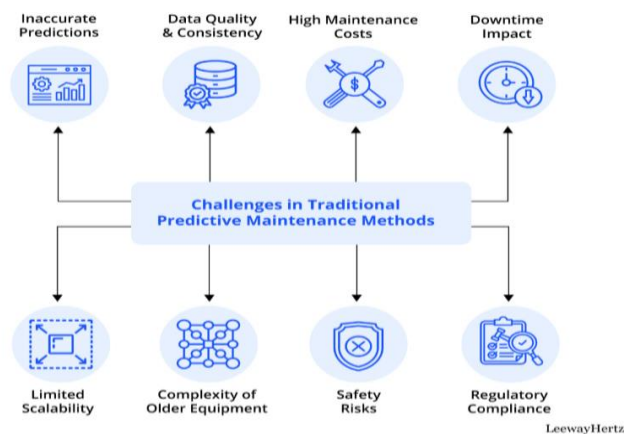


Figure 10. Challenges in traditional predictive maintenance methods (Takyar, 2023)



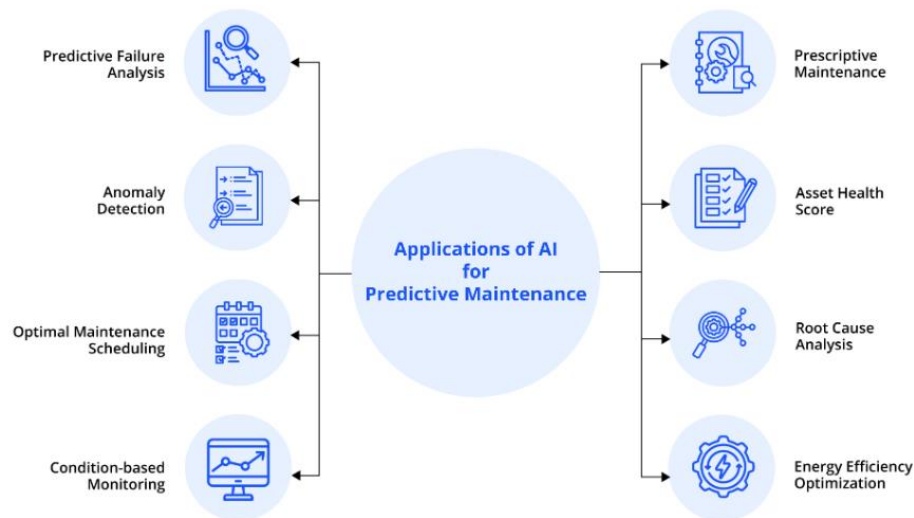
Table 6. Challenges in traditional predictive maintenance methods

Challenge	Impact
Limited data utilization	Restricted ability to capture real-time equipment performance and condition data
Reactive nature	Unexpected downtime, production losses, and higher repair costs due to maintenance initiated only after a problem occurs
Inaccurate predictions	False alarms or missed early signs of deterioration due to reliance on rule-based or threshold-based approaches
Data quality and consistency	Reduced reliability of predictions due to human error, inconsistent recording practices, and data entry mistakes
High maintenance costs	Increased maintenance expenses from emergency repairs, overtime labor, and expensive spare parts due to reactive maintenance
Downtime impact	Disrupted production schedules and decreased operational efficiency due to longer equipment downtime for inspections and repairs
Limited scalability	Inefficient use of human resources and time in industries with a large number of assets or complex machinery due to manual inspection-based methods
Complexity of older equipment	Difficulty and cost in retrofitting older equipment with sensors needed for modern predictive maintenance approaches
Lack of proactive maintenance	Over-maintenance or under-maintenance resulting from routine, calendar-based maintenance not aligned with actual equipment condition
Safety risks	Increased safety hazards to personnel and the environment from delayed or neglected maintenance due to the reactive nature of traditional methods
Regulatory compliance	Challenges in meeting safety and environmental regulations due to insufficient compliance documentation and traceability provided by traditional methods
Competitive disadvantage	Difficulty in competing with competitors adopting more advanced predictive maintenance strategies

4.1.3.2. USE CASES OF AI IN PREDICTIVE MAINTENANCE

To overcome these limitations, many industries are shifting toward **modern predictive maintenance strategies** that integrate **AI, Generative AI** (see dedicated chapter “Evolution Toward Generative AI” which highlights impacts of GenAI), **machine learning, and predictive analytics**. These advanced approaches enhance **prediction accuracy, minimize downtime, reduce maintenance costs, and improve asset reliability**.





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Figure 11. Use cases of AI in predictive maintenance (Takyar, 2023)

- **Machine Learning Models:** Traditional PdM relies heavily on machine learning models to analyse historical data and identify patterns indicative of potential failures. Algorithms such as Regression Models, Decision Trees, Random Forest, Support Vector Machines, and Neural Networks are commonly employed (Alexander Barinov, 2022).
- **Large Machine Learning Models (LMMs):** LMMs enhance PdM by leveraging vast amounts of data and sophisticated algorithms to improve the accuracy of failure predictions. These models can process and learn from complex datasets, making them more robust in predicting rare or infrequent failures (Johnson, 2023).
- **Deep learning (DL):** in data-intensive scenarios, advanced techniques like deep learning significantly enhance predictive capabilities. Deep learning algorithms excel at processing complex datasets, such as high-frequency sensor data, enabling them to detect subtle variations indicative of potential issues. We observed these benefits in our collaboration with a global provider of in-flight broadband services. Through the application of Machine Learning and advanced analytics, N-iX developed predictive models to monitor antenna health and anticipate potential failures. These models achieved over 90% accuracy in predicting equipment issues up to 30 days in advance. Consequently, this solution reduced Gogo's no-fault-found rate by 75%, optimized operational costs, and greatly enhanced the in-flight experience for passengers. (Yaroslav Mota, 2024).
- The study (Hatipoğlu et al., 2023) compared the performance of six **machine learning methods** - **Logistic Regression, Naive Bayes, Decision Trees, Support Vector Machines, Random Forest, and K-Nearest Neighbors** - alongside two **deep learning architectures, Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)**. The analysis was performed using the **Predictive Maintenance dataset from the UCI Machine Learning Repository**, with results assessed through four key metrics: **accuracy, precision, recall, and F1-score**.



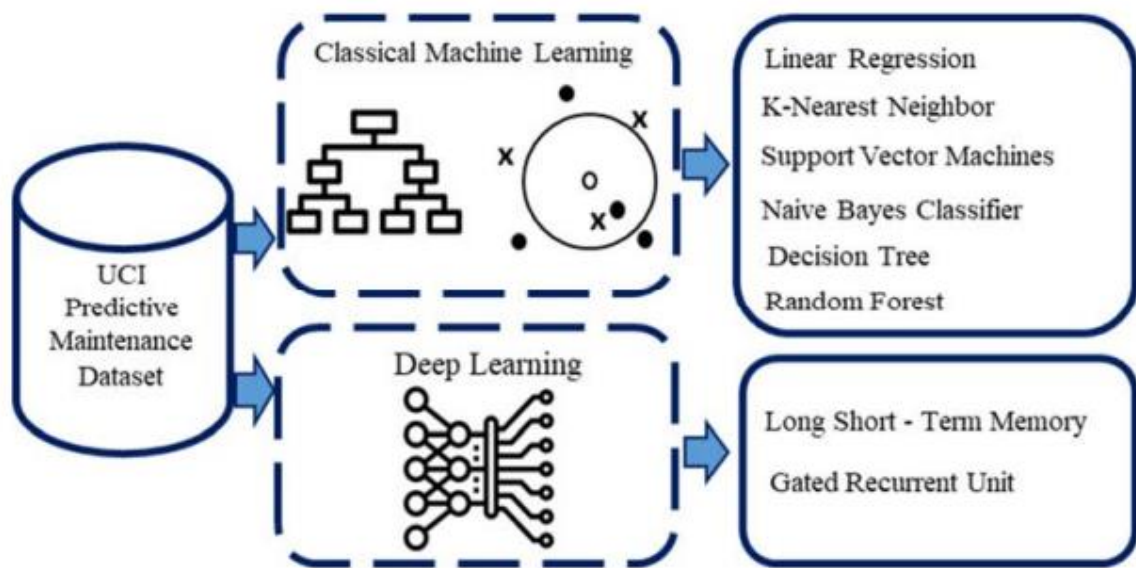
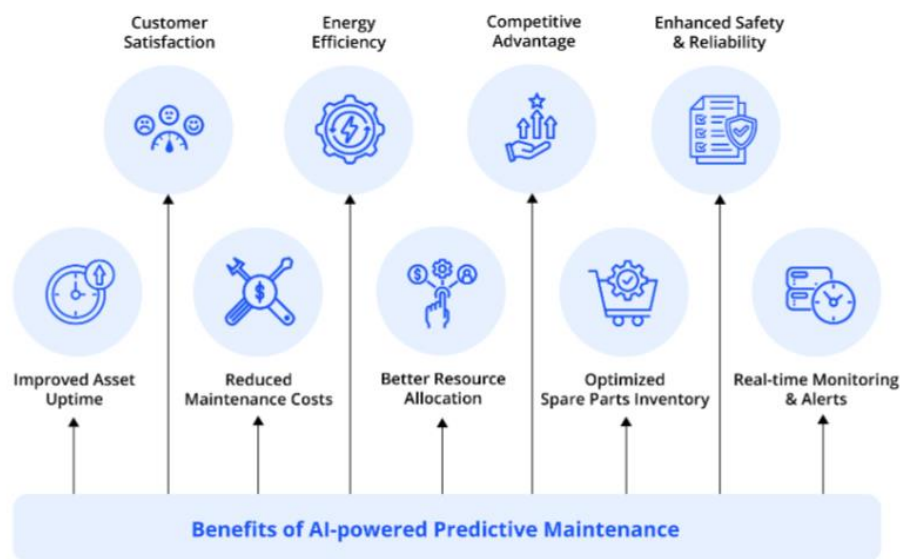


Figure 12. Predictive Maintenance system, names of the methods and the architectures (Hatipoğlu et al., 2023)

Results: In the **multi-class classification task**, the **deep learning models LSTM and GRU** achieved an accuracy of **97.51%**, while the **Random Forest (RF) machine learning model** outperformed them slightly with **98.26% accuracy**. For **binary classification**, used to compare results with existing studies, **RF, LSTM, and GRU** all demonstrated **over 97% accuracy**, highlighting their strong predictive performance

4.1.3.3. BENEFITS OF AI-POWERED PREDICTIVE MAINTENANCE

AI-driven predictive maintenance provides **significant advantages** across industries, enhancing **operational efficiency, cost reduction, and asset reliability**. The key benefits of AI-powered predictive maintenance include:



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Figure 13. Benefits of AI-powered predictive maintenance (Takyar, 2023)



4.1.4. MAINTENANCE DECISION SUPPORT SYSTEMS

- **Automated Maintenance Scheduling:** AI-driven decision-making optimizes maintenance interventions, balancing cost and efficiency (Yaroslav Mota, 2024).
- **Failure Risk Estimation:** AI models provide confidence intervals and reliability scores to maintenance teams (SAE Media, 2024).

4.1.5. DATA INTERPRETATION AND CONTEXTUALIZATION - ROLE OF LARGE LANGUAGE MODELS (LLMS) IN PDM

Before the advent of **Generative AI**, **Large Language Models (LLMs)** were primarily used for **Natural Language Processing (NLP)** tasks such as **text classification, translation, sentiment analysis, and question-answering**. These models were designed to **analyse, interpret, and extract insights** from textual data rather than generate entirely new content in a creative or dynamic manner.

How LLMs Process Data:

- **Understanding unstructured data:** Large Language Models (LLMs) can read and analyse **maintenance logs and technician notes**, which are often written in free-form text. Traditional AI models struggle with this type of data, but LLMs extract valuable insights from it (7Puentes, 2024).
- **Improving fault diagnosis:** By comparing **historical failure records** with real-time equipment data, LLMs help identify **root causes of machine breakdowns**, making diagnostics more precise (Neural concept, n.d.).
- **Rule-Based and Supervised Learning:** Early LLMs relied heavily on **statistical methods, rule-based algorithms, and supervised learning** with labelled. They required structured datasets where inputs were explicitly mapped to expected outputs, limiting their adaptability to new contexts. datasets (Neural concept, n.d.).

Early LLMs (Before Generative AI) enhance Predictive Accuracy

- **Pattern Recognition:** LLMs refine predictive models by identifying correlations beyond numerical data, leading to improved anomaly detection (Editor, 2019).
- **Adaptive Learning:** These models continuously improve through reinforcement learning, adapting to evolving operational conditions (IBM Business operations, 2023).

With limitations:

- **Rule-Based and Supervised Learning:**
 - Older LLMs depended on **predefined rules and structured datasets**, meaning they needed **clear input-output mappings** to function correctly (Neural concept, n.d.).
 - This made them **less adaptable** to new situations where unexpected inputs were present.
- **Limited Contextual Understanding:**
 - Early LLMs could **read and summarize text** but struggled to **generate meaningful new content** (IBM Business operations, 2023).
 - Instead of dynamically responding, they simply **retrieved and presented** the most relevant pre-trained responses.
- **Predictive, Not Generative:**
 - These models were good at **filling in missing words** or identifying **key insights from data** but **could not create new reports, synthetic datasets, or generate human-like responses** (Alexander Barinov, 2022).



- Their main use was **extracting knowledge**, not **writing reports** or **simulating maintenance scenarios**.
- Their responses were largely **retrieval-based**, meaning they selected the most relevant pre-trained outputs rather than dynamically creating new ones.

4.1.6. THREE TYPES OF PREDICTIVE MAINTENANCE

Predictive Maintenance has evolved into **three main types**, each differing in **objectives**, **data analysis methods**, and **outputs** (Fernando Brügge, 2023):

1. **Indirect Failure Prediction** – Estimates a machine's health score based on operational history and conditions.
 -  **Pros:** Scalable, cost-effective, uses existing data.
 -  **Cons:** Does not predict exact failure timing, reliant on historical data.
2. **Anomaly Detection** – Identifies irregularities in machine behavior without failure data, using **unsupervised learning**.
 -  **Pros:** Works with minimal data, highly scalable across machines.
 -  **Cons:** Does not specify failure timing, risk of false positives.
3. **Remaining Useful Life (RUL) Prediction** – Estimates how long a machine will function before failure, based on **condition indicators**.
 -  **Pros:** Provides **precise failure time estimates**, critical for industries needing advance maintenance planning.
 -  **Cons:** High computational cost, requires retraining for different machines and environments.

While **indirect failure prediction** has been widely used, research shows **anomaly detection** is gaining traction due to its adaptability and lower data requirements.

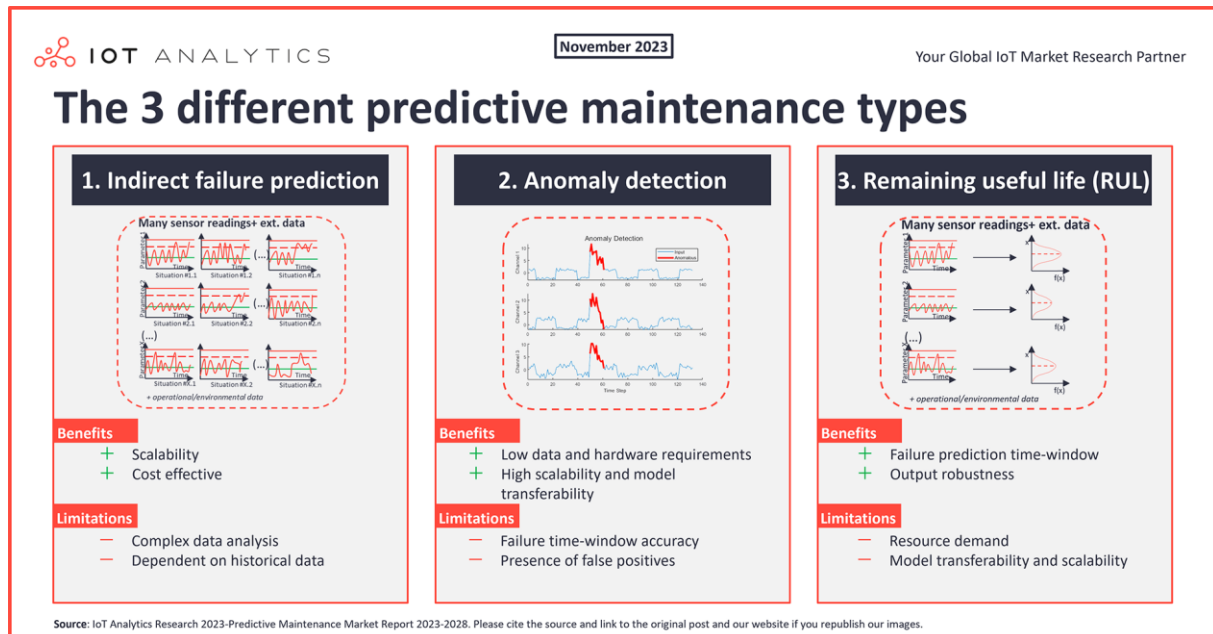


Figure 14. The 3 different types of Predictive Maintenance (Fernando Brügge, 2023)



4.1.7. KEY FEATURES OF PREDICTIVE MAINTENANCE SOFTWARE

Software dominated the predictive maintenance market, making up 44% of the industry in 2022. Despite variations among vendors, **six core features** are common across predictive maintenance software:

1. **Data Collection** – Gathers and normalizes asset health data. (Example: Predictronics' DAQ application synchronizes data collection across sensors.)
2. **Analytics & Model Development** – Identifies failure patterns and builds predictive models. (Example: Falkonry's Workbench enables low-code AI-driven analysis.)



Figure 15. Workbench's Quality Check screen displaying data points over time to help operators identify patterns ((Fernando Brügge, 2023)- Source: Falkonry)

3. **Pre-Trained Models** – Ready-to-use models for specific assets and failure modes. (Example: AspenTech's Mtell provides industry-specific templates.)
4. **Status Visualization & Alerts** – Communicates asset insights via dashboards and automatic alerts. (Example: SAS Asset Performance Analytics sends real-time failure notifications.)



Figure 16. SAS Asset Performance Analytics status dashboard showing data concerning abnormal events of selected assets (SAS Asset Performance Analytics, n.d.)((Fernando Brügge, 2023) - Source: SAS Institute)



5. **Third-Party Integration** – Connects with external software (ERP, MES, CMMS, SCADA). *(Example: SKF's condition monitoring integrates with plant control systems.)*

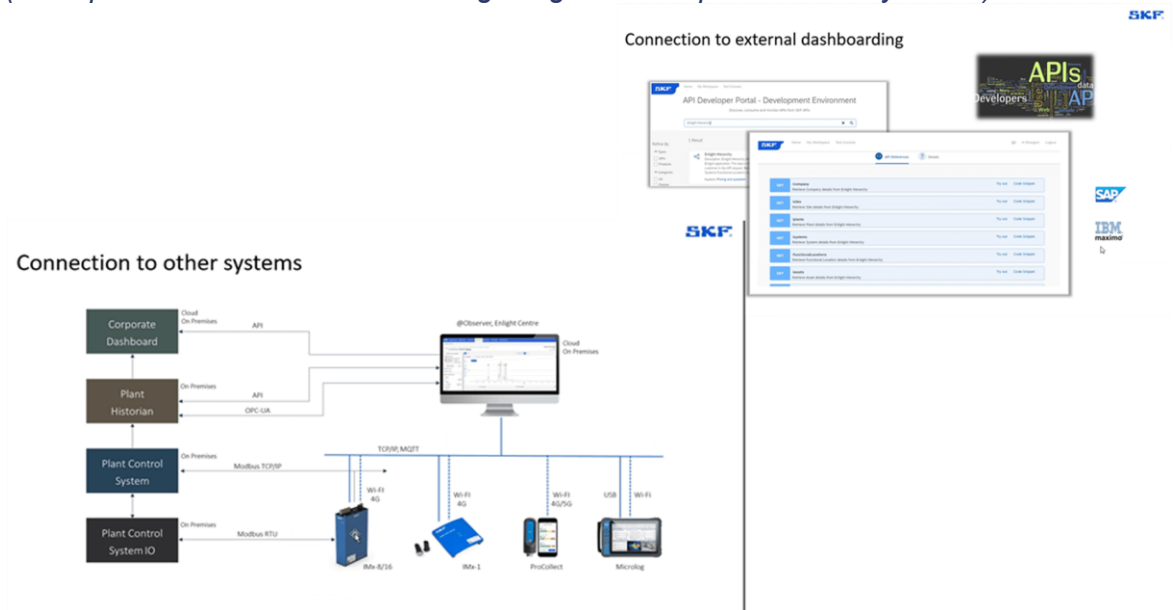


Figure 17. SKF offers an API Developer Portal to assist developers with third-party integrations, with example integrations shown as well ((Fernando Brügge, 2023) - Source: SKF)

6. **Prescriptive Actions** – Suggests corrective actions based on failure predictions. *(Example: Arundo's Marathon provides guided resolution workflows.)*

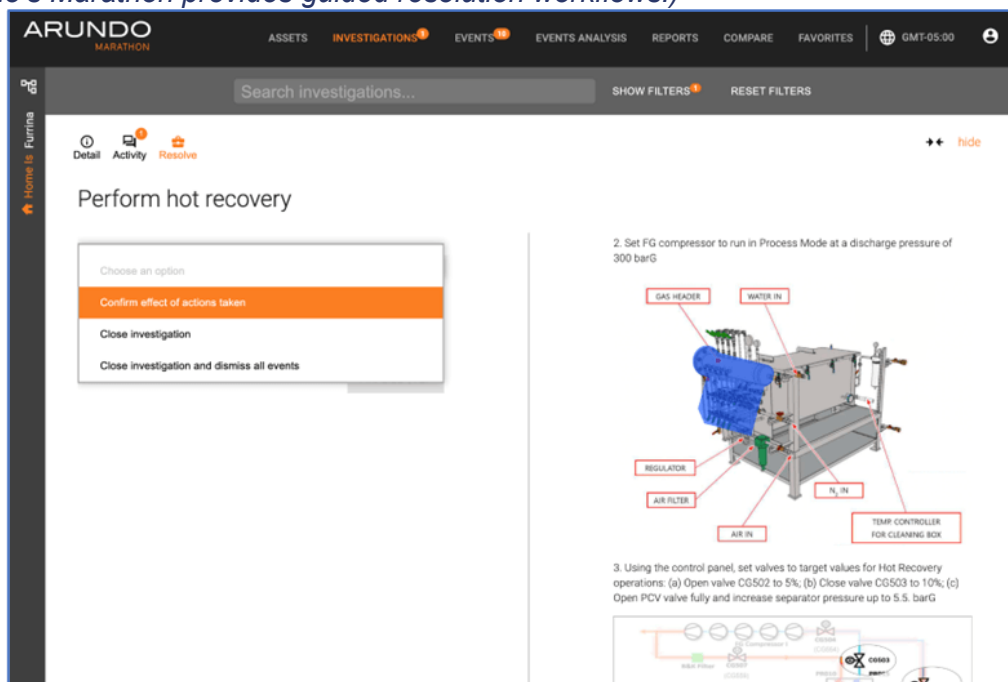


Figure 18. Marathon Investigations interface offers prescribed actions to address a potential issue ((Fernando Brügge, 2023) - Source: Arundo)

These features collectively enhance **predictive maintenance efficiency**, enabling **real-time monitoring**, **proactive decision-making**, and **improved asset reliability**.



4.2. PDM SIGNIFICANT CHALLENGES

Before the advent of **generative AI**, Predictive Maintenance (PdM) faced several major challenges.

4.2.1. DATA ACQUISITION AND QUALITY

- **Heterogeneous Data Sources:** Collecting consistent and high-quality data is difficult due to the variety of equipment and monitoring systems, leading to challenges in data interpretation.
- **Manual Data Collection:** Reliance on manual processes for data extraction and cleaning was labour-intensive and prone to errors, hindering timely and accurate maintenance decisions.
- **Limited Adaptability to Unstructured Data:**
- **Pre-generative AI LLMs** was less flexible in handling highly unstructured text, such as free-form technician notes in Predictive Maintenance (PdM).
- They required structured training datasets and often struggled with understanding domain-specific language outside their trained corpora.

(7Puentes, 2024; SAE Media, 2024)

4.2.2. INTEGRATION WITH LEGACY SYSTEMS

Compatibility Issues: Integrating PdM tools with existing infrastructure often required significant effort to ensure seamless interoperability, posing a barrier to effective implementation. (Johnson, 2023; Yaroslav Mota, 2024)

4.2.3. HIGH INITIAL INVESTMENT

Cost Barriers: Implementing traditional PdM required substantial upfront investment in expensive sensor networks, cloud storage, software, and skilled personnel, which could be prohibitive, especially for smaller organizations making it less accessible to SMEs (Johnson, 2023; Thomaz Cortes, Guillaume Decaix, Thomas Hansmann, Khoon Tee Tan, and Yi Zhou, 2021).

4.2.4. UNCERTAINTY IN PROGNOSTICS

Traditional PdM methods often struggled with accurately predicting equipment failures due to uncertainties in system parameters and degradation models, leading to either unnecessary maintenance or unexpected breakdowns (Alexander Barinov, 2022).

4.2.5. CYBERSECURITY IN INDUSTRIAL MAINTENANCE

As Predictive Maintenance (PdM) evolves with Industry 4.0, cybersecurity has become a major concern due to the increased integration of IoT devices, AI models, and cloud-based infrastructures. These advancements introduce vulnerabilities, making industrial control systems (ICS) and operational technology (OT) infrastructures more susceptible to cyberattacks. To mitigate these risks, initiatives like **DETECTA 2.0** focus on integrating cybersecurity measures into PdM, enhancing resilience for small and medium enterprises (SMEs). **Details are described in the dedicated chapter.**



4.3. EVOLUTION TOWARD GENERATIVE AI

With **Generative AI (post-2023)**, LLMs transitioned from analytical to creative systems, capable of **coherent, context-aware text generation, synthetic data creation, and intelligent responses to complex queries** (Horn, 2024).

What impact does generative AI have on PdM? Here are a few answers.

4.3.1. DATA QUALITY AND MODEL TRAINING

- **Data Augmentation:** One of the main challenges facing PdM is the scarcity of failure data, with traditional maintenance strategies being applied to prevent equipment failure. Generative AI, particularly Generative Adversarial Networks (GANs), helps address this by creating synthetic data that can be used to train machine learning models, thereby improving their robustness and accuracy (Alexander Barinov, 2022; Horn, 2024)
- **Enhanced Model Training:** By incorporating synthetic data, generative AI ensures that models are exposed to a wider range of failure scenarios, which enhances their predictive capabilities (Riccio et al., 2024).
- In **Predictive Maintenance**, this shift allows LLMs to **simulate maintenance reports, generate predictive insights, create synthetic training data** for improving AI-driven PdM models **and assist in knowledge extraction from unstructured maintenance logs**, features that were not possible with traditional LLMs. (7Puentes, 2024)

Revised Conclusion regarding the 3 types of Predictive Maintenance

While **anomaly detection** was gaining traction due to lower data needs, **Generative AI (Gen AI)** is transforming predictive maintenance by **strengthening all approaches**.

1. Enhancing Indirect Failure Prediction

- Gen AI **generates synthetic failure data**, improving models even when historical records are limited (Samana, 2023).
- This enhances predictive accuracy across **various operational conditions**, making indirect failure prediction more scalable.

2. Improving Anomaly Detection

- Gen AI **identifies normal and abnormal operational patterns more precisely**, reducing false positives.
- It refines unsupervised learning models by simulating **anomalous events** that rarely occur in real-world data.

3. Advancing RUL Prediction

- Gen AI **predicts degradation trends** and synthesizes missing condition indicators, making remaining useful life (RUL) estimates **more reliable**.
- It enables adaptive models **across different environments**, reducing retraining needs (Reuters, 2024a).
- As AI adoption grows in industrial settings, predictive maintenance is **shifting towards a hybrid approach**, integrating **multiple AI-driven techniques** rather than favouring a single dominant method. Leading companies like **GE Aerospace** and **Air France-KLM** are already leveraging **AI-powered predictive maintenance** to improve equipment reliability and reduce downtime (Reuters, 2024b; Root, 2023).



4.3.2. AUTOMATED MAINTENANCE STRATEGIES

Generative AI can also be used to develop automated maintenance plans and strategies, predicting the best times for maintenance activities and optimizing resource allocation (Neural concept, n.d.).

4.3.3. INTEGRATION WITH LEGACY SYSTEMS

Generative AI facilitates middleware development, enabling seamless integration of AI-driven PdM into existing infrastructures (Yaroslav Mota, 2024).

4.3.4. HIGH INITIAL INVESTMENT COSTS

AI-driven virtual sensors reduce dependency on hardware, while AI-based automation lowers workforce costs by optimizing maintenance planning (IBM Business operations, 2023).

4.3.5. EXPLAINABLE AI (XAI) AND INTERPRETABLE MACHINE LEARNING (IML)

The integration of Artificial Intelligence (AI), the Internet of Things (IoT), and human-machine interfaces connects hardware and software systems to optimize automation processes.

As the industrial landscape evolves toward Industry 5.0, the emphasis shifts from machine-centered to human-centered approaches. In this new paradigm, AI technologies assist human tasks to enhance productivity, highlighting the need for Explainable AI (XAI) and Interpretable Machine Learning (iML). These are essential for understanding and trusting complex PdM systems, as they make the decision-making processes of AI models transparent to users.

The distinction between **explainability** and **interpretability** in AI and ML is debated. Some researchers use the terms interchangeably for simplicity, while others argue they represent different concepts. A third view suggests one is a subset of the other. The survey (Logan Cummins, 2024) treats them as related but distinct, with some overlap, each highlighting unique aspects of machine learning.

This survey provides a foundational explanation of Explainable Artificial Intelligence (XAI), Interpretable Machine Learning (iML), and Predictive Maintenance (PdM) for readers from various backgrounds:

1. **Explainability vs. Interpretability:** While some researchers see these terms as interchangeable, others view them as distinct. The article treats them as related but separate concepts, with **XAI** focusing on understanding model outputs (typically through post-hoc methods like SHAP and LIME) and **iML** focusing on the interpretability of the model itself.
2. **Explainable Artificial Intelligence (XAI):** XAI seeks to clarify AI model predictions. Techniques are divided into:
 - **Model-Agnostic Methods** (e.g., SHAP, LIME), usable across model types.
 - **Model-Specific Methods** (e.g., Class Activation Mapping for CNNs), tailored to specific architectures.
 - **Local vs. Global Explanations**, where local explanations address individual predictions and global explanations give an overall model view.
3. **Interpretable Machine Learning (iML):** Unlike XAI, iML involves models with intrinsic interpretability, like logistic regression, where outputs are naturally understandable due to the model's simplicity.
4. **Predictive Maintenance (PdM):** PdM uses AI to predict mechanical failures in advance by applying tools such as:



- **Anomaly Detection** (to identify if a fault has occurred),
- **Fault Diagnosis** (to pinpoint the cause of faults),
- **Prognosis** (to predict remaining useful life or time to failure).

The model-specific explainable methods discussed in the document for predictive maintenance:

1. **Class Activation Mapping (CAM) and GradCAM:** CAM provides global explanations for CNNs by highlighting image regions associated with class predictions, using global average pooling layers. GradCAM enhances this by using gradient information for more focused explanations, showing important features used by the model.
2. **DIFFI (Depth-based Isolation Forest Feature Importance):** DIFFI explains isolation forests used for anomaly detection by ranking features based on their role in isolating anomalous data. This method has been applied to scenarios like anomaly detection in time-series data.
3. **LionForests:** A local explanation method for random forests that generates IF-THEN rules and visualizations, making feature contributions interpretable. This has been expanded to handle multi-label classifications in fault diagnosis.
4. **Saliency Maps:** For CNNs, saliency maps rank pixel importance by approximating the model's output as a linear function around the input, highlighting influential input features.
5. **ARCANA (Autoencoder-based Anomaly Root Cause Analysis):** ARCANA interprets autoencoder results for anomaly detection by identifying features that cause reconstruction errors. It has been applied to wind turbine maintenance to pinpoint causes of detected anomalies.

These methods enhance interpretability by leveraging specific architecture features, allowing users to understand model decisions better in tasks like fault diagnosis, anomaly detection, and root cause analysis.

Studies combining multiple explainability methods for predictive maintenance use different approaches:

1. **Stacked Approach:** Methods are applied sequentially. Jakubowski et al. used a quasi-autoencoder for anomaly detection with XGBoost as a surrogate model, enhancing explainability with SHAP's TreeExplainer.
2. **Simultaneous Approach:** Multiple methods are applied together for varied insights:
 - **Khan et al.** used LIME and SHAP on an MLP regressor for remaining useful life (RUL) predictions, finding similar yet distinct explanations.
 - **Serradilla et al.** applied ELI5 and LIME to a random forest model, showing feature importance locally and globally.
 - **Brito et al.** found general agreement between Local-DIFFI and SHAP for fault detection without ranking one above the other.
3. **Method Comparison:** Ferraro et al. assessed LIME and SHAP using identity, stability, and separability metrics, noting differences in explanation consistency across classes.
4. **AutoML Integration:** Li et al. used LIME and SHAP within AutoML platforms for vehicle data, achieving a workflow with built-in explainability, with TPOT proving most accurate.

These combinations enable richer insights across models and highlight method-specific strengths and limitations.

Among the 21 interpretable machine learning (IML) methods mentioned in the survey for predictive maintenance listed in annex 3, the 7 most frequently used & widely recognized are:

1. Attention Mechanisms – **Frequently used in deep learning models, especially in LSTMs and Transformers, to focus on critical input features.**



5. **Decision Trees** – One of the most fundamental interpretable models, allowing users to trace decisions through a hierarchical structure. Often used as a baseline in predictive maintenance.
11. **Explainable Boosting Machine (EBM)** – An extension of GAMs, combining boosting techniques with interpretability, making it a popular interpretable ML approach.
16. **Digital Twins** – Highly relevant for Industry 4.0 & predictive maintenance, as they create virtual representations of physical systems for simulation and failure prediction.
18. **Generalized Additive Models (GAMs)** – A strong alternative to black-box models, as they allow transparent, feature-wise interpretability.
20. **k-Nearest Neighbours (kNN)** – Simple and interpretable, commonly used for classification and predictive maintenance.
21. **Rule-Based Interpretations** – Widely applied for if-then logic, making predictions easy to understand in industrial settings.

The survey highlights several challenges and research directions in **Explainable Predictive Maintenance (XPM)**:

1. **Purpose of Explanations:** Explanations should be designed with specific audiences in mind, as different stakeholders (e.g., data scientists, project managers, mechanics) have unique needs for understanding model outputs. Current explanations often lack such audience-targeted customization, impacting the usefulness of explainability.
2. **Evaluation of Explanations:** Unlike performance metrics for machine learning models, evaluation of explanations has not been standardized. Various metrics, both objective (e.g., fidelity, stability, robustness) and subjective (e.g., trust, effectiveness, satisfaction), are proposed in literature. However, the need remains for a consistent framework to assess explanation quality comprehensively.
3. **Addition of Human Involvement:** A human-centered approach is necessary for XPM, where explanations should be tailored to different user types. This approach would involve identifying target audiences and adjusting explanations based on feedback, ultimately supporting a more effective human-AI partnership in predictive maintenance.
4. **Study Limitations:** The survey only covers a subset of XAI and iML methods applied to predictive maintenance, acknowledging that not all relevant algorithms are included. This limitation is noted as a boundary for the study's scope, with the potential for further exploration in the broader context of XPM.

In sum-up, As Industry 5.0 emphasizes human-centered AI, **Explainable AI (XAI)** and **Interpretable Machine Learning (iML)** are essential for trust in **Predictive Maintenance (PdM)**. While XAI clarifies black-box models post hoc, iML ensures inherent transparency, aiding decision-making in industrial settings. Future research should focus on **standardizing evaluation metrics, tailoring explanations to stakeholders, and improving human-AI collaboration** for more effective predictive maintenance solutions.

4.3.6. TASK-SPECIFIC LANGUAGE MODELS (SLMS): A NEW AI FRONTIER IN MAINTENANCE

While generative AI brings powerful capabilities for automation and predictive modelling, it often requires large-scale computing resources, raising concerns about energy consumption.

In contrast, **task-specific language models (SLMs)** are emerging as a **lightweight, energy-efficient alternative**, tailored for clearly defined industrial tasks. Their **lower computational footprint** makes them not only easier to deploy on edge devices or local infrastructure, but also **better aligned with green transition goals**.



Unlike large general-purpose models (LLMs) such as GPT-4, SLMs are smaller, more efficient AI models trained to perform one clearly defined task - such as interpreting maintenance logs, generating work orders, or summarizing sensor data anomalies (AI21 Labs, 2023; Fukushima, 2024).

SLMs are increasingly valuable in maintenance for their ability to:

- Deliver high accuracy in specialized contexts, reducing irrelevant or hallucinated outputs.
- Operate with lower computing requirements, making them suitable for edge deployment in industrial environments.
- Be rapidly trained and deployed, allowing SMEs to tailor AI tools to specific needs without the cost or complexity of LLMs.

For example, companies like Omundu are integrating task-specific language models into PdM platforms to offer expert-level decision support with minimal latency. These models allow technicians to interact with AI in natural language to retrieve insights or suggestions that are tightly aligned with operational vocabulary and standards (Omundu, n.d.).

4.3.7. CONCLUSION

Generative AI is revolutionizing PdM by enhancing failure prediction accuracy, automating maintenance scheduling, and generating synthetic training data. As AI adoption grows, PdM will shift toward hybrid models that integrate multiple AI techniques. However, challenges such as cybersecurity risks and model interpretability must be addressed to ensure widespread adoption. Companies that leverage GenAI effectively will gain a competitive advantage in predictive maintenance and asset management.

4.4. EMERGING MODELS & TECHNOLOGIES

The evolution of predictive maintenance models reflects a transition from static maintenance schedules to dynamic, data-driven strategies. These models incorporate continuous deterioration analysis, service effects modelling, and maintenance policy formulation to ensure timely interventions based on real-time data (Artesis, 2021)

As these technologies continue to evolve, the landscape of predictive maintenance is expected to transform significantly, paving the way for more efficient operations across various industries, including manufacturing, oil and gas, and power generation. (ateam_admin, 2023; pleasedontcode, 2024)

Several advancements are shaping the future of PdM:

4.4.1. STUDY 1 - NEW METHODOLOGICAL FRAMEWORK FOR OPTIMIZING PREDICTIVE MAINTENANCE

4.4.1.1. OBJECTIVES OF THE STUDY

The 2024 study (Riccio & Menanno, 2024) aims to develop a **novel predictive maintenance (PdM) framework** that integrates **machine learning (ML) with product quality (PQ) parameters**. Traditional PdM strategies mainly focus on equipment condition and failure prevention, but this study proposes a **quality-driven approach**, where product quality indicators are also used to optimize maintenance decisions. The objective is to determine the **optimal PdM strategy** based



on both **production efficiency** and **product quality** to reduce costs, improve machine reliability, and minimize defective products.

4.4.1.2. MAIN FINDINGS

- **Integration of ML and Product Quality for PdM**
 - The study establishes a direct link between machine operating conditions and product quality indicators.
 - By integrating PQ data into the PdM framework, the model can **predict potential failures** and **optimize maintenance schedules** to **minimize scrap rates**.
- **Development of a Three-Step Framework**
 - **Step 1:** Define key input variables (machine status, pressure, temperature, and PQ indicators like First Pass Yield - FPY).
 - **Step 2:** Build a **machine learning model** to predict PQ deviations based on operational data. The best-performing model is a **Bagged Tree Classifier (BTC)** with **91% accuracy**.
 - **Step 3:** Implement a **Fuzzy Inference Engine (FIE)** to recommend maintenance actions based on predicted product quality and machine conditions.
- **Case Study Application (Electromechanical Component Production Line)**
 - The framework was tested in a **production line for power transformers**.
 - The **vacuum mixer machine** was identified as the most critical element impacting PQ (85% of total waste).
 - A combination of **temperature and pressure monitoring** was used to anticipate failures in **vacuum pumps**, which directly affected product insulation quality.

4.4.1.3. RESULTS

- The framework demonstrated that **predicting maintenance needs based on product quality variations** leads to **significant cost savings and improved efficiency**.
- **Financial Impact:**
 - **50% reduction in machine downtime costs.**
 - **64% reduction in scrap-related costs.**

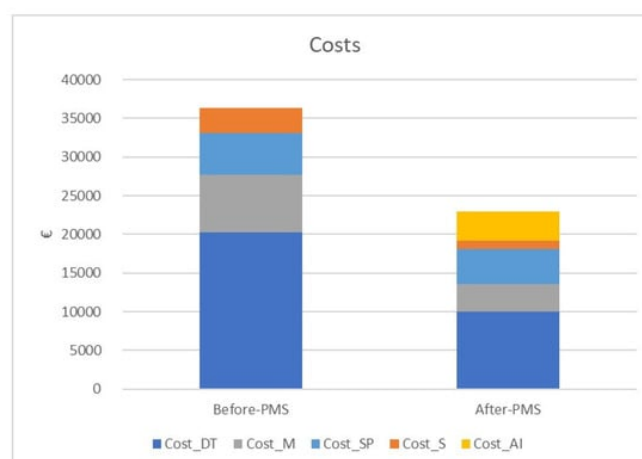


Figure 19. Cost comparison between data collection and model application (Riccio & Menanno, 2024)

- **Improved Reliability:**
 - At the same time, the optimization of the FPY index confirms that the inclusion in the model of a production quality index, which must be monitored and optimized, effectively



leads to an improvement in the continuity of operation of the machine (availability increases from 93.1% to 96.6%), when this index is dependent on some operating parameters of the machine itself

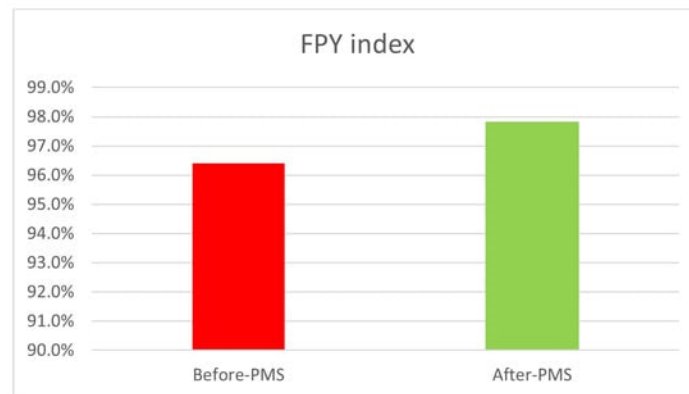


Figure 20. FPY comparison between As-Is phase and model application. (Riccio & Menanno, 2024)

- **92.8% of potential failures were confirmed** by thermographic inspections.
- Improvement in the MTBM (from 37.8 to 48.6 h).

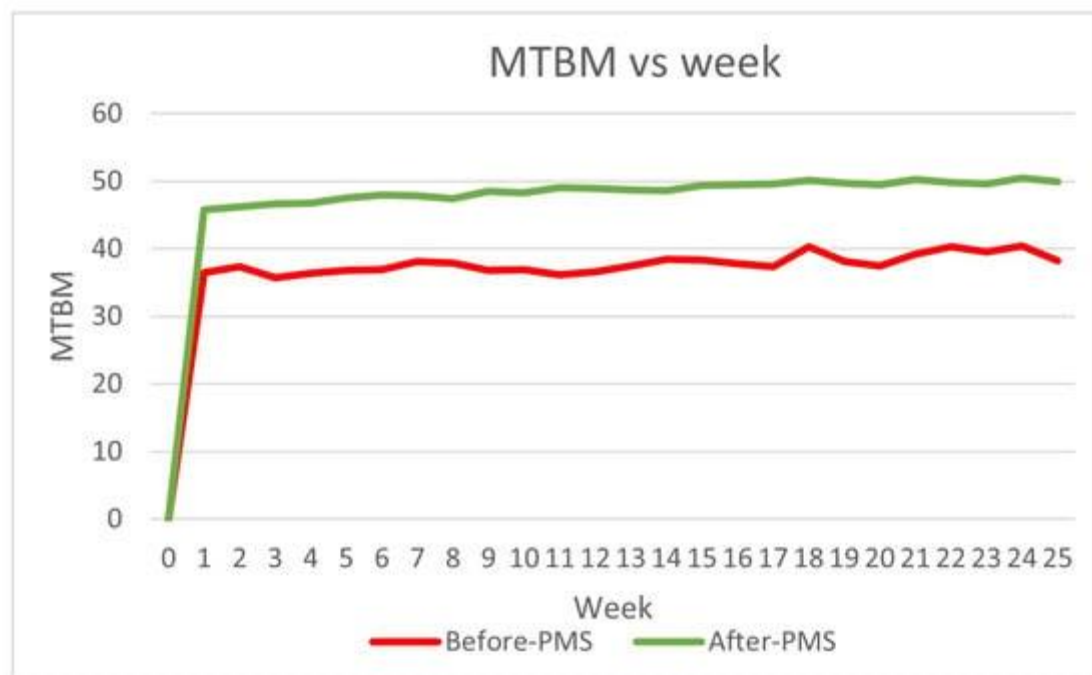


Figure 21. MTBM comparison between data collection and model application. (Riccio & Menanno, 2024)

¹ **MTBF** (Mean Time Between Failures) is a reliability metric that measures the average time elapsed between two consecutive failures of a system, component, or machine during normal operation. It is commonly used in predictive maintenance and reliability engineering to assess equipment durability and plan maintenance schedules

² **FPY (First Pass Yield)** is a **quality performance metric** that measures the percentage of products that are manufactured correctly **without requiring rework or repair** on the first attempt. It is commonly used in **manufacturing, production, and quality control** to assess process efficiency and effectiveness.

- **Challenges Identified:**



One failure was missed because it did not generate a temperature anomaly, highlighting limitations in the current sensor data integration.

4.4.1.4. CONCLUSION

The study proves that **integrating machine learning with product quality parameters enhances predictive maintenance strategies**. The proposed framework **reduces maintenance costs, minimizes defects, and improves machine reliability**. Future research should focus on **further optimizing the model**, incorporating **more diverse data sources**, and **expanding its application to other industrial sectors**.

4.4.2. STUDY 2 - ANOMALY DETECTION IN INDUCTION MOTORS USING REAL-TIME IOT DATA

4.4.2.1. OBJECTIVES OF THE STUDY

The study (Chevtchenko et al., 2023) aims to develop a **predictive maintenance model** using **anomaly detection in induction motors** by leveraging **real-time IoT data** and **machine learning (ML)** techniques. The primary goals are:

- To design a **low-cost, real-time anomaly detection system** for industrial equipment.
- To evaluate **different ML models** for detecting anomalies with minimal computational effort.
- To ensure an **optimal balance** between **anomaly detection accuracy, false positive rate, and inference speed** through **multiobjective optimization**.
- To create a **generalized framework** applicable across various industrial contexts.

4.4.2.2. MAIN FINDINGS

- **IoT-Driven Data Collection:** A **custom dataset** was created by fusing **vibration, temperature, and noise data** from IoT sensors attached to **induction motors**.
- **Preprocessing Techniques:** The study utilized **Fast Fourier Transform (FFT)**, **Wavelet Transform (WT)**, and **binning** to extract relevant features.
- **Machine Learning Models:** Three anomaly detection models were tested:
 - **One-Class Support Vector Machine (OC-SVM)**
 - **Isolation Forest (IF)**
 - **Local Outlier Factor (LOF)**
- **Optimization Strategy:** A **multiobjective optimization approach (NSGA-II algorithm)** was applied to optimize model hyperparameters for the best balance of sensitivity, specificity, and inference time.
- **Evaluation Metrics:** Models were assessed based on **sensitivity (true positive rate)**, **specificity (true negative rate)**, and **computational efficiency**.

4.4.2.3. RESULTS

Performance Comparison of Models

The study compared **three ML algorithms** based on their **sensitivity, specificity, and inference time** (average performance across validation and test datasets):

Table 7. A summary of the average evaluation results on the validation / test subsets



Algorithm	Sensitivity (%)	Specificity (%)	Inference Time (ms)
OC-SVM	73.1 / 47.9	63.4 / 36.5	0.43
Isolation Forest (IF)	88.9 / 86.3	61.6 / 67.4	21.40
Local Outlier Factor (LOF)	90.8 / 77.6	74.5 / 72.1	0.81

Key Observations

- **LOF achieved the best balance**, with the highest sensitivity and specificity at a reasonable computational cost.
- **FFT was consistently effective** for feature extraction, while **Wavelet Transform did not provide significant advantages**.
- **Principal Component Analysis (PCA) was beneficial**, reducing dimensionality without losing predictive accuracy.
- The **custom IoT sensor approach** effectively captured anomalies in **unbalanced loads, damaged bearings, and stator short circuits**.

4.4.2.4. CONCLUSION

The study successfully developed a **low-cost, real-time predictive maintenance system** using IoT sensors and ML algorithms for anomaly detection in **induction motors**.

- **LOF emerged as the most effective model**, providing a **high anomaly detection rate with minimal computational effort**.
- The **multiobjective optimization approach** helped balance **accuracy, false positives, and inference speed**, ensuring a **practical and scalable** solution.
- The methodology is **generalizable**, allowing adaptation to **various industrial contexts** beyond induction motors.

4.4.2.5. FUTURE RESEARCH DIRECTIONS:

- **Explore ensemble models** to reduce overfitting and improve robustness.
- **Evaluate deep learning models** (e.g., **Variational Autoencoders (VAEs)**) for improved anomaly detection.
- **Expand the dataset** with real-world industrial machines to enhance model adaptability.

This research demonstrates **the potential of integrating IoT and ML** to create **cost-effective, real-time predictive maintenance solutions**, reducing equipment failures and operational costs.

4.4.3. STUDY 3 - "TRANDRL: A TRANSFORMER-DRIVEN DEEP REINFORCEMENT LEARNING ENABLED PRESCRIPTIVE MAINTENANCE FRAMEWORK"

4.4.3.1. OBJECTIVES OF THE STUDY

The study (Zhao et al., 2024) presents **TranDRL**, an advanced **prescriptive maintenance framework** that integrates **Transformer-based neural networks** and **Deep Reinforcement**



Learning (DRL) to optimize **predictive and prescriptive maintenance**. The objectives of this study are

- **Improve Remaining Useful Life (RUL) estimation** by leveraging Transformers to process complex IoT sensor data.
- **Optimize maintenance decision-making** using DRL, reducing unexpected failures and balancing costs.
- **Incorporate human feedback** into reinforcement learning (RLHF) to enhance decision trustworthiness and model interpretability.
- **Enable federated learning** for scalable deployment across multiple machines without data centralization.

4.4.3.2. MAIN FINDINGS

- **Transformers outperform traditional RUL prediction models:** Compared to NBeats and DeepAR, Transformers demonstrate superior performance in capturing **long-term dependencies in industrial data**.
- **DRL-based maintenance scheduling minimizes downtime and costs:** Algorithms such as **PPO (Proximal Policy Optimization)** provide the best balance between exploration and exploitation in maintenance planning.
- **Human feedback enhances model reliability:** The inclusion of **expert-based reinforcement learning** reduces decision variability and improves the robustness of maintenance recommendations.
- **Federated learning enables multi-machine deployment:** The TranDRL model can generalize predictive maintenance insights across **different industrial assets** without requiring raw data sharing.

4.4.3.3. RESULTS

- **RUL Prediction Performance**
 - The Transformer-based model outperforms **DeepAR and NBeats** in predicting **RUL for NASA C-MAPSS datasets**.
 - **Federated learning approach** maintains high RUL prediction accuracy across multiple machines while ensuring **data privacy**.
- **Maintenance Decision Optimization with DRL**
 - DRL models (DQN, SAC, PPO) are compared for **optimal maintenance scheduling**.
 - **PPO achieves the highest total reward**, effectively balancing maintenance timing and cost.
 - **Human-in-the-loop RL** refines decision consistency and improves interpretability.

4.4.3.4. CONCLUSION

The **TranDRL framework** successfully integrates deep learning and reinforcement learning to improve predictive maintenance outcomes. Its key contributions include **enhanced RUL estimation, intelligent maintenance scheduling, and scalable federated learning deployment**. The study highlights **practical applications in industrial IoT**, demonstrating **significant potential for reducing machine downtime, optimizing maintenance costs, and improving operational efficiency**.



4.4.3.5. FUTURE RESEARCH DIRECTIONS

- Extending **human-in-the-loop learning** to improve trust in AI-driven maintenance decisions.
- **Incorporating multimodal sensor data** (including images) for more comprehensive asset monitoring.
- **Validating the model in real-world industrial settings** to assess scalability and adaptability.

5. IMPACT OF PDM IN MAINTENANCE ACTIVITIES ON SMES

As described previously, Predictive Maintenance (PdM) is an advanced maintenance strategy that leverages data analytics, artificial intelligence (AI), and the Industrial Internet of Things (IIoT) to predict and prevent equipment failures before they occur. While large enterprises have been pioneers in adopting PdM, small and medium-sized enterprises (SMEs) increasingly recognize its potential to enhance operational efficiency and reduce costs.

5.1. THE ROLE OF PDM IN SMES

SMEs often face resource constraints, making unplanned downtime particularly costly. Predictive Maintenance (PdM) enables these businesses to shift from reactive and preventive maintenance strategies to a more proactive approach that ensures equipment longevity, optimizes maintenance schedules, and minimizes operational disruptions.

5.1.1. BENEFITS FOR SMES

Implementing PdM can bring numerous advantages to SMEs, including cost savings, efficiency improvements, and resource optimization. The key benefits are:

- **Cost Savings:** PdM can significantly reduce maintenance costs by up to 40% and decrease downtime by as much as 50% (Siemens, 2023). By predicting failures in advance, companies can avoid emergency repairs, which tend to be more expensive due to urgency and unplanned spare parts purchases.
- **Enhanced Equipment Lifespan:** By monitoring asset conditions and predicting potential failures, SMEs can extend the operational life of machinery. This prevents premature replacements and saves capital investment in new equipment (Scaife, 2024).
- **Improved Productivity:** Reduced breakdowns lead to increased equipment uptime, ensuring uninterrupted production. This minimizes workflow disruptions and enhances output quality, allowing businesses to meet customer demands more effectively.
- **Optimized Resource Allocation:** Maintenance teams can focus on preventive strategies and high-priority tasks rather than constantly addressing emergency repairs. This improves workforce efficiency and reduces stress among employees (Riccio & Menanno, 2024).
- **Energy Efficiency:** Predictive analytics can identify inefficiencies in machinery operations, leading to optimized energy consumption. By addressing anomalies early, SMEs can lower electricity costs and contribute to sustainability goals (Siemens, 2025).



5.1.2. CHALLENGES IN PDM IMPLEMENTATION

Despite its benefits, PdM adoption in SMEs is not without challenges. These range from financial and technical hurdles to organizational resistance. Some of the most common challenges include:

- **Data Quality Issues:** PdM systems rely on accurate, high-quality data for reliable predictions. However, many SMEs struggle with data collection due to outdated infrastructure and inconsistent record-keeping (Hunkar Toyoglu, Andy Lin, John Knapp, Jonathan Van Wyck, Selena Rose, and Arthur Pentecoste, 2023).
- **High Initial Investment:** Implementing PdM requires investing in sensors, cloud storage, and data analysis tools. The upfront costs may be a barrier for SMEs with limited financial resources (Berger, 2018).
- **Lack of Digital Maturity:** Many SMEs lack the necessary digital infrastructure and expertise to support PdM technologies. This makes integration and utilization of predictive analytics challenging (Siemens, 2023).
- **Skill Gaps:** Effective PdM implementation requires expertise in data science, machine learning, and IoT technology. SMEs often struggle to find or train employees with these technical skills (Scaife, 2024).
- **Resistance to Change:** Maintenance teams accustomed to traditional maintenance methods may be hesitant to adopt PdM solutions. Overcoming this resistance requires proper training and change management strategies (Thomaz Cortes, Guillaume Decaix, Thomas Hansmann, Khoon Tee Tan, and Yi Zhou, 2021).
- **Data Integration Challenges:** Integrating PdM systems with legacy equipment and existing IT infrastructure can be complex. Compatibility issues may arise, requiring customized solutions (Riccio & Menanno, 2024).
- **Cybersecurity Risks:** Cloud-based PdM solutions introduce potential cybersecurity vulnerabilities. SMEs must ensure data protection measures are in place to safeguard sensitive maintenance data (Goncharov, 2023).

5.2. BEST PRACTICES FOR SMES IMPLEMENTING PDM

To maximize the benefits of PdM while overcoming common challenges, SMEs should follow best practices that facilitate smooth adoption and effective utilization.

- **Identify Critical Assets:** SMEs should prioritize high-value assets where failures would have the most significant impact on operations. Focusing on these assets ensures that PdM delivers the highest return on investment.
- **Start with Pilot Projects:** Instead of a full-scale implementation, SMEs should begin with small-scale pilot programs. This approach helps validate PdM's feasibility, assess ROI, and refine strategies before company-wide deployment.
- **Leverage External Expertise:** Collaborating with technology providers, consultants, or PdM specialists can help bridge knowledge gaps and accelerate implementation. These experts provide guidance on best practices and system integration (Thomaz Cortes, Guillaume Decaix, Thomas Hansmann, Khoon Tee Tan, and Yi Zhou, 2021).
- **Invest in Training:** Employees must be upskilled in data analytics, machine learning, and digital maintenance tools to effectively use PdM solutions. Training programs ensure smooth adoption and long-term success (Riccio & Menanno, 2024).
- **Use Cloud-Based Solutions:** Cloud computing enables SMEs to adopt PdM without requiring extensive on-premise infrastructure. Cloud-based platforms provide scalability, remote access, and lower maintenance costs (Infraspeak, 2023).



5.3. IMPACT ON ORGANIZATIONS

The successful implementation of PdM transforms an organization's maintenance strategy, enhancing operational efficiency, reducing downtime, and increasing flexibility in scheduling maintenance activities and production shutdowns. Key organizational Impact include:

- **Optimized Maintenance Processes:** PdM shifts organizations from reactive or preventive maintenance to a predictive model, ensuring interventions are performed only when necessary. This approach optimizes asset utilization, reduces unexpected failures, and improves resource allocation (Hunkar Toyoglu, Andy Lin, John Knapp, Jonathan Van Wyck, Selena Rose, and Arthur Pentecoste, 2023).
- **Minimized Unplanned Downtime and Increased Flexibility:** By identifying potential failures in advance, PdM reduces unplanned equipment failures by 20 to 40%, allowing organizations to schedule maintenance activities and production shutdowns strategically. This flexibility helps align maintenance with production cycles, minimizing disruptions and ensuring operational continuity (Hunkar Toyoglu, Andy Lin, John Knapp, Jonathan Van Wyck, Selena Rose, and Arthur Pentecoste, 2023).
- **Extended Equipment Lifespan and Cost Efficiency:** By proactively addressing maintenance needs, businesses can extend machinery durability and reduce unnecessary interventions, leading to lower maintenance costs and improved efficiency (Thomaz Cortes, Guillaume Decaix, Thomas Hansmann, Khoon Tee Tan, and Yi Zhou, 2021).
- **Adoption of New Business Models (MaaS):** The rise of Maintenance as a Service (MaaS) is facilitated by PdM, enabling SMEs to outsource maintenance services more efficiently. This reduces capital expenditures, enhances predictive insights, and ensures better uptime and service quality (Infraspeak, 2023).
- **Proactive Strategy Over Traditional After-Sales Service:** PdM shifts the focus from reactive repairs to proactive planning, ensuring potential failures are detected and resolved before they impact production. This transition enhances operational resilience and reduces dependency on after-sales service interventions (Riccio & Menanno, 2024).

5.4. IMPACT ON THE WORKFORCE

PdM adoption requires an evolution in workforce skills and a transformation of traditional maintenance roles.

5.4.1. TRANSFORMATION OF ROLES

The shift to PdM also brings changes in workforce roles. Traditional maintenance technicians are increasingly required to oversee PdM systems rather than performing reactive repairs. This transition fosters the emergence of new job functions that bridge IT, operations, and maintenance. Key role transformations include:

- **Reskilling Maintenance Technicians:** Transitioning towards overseeing PdM systems. As a result, technicians must develop expertise in interpreting data-driven insights and working with predictive analytics tools.
- **Emergence of New Positions:** PdM analysts and digital maintenance strategists. These roles focus on optimizing maintenance strategies using predictive insights and ensuring seamless system integration.
- **Enhanced IT-Operations Collaboration:** Strengthened links between IT, operations, and maintenance teams (Thomaz Cortes, Guillaume Decaix, Thomas Hansmann, Khoon Tee Tan, and Yi Zhou, 2021). This collaboration helps in the effective implementation and management of PdM solutions across various business units.



5.4.2. RELATIONSHIP BETWEEN PDM AND MAINTENANCE AS A SERVICE (MAAS)

The emergence of Maintenance as a Service (MaaS) is making PdM more accessible for SMEs. This model offers:

- **MaaS as a Facilitator for SMEs:** By reducing the complexity of adopting PdM by outsourcing certain maintenance services to specialist suppliers, SMEs can benefit from expert advice and avoid having to build up extensive in-house technical capabilities. (Infraspeak, 2023).
- **Cost Optimization:** Subscription-based maintenance models make PdM more accessible. These models allow SMEs to pay for maintenance services based on actual usage, eliminating large upfront costs and improving budget predictability.
- **Partnerships with Specialized PdM Providers:** Accelerating adoption for SMEs. By collaborating with PdM service providers, SMEs can quickly deploy predictive maintenance solutions without the need for extensive internal expertise.

5.4.3. EVOLVING SKILLSET FOR PREDICTIVE MAINTENANCE (PDM) IN SMES

As PdM systems become more integrated into SMEs, maintenance personnel must develop a diverse skillset encompassing **technical, analytical, and soft skills** to effectively monitor, interpret, and act upon predictive maintenance insights.

Key skills include:

5.4.3.1. TECHNICAL AND ANALYTICAL SKILLS

These skills involve hands-on expertise with PdM technologies, ensuring proper implementation and maintenance of systems and are critical for interpreting PdM data, optimizing asset performance, and making data-driven decisions.

- **IoT Integration and Sensor Management:** Understanding IoT-based PdM tools, sensor networks, and connectivity protocols is essential for deploying and maintaining predictive maintenance solutions (Siemens, 2025).
- **Cybersecurity Awareness and Risk Mitigation:** As maintenance data becomes digitized, professionals must be aware of cybersecurity risks, data protection strategies, and secure system architectures (Goncharov, 2023).
- **Explainable AI (XAI) and Interpretable Machine Learning (iML):** Employees need to understand how AI-driven PdM models generate insights and ensure these predictions can be trusted and acted upon effectively (Logan Cummins, 2024).
- **Data Analytics and Machine Learning:** Maintenance personnel must be proficient in predictive modeling, statistical analysis, and failure pattern recognition to anticipate potential breakdowns and optimize asset performance (Scaife, 2024).
- **Performance Monitoring and Data-Driven Decision-Making:** The ability to assess PdM reports, detect anomalies, and refine maintenance strategies based on real-time analytics is essential for maximizing efficiency and minimizing downtime.



5.4.3.2. SOFT SKILLS

With the increasing shift towards service-based maintenance models, professionals must develop strong interpersonal and managerial skills.

- **Supplier and MaaS Relationship Management:** As SMEs transition to Maintenance as a Service (MaaS), professionals need skills in supplier management, contract negotiation based on the SME's existing procurement process, and performance evaluation to ensure seamless service integration. Understanding service-level agreements (SLAs) is crucial for maintaining high service quality.
- **Cross-Functional Collaboration and Communication:** Effective communication with IT teams, data scientists, and operational managers is necessary to align maintenance strategies with broader business goals.
- **Adaptability and Continuous Learning:** Given the rapid advancements in PdM technology, maintenance professionals must stay updated on industry trends, emerging technologies, and best practices to maintain operational excellence

By developing a well-rounded skillset that balances technical, analytical, and soft skills, maintenance personnel can successfully navigate the evolving landscape of predictive maintenance in SMEs.

5.5. CASE STUDY

Case studies demonstrate real-world applications of PdM, highlighting tangible benefits for SMEs across industries.

5.5.1. DESIGN & IMPLEMENTATION OF AUTOMATIC MACHINE CONDITION MONITORING AND MAINTENANCE SYSTEM IN LIMITED RESOURCE SITUATIONS

Source : (Ripon et al., 2024)

- **Industry:** Various. SMEs across different sectors struggle with the implementation of predictive maintenance due to cost and resource constraints.
- **Challenge:** Lack of infrastructure, skilled manpower, and financial resources to implement traditional predictive maintenance systems. Many SMEs find it difficult to deploy advanced maintenance solutions due to these limitations.
- **Solution:** Development of a cost-effective Data Acquisition System (DAS) and the application of feature engineering and data reduction methods to automate fault detection and diagnosis. By leveraging existing low-cost technologies, this system provided SMEs with an affordable and scalable maintenance solution.
- **Results:**
 - Achieved 89% accuracy in data collection compared to professional manual monitoring systems. This demonstrated that cost-effective solutions could provide reliable results comparable to high-end industrial systems.
 - Prediction accuracy greater than 95% during training and 100% during testing new samples, demonstrating the feasibility of implementing PdM in resource-limited settings. The success of this approach highlights the potential for widespread adoption in SMEs with minimal investment.



5.6. FUTURE TRENDS IN PDM FOR SMES

PdM is expected to evolve significantly in the coming years, driven by technological advancements and changing industry needs.

- **Edge Computing:** Real-time processing of sensor data at the source will improve response times (Siemens, 2025). By reducing the need for cloud-based processing, edge computing enables faster decision-making and enhances system reliability.
- **Subscription-Based Maintenance (MaaS):** SMEs can access PdM through pay-per-use models, reducing upfront costs (Infraspeak, 2023). This shift allows businesses to scale their maintenance capabilities as needed without significant initial investments.
- **Advanced AI Models:** More sophisticated predictive algorithms will enhance accuracy and reliability (Riccio & Menanno, 2024). AI-driven maintenance solutions will improve fault detection, optimize scheduling, and provide deeper insights into asset health, enabling SMEs to make data-driven decisions with greater confidence.

By staying ahead of these trends, SMEs can harness PdM to drive efficiency, reduce costs, and remain competitive in an increasingly digital and automated landscape. Embracing these innovations will not only improve operational performance but also position SMEs for long-term success in the evolving industrial ecosystem.

5.7. RESULTS OF PDM SURVEY SENT TO SMES

5.7.1. OVERVIEW OF THE SURVEY

To assess the adoption and impact of Predictive Maintenance (PdM) among Small and Medium-sized Enterprises (SMEs), a survey has been conducted across five European countries: France, Germany, Slovenia, Sweden, and Italy.

The survey gathered insights on **company size, primary industry sector, current maintenance practices, technological adoption, workforce impact, and future perspectives on PdM**. The results provide valuable data on the challenges and opportunities SMEs face in integrating PdM into their operations.

A total of 103 SMEs has been invited to participate, with 26 companies responding providing the following origin and size distribution:

5.7.2. ANALYSIS AND RELIABILITY OF THE SURVEY RESULTS

With a response rate of 25% out of a total of 103 requests for information sent to SMEs, the results indicate a trend that should be taken into consideration (see statistics provided in the chapter on methodology).

5.7.3. GENERAL INFORMATION ON THE SURVEYED SMES

5.7.3.1. SIZE DISTRIBUTION OF RESPONDING SMES

The survey gathered responses from 26 SMEs across five countries: France, Germany, Slovenia, Sweden, and Italy. The distribution of responses per country shows notable variations:



The high response rate in France suggests strong engagement with the survey, whereas Germany, despite having the highest number of contacted SMEs, had a lower response rate (15%). The engagement level in Slovenia was moderate, with just under half of the contacted companies responding. Italy had a complete response rate, but only one SME was included. Sweden had the lowest engagement rate, with one response out of the 20 countries contacted.

Table 8. SME Survey Response Distribution by Country

Toward SMEs	Country	Number of Companies	Number of answers
	FR	11	11
	GER	60	9
	SI	11	4
	SWE	20	1
	IT	1	1
Total SMEs		103	26

5.7.3.2. SIZE OF ORGANIZATIONS

The survey categorized SMEs into four size groups based on the number of employees:

- Micro (1-9 employees)
- Small (10-49 employees)
- Medium (50-249 employees)
- Large (250+ employees) (although large companies are not typically SMEs, they were still included in some responses)

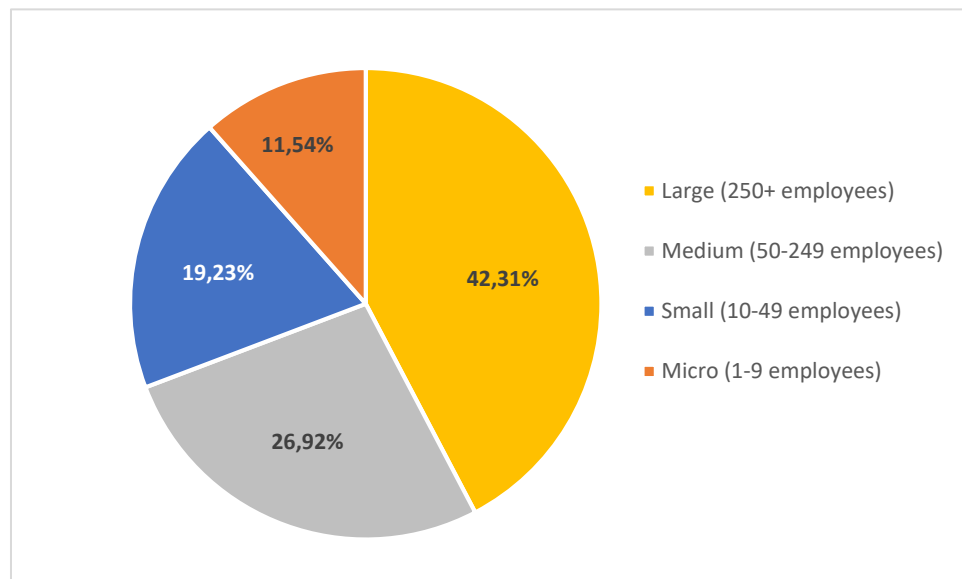


Figure 22. Size Distribution of Responding SMEs



5.7.3.3. SIZE OF ORGANIZATIONS PER COUNTRY

France and Germany have representation across medium and large categories, with additionally small category in Germany. Italy has one medium-sized organization. Slovenia and Sweden are mainly represented by small and micro-sized organizations.

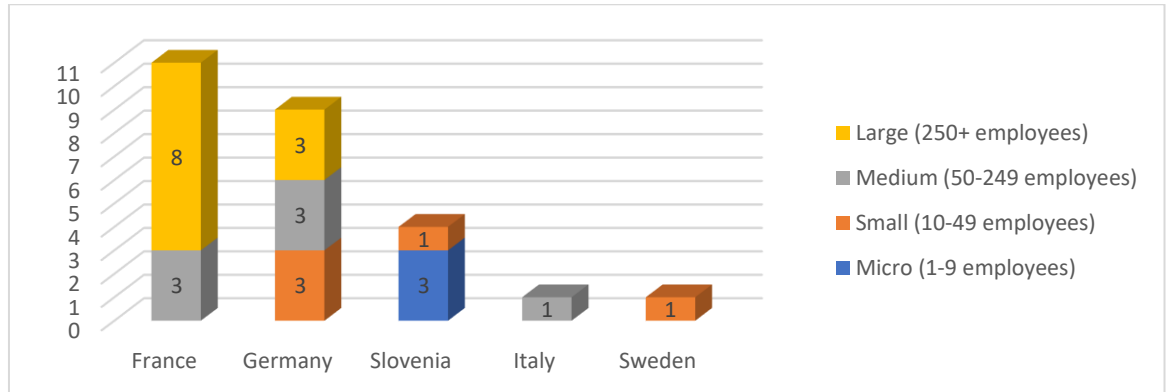


Figure 23. Size of organizations per country

Responses from larger organizations might influence the survey's overall findings, potentially shifting the focus toward issues faced by medium-to-large enterprises rather than micro and small SMEs.

5.7.3.4. SIZE OF ORGANIZATIONS WHICH ANSWERED PER PRIMARY INDUSTRY SECTOR

The participating companies belonged to various sectors, mainly in **Machinery, Equipment** and **Automotive** industries:

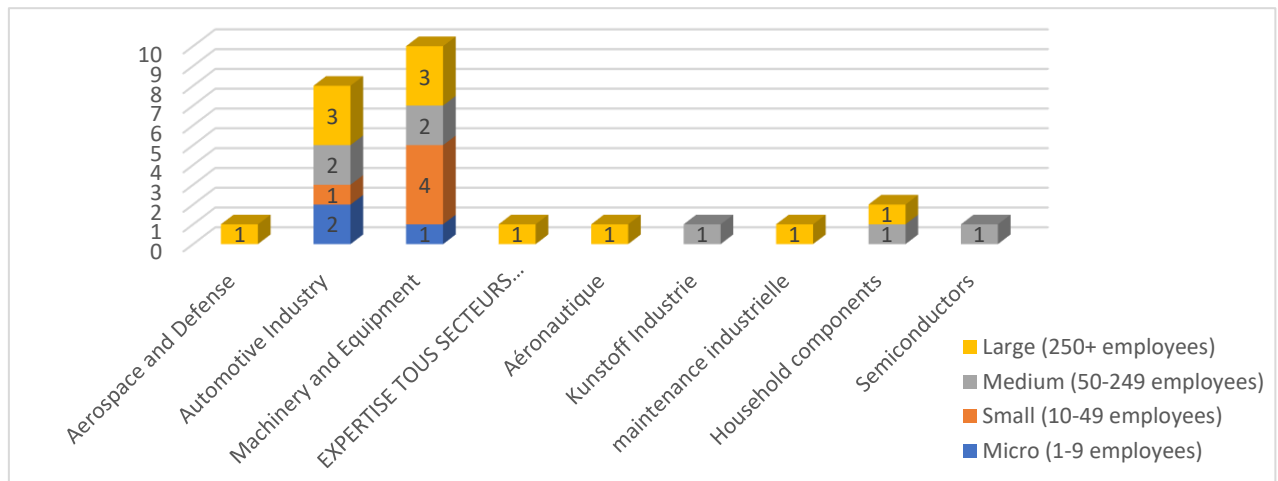


Figure 24. Size of organizations which answered per primary industry sector

5.7.3.5. ROLES WITHIN THE COMPANY

The survey also analysed the roles of respondents within their companies. The key findings include:

- A mix of company decision-makers, including maintenance managers and executives, participated.



- The presence of maintenance professionals suggests that the survey results reflect practical, on-the-ground insights into predictive maintenance (PdM) rather than just strategic or theoretical perspectives.
- Larger companies tend to have dedicated maintenance roles, while smaller businesses might have employees with multiple responsibilities.

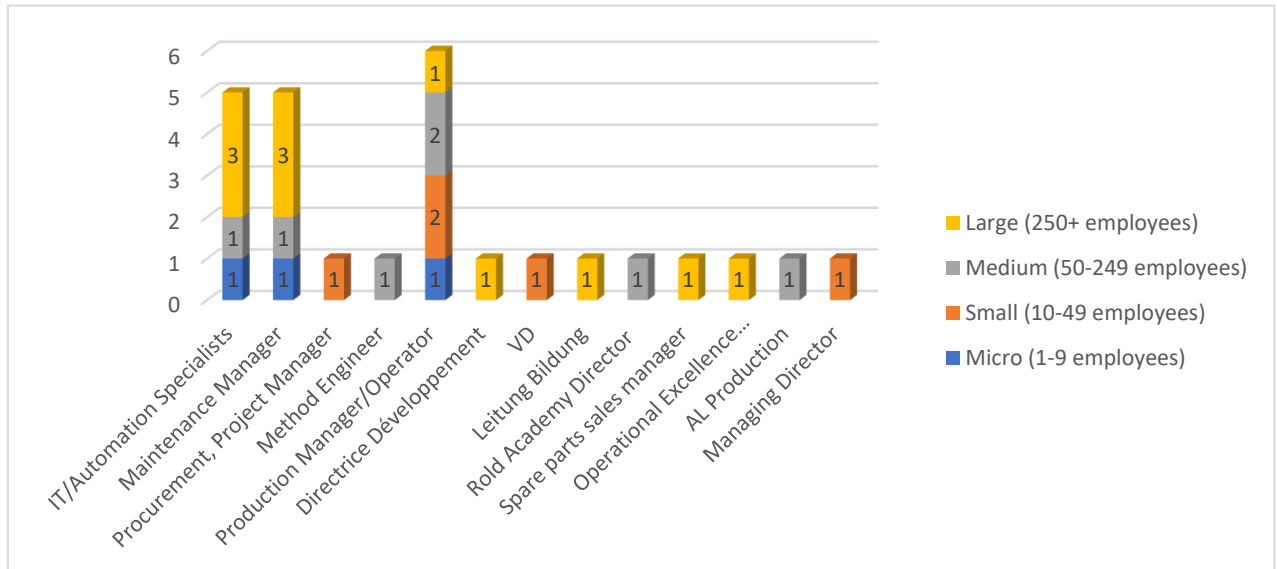


Figure 25. Roles within the company

5.7.3.6. SUMMARY OF THE OVERVIEW OF THE SURVEY

The dataset provides a clear understanding of the size and distribution of responding SMEs, their industry sectors, and roles within the organizations. The data suggests:

- Strong participation from French SMEs, with Germany contributing a significant number of responses despite a lower response rate.
- A diverse representation of company sizes, though medium-sized companies dominate.
- A high level of participation from industries requiring predictive maintenance solutions.
- A good mix of operational and strategic decision-makers responding to the survey, ensuring a well-rounded perspective on the issues faced by SMEs.

5.7.4. CURRENT STATE OF PDM ADOPTION IN SMES

The survey results indicate that while **SMEs recognize the importance of Predictive Maintenance (PdM)** in enhancing efficiency and competitiveness, **its adoption remains at an early stage for many companies.**

5.7.4.1. TYPES OF MAINTENANCE STRATEGIES IN USE (REACTIVE, PREVENTIVE, PREDICTIVE).

The majority of SMEs still **rely on reactive or preventive maintenance strategies**, with **predictive approaches slowly gaining traction**, particularly among larger and more digitally mature companies.



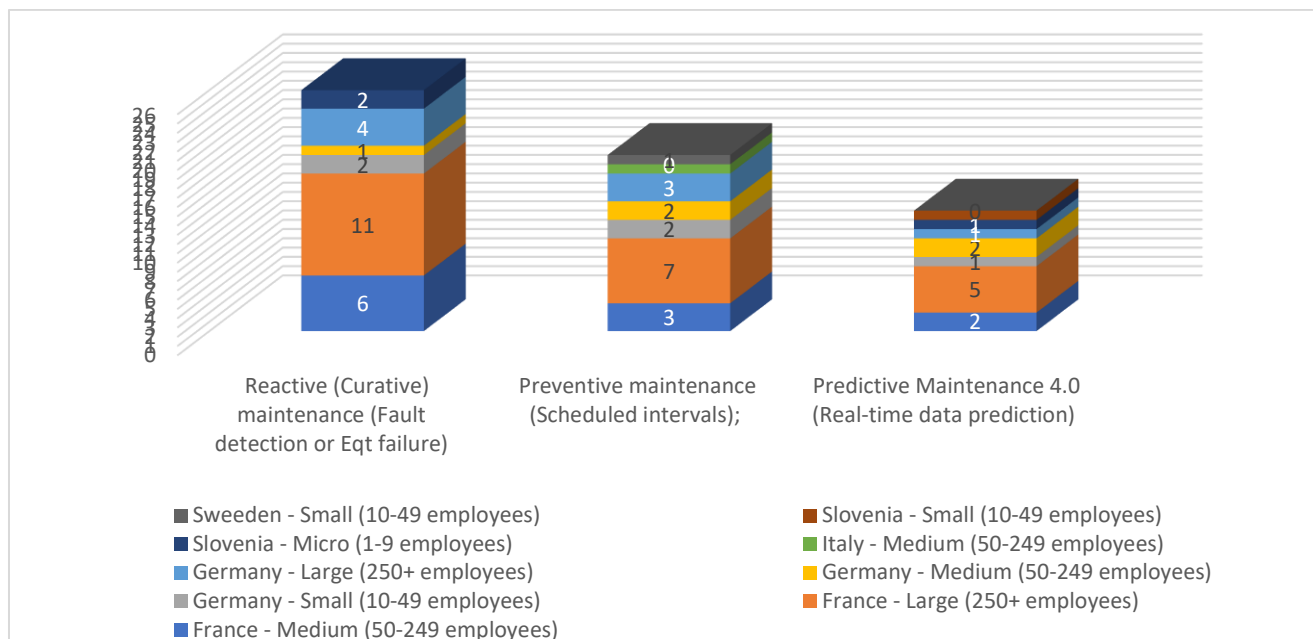


Figure 26. Maintenance process currently implemented

5.7.4.2. SMES' PREPAREDNESS TO ADOPT PDM AND EMERGING TECHNOLOGIES.

In addition, SMEs exhibit **moderate readiness** for adopting **emerging PdM, digital, and green transition trends**, with many still in the **early stages of implementation**.

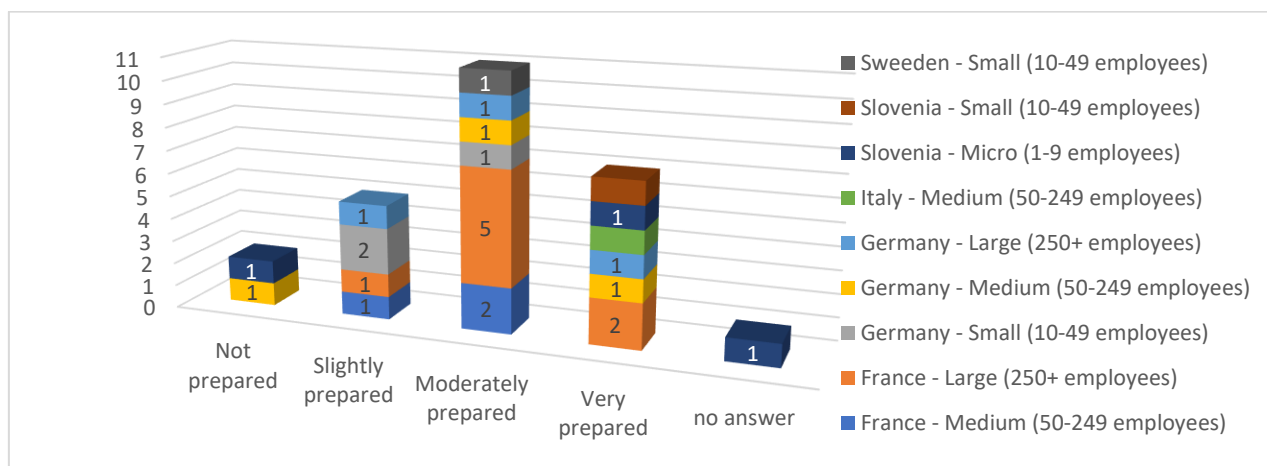


Figure 27. How prepared are the companies to adopt emerging PdM Digital and Green Transition trends?

5.7.4.3. BARRIERS TO ADOPTION (COST, EXPERTISE, INTEGRATION CHALLENGES).

The survey results reveal that the **main barriers to PdM adoption** for SMEs include **high implementation costs, lack of in-house expertise, and limited knowledge of predictive technologies**. When it comes to the difficulties encountered by companies when it comes to **data, data collection, quality and security** were identified as the **main obstacles**, ahead of the issue of data storage.





Figure 28. What are the main barriers your organization faces in adopting PdM technologies?



Figure 29. What data challenges do you encounter with PdM?

5.7.5. PDM'S IMPACT ON SMES' MARKET STRATEGY

SMEs increasingly view PdM as a **strategic investment** rather than just an operational improvement. The ability to **reduce costs, improve reliability, and support sustainability goals** makes PdM a key driver for **long-term competitiveness in Industry 4.0**.

Despite the identified obstacles, most SMEs acknowledge that PdM is shaping their **business positioning and market approach**. The results of this survey highlight that for SMEs:

- It's mainly **very important to adopt predictive technologies** and new digital trends like IoT and Ai to **enhance maintenance practices**.
- **PdM is definitively essential** for **staying competitive** in their industry.
- **PdM can influence** their **organisation's market strategy** or **competitive positioning**.



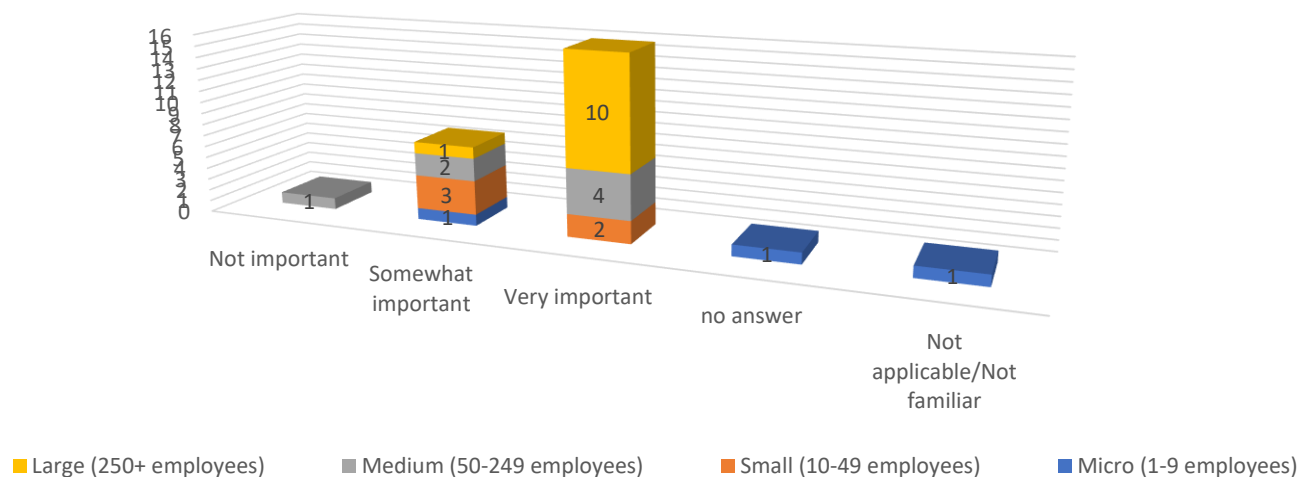


Figure 30. How important is it to adopt predictive technologies and new digital trends like IoT and AI to enhance maintenance practices?

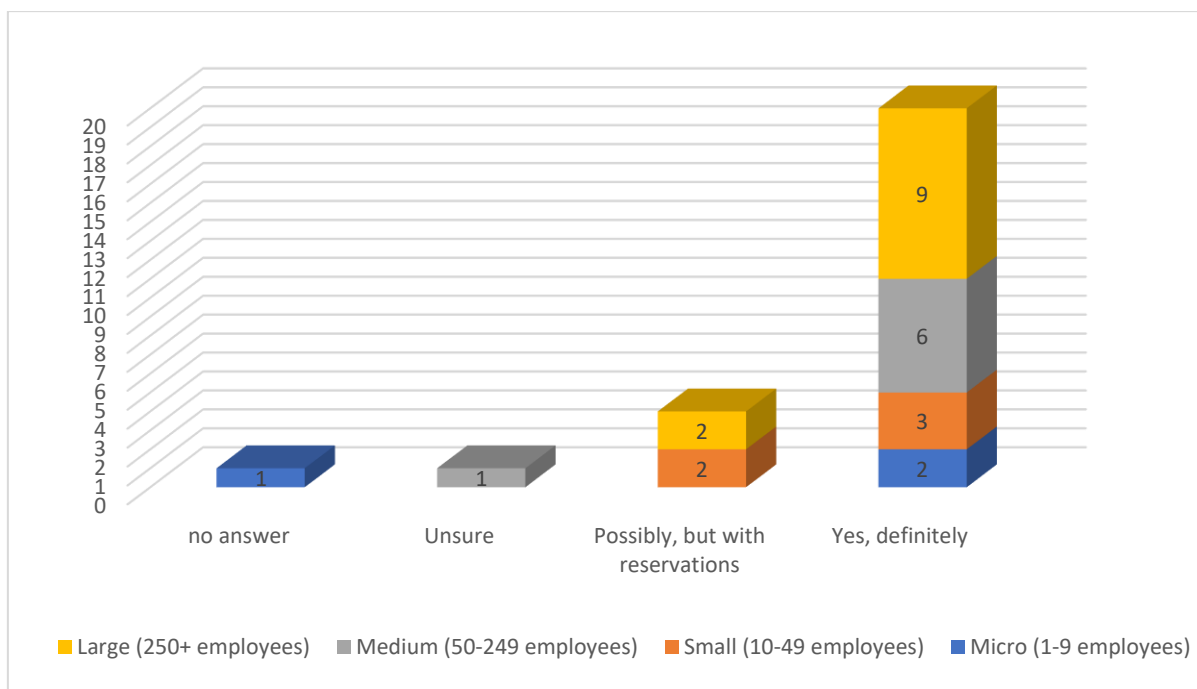


Figure 31. Do SMEs perceive PdM as essential for staying competitive in their industry?

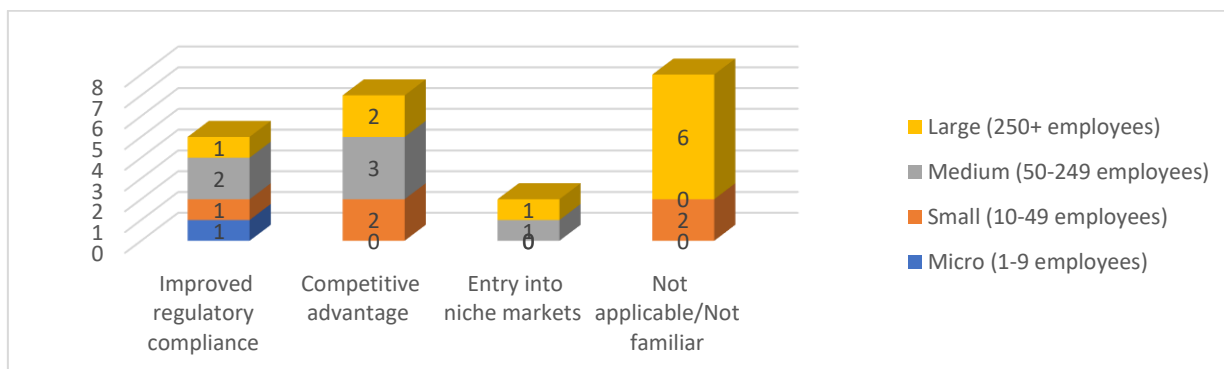


Figure 32. How has PdM influenced your organisation's market strategy or competitive positioning?



5.7.6. HOW SMES ARE PREPARING FOR THE FUTURE

5.7.6.1. COST CHALLENGES

To address the **cost challenge** of PdM adoption, SMEs are exploring **budget reallocation, project-based funding, and long-term cost-saving strategies**. Some companies are also seeking **external financial support, partnerships, and scalable cloud-based PdM solutions** to reduce upfront investment while maximizing operational efficiency

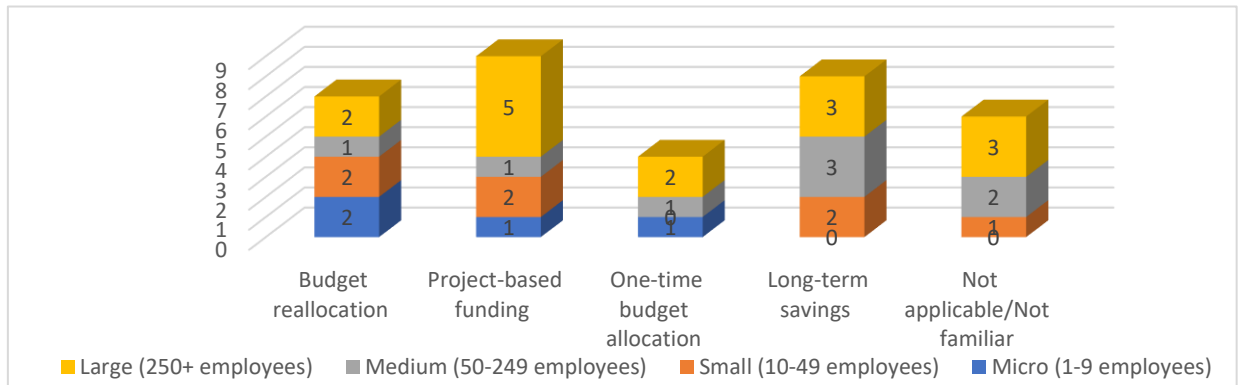


Figure 33. How does your organization address the cost challenges associated with PdM adoption?

5.7.6.2. IMPACT ON JOB ROLES

The survey results indicate that SMEs identify **job transformations**. Many respondents anticipate that **new roles will emerge**, while others believe that **existing roles will evolve** to incorporate data analysis, predictive modeling, and AI-driven diagnostics.

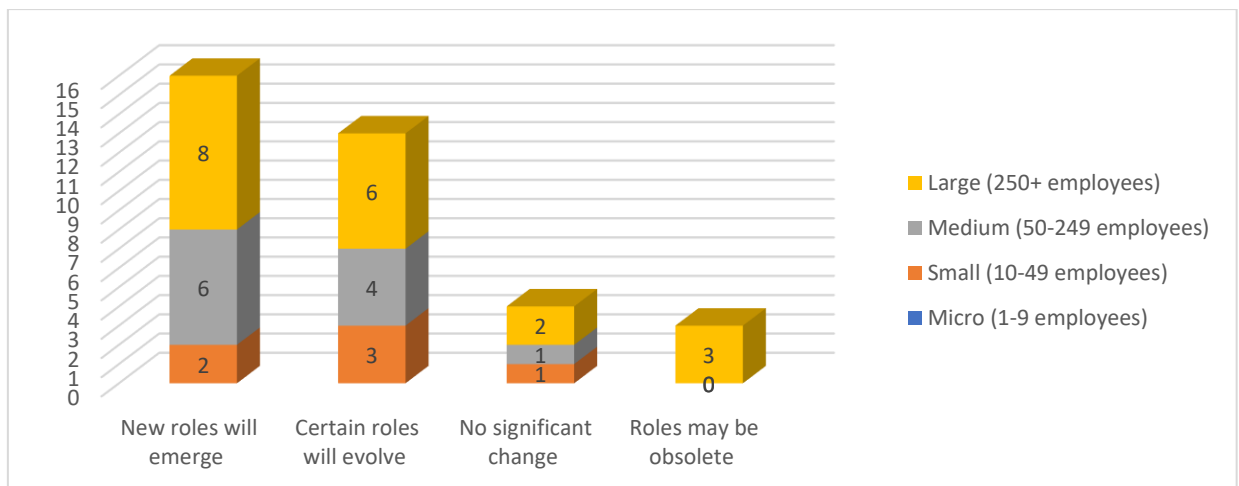


Figure 34. How do you anticipate PdM will impact job roles within your organization?

However, when asked about their **preparedness to manage these job changes**, responses varied: while some organizations have started implementing **upskilling programs and training initiatives**, a significant number remain **only partially prepared**, highlighting a **need for more structured workforce development strategies** to ensure a smooth transition.



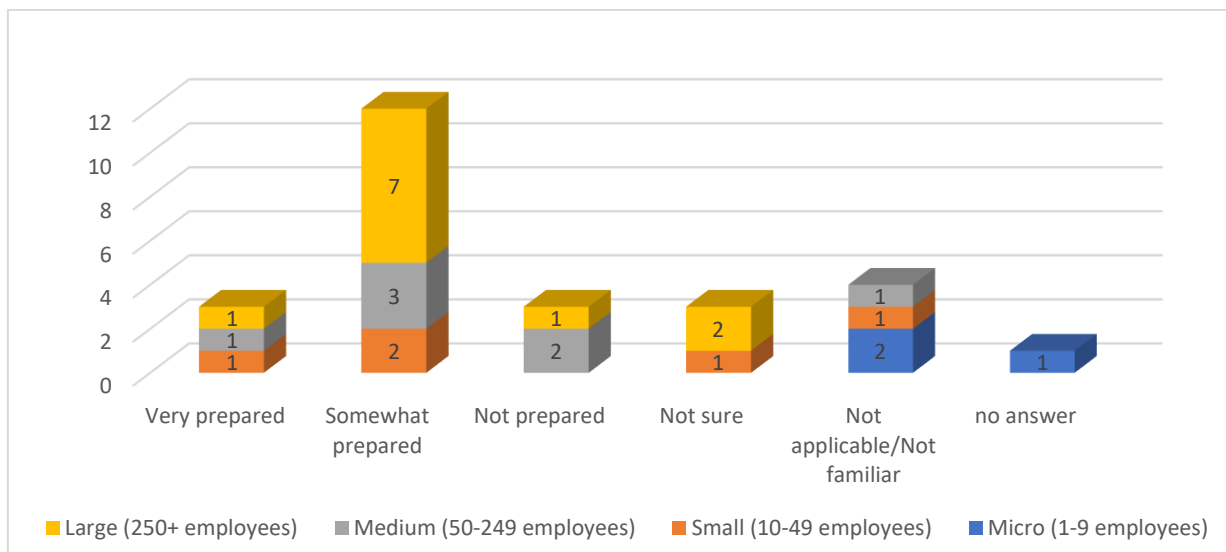


Figure 35. How prepared is your organization to manage job changes related to PdM adoption?

The survey results indicate that SMEs are adopting **various strategies to prepare for the anticipated growth of PdM technologies**, with approaches ranging from **internal capacity building and workforce training to external partnerships and technology investments**. While some organizations are **developing in-house expertise** to support PdM adoption, others rely on **external service providers, collaborative industry initiatives, or hybrid approaches** to integrate predictive maintenance into their operations.

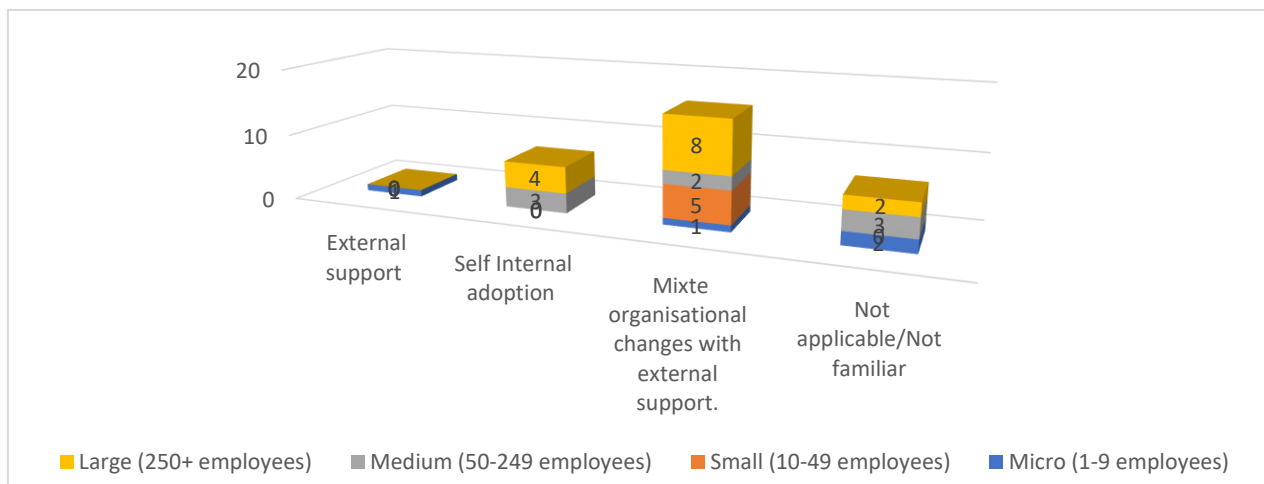


Figure 36. How is your organization preparing for the anticipated growth of PdM technologies?

5.7.6.3. TRAINING & WORKFORCE UPSKILLING

The survey results reveal a **strong demand for additional educational support** in key areas related to **digital and green technologies in PdM**, with SMEs expressing a **high level of interest** in training programs that enhance their workforce's capabilities. **AI, IoT, cybersecurity, and sustainability** emerge as the **critical fields** where employees require **technical training, awareness, and skill development**.

In particular, **data analytics, predictive modeling, and IoT-based monitoring** are seen as **essential competencies** for successfully implementing PdM strategies. **Cybersecurity training** is also a growing concern, as companies recognize the importance of **protecting predictive maintenance systems from cyber threats**. Additionally, while **sustainability-focused training**



ranks slightly lower in priority, SMEs acknowledge its role in **optimizing energy efficiency and reducing environmental impact**.

The survey reveals that **training needs in the fields of IoT and AI focus** primarily on developing **technical expertise** while raising **awareness of tech-green** principles, ensuring that innovation is aligned with sustainable principles.

The level of interest in **digital and green transition trends linked to PdM training** tend to focus on **advanced applications of AI and IoT at higher qualification levels (EQF 5-6)** to build foundational knowledge.

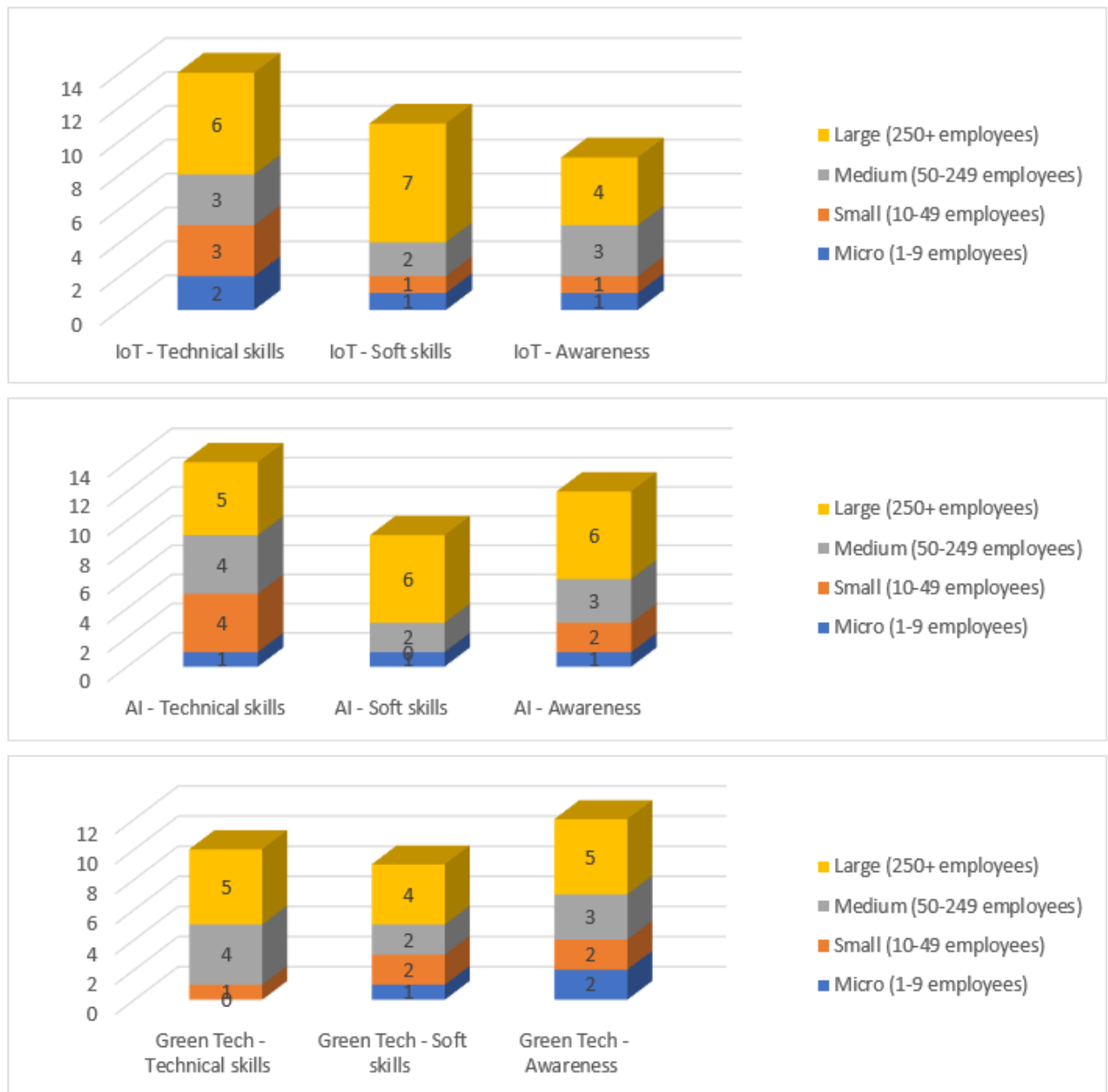


Figure 37. In which areas do employees in your organization need additional educational support to effectively use digital and green technologies in PdM?



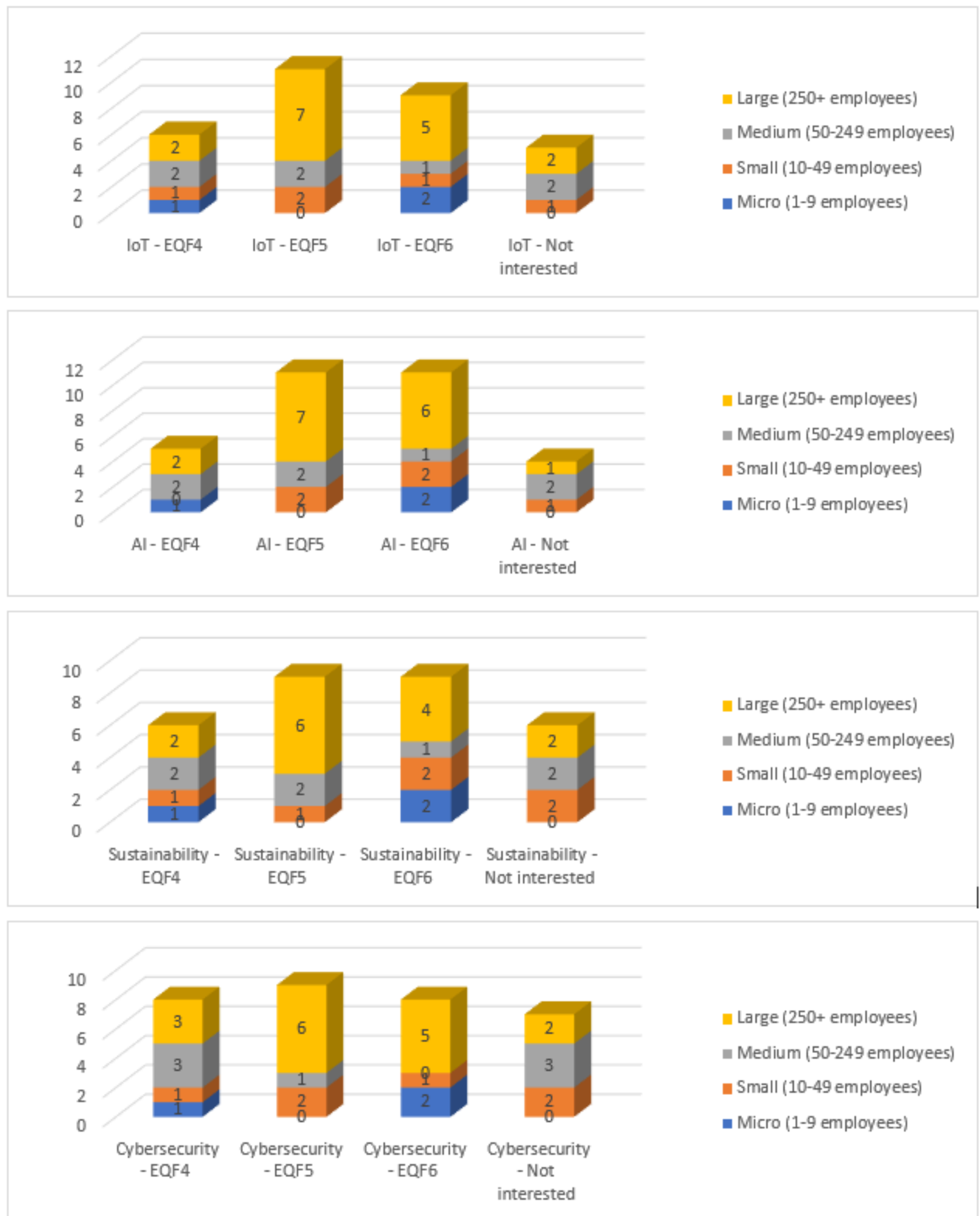


Figure 38. How interested are you in new digital and green transition trends linked to PdM training?



While **larger SMEs** tend to favour in-house development, **smaller companies** prefer external training providers, all preferring in-person workshop format.

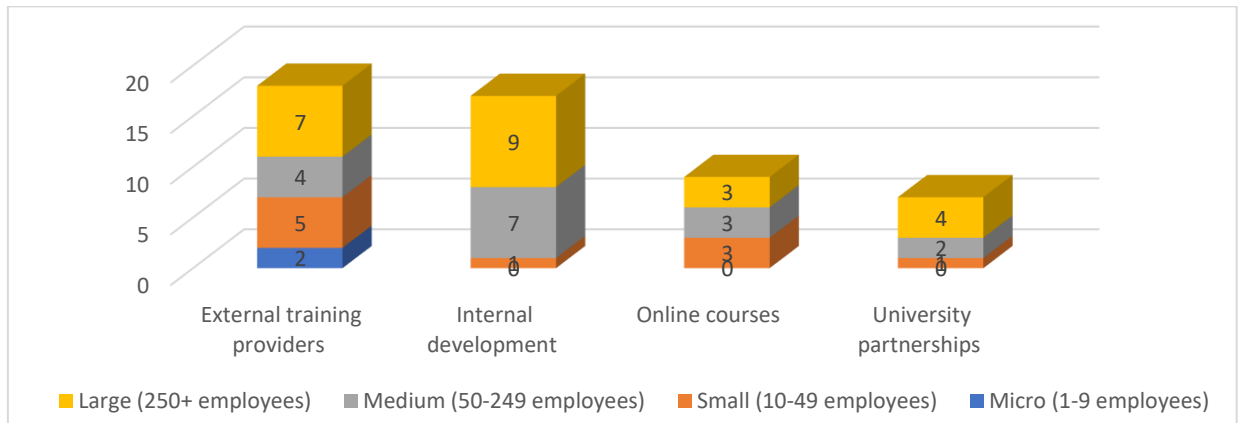


Figure 39. How does your organization prefer to access training?

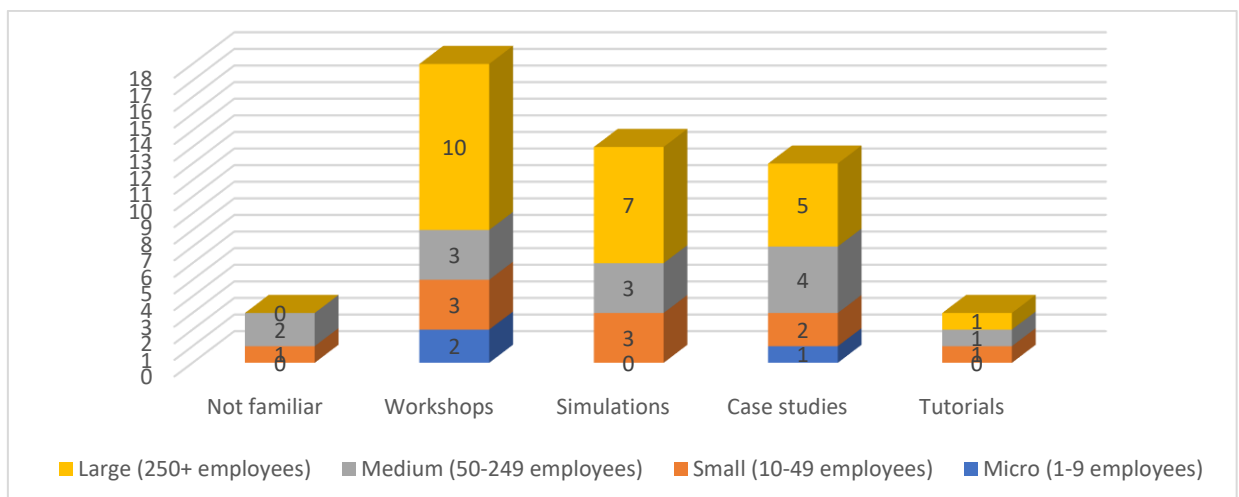


Figure 40. What are the preferred formats for PdM training?

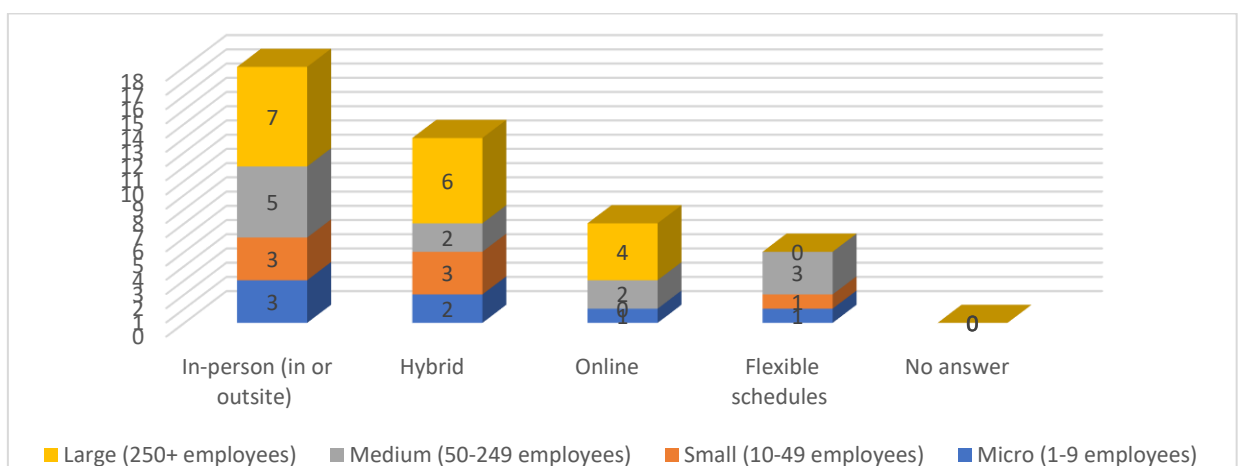


Figure 41. What types of training would best support your workforce for PdM?

These findings highlight the **urgent need for tailored training initiatives** that address both **technical and sustainability-related skills**. By bridging the **digital and green skills gap**, SMEs will be better equipped to **leverage PdM effectively, enhance operational efficiency, and align with Industry 4.0 and sustainability goals**.



5.8. FUTURE PERSPECTIVES & RECOMMENDATIONS

Looking ahead, SMEs recognize the **growing importance of Predictive Maintenance (PdM)** and the need to **overcome barriers related to cost, skills gaps, and technological integration**. To accelerate adoption and **maximize the benefits of PdM**, SMEs must explore **strategic approaches, partnerships, and new service models** that support a **scalable and cost-effective transition**.

5.8.1. EXPANDING ACCESS TO FINANCIAL SUPPORT AND TECHNOLOGY ADOPTION

Ensuring SMEs can effectively adopt Predictive Maintenance (PdM) technologies requires improved access to financial resources, strategic partnerships, and innovative service models that reduce cost and implementation barriers. The following axis can be explored:

- **Increase access to funding programs** – Government incentives, EU grants, and industry-backed financial support should be leveraged to reduce the **high initial investment costs** associated with PdM technologies.
- **Promote technology partnerships** – Collaborations with technology providers, industrial associations, and research institutions can help SMEs **integrate IoT, AI, and cloud-based PdM solutions** with minimal disruption to existing operations.
- **Encourage SMEs to explore Maintenance-as-a-Service (MaaS)** – Many SMEs struggle with **high upfront costs and the lack of in-house expertise** needed to implement PdM. By contracting **MaaS providers**, SMEs can **access advanced PdM capabilities without the need for major infrastructure investments**, benefiting from **subscription-based, scalable maintenance solutions**.

5.8.2. INVESTING IN WORKFORCE TRAINING AND DIGITAL SKILLS DEVELOPMENT

To maximize the benefits of PdM technologies, SMEs must invest in workforce training, equipping employees with the necessary digital skills and technical expertise to manage AI-driven predictive analytics, IoT integration, and cybersecurity.

- **Develop targeted training programs** – Upskilling employees in **AI-driven predictive analytics, IoT integration, and cybersecurity** is crucial for PdM adoption. Industry-specific training should be adapted to **SME needs, company size, and technical readiness**.
- **Promote hybrid learning models** – SMEs favor flexible training formats such as **online courses, workshops, and simulations**, which should be made more accessible through collaborations with **universities, technical schools, and industrial training centres**.

5.8.3. OPTIMIZING PDM STRATEGIES FOR LONG-TERM COMPETITIVENESS

For SMEs to remain competitive, PdM strategies must be implemented in a scalable, cost-effective manner, leveraging cloud technologies and sustainability-driven approaches to enhance operational efficiency and regulatory compliance.



- **Adopt a phased approach to PdM implementation** – SMEs can start with **pilot projects focusing on critical assets**, gradually expanding PdM across operations as **ROI becomes evident**.
- **Leverage cloud-based PdM solutions** – Cloud computing enables SMEs to **scale maintenance operations without requiring costly infrastructure**, allowing them to analyse **real-time machine data** remotely.
- **Integrate sustainability into PdM strategies** – PdM should be aligned with **green transition objectives**, helping SMEs **optimize energy consumption, reduce waste, and comply with environmental regulations**.

6. IMPACT OF PDM ON TRAINING AND TRAINING CENTRES

6.1. STATE OF THE ART IN MAINTENANCE TRAINING

6.1.1. LEARNER-CENTRIC MODEL APPROACH

The Certified European Maintenance Professionals project, part of the Erasmus+ Programme, aims to strengthen the competitiveness of European industries by enhancing the skills of maintenance professionals across member states. This transnational initiative addresses the skills gap in maintenance management, emphasizing the need for formal training aligned with industry demands in automation, digitalization, and predictive maintenance. By focusing on vocational education and incorporating the European Centre for the Development of Vocational Training (CEDEFOP) guidelines, the project facilitates the validation of both formal and informal learning. Key outcomes include the establishment of standardized qualifications for various maintenance roles and a comprehensive fostering lifelong learning and unifying maintenance practices across Europe.

The project emphasizes a learner-centric model, adapting needed skills to different EQF levels, which allows learners to follow a progression suited to their skills and career goals. This approach makes learning more relevant and personalized for each student, whether they are new entrants or experienced professionals seeking upskilling.

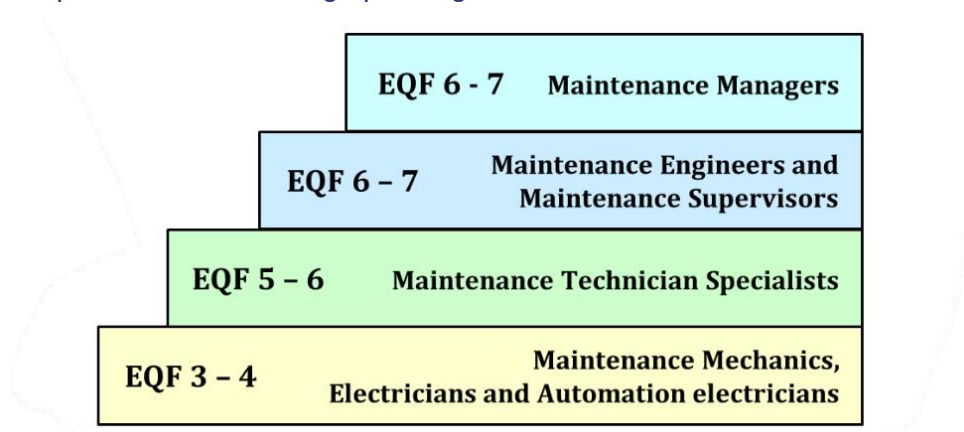


Figure 42. Maintenance Qualification Staircase



Example mentioned:

At the European Qualifications Framework (EQF) Level 6, maintenance engineers and supervisors are expected to demonstrate:

- **Technical Knowledge:** In predictive, preventive, and corrective maintenance, including advanced methods for condition monitoring.
- **Skills:** Ability to analyse data from maintenance systems, develop maintenance plans, and implement improvements.
- **Autonomy and Responsibility:** Decision-making in maintenance strategy implementation, optimizing processes, and ensuring safety and compliance, including Predictive Maintenance strategy.

See References in source (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id219, n.d.)

EN 17007:2017-ACT – Act preventively and/or correctively on the items to maintain:

Table 9. Qualifications for Maintenance Engineers and Supervisors (EQF level 6)

Subject	Knowledge (should be able to)	Skills (should be able to)	Responsibility and Autonomy (should be able to)
Preventive maintenance	– Describe preventive maintenance and the different strategies to ensure a high dependability	– Plan and implement effective preventive maintenance plans	– Analyse and optimize the process for all preventive maintenance tasks
Predetermined maintenance	– Describe methods and techniques for predetermined maintenance – Describe how to perform predetermined maintenance	– Realize plans for predetermined maintenance	– Analyse and optimize the process for all predetermined maintenance tasks
Condition-based maintenance	– Describe methods and techniques for condition-based maintenance (e.g. subjective and objective condition-based maintenance methods) – Describe different types of condition monitoring systems (e.g. continuous, by intervals, on request, centralized or decentralized) – Describe P-F Interval and how it is used – Describe methods and techniques for inspection (condition-based maintenance)	– Decide about and carry out plans for the intervals between inspections and condition-based maintenance – Carry out a suitable plan for inspection and a condition-based maintenance system – Decide and communicate where non-predictive maintenance should be carried out	– Analyse and optimize the process for all condition-based maintenance tasks
Predictive maintenance	– Describe how to perform predictive maintenance – Describe predictive maintenance methods	– Decide about and carry out plans where Predictive Maintenance should be carried out	– Analyse and optimize the process for all predictive maintenance tasks



	– Describe the difference between predictive and non-predictive maintenance – Describe how to perform non-predictive maintenance – Describe non-predictive maintenance methods	– Use suitable systems for predictive maintenance	
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6.1.2. EXPERTISE IN PREDICTIVE TECHNOLOGIES

The PdM specialist (PdM Specialists, n.d.) offers EQF Level 5 training program in both on-site and online training in predictive maintenance. It covers topics such as vibration analysis, software setup, and data collection. The training emphasizes building practical, hands-on skills required for predictive diagnostics and maintenance tasks. It's suitable for technicians looking to enhance their expertise in predictive technologies.

6.2. EVOLUTION OF MAINTENANCE TRAINING IN THE DIGITAL AGE

The landscape of maintenance training is rapidly evolving with the integration of digital tools, advanced methodologies, and predictive maintenance strategies. Traditional hands-on learning is being transformed by Industry 4.0 technologies, requiring maintenance professionals to adapt to new methodologies that enhance efficiency, reduce downtime, and align with industry demands.

- **Integration of Digital Technologies:** Augmented Reality (AR), Virtual Reality (VR), and digital twins are becoming essential components of training programs. These technologies provide immersive learning experiences, enabling trainees to simulate real-world maintenance scenarios in a risk-free environment (United Nations Educational, Scientific and Cultural Organization & UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, 2021).
- **Data-Driven and Predictive Maintenance Training:** AI-powered analytics, IoT-enabled monitoring systems, and automated diagnostics are reshaping how maintenance professionals interpret system anomalies. These advancements facilitate predictive and condition-based maintenance strategies, minimizing equipment failures and optimizing operational efficiency (United Nations Educational, Scientific and Cultural Organization & UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, 2021).
- **Certification and Standardization:** Programs such as Erasmus+ and ISO certifications ensure uniform skill levels and competencies across countries, fostering a standardized approach to maintenance training. These initiatives provide structured learning paths, validate professional expertise, and ensure industry readiness (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id 31, n.d.).
- **Alignment with Industry 4.0 Needs:** Training curricula are increasingly incorporating AI, IoT, and cybersecurity to equip professionals with skills relevant to modern industrial environments. Digital twins, remote monitoring, and smart factory operations are now integral to maintenance training, preparing workers for the demands of automated and interconnected production (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id 31, n.d.).
- **Hybrid Learning Models:** The combination of online modules, simulation-based learning, and in-person practical training enhances accessibility and effectiveness. This blended



approach allows professionals to upskill while managing their work commitments, ensuring continuous adaptation to technological advancements in the field.

6.3. CHALLENGES AND OPPORTUNITIES FOR TRAINING CENTRES

Training centres play a pivotal role in bridging the skill gap and ensuring that professionals are equipped to handle modern PdM solutions. However, this transition presents several challenges and opportunities:

- **Modernization of educational infrastructures:** Training centres must upgrade their facilities to integrate PdM tools, such as sensors, data analytics software, and cloud-based monitoring systems. This requires investment in advanced equipment, as well as training for instructors to effectively teach new technologies (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id219, n.d.).
- **Development of hybrid training formats:** To meet industry demands, training programs must adopt a hybrid approach, combining in-person and virtual learning experiences. Online platforms and virtual labs provide flexibility while ensuring trainees gain practical experience through interactive simulations and hands-on training (United Nations Educational, Scientific and Cultural Organization & UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, 2021).
- **Strengthening collaborations with industrial partners:** Partnerships with industry leaders allow training centres to provide hands-on PdM experiences through apprenticeships, internships, and collaborative projects. These initiatives enhance trainees' exposure to real-world challenges and prepare them for seamless integration into the workforce (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id219, n.d.).

6.4. SKILLS TRAINED AND IMPACT OF PDM

Predictive Maintenance (PdM) is reshaping the skillset required for maintenance professionals. The following key competencies are essential for the evolving landscape:

- **Technical skills:** Mastery of AI-driven diagnostics, IoT sensor management, data interpretation, and machine learning applications in maintenance. These skills allow professionals to predict equipment failures and optimize maintenance schedules effectively (United Nations Educational, Scientific and Cultural Organization & UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, 2021).
- **Analytical skills:** Proficiency in big data analysis, root cause analysis, and decision-making based on predictive analytics. Maintenance professionals must be able to interpret complex data sets and derive actionable insights to prevent unexpected failures (United Nations Educational, Scientific and Cultural Organization & UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, 2021).
- **Soft skills:** Adaptability to digital tools, teamwork in smart factories, and real-time problem-solving. As maintenance roles become increasingly collaborative and technology-driven, professionals need strong communication and critical thinking skills to work effectively with cross-functional teams (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id219, n.d.).



- **Cybersecurity awareness:** Understanding and implementing cybersecurity best practices to protect maintenance-related data and IoT-connected systems. With the rise of connected equipment, maintenance professionals must ensure systems are secure from cyber threats and vulnerabilities (United Nations Educational, Scientific and Cultural Organization & UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training, 2021).

The impact of PdM on training programs is profound, shifting the focus from reactive and preventive maintenance strategies to proactive and predictive models, reducing downtime and improving asset longevity.

6.5. THE ROLE OF MAAS IN TRAINING

Maintenance-as-a-Service (MaaS) is emerging as a key enabler in training maintenance professionals by providing access to cutting-edge PdM technologies and real-world applications.

- **Access to PdM technologies via collaborative cloud platforms:** Cloud-based solutions allow learners to work with real-time data and predictive models. By interacting with cloud-hosted predictive maintenance tools, learners can analyse real-world data and develop expertise in using these technologies (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id219, n.d.).
- **Use of simulations and real-world case studies:** Simulation tools and digital twins enable learners to practice PdM techniques in a risk-free environment. Virtualized models of industrial equipment allow learners to experiment with different maintenance scenarios, improving their problem-solving skills before working on actual machinery (Campus of the Czech University of Life Sciences in Prague & Slovenian Maintenance Society - Id219, n.d.).

By embracing these advancements, training centres can effectively prepare future maintenance professionals for the evolving demands of the industry.

6.6. RESULTS OF PDM SURVEY SENT TO VET CENTRES

6.6.1. OVERVIEW OF THE SURVEY

To evaluate the current state of training programs related to emerging digital technologies 4.0 in PdM) among Vocational Education Training Centres (VET Centres), a survey was conducted across five European countries: France, Germany, Slovenia, Sweden, and Italy. This survey also looks at how training centres can adjust their programs to these technological changes and the needs of the industry, by examining the strategies in place or planned to integrate these innovations, the challenges faced, the resources needed, and opportunities for industry collaboration.

The survey was sent to 52 training centres. The results are based on responses received from a total of 25 training centres.

The survey is divided into several key sections: general information about the training centres, courses related to emerging digital technologies 4.0, short, medium, and long-term development plans, alignment with industry needs, financial investments and funding options, teacher training and collaboration, challenges and industry cooperation, and skills and teaching resources.



6.6.2. ANALYSIS AND RELIABILITY OF THE SURVEY RESULTS

With a response rate of 48% out of a total of 52 requests for VET centres, the results indicate a trend that should be taken into consideration (see statistics provided in the methodology chapter).

6.6.3. GENERAL INFORMATION ON THE SURVEYED TRAINING CENTRES

The survey results provide a detailed overview of the training centres that participated, highlighting their geographical distribution, size, areas of specialization, roles of respondents, and the number of graduates per year.

Most of the training centres that responded are located in Slovenia (64%), followed by France (24%), Germany (8%), and Italy (4%).

The results show that most centres are medium to large in size, with 44% having between 500 and 999 students and 28% having more than 1,000 learners.

Industrial training is the main area of focus (64%). However, other sectors are also represented, including the tertiary sector (16%) and the automotive sector (4%), suggesting that digital technology training is expanding into different fields.

The respondents hold key positions within their institutions: 24% are training directors, and 32% are school managers or directors. This indicates that nearly 50% of the participants hold decision-making roles regarding the integration of new technologies. The remaining respondents hold other positions, such as teachers (24%) and administrative staff (16%).

The training centres vary significantly in the number of students graduating each year. While 36% of the centres graduate only between 1 and 99 learners per year, there is also a considerable percentage (24%) of centres that graduate between 100 and 299 students. Additionally, a group of centres has a greater impact, graduating more than 300 learners annually.

Table 10. VET Centre Survey Response Distribution by Country

Toward	Country	Number of Companies	Number of answers
VET	FR	11	6
	GER	14	2
	SI	16	16
	SWE	10	
	IT	1	1
Total VET		52	25

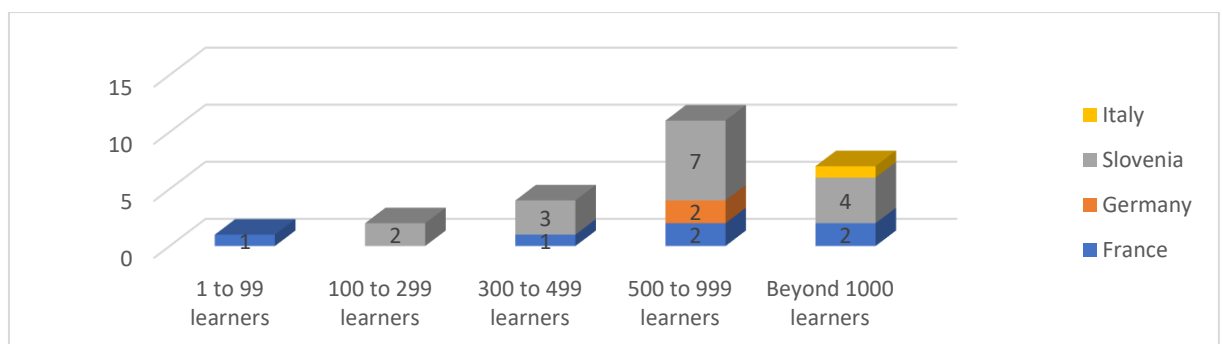


Figure 43. Size of organizations per country



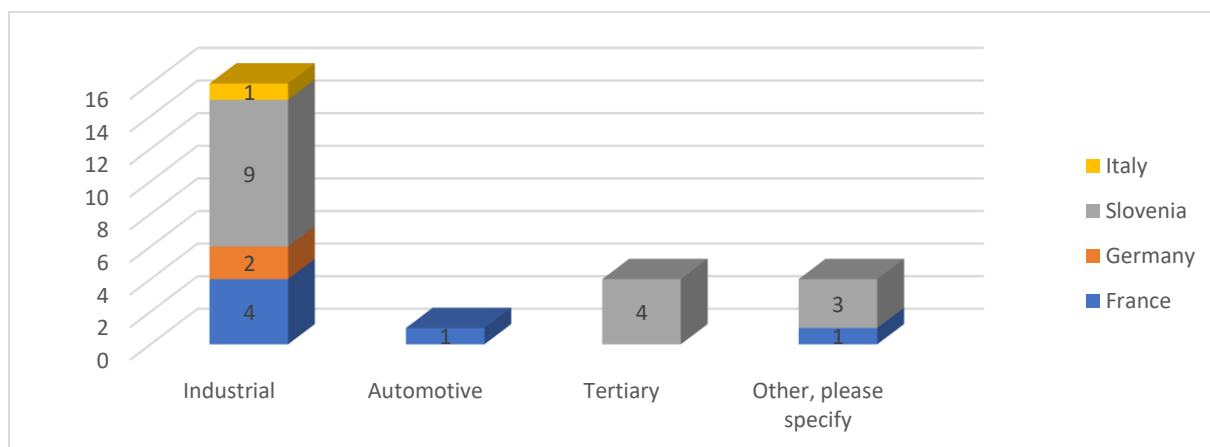


Figure 44. What is the main area of professional training provided by your centre?

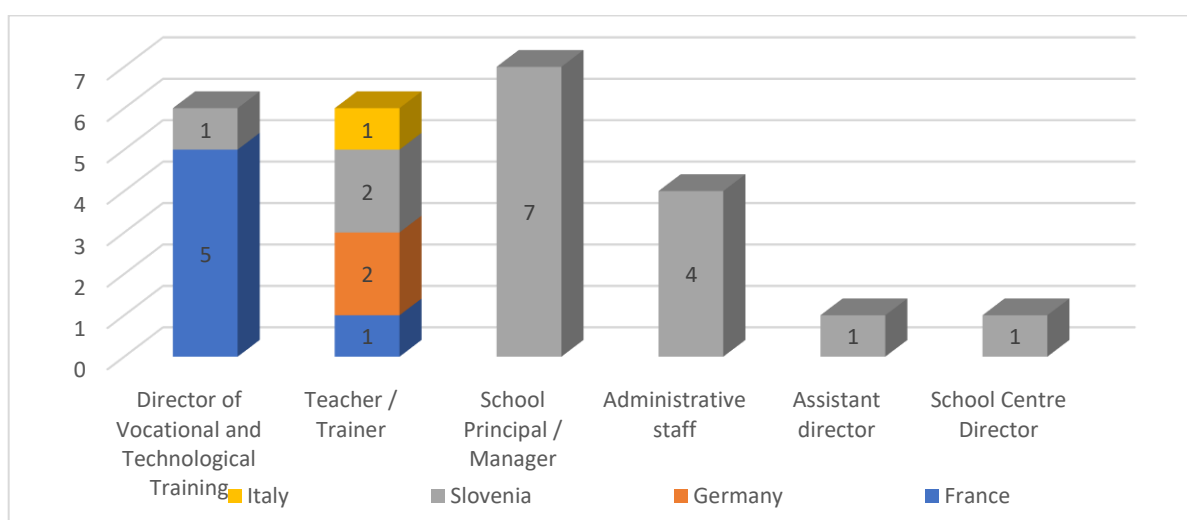


Figure 45. What is your role within the institution?

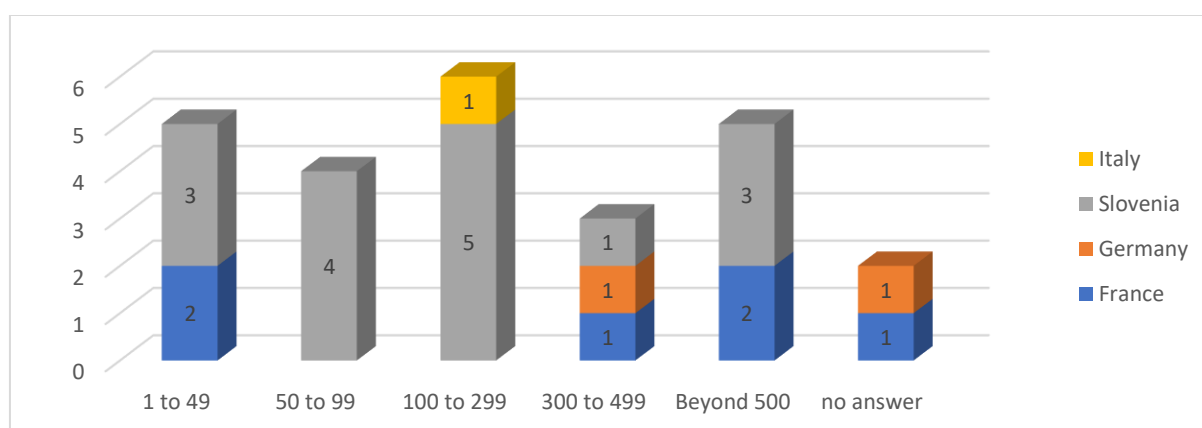


Figure 46. How many students graduate each year?

6.6.4. CURRENT STATE OF TRAINING PROGRAMS AND CENTRES'S AUTONOMY

In Europe, training centres do not always have full autonomy, as in many cases, they must follow guidelines established by hierarchically superior institutions. These guidelines often come from government bodies, such as ministries of education, which have the authority to define policies and



regulatory frameworks that the centres must adhere to. This hierarchical structure ensures coherence and quality in training at the national level, but limits the centres' ability to make completely independent decisions regarding their programs and teaching methods.

In light of this situation, it seemed interesting to us to understand the level of autonomy of the surveyed training centres. The results show that the majority of training centres report having limited (44%) or partial (36%) autonomy in adapting their programs to new technologies. Only 4% have full autonomy, while 8% state that they have none at all. These results highlight a significant constraint for most centres, as they often rely on external input to implement changes in their programs.

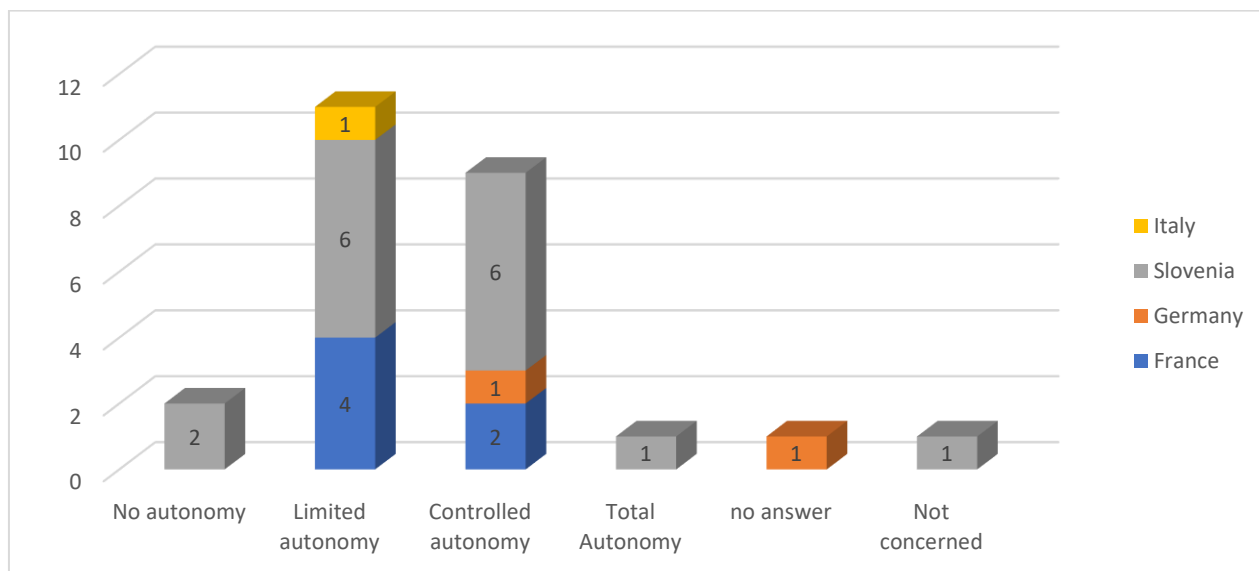


Figure 47. What is your establishment's capacity to adapt the content of its training courses to developments linked to trends such as IoT, AI, cyber security and sustainability in the maintenance professions?

The next table presents a wide range of educational programs organized by European Qualifications Framework (EQF) levels, focusing on key disciplines such as IoT (Internet of Things), Artificial Intelligence (AI), Cybersecurity, Sustainability, and Cloud Computing. Below is a brief analysis of the obtained data:

Programs in IoT are available from EQF 4 to EQF 6, covering topics such as smart electrical installations and industrial maintenance, with a strong focus on innovation for industry. This reflects a growing need for professionals trained in the creation and implementation of smart devices, as well as their integration into industrial systems.

Regarding cybersecurity, courses cover security and protection of information systems at various levels, combining theoretical content with practical training. Ethical hacking is an essential part of the curriculum, highlighting the need for professionals capable of protecting information systems from cyberattacks. The programs provide comprehensive training to address digital risks and threats.

Artificial Intelligence (AI) is integrated into programs from EQF 4 to EQF 6, focusing on its application in computer science, advanced networks, and industrial maintenance. The inclusion of AI in these educational levels suggests a strong demand for skills to develop, implement, and manage AI-based solutions, which are becoming essential in sectors like manufacturing, IT, and industrial automation.

Educational programs related to sustainability cover areas such as efficient use of tools, renewable energy, and sustainable industrial processes. These courses include both technical training and



environmental management, emphasizing the importance of integrating sustainable practices into industrial processes and the development of greener and more efficient technologies.

Although the term Cloud Computing is not explicitly mentioned, courses covering server systems and advanced networks are closely related to cloud infrastructure. Mastering server systems and network management is crucial for building and managing cloud platforms, underscoring the relevance of these skills in the digital world and the ongoing digital transformation across various sectors.

Table 11. Courses taught in the field of emerging 4.0 technologies (IoT, AI, Cyber, Sustainability, Cloud)

Country	Courses
France	• BAC STI2D: Baccalaureate in Sciences and Technologies of Industry and Sustainable Development (EQF 4) • BAC PRO CIEL: Vocational Baccalaureate in Cybersecurity, Computer Science, and Electronic Networks (EQF 4) • BAC PRO TRPM: Vocational Baccalaureate in Mechanical Product Manufacturing Technician, specializing in Production Execution and Monitoring (EQF 4) (France) • BTS CIEL: Higher Technician Certificate in Cybersecurity, Computer Science, and Electronic Networks (EQF 5) • BTS CPRP: Higher Technician Certificate in Conception of the Product Development Process (EQF 5) • BTS CRSA: Higher Technician Certificate in Design and Production of Automated Systems (EQF 5) • LICENCE PRO Conception et Production de Systèmes Electroniques: Vocational Degree in Design and Production of Electronic Systems (EQF 6) • LICENCE PRO CAPPI: Vocational Degree in Design and Improvement of Industrial Processes and Procedures (EQF 6)
France	• BTS CPRP: Higher Technician Certificate in Conception of the Product Development Process (EQF 5) • BTS CIEL: Higher Technician Certificate in Cybersecurity, Computer Science, and Electronic Networks (EQF 5)
France	• BTS CRSA: Higher Technician Certificate in Design and Production of Automated Systems (EQF 5) • Sustainability : BTS STI2d: Higher Technician Certificate in Sciences and Technologies of Industry and Sustainable Development (EQF 5) • BTS CPI: Higher Technician Certificate in Design of Industrial Products (EQF 5)
France	• IoT and AI: Higher Technician Certificate in Industrial Maintenance • IoT, Cybersecurity, AI: Licence Pro MMB: Vocational Degree in Biomedical Equipment Maintenance • IoT, Cybersecurity, AI: Licence Pro MIF: Vocational Degree in Maintenance of the Industry 4.0
France	• BTS CRSA: Higher Technician Certificate in Design and Production of Automated Systems (EQF 5) • Robotics module
Slovenia	• Digital teaching
Slovenia	• IoT -> BUT GMP: University Bachelor of Technology in Mechanical and Production Engineering, specializing in Innovation for Industry (EQF 6)
Slovenia	• Information Technology and User Interface: Digital Teacher Project - Your Key to Success in the Digital Age - Webinar 1 and 2
Slovenia	• Sustainability
Slovenia	• User Interface • Efficient use of tools
Slovenia	• Ethical Hacking - Practical Training • Cybersecurity • Artificial Intelligence in Information Technology - Practical Training • Artificial Intelligence • Server Systems • Advanced Computer Networks
Slovenia	• Digitalization (EQF 7)



Slovenia	• Sustainability • User Interface
Slovenia	• Sustainability EQF 5
Slovenia	• IoT Smart Electrical Installations at Vocational High School and Higher Technical School • Sustainability, Efficient use and renewable energy sources at Higher Technical School • Cybersecurity, Security and protection at Higher Technical School • Cybersecurity, Information Systems Protection at Higher Technical School
Italy	• Systems and Networks (EQF 4) • Technologies and Design of Information and Telecommunication Systems (EQF 4) • Computer Science (EQF 4) • Telecommunications (EQF 4) • Project Management, Business Organization (EQF 4)

6.6.5. FUTURE TRAINING DEVELOPMENTS

The graph demonstrates that while many institutions have started adapting, a significant portion still operates within long transition periods (2-5 years or beyond). Given the rapid evolution of AI, IoT, and cybersecurity in maintenance, even the 2-5 year timeframe might slow down workforce competitiveness in some regions. Institutions in the 6+ year category risk producing graduates unprepared for Industry 4.0.

AI and Sustainability seem to be the key priorities,

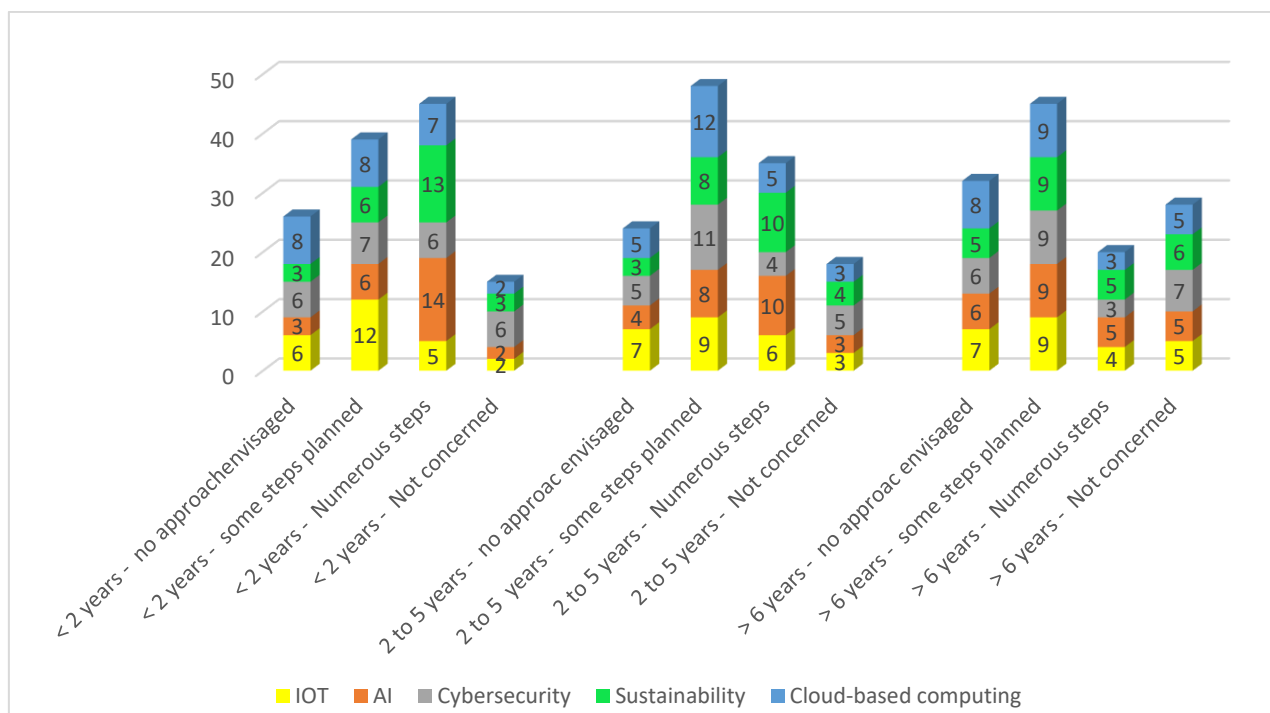


Figure 48. Are steps being taken to develop content in line with the trends cited in the maintenance professions?

6.6.6. INTEGRATION WITH INDUSTRY NEEDS

It is interesting to observe how the majority of training centres strongly prefer to promote the practical application of predictive maintenance (PdM) concepts in maintenance training programs through partnerships with manufacturers rather than universities. In this regard, the use of virtual simulation has also been highlighted as a valuable resource for this purpose.

Training centres view partnerships with the industry not only as a way to apply practical training but also as a means to integrate real-time industrial needs into their programs. In this context,



hands-on experience in training centres also represents a significant opportunity. To a lesser extent, the creation of specific modules or hybrid training has been considered.

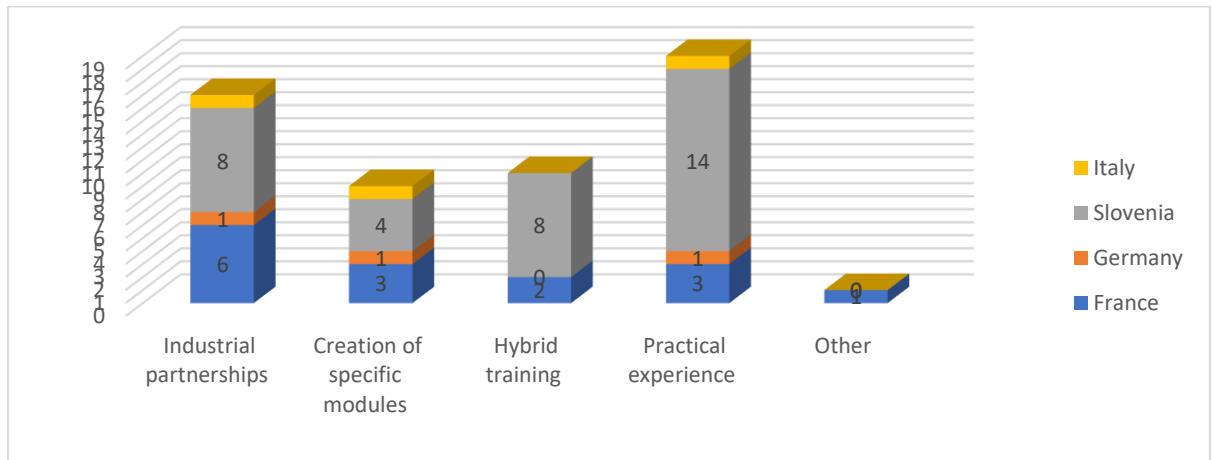


Figure 49. What opportunities or possibilities could your establishment envisage, or has it already envisaged, for integrating real-time industrial needs such as those linked to predictive maintenance into training programmes, where possible?

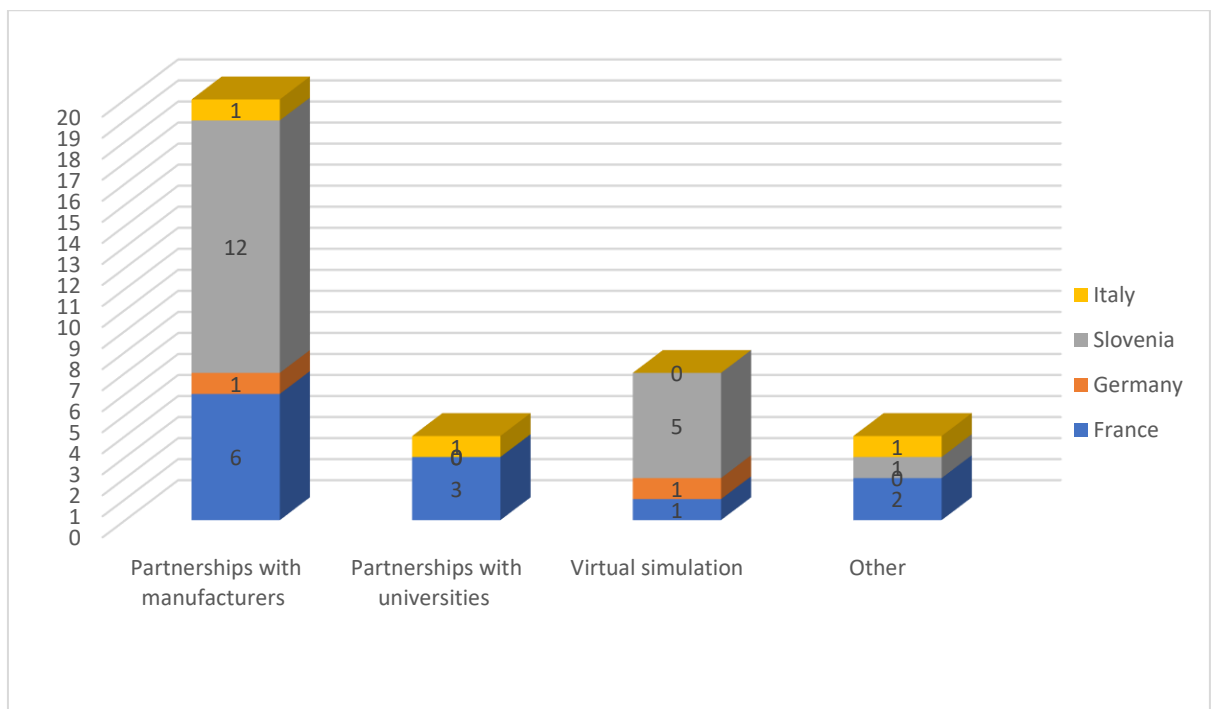


Figure 50. What approaches does your institution favour to reinforce the practical application of predictive maintenance (PdM) concepts in maintenance training programmes?

Most centres primarily depend on public funding, while also pursuing industry partnerships and collaborative projects with other VET centres, with fewer relying on their own funds. This suggests the need to diversify funding sources to support technological advances in training.



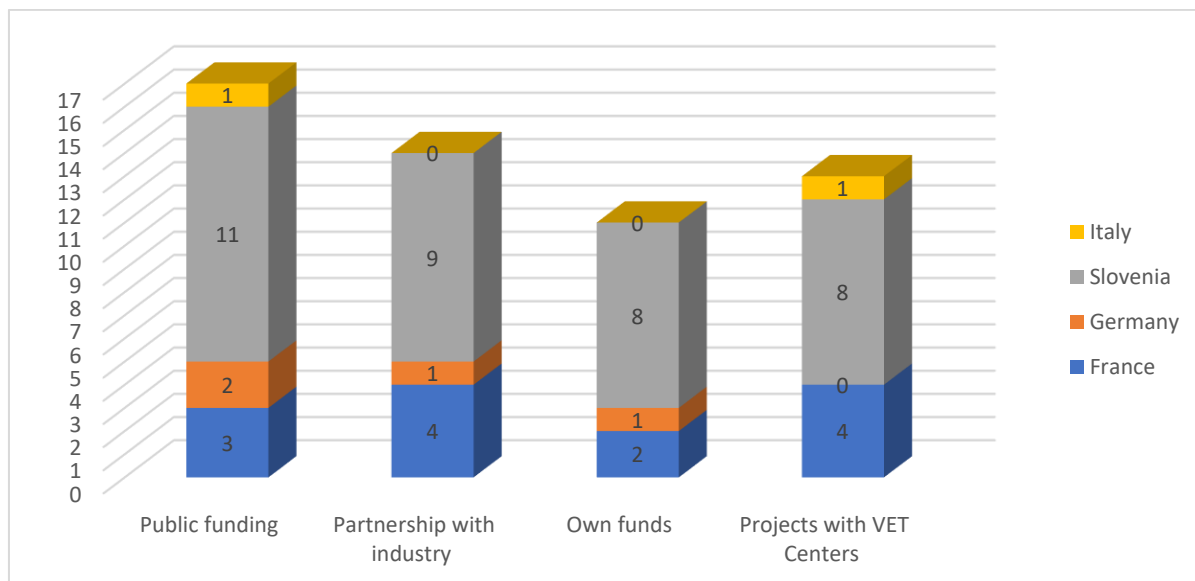


Figure 51. What financial solutions are envisaged to develop access to the latest technological advances within maintenance training programmes?

6.6.7. TEACHER TRAINING AND COLLABORATION

Regarding the strategies implemented or considered necessary to train trainers and teachers in advanced technologies, most centres (64%) focus on "technology watch," helping teachers stay updated with the latest trends. Other important strategies include "external training and certification" (44%), which provides specialized and recognized skills, and "practical workshops" (32%), offering direct hands-on experience. However, fewer centres mentioned "industrial immersion" (8%) or "new technologies day with VET Centres" (16%), suggesting that these methods are less common, although valuable for integrating industry experience into training.

Most centres (48%) show a tendency to have occasional collaborations with other centres and organizations in order to promote coherence in maintenance training courses, indicating a flexible approach but without long-term commitments. About 16% of centres have no active collaboration, showing that some prefer to operate independently. Only 12% have strong partnerships, and a small percentage (4%) foresee future collaborations. This situation shows a tendency towards occasional collaborations and a weakness when it comes to establishing strong, long-lasting partnerships.

The development of interdependent training pathways is supported by most centres (48%) through "industrial collaboration," which aligns training with real market needs. "Common training frameworks" (52%) are also common, enabling standardization of programs between institutions. However, only 20% of centres are interested in "joint certifications," indicating that there is still limited focus on creating shared credentials with other training centres. Around 32% show little interest in these interdependent projects, suggesting a preference for maintaining autonomy and control over their own training programs.



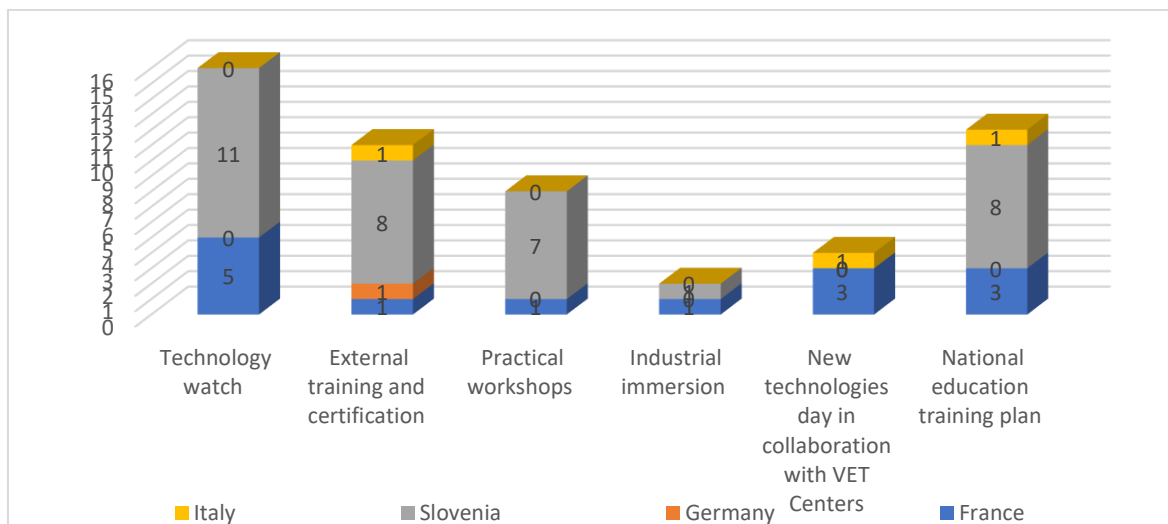


Figure 52. What strategies are in place or needed to train trainers and teachers in advanced technologies?

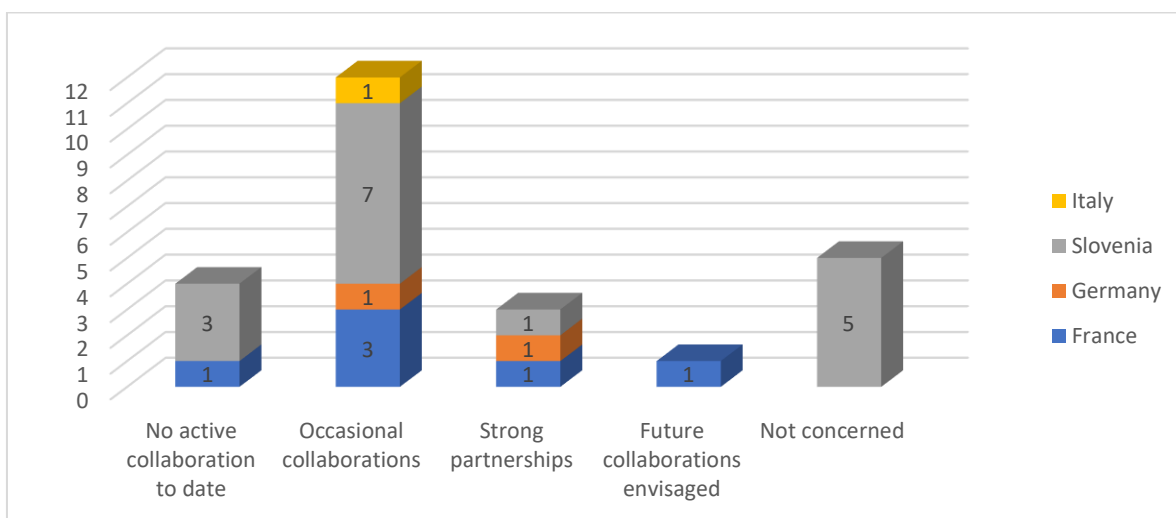


Figure 53. What collaborative strategies have been put in place or are envisaged with other training centres and other organisations to promote coherence in maintenance training courses?

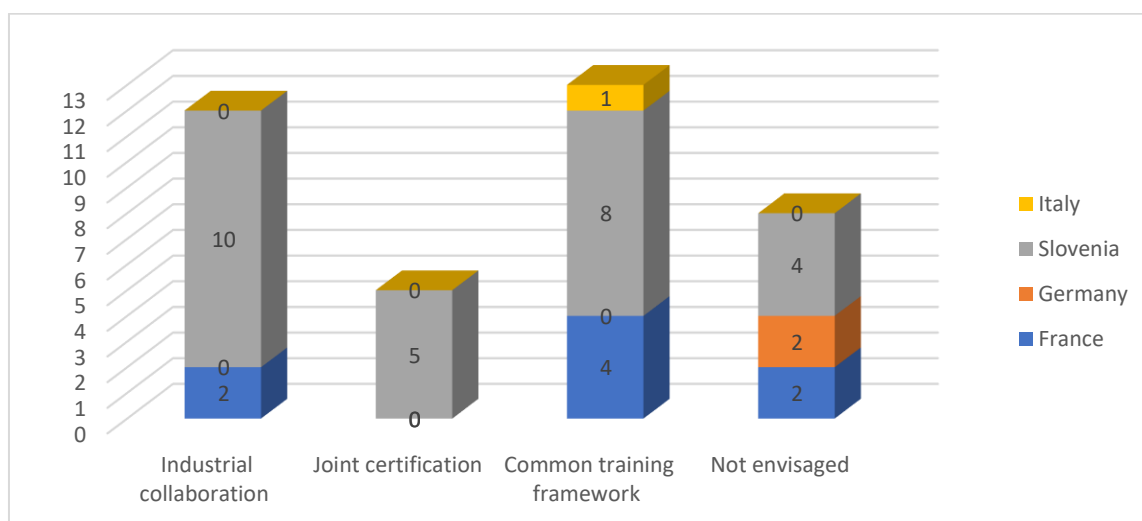


Figure 54. How do you envisage the development of interdependent training pathways through collaboration between establishments with different areas of interest in maintenance training?



6.6.8. CHALLENGES AND INDUSTRY COOPERATION

Regarding the preferences of training centres for strengthening their links with industry, 32% prioritize regular evaluations of their training programs with industrial partners. A higher proportion, 36%, favor industrial advisory councils, which provide direct and specialized feedback to improve training programs. Additionally, 24% of centres are interested in other types of strategies. Finally, 32% believe that cooperation links remain limited.

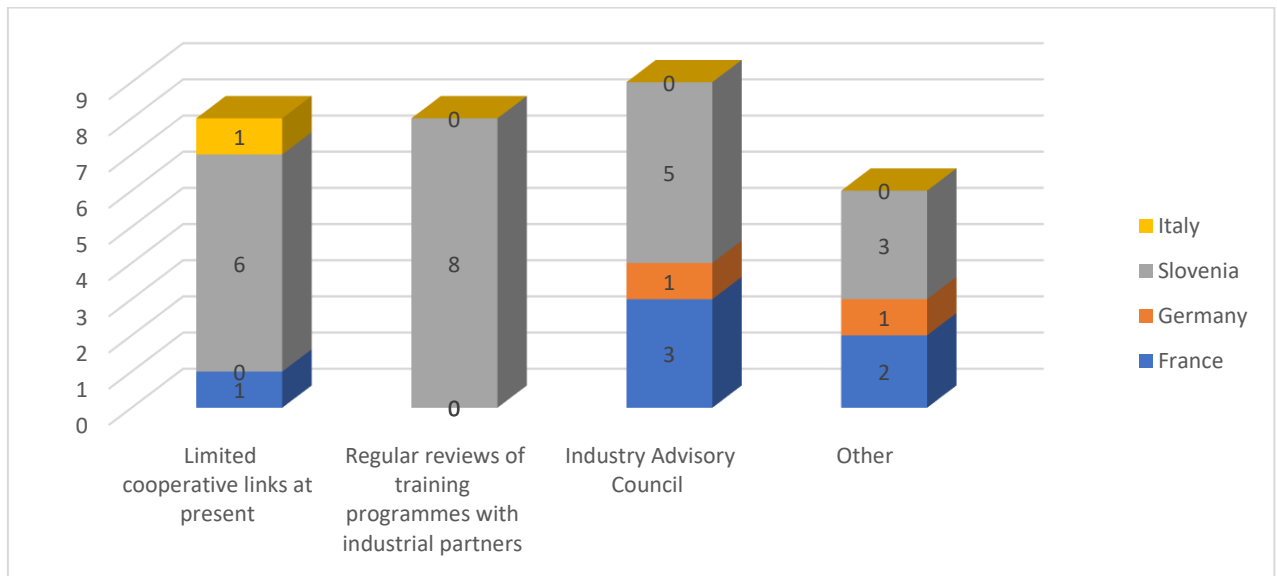


Figure 55. How can cooperation with industry professionals be strengthened to better align teaching content with current and future needs in predictive maintenance (PdM) and related fields?

6.6.9. SUMMARY OF THE SURVEY'S RESULTS

The majority of the surveyed centres are located in Slovenia, followed by France, Germany, and Italy. Forty-four percent of the centres have between 500 and 999 students, while 28% have more than 1,000 students. The number of students graduating annually varies, with some centres graduating fewer than 100 students, while others exceed 300 graduates per year.

Most of the respondents hold decision-making positions, such as training directors or school managers, indicating that the survey collected input from individuals with the authority to influence the integration of new technologies.

As expected, most of the training centres (64%) are in the industrial sector of the centres. However, training is also provided in other sectors, such as the tertiary and automotive.

Adoption of New Technologies and Autonomy

Training centres report limited or partial autonomy in adapting their programs to new technologies, with only a few centres having full autonomy. Training centres report limited or partial autonomy in adapting their programs to new technologies, with only a few centres having full autonomy. These centres see their ability to adapt as being limited by hierarchically superior institutions with real decision-making power. This dependence can also lead to a lack of speed in decision-making processes or increase bureaucracy. Despite this situation, Progress is being made in key areas such as Artificial Intelligence (AI), sustainability, cybersecurity, IoT, and cloud computing, with AI and sustainability being the most dynamic areas in the short, medium, and long term. However, a decrease in the number of planned actions is observed over the long term, indicating a lack of sustained commitment. The most recurring courses across the areas of IoT, cybersecurity, AI, and



sustainability include cybersecurity programs (with a focus on ethical hacking and information systems protection), IoT courses related to industrial maintenance and smart electrical installations, and AI integrated into IT and network systems. Sustainability is frequently addressed through programs focused on energy efficiency, renewable energy, and sustainable industrial processes. Courses on server systems and advanced networks are closely linked to cloud computing, although not explicitly mentioned. These programs listed (see relevant table “Courses taught in the field of emerging 4.0 technologies”) reflect the growing demand for professionals with skills in these key technological areas.

For instance, in France, IoT and AI technologies are already integrated in “Higher Technician Certificate in Industrial Maintenance” and “Licence Pro MIF: Vocational Degree in Maintenance of the Industry 4.0” trainings.

Collaborations

The centres recognize the importance of industrial partnerships, practical experience, and, to a lesser extent, the creation of specific modules and hybrid training to integrate real-time industry needs. They prefer to partner with the industry rather than universities for this integration.

Most centres collaborate occasionally with other centres and organizations, but long-term partnerships are less common. Industrial collaboration and common training frameworks are the most used strategies for interdependent training pathways, although joint certifications have limited interest. Many centres prefer to maintain autonomy and control over their training programs rather than create shared credentials.

Most centres collaborate occasionally with other centres and organizations, but long-term partnerships are less common. Industrial collaboration and common training frameworks are the most used strategies for interdependent training pathways, although joint certifications have limited interest. Many centres prefer to maintain autonomy and control over their training programs rather than create shared credentials.

Funding Sources and Instructor Training

44% of the polling centres have their own income, however, a larger percentage has indicated obtaining funds from public sources or industry funds.

Training centres favor strategies such as “technology watch,” external training and certifications, and practical workshops, or guidance from national education training plans, rather than methods like industrial immersion.

Outlook

Thanks to the content of this report, the next step should be to assess the extent to which these emerging technologies are integrated into training programmes, ensuring that they remain up to date with the latest advances and meet the needs of SMEs.

6.7. SUMMARY

Recent technological advancements have transformed the way maintenance is perceived within companies. This presents both opportunities and challenges for Training Centres, which must adapt their programs to the evolving needs of the industry.

Through our literature review, we have identified that a standardization process has already begun in the training sector, considering new requirements, competencies, and roles within the field of maintenance.



6.7.1. CERTIFICATION AND STANDARDIZATION PROCESSES

Programs such as *Erasmus+* and certifications like *ISO* aim to promote certification and standardization, contributing to increased business productivity at the European level.

The *European Qualifications Framework (EQF)* has been a key tool in this process. For example:

- At Level 6 of this framework, a maintenance professional must have knowledge of predictive, preventive, and corrective maintenance, including advanced monitoring techniques. They are also expected to analyse data, develop plans, and implement improvements while having the autonomy to make decisions that optimize processes, ensuring safety and regulatory compliance.
- At EQF Level 5, a specialist must be able to address topics such as vibration analysis, software configuration, data collection, predictive diagnostics, and maintenance execution.

6.7.2. REQUIRED SKILLS IN THE MAINTENANCE SECTOR

Maintenance professionals must not only possess technical and analytical skills, such as AI-based diagnostics or IoT sensor management, but also transversal competencies, known as **soft skills**. These include: Teamwork, Real-time problem-solving, Multifunctionality Communication skills

Four major areas of maintenance have been identified:

- Preventive Maintenance: Focuses on strategies to ensure high reliability through planning and implementation of effective plans.
- Predetermined Maintenance: Relies on predefined methods and techniques for scheduled interventions.
- Condition-Based Maintenance: Uses subjective and objective techniques to establish inspection intervals and optimize processes.
- Predictive Maintenance: Applies advanced methods to anticipate failures, differentiating itself from non-predictive maintenance and optimizing its application through appropriate systems.

6.7.3. IMPACT OF NEW TECHNOLOGIES ON MAINTENANCE

The technological advancements with the greatest impact in the sector include: Internet of Things (IoT), Artificial Intelligence (AI), Cybersecurity, Sustainability (Durabilité), Maintenance-as-a-Service (MaaS), based on cloud-based collaborative platforms.

According to the survey results, training centres are integrating these technologies into their programs. AI and Sustainability are the areas with the most initiatives undertaken.

However thanks to the content of this report, the next step should be to assess the extent to which these emerging technologies are integrated into training programmes, ensuring that they remain up to date with the latest advances and meet the needs of SMEs.

6.7.4. INNOVATIONS IN VOCATIONAL TRAINING

The education sector has also evolved with the adoption of new teaching strategies. Some of the most notable tools include:

- Hybrid learning (*training hybrid*), which combines online modules, simulations, and in-person practical training to enhance accessibility and effectiveness.
- Digital twins, which allow maintenance processes to be simulated in a virtual environment.
- Augmented Reality (AR) and Virtual Reality (VR), which facilitate training in simulated environments.



According to the survey results, *training hybrid* and *virtual simulation* have been widely implemented by training centres as part of their adaptation process.

6.7.5. COOPERATION BETWEEN TRAINING CENTRES AND INDUSTRY

Another emerging opportunity is the increasing collaboration between institutions.

- The majority of training centres recognize the importance of industrial partnerships to integrate real-time industrial needs.
- The survey also identified a significant gap between cooperation with manufacturers and cooperation with universities, with the former being much more frequent.
- Training centres prefer to partner with companies rather than with other educational institutions.

Furthermore, when examining initiatives to promote training standardization, survey results show that collaborations with other centres are usually only occasional. However, interinstitutional cooperation also enhances collaboration with businesses.

6.7.6. CHALLENGES FOR TRAINING CENTRES

Despite the opportunities, training centres face significant challenges, especially in adapting their programs to industry needs. A key issue is autonomy. For example, only 5% of the surveyed centres have full control over updating their programs, while the majority face considerable limitations. Financial constraints further exacerbate this situation, as technological advancements require substantial investments in advanced equipment and continuous teacher training. According to the survey results, only 44% of the centres have their own funding, while 68% rely on public funds and 56% on industry partnerships.

To address these challenges, training centres have implemented strategies to improve teacher training, such as the use of technology watch, external training and certifications, practical workshops, and guidance from national education plans. However, survey data indicate that industrial immersion is the least prioritized aspect of teacher training, highlighting a gap between teacher preparation and the real demands of the industry.



7. PDM: A DRIVING FORCE FOR THE GREEN TRANSFORMATION

Predictive maintenance (PdM) plays a pivotal role in the green transformation of the manufacturing industry by significantly reducing environmental impact. By leveraging data-driven technologies, PdM optimizes machine performance, extends equipment lifespan, and minimizes resource consumption, contributing to sustainability efforts across industrial sectors.

One of PdM's key environmental benefits is its ability to reduce material waste. By predicting and preventing failures, unnecessary repairs and part replacements are minimized, leading to lower material consumption and a reduction in industrial waste. Additionally, the extended operational life of machinery decreases the need for new equipment production, thereby reducing the extraction of raw materials and associated environmental degradation (Dilda, V. et al, 2017)

Another major contribution of PdM to sustainability is its impact on energy efficiency. Well-maintained machines operate more efficiently, consuming less energy and reducing CO2 emissions. According to (Hector, J., & Panjanathan, 2024), advancements in IoT and real-time monitoring enable manufacturers to detect inefficient operating conditions early, allowing for timely adjustments that lower overall energy use. This proactive approach directly supports energy conservation efforts and helps industries align with global carbon neutrality goals.

Furthermore, PdM optimizes global supply chains by reducing unnecessary transportation and logistics emissions. Efficient maintenance planning decreases emergency part shipments and machine downtime, streamlining production schedules and minimizing the need for excessive safety stock. This optimization leads to better coordination of material flows, ultimately decreasing the carbon footprint of logistics networks (Staufen AG, 2020).

PdM also supports sustainable decision-making within organizations. The integration of predictive analytics into decision support systems (DSS) allows manufacturers to balance economic and environmental priorities effectively. By leveraging data-driven insights, companies can implement maintenance strategies that not only enhance operational efficiency but also align with sustainability goals (Hector, J., & Panjanathan, 2024).

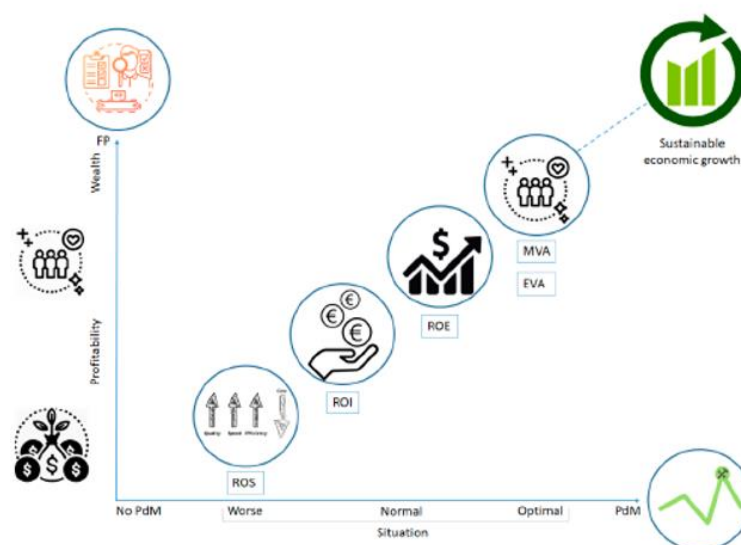
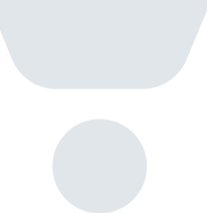


Figure 56. A synthesis of the results - (Hector, J., & Panjanathan, 2024).





Additionally, PdM fosters a circular economy by promoting resource efficiency and reducing the environmental burden of manufacturing. By extending the lifecycle of machinery and preventing unplanned failures, manufacturers can lower their overall material footprint and enhance long-term sustainability.

In addition to optimizing asset usage and reducing waste, recent advances in AI are further contributing to greener industrial practices. **Task-specific language models (SLMs)**, which require significantly less energy to train and operate than large general-purpose AI models, are a promising development in this direction. When applied to maintenance tasks - such as real-time diagnostics, report generation, or alarm interpretation - SLMs deliver targeted intelligence with **minimal environmental impact**, aligning predictive maintenance practices with sustainability objectives (Anjanava Biswas, 2024).

In conclusion, predictive maintenance is a key enabler of the green transformation of the manufacturing industry. By optimizing machine efficiency, reducing waste, and minimizing energy consumption, PdM helps companies meet sustainability targets while improving profitability. As digital and IoT advancements continue to enhance PdM capabilities, its role in driving environmentally responsible manufacturing will only become more pronounced.



8. EXPERTS' EVALUATION

Contributing Experts:

The following experts, all actively engaged in the field of Training and/or Predictive Maintenance, provided insights and evaluations based on their level of experience and involvement.

France:

- Hervé Danton - Expert - Mecanic Vallée
- Stéphane Blanchard - Mission officer – Industry 4.0 - AD'OCC
- Landry Bourguignon - IA-IPR STI – Academic inspector
- Thierry Ameye - Industry 4.0 and Business Transformation - CETIM
- Pierre Carillo - Teacher - IUT Limousin
- Patrick Fauchère - Teacher - IUT Limousin

Slovenia:

- Samo Čretnik - Professor - TŠCMB
- Helena Jerman - Professor - ŠC Ljubljana
- Igor Hanc - Expert and director - ŠC Škofja Loka

Germany:

- Study Program Management Engineering - DHBW Mannheim
- Vice President - TPM Institute Detroit

The feedback collected from these stakeholders - including industry professionals, training institutions, and technical experts - reflects a strong and consistent endorsement from industry professionals, training institutions, and technical experts. Each chapter was assessed both quantitatively and qualitatively. The introductory sections were appreciated for clearly presenting the purpose and scope, although several readers recommended a more detailed explanation of the methodology due to its inherent complexity. The core chapters on technological foundations and practical impacts received excellent ratings, especially for their clarity and relevance to industrial challenges.

Overall, the report is recognized for its **high relevance, clear structure, and strategic value**, with average evaluation scores approaching the highest ratings across most sections.

Table 12. Quantitative Evaluation – (detail available in Annex 5):

Evaluation by category	Averages out of 4
Alignment with Industry and Training Needs	3,80
Clarity of Purpose and Structure	3,81
Relevance and Insightfulness of Content	3,86
Understanding of Methodology and Analytical Approach	3,83
Usefulness of Surveys and Data Interpretation	3,61
Overall Total	3,76

Experts emphasized several standout qualities that contribute to the report's effectiveness and impact:

- **Usefulness and Clarity:** Experts unanimously found the report useful and well-organized, with a logical progression that supports understanding of complex topics such as emerging technologies, market evolution, and maintenance strategies.
- **Strategic and Practical Relevance:** The report's alignment with industrial realities and the strategic needs of SMEs was particularly praised. Stakeholders emphasized its potential as



a guiding document for investment planning and organizational adaptation in the field of predictive maintenance.

While the report was positively received overall, some experts challenged several key aspects, including the connection between PdM and MaaS, which has been found unfortunate, as PdM can also be operated well as an internal service, while others formulate concerns about the limited relevance of generative AI for PdM, given the need for reliable, non-creative data interpretation.

Integration of Expert Input: Beyond merely evaluating the report, expert feedback played a proactive role in shaping and enhancing its content. The comments received were instrumental in driving targeted improvements to the final version. Notable updates include:

- Clearer presentation of **barriers faced by SMEs**, now included in the executive summary.
- Terminological alignment with **NF EN 13306** standards.
- The addition of emerging themes such as **prescriptive maintenance** and **Task-Specific Language Models (SLMs)**.
- An acknowledgment of the need for **deeper exploration of evolving skills**, with a dedicated focus which will be integrated into a separate work package 5 - “Human-Centric Learning for Advanced Manufacturing”.



9. OUTLOOKS AND CONCLUSION

9.1. OUTLOOK: FUTURE TRENDS AND OPPORTUNITIES

This report builds on a rich combination of literature analysis, technological review, and most importantly, field-based insights gathered through two dedicated surveys sent to SMEs and VET Centres across several European countries. These surveys have provided valuable ground-level perspectives on the current maturity level, barriers, expectations, and training needs related to Predictive Maintenance (PdM).

The results show that SMEs increasingly recognize the value of PdM, particularly for improving efficiency, reducing unplanned downtime, and supporting sustainability goals. However, many face persistent obstacles such as integration costs, lack of internal expertise, and limited capacity to train or upskill staff. On the other hand, VET institutions acknowledge the need to align curricula with emerging technologies, but still struggle to integrate key PdM-related competencies such as AI, IoT, and data-driven maintenance strategies into existing programs.

These findings highlight the importance of dual qualification pathways, hybrid learning models, and closer collaboration between VET Centres and industry to ensure future workers are equipped for the evolving demands of maintenance roles in digital and sustainable manufacturing environments.

As Predictive Maintenance (PdM) continues to evolve, its future will be shaped by **technological advancements, service-based models, cybersecurity concerns, and workforce development**. Several key trends will define the next phase of PdM adoption and its role in industrial transformation.

9.1.1. INTEGRATION OF GENERATIVE AI FOR ENHANCED PREDICTIVE MODELS

The integration of Generative AI into predictive maintenance will enhance predictive accuracy, improve transparency in AI-driven decision-making, and automate diagnostics to optimize maintenance processes.

- Generative AI will **improve predictive accuracy** by creating **synthetic failure data**, particularly for industries with **limited historical data on machine breakdowns**.
- The adoption of **Explainable AI (XAI)** will provide **greater transparency** in AI-driven PdM decisions, making predictive insights **more interpretable and actionable for technicians**.
- AI-powered **automated diagnostics and prescriptive maintenance solutions** will optimize **decision-making and reduce manual intervention** in maintenance planning.

9.1.2. EXPANDING ADOPTION OF PDM-AS-A-SERVICE (PDMAAS)

The evolution of PdM into a subscription-based service model will make predictive maintenance more accessible to SMEs, foster industry collaborations, and drive the adoption of Equipment-as-a-Service (EaaS).

- The **subscription-based PdM model** will lower cost barriers, making PdM **more accessible to SMEs** by eliminating the need for heavy upfront investments.
- **OEMs (Original Equipment Manufacturer) and industrial service providers** will increasingly collaborate to deliver **integrated, scalable PdM solutions**, allowing



- businesses to **outsource maintenance expertise while improving operational efficiency**.
- The rise of **Equipment-as-a-Service (EaaS)** will further support predictive maintenance, as manufacturers offer machines with built-in PdM capabilities under pay-per-use contracts.

9.1.3. ADVANCED CYBERSECURITY FOR INDUSTRIAL IOT

As IoT-enabled predictive maintenance systems grow, strengthening cybersecurity measures will be critical to protecting industrial data, ensuring system reliability, and mitigating emerging cyber threats.

- As **IoT-enabled predictive maintenance systems** expand, **cybersecurity threats** will increase, requiring **AI-driven security solutions** to protect **real-time industrial data and connected assets**.
- **Initiatives like DETECTA 2.0** will lead the way in developing **robust cybersecurity frameworks** tailored for PdM environments, ensuring data integrity and system reliability.
- Companies will adopt **zero-trust architectures** and **secure-by-design principles** to mitigate cyber risks associated with cloud-based and edge computing solutions in maintenance operations.

9.1.4. ALIGNMENT OF TRAINING WITH INDUSTRY 5.0

The transition to AI-driven predictive maintenance will require continuous workforce upskilling, new training models, and the integration of advanced learning tools to align with Industry 5.0 demands.

- As PdM shifts towards **AI-driven automation**, maintenance professionals will require **new competencies in AI, IoT, cybersecurity, and data analytics** to remain competitive.
- **Lifelong learning models** and **micro-credentialing programs** will become the norm, enabling workers to **continuously update their skills** as new PdM technologies emerge.
- Training institutions will need to **bridge the skills gap** by integrating **real-world case studies, AI-powered simulations, and hybrid learning formats** into maintenance training programs.

9.2. CONCLUSION

Predictive Maintenance (PdM) is no longer just a **technological upgrade** - it is a **strategic necessity** for **industrial competitiveness, efficiency, and sustainability**. As a key enabler of **Industry 4.0 and the transition toward Industry 5.0**, PdM is reshaping maintenance operations through **AI, IoT, Digital Twins, and Generative AI**, offering **unprecedented predictive capabilities**.

While **large enterprises** are advancing rapidly, **SMEs still face significant barriers** such as **high implementation costs, lack of expertise, and integration challenges**. Overcoming these obstacles requires **scalable solutions** like **PdM-as-a-Service (PdMaaS)**, enabling businesses to access advanced maintenance strategies without **large upfront investments**.

Beyond technology, the **workforce is undergoing a major transformation**. Maintenance professionals must develop **data analytics, AI-driven diagnostics, and cybersecurity skills** to effectively implement PdM solutions. However, **Vocational Education and Training (VET) institutions** are still struggling to align curricula with **emerging digital trends**. Strengthening **industry-academic partnerships**, integrating **hybrid training models**, and incorporating **real-world PdM case studies** will be essential to closing the **skills gap** and preparing professionals for the **increasing digitalization of industrial maintenance**. **Lifelong learning models and**



micro-credentialing programs will become the norm, ensuring that workers can continuously update their competencies and remain adaptable in a rapidly evolving technological landscape.

PdM also plays a **crucial role in the green transition**, optimizing **energy consumption, reducing waste, and reinforcing sustainability goals** in manufacturing. However, **long-term engagement** from training centres and businesses remains inconsistent, with many still hesitant to commit to **full-scale adoption**. **Emerging task-specific language models (SLMs) offer promising perspectives on the relationship between model efficiency and energy consumption.**

To fully unlock PdM's potential, **cross-sector collaboration, investment in digital infrastructure, and scalable training programs** are critical. **Financial support, policy incentives, and closer cooperation between SMEs, training institutions, and technology providers** will accelerate adoption and workforce readiness. Furthermore, the **rise of Maintenance-as-a-Service (MaaS)** signals a shift toward **service-oriented maintenance models**, making PdM **more accessible and adaptable** to businesses of all sizes.

Nonetheless, **some experts have challenged the relevance of MaaS** for SMEs, other questioned the suitability of **Generative AI** for PdM, highlighting the need for reliable, data-grounded decision-making rather than creative outputs.

Far from being a limitation, these remarks offer a **valuable opportunity to stimulate discussion** around the practical applicability of PdM-related innovations. The report is **not meant to present one-size-fits-all solutions**, but rather to **serve as a shared framework for understanding PdM challenges**, sparking reflection and dialogue among industry, training providers, and policymakers. **All statements and proposals presented throughout the report are based on referenced publications, expert interviews, academic articles, and field surveys**, ensuring the content is both evidence-based and representative of current thinking. This open approach helps adapt strategies to diverse contexts and supports more grounded and inclusive implementation paths.

Ensuring a **cohesive strategy** between **technology adoption, workforce upskilling, and sustainable practices** will be crucial for **future-proofing maintenance strategies** and securing the **competitiveness of European industries in the digital era.**



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13. ANNEX

13.1.ANNEX 1 - TARGET AUDIENCE OF SURVEYS

COUNTRY	TARGET AUDIENCE	Distribution list
FRANCE	EXPERT	3DS
		Adocc
		Aerospace valley
		AFDET
		Afnor
		CETIM
		Efficairn
		Ministère éducation
	SMEs	ACTEMIUM
		AD INDUSTRIE
		FIGEAC AERO
		FIVES MACHNING
		FIVES MAINTENANCE
		IUT Rodez
		LISI BLANC AERO
		MECABRIVE
		MET ENERGIE
		RATIER FIGEAC
		ROBERT BOSCH
		UMICORE VM ZINC
		VPM AUTOMATION
	VET CENTRES	ALEXIS MONTEIL
		ANTOINE BOURDELLE
		DEODAT DE SEVERAC
		GASTON MONNERVILLE
		INEMA
		INU Champollion
		IUMM
		IUT Figeac
		IUT Limousin
		IUT Rodez
GERMANY	SMEs	ASYS Group
		BoschRexroth
		Braun Steine
		Büchel Luftreinhaltung und Anlagenbau
		BWF Profiles
		Carl Zeiss AG



		DAIMLER TRUCK
		Gebr. Binder
		Grünbeck Wasseraufbereitung GmbH
		GUTMANN-GROUP
		HAUFF Technik
		Heidelberg Manufacturing Deutschland
		Hillenbrand
		IHK Ostwürttemberg
		INDEX Werke
		Inneo
		Klueber
		KÖHN
		LEITZ
		LIEBHERR
		MAN
		MAPAL
		MEFFLE
		MegMee
		Mitsubishi Electric Europe B. V.
		NAGEL Spanntechnik
		Pfeifer Metalltechnik
		robatherm GmbH & Co. KG
		ROBERT BOSCH
		Rosenberger
		RR-RIEGER
		Schaerer AG
		Schellenberg
		Schuck Group GmbH
		SIAL
		Siemens AG
		Sortimo International GmbH
		Stark Gummiwalzen GmbH
		TE Connectivity
		TUH GmbH
		WESSER SPK
		WIELAND Werke
		Yanmar
	VET CENTRES	Carl-Benz-Schule Karlsruhe
		Claude-Dornier FN
		GARP
		Gewerbliche Schule Geislingen
		Gewerbliche Schule Gmünd
		Gewerbliche Schule Göppingen
		Heid-Tech Heidenheim
		Robert-Bosch-Schule-Ulm
		Rolf-Benz-Schule



SLOVENIA	SMEs	Technische Schule Aalen
		Danfoss Trata
		FANUC
		Grammer Automotive Slovenija
		GZS
		Hisense Gorenje
		Kopa d.d.
		LTH Castings
		MIC Škofja Loka
		MIEL
		Robeta
		TGK
	VET CENTRES	Academia
		B&B
		Erudio
		IC Geoss
		ŠC Celje
		ŠC Kranj
		ŠC Ljubljana
		ŠC Nova Gorica
		ŠC Novo mesto
		ŠC Postojna
		ŠC Ptuj
		ŠC Ravne
		ŠC Škofja Loka
		ŠC Velenje
		TŠC Maribor
SWEDEN	SMEs	ACFloby
		Alleima
		Elektroautomatik
		FPanalyzer
		Hifa
	VET CENTRES	Alströmergymnasiet
		Dacapo gymnasiet
		Edumate
		Mark Gymnasieskola
		Nösnäsgymnasiet
		Uddevalla Gymnasieskola
		Volvogymnasiet



13.2.ANNEX 2 - SCOPE OF FORECAST

GLOBAL PDM MARKET DEVELOPMENT

Category	Sub-category	Details
By Application	Asset Tracking	
	Condition Monitoring	
	Maintenance Scheduling	
	Predictive Analytics	
	Remote Monitoring	
By Component	Hardware	
	Software	Integrated Standalone
By Deployment	Cloud-based	
	On-premise	
By End-use	Energy and Utilities	
	Healthcare	
	IT and Telecom	
	Logistics and Transportation	
	Manufacturing	
	Military and Defense	
	Others (Chemicals, Paper and Printing and Agriculture, etc.)	
By Enterprise Type	Large Enterprises	
	Small and Mid-sized Enterprises (SMEs)	
By Region	Asia Pacific	ASEAN
		China
		India
		Japan
		Oceania
		Rest of Asia Pacific
		South Korea
	Europe	Benelux
		France
		Germany
		Italy
		Nordics
		Rest of Europe
		Russia
		Spain
		U.K.
	Middle East & Africa	GCC
		Israel
		North Africa



		Rest of Middle East & Africa
		South Africa
		Turkey
	North America	Canada
		Mexico
		U.S.
	South America	Argentina
		Brazil
		Rest of South America
By Technology	Advance Analytics	
	Artificial Intelligence and Machine Learning	
	Digital Twin	
	IoT	
	Others (Modern Database, ERP, etc.)	



13.3.ANNEX 3 - 21 INTERPRETABLE MACHINE LEARNING (IML) METHODS

(Logan Cummins, 2024)

1. **Attention Mechanisms:** Used in neural networks to focus on important parts of input data, enhancing interpretability by highlighting relevant features for predictions.
2. **Fuzzy-Based Systems:** Employ fuzzy logic to handle uncertainty and imprecision, providing rule-based interpretations of model outputs.
3. **Knowledge-Based Systems:** Use pre-existing domain knowledge in predictive models to enhance interpretability, often through symbolic representation.
4. **Interpretable Filters:** Introduce filters within neural networks that have physically meaningful representations, helping explain the model's focus.
5. **Decision Trees:** A classic method that splits data into nodes based on feature values, making it straightforward to trace how decisions are made.
6. **Fault Trees:** Visual representations of failure paths in systems, showing how various faults can lead to system breakdowns.
7. **Physical Constraints:** Integrate real-world constraints into models to ensure predictions are interpretable and adhere to known physical laws.
8. **Statistical Methods:** Use statistical analysis to identify feature importance, enhancing transparency in decision-making.
9. **Graph Attention Networks (GATs):** Extend attention mechanisms to graph-structured data, making it possible to interpret relationships within networks.
10. **Gaussian Mixture Models (GMMs):** Probabilistic models that identify clusters within data, with each cluster providing interpretable patterns of behavior.
11. **Explainable Boosting Machine (EBM):** A model using generalized additive models (GAMs) that combines boosting techniques with interpretability.
12. **Hidden Markov Models (HMMs):** Used for sequential data, where states are interpretable stages of degradation in maintenance contexts.
13. **Sparse Networks:** Reduce the number of parameters in a model, making it more interpretable by focusing on the most influential features.
14. **Prototype Learning:** Uses representative examples (prototypes) from the dataset to explain predictions, offering a clear link between input and output.
15. **Signal Temporal Logic (STL):** A method for defining time-bound rules in data, often used for monitoring temporal behaviors in predictive maintenance.
16. **Digital Twins:** Virtual models of physical assets that allow interpretability through simulation of various failure scenarios.
17. **Symbolic Life Models:** Use symbolic representations to model stages in the life of a system, aiding in understanding failure timelines.
18. **Generalized Additive Models (GAMs):** Models that additively combine features, providing clear interpretability by isolating each feature's effect.
19. **Mahalanobis-Taguchi System (MTS):** Uses statistical distances to classify data points, offering interpretable insight into how features deviate from normal operation.
20. **k-Nearest Neighbors (kNN):** Classifies instances based on similarity to neighboring data points, where decisions can be traced to specific neighbors.
21. **Rule-Based Interpretations:** Provide explanations in "if-then" format, making decisions easy to understand by breaking down predictions into rule sets.



13.4. ANNEX 4 - EXAMPLES OF MAINTENANCE TRAINING COURSES

Country	Source	Training course description	EQF Level
France	IUT Rodez https://www.iut-rodez.fr/fr/les-formationen/lp-mif-maintenance-40/lp-maintenance-industrie-futur-presentation	Professional Bachelor's Degree in Maintenance for the Industry of the Future (Industry 4.0): The objective is to train employees capable of implementing connected maintenance projects within industrial companies, by selecting, installing, and configuring the necessary equipment and software.	EQF 6
	INU Champollion https://www.univ-jfc.fr/licences-professionnelles/maintenance-et-technologie-organisation-de-la-maintenance	Professional Bachelor's Degree in Maintenance and Technology: It aims to train future managers responsible for the technical sector and the supervision of services related to the maintenance of equipment or vehicles in the fields of agro-equipment, public works machinery, handling equipment, and industrial vehicles.	EQF 6
	Lycée Gaston Monnerville https://gaston-monnerville.mon-ent-occitanie.fr/actualites/orientation/je-suis-en-classe-de-3eme/le-bac-professionnel-maintenance-des-systemes-de-production-connectes-au-lycee-gaston-monnerville-37625.htm?URL_BLOG_FILTRE=%3FDATE%3DTOUS%235332	Professional Baccalaureate in Maintenance of Connected Production Systems: It prepares students to ensure preventive, improvement, and corrective maintenance (maintenance and repair) of all automated equipment used in manufacturing, handling, distribution, and packaging. Activities include troubleshooting industrial equipment, as well as testing electrical, pneumatic, hydraulic, and mechanical energy systems. The skills developed include repairing an industrial system by replacing (standard exchange) mechanical, electrical, pneumatic, or hydraulic components. The training also includes participating in testing and commissioning new equipment, as well as monitoring equipment through appropriate measurements to ensure proper functioning.	EQF 4
	Lycée Alexis Monteil https://alexis-monteil.mon-ent-occitanie.fr/informations-pratiques/enseignements/lycee-professionnel/bac-pro-maintenance-des-systemes-de-production-connectes-14362.htm	Professional Baccalaureate in Maintenance of Connected Production Systems: The tasks involve performing preventive maintenance operations such as component exchanges, adjustments, lubrication, and checking levels, pressure, and part clearances. It also includes wiring and modifying electrical, pneumatic, and hydraulic circuits, selecting components, and connecting them. The role requires decoding and analyzing electrical, pneumatic, and hydraulic diagrams, identifying components and their functions. Additionally, it involves fabricating welded mechanical parts, disassembling and repairing mechanical sub-assemblies, analyzing mechanical movements, diagnosing faults through tests and	EQF 4



		measurements, installing and commissioning systems, and implementing safety measures.	
	Cité scolaire Jean Jaurès https://jaures-saint-affrique.mon-ent-occitanie.fr/parents-et-eleves/les-formations/lycee-professionnel/	Professional Baccalaureate in Maintenance of Connected Production Systems: The job will be to fix, repair, diagnose, install, and adjust equipment. It lasts 3 years, with practical lessons. It includes 22 weeks of hands-on training in different sectors like wind energy, agri-food, and more. This job is rewarding and offers many job opportunities, especially in wind energy maintenance. You can also continue your studies with a Higher National Diploma . After finishing the training, graduates can work in various industries like agri-food, pharmaceuticals, automotive, agriculture, textiles, chemicals, aeronautics, and wind energy production. They can also work in public services like hospitals, the military, municipalities, water treatment, SNCF, and more.	EQF 4
	Lycée Déodat de Séverac https://maforpro-occitanie.fr/nos-formations/bts-maintenance-des-systemes-option-systemes-de-production-1490	Higher National Diploma in Systems Maintenance, Production System Option: The senior technician must be capable, within a maintenance department of a production unit or a technical service company/after-sales service, of carrying out corrective and preventive maintenance interventions, improving operational safety, and integrating new systems.	EQF 5
	Lycée Gaston Monnerville https://maforpro-occitanie.fr/nos-formations/bts-maintenance-des-systemes-option-systemes-de-production-1490	Higher National Diploma in Systems Maintenance, Production System Option: The senior technician must be capable, within a maintenance department of a production unit or a technical service company/after-sales service, of carrying out corrective and preventive maintenance interventions, improving operational safety, and integrating new systems.	EQF 5
	Lycée Alexis Monteil https://maforpro-occitanie.fr/nos-formations/bts-maintenance-des-systemes-option-systemes-de-production-1490	Higher National Diploma in Systems Maintenance, Production System Option: The senior technician must be capable, within a maintenance department of a production unit or a technical service company/after-sales service, of carrying out corrective and preventive maintenance interventions, improving operational safety, and integrating new systems.	EQF 5



	UIMM / CFAI-AFPI: https://www.pole-formation-lda.fr/formation/bts-ms-maintenance-des-systemes-option-systeme-de-production/	Higher National Diploma in Systems Maintenance, Production System Option: It trains specialists in maintenance and provides students with technological, organizational, and interpersonal skills. The Production Systems option enables students to master the operation of production systems in order to communicate effectively with operators and/or decision-makers.	EQF 5
Germany	bbw-seminare	Predictive Maintenance in Training: Introduce predictive maintenance basics, compare maintenance types, and highlight benefits. Cover condition monitoring, sensor technology, digital integration, dynamic maintenance planning, and implementation strategies.	EQF 4
	Vdi-wissensforum	Seminars "Condition-/ Prozessmonitoring & Predictive Maintenance" Condition Monitoring and Process Monitoring: Covers predictive maintenance fundamentals, process and condition monitoring, and key influencing factors. Introduces signal acquisition via sensors and control data, condition monitoring methods, and relevant standards. Explores process monitoring challenges, big data analysis infrastructure, and advanced evaluation techniques.	EQF 6
Slovenia	Agency POTI: agencija-poti.si	Operation and Maintenance of Electrical Installations and Equipment: Provider: Agency POTI Description: Professional training providing guidelines for the safe operation and maintenance of electrical installations and equipment in compliance with regulations and standards.	SOK/EQF 4-5
	Maintenance Association of Slovenia (DVS): drustvo-dvs.si	Basics of Vibration Diagnostics and Bearing Selection, Installation, and Lubrication Provider: Maintenance Association of Slovenia (DVS) Description: Training covering vibration diagnostics and the selection, installation, and lubrication of rolling bearings.	SOK/EQF 5-6
	Secondary Education Centre Ljubljana (SIC Ljubljana): siclj.si	Mechanic Training Program Provider: Secondary Education Centre Ljubljana (SIC Ljubljana) Description: Training for the maintenance and servicing of motor vehicles, suitable for automotive technicians or mechanics.	SOK/EQF 4
	Chamber of Craft and Small Business of Slovenia (OZS): ozs.si	Training and Certification for Cooling Equipment Technicians Provider: Chamber of Craft and Small Business of Slovenia (OZS) Description: Training for technicians involved in	SOK/EQF 4–5



		installing, maintaining, and servicing refrigeration equipment and handling refrigerants.	
	Training Centre for Protection and Rescue of the Republic of Slovenia: gov.si	Training in Equipment and Infrastructure Maintenance for Emergency and Rescue Services Provider: Training Centre for Protection and Rescue of the Republic of Slovenia Description: Programs focused on the maintenance of equipment and infrastructure used in protection, rescue, and disaster relief.	SOK/EQF 5–6
	ZVD Institute for Occupational Safety: zvd.si	Inspection and Maintenance of Children's Playgrounds and Equipment Provider: ZVD Institute for Occupational Safety Description: Training for the safe inspection and maintenance of playgrounds and children's play equipment.	SOK/EQF 4–5
Italy	Formazione Michelangelo	"Maintenance Specialist Course" The Maintenance Specialist Course was created with the aim of certifying maintenance technicians and ensuring high-quality standards in the management of company assets.	EQF 4-5
	Festo C.T.E	"Maintenance Specialist Course" Autonomy and efficiency in operational maintenance for the improvement of maintenance department KPIs. Meets the mandatory training requirements for access to Level 1 Maintenance Competency Certification	EQF 4-5

13.5. ANNEX 5 - PDM REPORT QUOTATION FROM EXPERTS

Table 13. Result of the PdM Report quotation from experts

Chapter	Question	Average on a score of 4
Overall	Does the report seem useful, relevant, and reliable to you?	3,89
1	Is the purpose of the report clearly explained?	4,00
1	Does the methodology allow you to understand the different steps?	3,83
2	Do the definitions of Maintenance and its different strategies presented seem clear and appropriate?	3,73
3	Does the recent and rapid evolution of the market towards a new approach to Maintenance seem clearly explained?	4,00
3	Does the presentation of the market's evolution since 2018 clearly help you understand the issues?	3,91
3	Do the findings on Maintenance as a Service seem interesting to you?	3,64



4	Does this chapter allow you to clearly understand how Predictive Maintenance works?	3,80
4	Does this chapter allow you to clearly understand the challenges of Predictive Maintenance?	3,80
4	Does this chapter help you understand the solutions provided by new technologies in Predictive Maintenance?	4,00
4	Do you find that the case studies presented are relevant and provide answers to problems and challenges?	3,80
5	Does this chapter help you understand the benefits and challenges of Predictive Maintenance in companies?	4,00
5	Does this chapter help you understand the future trends of Predictive Maintenance in companies?	3,80
5	Is the impact of Predictive Maintenance on the workforce clearly explained?	3,80
5	Does the presented case study seem useful to you and make you want to learn more?	3,90
5	Does this chapter help you understand the companies' needs in terms of skills and connections?	4,00
5	Impact of PdM in Maintenance Activities on SMEs: the survey seems useful and pertinent to you	3,60
5	Impact of PdM in Maintenance Activities on SMEs: the questions seem pertinent to you	3,80
5	Impact of PdM in Maintenance Activities on SMEs: the results are clearly explained and described	4,00
5	Impact of PdM in Maintenance Activities on SMEs: the results can be considered reliable	3,50
5	Impact of PdM in Maintenance Activities on SMEs: the sample seem representative to you	3,10
6	Is the state of the art in Predictive Maintenance clearly presented?	3,44
6	Does this chapter help you understand the impact of new technologies on maintenance trainings?	3,78
6	Does this chapter help you understand the opportunities and challenges for training centres?	3,78
6	Does this chapter help you understand the needs of training centres related to new skills required?	3,67
6	Impact of PdM on Training and Training Centres: the survey seems useful and pertinent to you	3,56
6	Impact of PdM on Training and Training Centres: the questions seem pertinent to you	3,67
6	Impact of PdM on Training and Training Centres: the results are clearly explained and described	4,00
6	Impact of PdM on Training and Training Centres: the results can be considered reliable	3,56
6	Impact of PdM on Training and Training Centres: the sample seem representative to you	3,33
7	Do you think this chapter is clear and well-documented enough?	4,00
8	Do you think this chapter effectively summarizes outlooks and future trends?	4,00
8	Do you believe this chapter provides a strong conclusion and relevant recommendations?	3,56





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