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Article

Proposal for a Sustainable Model for Integrating Robotic Process Automation and Machine Learning in Failure Prediction and Operational Efficiency in Predictive Maintenance

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Abstract: This paper proposes a sustainable model for integrating robotic process automation (RPA) and machine learning (ML) in predictive maintenance to enhance operational efficiency and failure prediction accuracy. The research identified a key gap in the literature, namely the limited integration of RPA, ML, and sustainability in predictive manufacturing, which led to the development of this model. Using the PICO methodology (Population, Intervention, Comparison, Outcome), the study evaluated the implementation of these technologies in Alpha Company, comparing results before and after the model's adoption. The intervention integrated RPA and ML to improve failure prediction accuracy and optimize maintenance operations. Results showed a 100% increase in mean time between failures (MTBF), a 67% reduction in mean time to repair (MTTR), a 37.5% decrease in maintenance costs, and a 71.4% reduction in unplanned downtime costs. Challenges such as initial implementation costs and the need for continuous training were also noted. Future research could explore integrating big data and AI to further improve prediction accuracy. This model demonstrates that integrating RPA and ML leads to operational improvements, cost reductions, and environmental benefits, contributing to the sustainability of industrial operations.

Keywords: RPA; machine learning; integration systems; predictive maintenance; SIRPM

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1. Introduction

Predictive maintenance has emerged as an increasingly important strategy for optimizing the operation of complex industrial systems, enabling the anticipation of failures and the prevention of unforeseen downtime. However, current solutions face significant challenges. The integration of data from diverse sources, the complexity of predictive models, and the lack of scalability in conventional approaches continue to pose substantial obstacles. For instance, in the automotive industry, failures in high-precision machinery often lead to extended downtimes, increasing operational costs and affecting production. In the cardboard packaging industry, failures in critical equipment can halt entire production lines, resulting in unforeseen costs, delivery delays, and a significant loss of competitiveness. These issues underscore the urgent need for more effective and adaptable solutions in predictive maintenance [1].

Although current technologies enable more accurate failure predictions, the implementation of solutions remains a challenge, particularly due to data integration, the complexity of predictive models, and the lack of scalable approaches. The digitization of industrial operations and the growing adoption of automation have driven innovation in this field. Robotic process automation (RPA) has emerged as an efficient solution to automate repetitive, rule-based tasks, freeing up resources for more strategic activities and enabling greater precision in operations. When combined with machine learning (ML) techniques, RPA not only improves failure prediction accuracy but also enhances operational agility and efficiency [2].

In this context, this article proposes an innovative and sustainable model that integrates RPA and ML for failure prediction and the improvement of operational efficiency in predictive maintenance. The model aims not only to increase the accuracy of predictions but also to promote sustainability in its three dimensions, which are environmental, social, and economic. Environmentally, the integration of these technologies can significantly reduce resource consumption and CO_2 emissions by preventing unexpected failures and optimizing energy and material use. Socially, the model proposes a better allocation of human resources, enabling workers to focus on more strategic tasks, such as data analysis and innovation, rather than dealing with repetitive tasks or emergency issues. Economically, the reduction in operational and maintenance costs can enhance competitiveness and profitability, contributing to long-term financial sustainability [2].

The specific problem addressed by this study is the inefficiency of traditional predictive maintenance systems. These models often fail to anticipate failures effectively, leading to unforeseen downtimes and high maintenance costs. The proposed RPA and ML model seeks to overcome these limitations, allowing for accurate failure prediction and optimized resource management. For example, in a company within the cardboard packaging sector, the implementation of this model resulted in a 66.67% reduction in unplanned downtime events and a 52% decrease in average repair costs, leading to greater efficiency and profitability.

The need to adopt the RPA and ML model is evident, given the increasing reliance on technological solutions in industries. Traditional predictive maintenance models are often neither scalable nor sufficiently accurate for the demands of modern industrial operations. The integration of automation and real-time advanced data analytics enables swift and effective intervention while also offering flexibility to adapt to different contexts and industrial sectors [3].

The unique contribution of this work lies in the practical and innovative application of the integrated RPA and ML model in predictive maintenance. This study not only seeks to enhance the efficiency of industrial processes but also demonstrates how emerging technologies can contribute to sustainability, expanding the possibilities for adaptation and implementation across various industries. The proposed model offers significant value for small and medium-sized enterprises, such as Alpha, which face similar challenges related to unplanned downtime and high maintenance costs.

The structure of this article is as follows: Section 2 provides a comprehensive review of the state of the art, addressing the concepts of predictive maintenance, RPA, and ML and exploring the integration of these technologies in failure prediction and operational efficiency improvement. Section 3 describes the methodology adopted, justifying the choice of the PICO approach and explaining the hypothesis formulation process. Section 4 presents the proposed model and its advantages over existing models. Section 5 illustrates the practical application of the model through a case study. In Section 6, the results are analyzed, discussing the implications of RPA and ML integration in failure prediction and operational efficiency, with a focus on sustainability aspects. Finally, Section 7 concludes the article, summarizing the main findings and suggesting directions for future research.

In summary, this article aims to deepen the understanding of the integration between RPA and ML for failure prediction and the optimization of operational efficiency in predictive maintenance, highlighting the social, economic, and environmental benefits of applying these emerging technologies.

2. State of the Art

Predictive maintenance has emerged as one of the most effective approaches for improving operational efficiency and increasing equipment durability across various industrial sectors. This practice relies on a continuous monitoring of operational parameters and the use of advanced analytical models to predict equipment failures or degradation, allowing for maintenance to be carried out at the right moment before a failure occurs [4]. The main goal of predictive maintenance is to maximize equipment availability, reduce operational costs, prevent unexpected downtime, and improve system safety and reliability [5].

Predictive maintenance is characterized by a data-driven and predictive analysis approach, which differs from traditional methods such as corrective and preventive maintenance. Instead of performing maintenance at fixed intervals or waiting for equipment failure, the aim is to anticipate failures based on real-time data and analytical models, enabling precise, scheduled interventions. This type of maintenance not only reduces costs but also increases efficiency by optimizing asset lifecycles and improving overall operational performance [6].

The automation of processes and advanced data analysis have played an increasing role in predictive maintenance, with robotic process automation (RPA) and machine learning (ML) being the two most important technologies in this context.

Robotic process automation (RPA) refers to the use of software to automate repetitive, rule-based tasks within computational systems. RPA is essential for collecting and processing large volumes of data from monitoring sensors, maintenance management systems, and Internet of Things (IoT) devices. Automating these processes eliminates the need for human intervention in administrative tasks, allowing operators to focus on deeper analyses and strategic decisions [7].

On the other hand, machine learning (ML), a subfield of artificial intelligence (AI), enables computer systems to learn from data and dynamically adjust as new information is acquired. In industrial settings, ML is used to analyze sensor data, monitor operational conditions, and predict failures by identifying patterns and anomalies that might go unnoticed during traditional inspections. This predictive capability contributes to a significant shift in asset maintenance, making it more effective and cost-efficient [8].

The integration of RPA and ML in predictive maintenance has brought significant benefits to various industries. A clear example of RPA application is the automation of data collection processes, where equipment condition sensors transmit real-time information to maintenance management systems. RPA can process these data and automatically forward them to maintenance teams or monitoring systems for further analysis. In terms of machine learning, neural networks are often used to predict failures by analyzing large volumes of historical data and identifying trends and patterns that indicate the onset of an impending failure [9].

However, despite these technological advancements, some limitations remain. The main issue concerns the dependence on data quality. The effectiveness of ML algorithms depends on the quality of the data used to train the models. Inaccurate or incomplete data can compromise the accuracy of predictions, leading to incorrect diagnoses. Additionally, implementing RPA and ML requires significant investments in infrastructure and the need for specialized training for system operation and maintenance [10]. Another limitation is the need to customize ML models for each type of asset and industrial environment, which can be costly and complex.

Predictive maintenance, supported by RPA and ML technologies, has proven particularly beneficial in the manufacturing sector, where operational efficiency and minimizing unplanned downtime are critical to productivity. RPA plays a key role in automating administrative and operational processes, such as scheduling maintenance, sending alerts, and managing spare parts inventory. The integration of RPA with predictive maintenance systems allows operations to be more efficient and less prone to human errors, which is essential in high-demand production environments.

The use of ML in manufacturing, in turn, is one of the greatest advances in predictive maintenance. ML systems can monitor a range of operational parameters of equipment in real time, such as temperature, vibration, pressure, and wear, identifying failure patterns that may indicate imminent failures. These systems enable more effective interventions, reducing corrective maintenance costs and extending equipment lifespan while also minimizing production costs by avoiding unplanned downtime [11].

Furthermore, the combination of RPA and ML creates a closed-loop cycle of monitoring and action, where failures can be predicted and interventions can be carried out autonomously without the need for constant manual interaction. This not only improves operational efficiency but also contributes to sustainability by reducing resource waste and extending asset lifespans. This cycle optimizes equipment usage and minimizes the environmental impact of industrial operations, aligning with the principles of a circular economy [11].

The application of predictive maintenance results in significant improvements in operational efficiency, as it enables the identification of failures before they occur, preventing unexpected downtime and the associated costs of emergency repairs. Maintenance is carried out only when necessary, reducing operational costs and improving resource utilization [11]. Sustainability is also supported, as predictive maintenance helps reduce material and energy waste by ensuring that equipment operates optimally and preventing catastrophic failures that could lead to large amounts of waste.

Additionally, the use of RPA and ML, by automating processes and optimizing data analysis, contributes to the efficiency of maintenance and operational processes, reducing human errors and improving decision-making accuracy. These technologies are fundamental to the digital transformation of industrial maintenance, creating intelligent and autonomous systems that ensure greater reliability and efficiency in operations [11].

Sustainability, a critical aspect of modern industrial practices, is built on three foundational pillars, namely economic, social, and environmental pillars. These pillars emphasize efficient resource utilization, equitable societal impact, and environmental preservation, respectively. Predictive maintenance aligns with these principles by enabling operations that are both cost-effective and environmentally responsible. Through its focus on efficiency and proactive management, predictive maintenance contributes to sustainable practices, ensuring that industries meet present needs without compromising future resources [11].

The integration of predictive maintenance technologies, such as robotic process automation (RPA) and machine learning (ML), further enhances sustainability outcomes. Economically, these technologies reduce costs by optimizing equipment lifecycles and minimizing unplanned downtime. Socially, they improve workplace safety by identifying and mitigating potential hazards before they lead to failures. Environmentally, predictive maintenance lowers energy consumption and material waste, reinforcing a commitment to reducing industrial footprints. This approach is particularly relevant in the context of a circular economy, where waste is minimized and resource value is preserved across operational processes [12–14].

By seamlessly embedding sustainability into predictive maintenance strategies, industries can achieve a balanced approach that maximizes operational efficiency while addressing ecological and societal responsibilities [15,16]. The proactive nature of predictive maintenance, supported by advanced analytical tools, allows organizations to extend asset lifespans, reduce waste, and operate more sustainably. This integration not only supports long-term business resilience but also underscores the role of predictive maintenance in advancing broader sustainability objectives within industrial ecosystems [12,17].

In summary, the integration of RPA and ML technologies in predictive maintenance represents a significant advancement in operational efficiency, failure prediction, and sustainability. These technologies not only improve asset management but also provide a more sustainable approach for companies seeking to optimize their resources and reduce environmental impact while respecting the pillars of sustainability, namely the economic, social, and environmental pillars.

3. Methodology

3.1. Method

The PICO methodology (Population, Intervention, Comparison, Outcome) has been widely used in scientific research due to its ability to provide a clear and well-defined framework for systematically analyzing research questions. When applied rigorously, this approach enables an objective and detailed evaluation of the relationships between key elements of the study, ensuring more accurate investigations free from the subjective biases often present in narrative reviews [18]. PICO has proven to be a valuable tool not only in medical and healthcare fields but also across various other areas of research, such as engineering, social sciences, and technology, as highlighted by recent studies (include updated references) [19–21]. This methodology facilitates the formulation of specific research questions and the selection of relevant studies, ensuring that data are handled consistently and comparably [19].

In this study, the use of the PICO methodology is based on the need to structure the analysis in a way that integrates various dimensions of the research problem, offering a comprehensive and objective view of the adoption of robotic process automation (RPA) and machine learning (ML) in predictive maintenance systems. Adapting this methodology to the specific context of automation and artificial intelligence technologies allows for a clear focus on the variables of interest and provides a precise assessment of the impact of implementing these technologies on organizations' operational performance [20].

In this study, the "population" refers to organizations that have adopted or are considering implementing RPA and ML solutions within the realm of predictive maintenance. Defining the population is crucial to ensuring that the results are relevant and applicable to sectors facing similar challenges related to maintenance and the integration of intelligent systems [22]. Focusing on companies that are applying advanced technologies to optimize processes and increase operational efficiency allows for an in-depth analysis of adoption practices and their impact on specific industrial environments.

The "intervention" in this study refers to the adoption of RPA and ML technologies aimed at improving failure prediction models, thereby increasing the efficiency of maintenance operations. The choice of this intervention is supported by growing evidence that integrating RPA and ML can provide significant benefits, such as improved accuracy in failure predictions and reduced operational costs. Additionally, it is crucial that the implementation of these technologies is carried out in a sustainable manner, adhering to environmental, social, and economic principles, contributing to a more responsible business model aligned with sustainability goals (include updated references on RPA and ML applied to predictive maintenance) [23–25].

The "comparison" in this study is made between the state of organizations before and after the implementation of RPA and ML technologies. To develop the analytical model, a review of previous studies was conducted, covering relevant topics and approaches. This review helped identify gaps in the literature and best practices, which were incorporated into the proposed model. The comparison aims to assess the impacts of adopting these technologies on organizational operational efficiency, with a focus on improving failure predictions and optimizing maintenance processes. The study also seeks to determine how the implementation of these technologies can address common issues faced by companies, such as lack of maintenance control, and identify tangible benefits, such as reduced unexpected failures, lower operational costs, and increased reliability in maintenance processes.

The "outcome" expected from this study is the identification of substantial improvements in the operational efficiency of organizations that adopt the proposed model. The application of the PICO methodology will allow for the formulation of robust hypotheses and conducting an analysis based on concrete data, facilitating the objective measurement of results. This will provide a clearer understanding of how the implementation of RPA and ML can optimize predictive maintenance while promoting sustainability in industrial operations across environmental, social, and economic dimensions.

The methodology used in this study involved a detailed analysis of a rigorously selected set of relevant data sources. The PICO approach was applied to select the articles, with well-defined inclusion and exclusion criteria. Initially, the articles were identified through a bibliographic search, and the screening process involved reviewing titles and abstracts, prioritizing studies that directly addressed the integration of RPA, ML, predictive maintenance, and sustainability. Articles that did not meet the relevance criteria or were not directly related to the topic were discarded, resulting in a final selection of studies that significantly contribute to the research [26].

The information extracted was based on contributions from experts in the fields of RPA, ML, predictive maintenance, and sustainability. The collection of articles was carried out from renowned scientific databases, such as the "B-on" platform, https://www.b-on.pt/) (accessed on 10 November 2024), which provides access to peer-reviewed scientific publications. "B-on" is a widely accessible platform, including articles indexed in databases such as ISI WOS and Scopus, ensuring that the selected sources are comprehensive and relevant to the subject matter.

Thus, the use of the PICO methodology offers a clear framework for the analysis and interpretation of the collected data, facilitating the connection between the formulated hypotheses and the evidence found in the literature.

The inclusion criteria were as follows:

- Articles directly addressing the implementation or evaluation of RPA and ML in predictive maintenance.
- Publications discussing the relationship between these technologies and sustainability in its various aspects (environmental, social, and economic).
- Studies conducted between 2010 and 2024.
- Articles published in peer-reviewed journals and available in full text.

The following types of publications were excluded:

- Articles that do not directly address the implementation of RPA and ML or that cover areas unrelated to predictive maintenance.
- Works that do not significantly discuss sustainability aspects.
- Publications that are not available in full text or are difficult to access.
- Studies that are not based on empirical methodologies or that do not provide clear quantitative and qualitative data on the impacts of the technologies.

This rigorous selection process ensured that the analysis was based on high-quality sources directly relevant to the study of the effects of adopting RPA and ML in predictive maintenance and sustainability.

The central research question and the hypotheses that guided this study were appropriately formulated.

Central Research Question (CRQ)

CRQ: how can the integration of robotic process automation (RPA) and machine learning (ML) improve failure prediction and operational efficiency in predictive maintenance systems, considering sustainability in its environmental, social, and economic dimensions?

Hypotheses (H)

H1. *The integration of RPA and ML improves accuracy in predicting failures in industrial systems, reducing downtime and operational costs.*

H2. *The implementation of a sustainable RPA and ML model in predictive maintenance contributes to operational efficiency, promoting environmental (such as reduced waste and energy), social (better allocation of human resources), and economic (cost reduction and increased profits) benefits.*

This study aims to provide a detailed view on how the combination of robotic process automation (RPA) and machine learning (ML) can enhance failure prediction and increase operational efficiency in predictive maintenance systems while promoting, at the same time, sustainability in its environmental, social, and economic aspects.

The two hypotheses presented support the idea that the combination of RPA and ML brings operational benefits and can also be a fundamental approach for a more sustainable maintenance model. The first hypothesis (H1) suggests that the integration of RPA and ML improves failure prediction accuracy and reduces operational costs by improving maintenance processes, resulting in less downtime and greater equipment longevity. This progress is essential for reducing waste and costs, aligning with the economic objectives of sustainability.

The second hypothesis (H2) is based on the premise that the adoption of a sustainable model, which combines RPA and ML in predictive maintenance, optimizes operational efficiency and also brings considerable benefits in sustainability. The expectation is that by reducing failures and optimizing maintenance interventions, it will be possible to minimize the waste of natural resources and the use of energy, favoring more sustainable business practices. Furthermore, by enabling more effective management of human resources, this model can improve social well-being in organizations by freeing professionals for tasks of greater strategic and analytical value while contributing to a more profitable and resilient economic model.

To carry out the search process central to this study, the researchers utilized the online scientific library offered by the Portuguese Foundation for Science and Technology, concentrating on three specific groups (Group 1, Group 2, Group 3, and Group 4), as detailed in Table 1.

The research tests were carried out using the "B-on" platform, utilizing the OR operator to link either the title, keywords (KWs), or abstract (AB) within the three defined groups.

Following this, filters were applied to the sets of publications obtained during the research process, and the results, in terms of the number of publications, are summarized in Table 2.

Table 1. Groups searched through "B-on".

Group 1	Group 2	Group 3	Group 4
"RPA" OR "Robotic Process Automation" OR "Intelligent Process Automation" OR "Digital Process Automation" OR "Business Workflow Automation"	"Machine Learning" OR "ML Algorithms" OR "Supervised Learning" OR "Unsupervised Learning" OR "Reinforcement Learning" OR "Deep Learning"	"Predictive Maintenance" OR "Condition-Based Maintenance" OR "Maintenance Optimization"	"Sustainability" OR "Sustainable" OR "Social Sustainability" OR "Environment" OR "Environmental Sustainability" OR "Economic Sustainability" Or "Sustainable Development"

Table 2. Publications obtained through B-on after the application of some filters.

	Set 1	Set 2	Set 3
Initial Result:	436	825	2970
1—Restrict to Peer-Reviewed	352	792	2318
2—From 2010 to 2024	351	780	2300
3—Language: English	238	200	1667
4—Restrict to Full Text	227	200	1530

Following the application of the filters, the titles, keywords, and abstracts of each paper were examined to select those most closely related to the research topic. Initially, a total of 4231 articles was retrieved. After the filters were applied, 1957 remained, of which only 37 were directly relevant to the study's focus.

Figure 1 shows a flowchart outlining the process of the literature search and the screening procedure followed in this study.

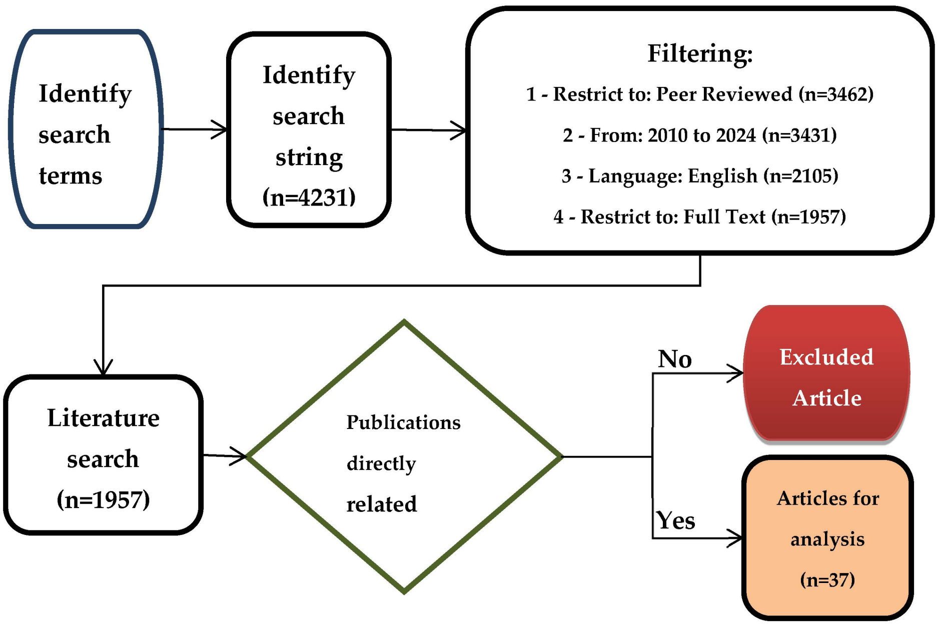

Figure 1. Flow diagram of the literature search and respective screening.

3.2. Articles Synthesis and Analysis

This section provides a detailed summary and analysis of the articles most pertinent to the topic being investigated. Table 3, shown below, lists the 37 selected articles along with the models discussed in each. This table was designed to classify the contributions of each study and was carefully constructed based on a thorough search of academic databases.

Table 3. Identified articles and the respective themes of the articles found.

Themes of the Articles Articles (Author/Year/Ref.)	Predictive Maintenance	Robotic Process Automation	Machine Learning	Type of Contribution	Pillars of Sustainability Identified in the Articles
[26] Zhang, X.; Liu, T.; Wang, H. (2020)	x		x	Review	Environmental
[27] Bai, X.; Li, J.; Zhang, Y. (2020)	x		x	Model	Environmental
[28] Vasiliadis, L.; Manitsaris, S.; Kapsalis, A. (2021)		x		Case Study	Economic, Social
[29] Lubis, L.; Sembiring, D. (2023)		x		Case Study	Economic
[30] Martínez-Gomez, J.; Martínez, P.; Ramos, F. (2021)	x		x	Review	Environmental
[31] Singh, R.; Singh, A.; Pandey, P. (2020)	x			Review	Environmental
[32] Xu, B.; Yu, D.; Hu, X. (2021)	x			Review	Environmental
[33] Santos, G.; Oliveira, J.; Silva, P. (2021)		x		Case Study	Economic
[34] Chen, W.; Liu, Z.; Yang, F. (2020)	x		x	Review	Environmental
[35] Anwar, A.; Mohd Ali, N.; Ali, I. (2020)	x		x	Case Study	Environmental
[36] Chen, J.; Zhang, H.; Ma, Q. (2020)		x		Case Study	Social, Economic
[37] Li, Y.; Ma, Y.; Liu, L. (2021)	x		x	Review	Environmental
[38] Pisacane, O.; Potena, D.; Antomarioni, S.; Bevilacqua, M.; Ciarapica, F.; Diamantini, C. (2020)	x			Case Study	Environmental
[39] Balaraman, K.; Palaniappan, S.; Zhuang, J. (2021)			x	Review	Environmental
[40] García, F.; López, J.; Díaz, R. (2021)	x			Review	Environmental
[41] Lee, J.; Davari, H.; Singh, J. (2021)	x			Case Study	Environmental
[42] Ribeiro, P.; Silva, F.; Rocha, A. (2021)	x			Case Study	Environmental
[43] Sharma, N.; Garg, H.; Arora, A. (2021)	x			Case Study	Environmental
[44] Li, X.; Zuo, H.; Wang, J. (2020)	x			Review	Environmental
[45] Basu, R.; Kumbhar, D.; Acharya, R. (2021)	x			Review	Environmental

Table 3. *Cont.*

Themes of the Articles Articles (Author/Year/Ref.)	Predictive Maintenance	Robotic Process Automation	Machine Learning	Type of Contribution	Pillars of Sustainability Identified in the Articles
[46] Koumpis, M.; Jantunen, E.; Hildreth, P. (2021)		x		Case Study	Economic
[47] Cheng, Y.; Zhou, J.; Zhao, Y. (2020)	x			Case Study	Environmental
[48] Alves, S.; Silva, J.; Lima, J. (2021)		x		Case Study	Economic, Social
[49] Patil, A.; Nair, M.; Thomas, S. (2021)	x		x	Case Study	Environmental
[50] Zhang, M.; Wang, Y.; Zhou, F. (2021)	x		x	Case Study	Environmental
[51] Meyer, D.; Redi, J.; Smith, T. (2021)	x			Case Study	Environmental
[52] Wang, H.; Shi, X.; Xie, L. (2021)	x			Review	Environmental
[53] Jafari, M.; Rezaei, M.; Darvishi, M. (2020)		x		Review	Economic
[54] Pratap, P.; Soni, A.; Kumar, M. (2020)	x		x	Review	Environmental
[55] Wang, H., Zhang, W., Yang, D.; Xiang, Y. (2023).	x		x	Review	Environmental
[56] Patrício, L.; Varela, L.; Silveira, Z. (2024)		x		Model	Social, Environmental
[57] Costa, C.R.S.; Patrício, L.; Ferreira, P.; Varela, L.R. (2023)		x		Case Study	Environmental
[58] Patrício, L.; Costa, C.R.S.; Fernandes, L.P.; Varela, M.L.R. (2023)		x		Model	Economic
[59] Patrício, L.; Avila, P.; Varela, L.; Cruz-Cunha, M.M.; Ferreira, L.P.; Bastos, J.; Castro, H.; Silva, J. (2023)		x		Review	Economic, Social, Environmental
[60] Patrício, L.; Costa, C.R.S.; Varela, L.; Cruz-Cunha, M.M. (2024)		x		Review	Economic, Social, Environmental
[61] Daase, C., Pandey, A., Staegemann, D.; Turowski, K. (2023)		x		Model	Economic, Social, Environmental
[62] Patrício, L.; Costa, L.; Varela, L.; Ávila, P. (2023)		x		Model	Economic, Social, Environmental
% Themes p/articles	59%	27%	30%		

The chosen articles were thoroughly read and analyzed to identify the key themes and methodologies explored. These themes were subsequently organized into a table, with each column representing a specific theme and the rows listing the articles, marked according to the models discussed. Furthermore, the articles were categorized based on the pillars of sustainability they address, providing a valuable overview to highlight gaps in the existing literature and potential areas for future research.

3.3. Synthesis of the Results

From the analysis of the previous tables, the following main points can be emphasized:

- Prevalence of predictive maintenance: 59% of the articles focus on predictive maintenance, making it the most explored technology.
- Environmental focus: the majority of articles highlight the environmental pillar of sustainability, with an emphasis on reducing environmental impacts.
- Economic sustainability: the economic pillar is also widely addressed, particularly in studies on automation and process optimization.
- Less focus on social sustainability: social sustainability is mentioned less frequently, indicating limited focus on this pillar.
- Predominance of case studies and reviews: 33% of the articles are case studies and 45% are reviews, reflecting the consolidation of practical and theoretical knowledge.
- Models and practical applications: 16% of the article's present models, reflecting the practical application of technologies for sustainability.
- Emerging technologies: automation and machine learning are linked to sustainability, focusing on efficiency and cost reduction.

4. Model (SIRPM)

4.1. Proposal for a Model (SIRPM)

This paper proposes an innovative model focused on the sustainable integration of robotic process automation (RPA) and machine learning (ML) in predictive maintenance systems. The objective is to enhance operational efficiency, improve failure forecasting, and reduce maintenance costs. Named SIRPM—sustainable integration of robotic process automation (RPA) and machine learning (ML) in predictive maintenance (PM)—this model provides a flexible yet structured approach that follows a set of well-defined criteria, ensuring the successful integration of these technologies into existing maintenance systems.

While the model adheres to a structured set of criteria, it is adaptable in terms of the specific algorithms and technological solutions applied, allowing for alignment with the technological environment and needs of each organization. This flexibility is crucial, as it enables the model to accommodate a variety of industrial settings while still meeting sustainability goals and optimizing maintenance processes.

The model aims to enhance the accuracy of failure predictions and operational efficiency by automating repetitive, rule-based tasks through RPA and leveraging ML algorithms to process large volumes of real-time data. By predicting failures before they occur, organizations can optimize resource allocation, minimize material and energy waste, and extend the lifespan of equipment.

This approach is designed to support a responsible and sustainable integration of RPA and ML into maintenance systems, balancing technological advancements with environmental, social, and economic considerations. The criteria that guide the application of these technologies ensure that the integration aligns with the organization's overall objectives without compromising sustainability goals.

Furthermore, the model is designed with interoperability in mind, ensuring seamless integration with existing systems such as CMMS, ERP, and IoT platforms without requiring major infrastructure overhauls. This guarantees that companies can apply predictive maintenance solutions without disrupting their existing operations.

The model's implementation is structured in several phases, each with specific objectives that ensure both operational and sustainability goals are met. These phases are illustrated in Figure 2, which highlights the main benefits and improvements resulting from the model's adoption.

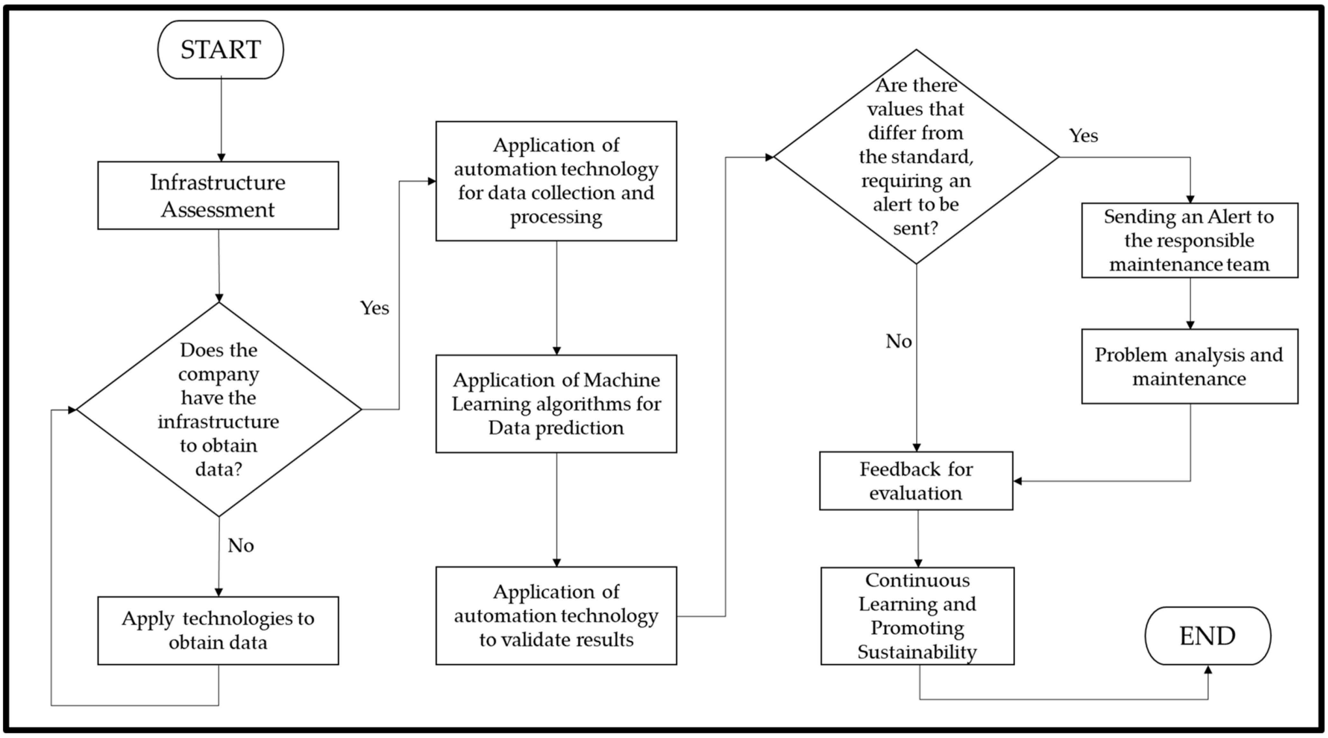

Figure 2. Diagram of proposal for a sustainable model (SIRPM).

Due to the flexibility inherent in the model, it can be customized to meet the unique needs and technological landscapes of various organizations. This ensures that the model evolves with the technological landscape of the company, providing a sustainable and adaptable predictive maintenance solution.

The phases of the SIRPM model are presented below, outlining the structured steps required to implement a sustainable and efficient integration of RPA and ML in predictive maintenance systems. Each phase focuses on a specific objective, ensuring a comprehensive approach to achieving operational and sustainability goals.

- Phase 1: Infrastructure Assessment: The organization's technological readiness is evaluated to ensure the presence of smart sensors and reliable connectivity for data collection (Table 4). A company's ability to obtain data from its machines depends on specific KPIs related to the infrastructure's capacity and flexibility. Initially, the company must verify if it has the means to gather relevant data from the respective machines. If such capabilities are lacking, the installation of sensors or equipment capable of measuring key variables becomes necessary. These variables can include metrics such as the number of completed items, temperature, pressure, or other factors specific to the machine and study objective. The decision regarding whether the infrastructure is sufficient for data collection also considers KPIs such as the following:
    - Frequency of data collection: the capability to capture and process data at the intervals required for meaningful analysis.
    - Representativeness of data: the degree to which the captured data reflects the performance and conditions of the machine under study.
    - Storage capacity: the available space in local devices (e.g., hard drives) or cloud solutions to accommodate the volume of collected data.

- Scalability: the flexibility of the infrastructure to adapt to variations in demand, including the potential need for future expansions.
- After assessing the adequacy of data collection and infrastructure, the organization must determine the appropriate storage solution—either local storage or cloud-based platforms. This decision is guided by the KPIs outlined above. Cloud storage is often preferred in scenarios requiring high integration and real-time data analysis, as it aligns with Industry 4.0 principles and enables enhanced connectivity and interoperability.

Table 4. Assessment criteria and description for Phase 1: Infrastructure Assessment.

Phase 1: Infrastructure Assessment		
	Assessment Criteria	**Description**
1.	Is there infrastructure to collect real-time data?	• Confirm the presence of smart sensors (IoT) and devices installed on machines to collect data such as temperature, vibration, pressure, etc.
2.	Is there connectivity between the infrastructure and data collection platforms?	• Verify if there is efficient communication between sensors and storage and analysis platforms (e.g., Wi-Fi networks, 5G, or industrial connectors).

- Phase 2: Automation of Data Collection and Processing: data collection, preprocessing, and validation are automated using RPA to guarantee data accuracy and readiness for analysis (Table 5).

Table 5. Assessment criteria and description for Phase 2: Automation of Data Collection and Processing.

Phase 2: Automation of Data Collection and Processing		
	Assessment Criteria	**Description**
3.	Data collection through RPA technology automation.	• Use robotic process automation (RPA) to collect data directly from sensors or integrated systems.
4.	Data processing through RPA technology automation.	• Automate data preprocessing: cleaning, normalization, and standardization to ensure data are ready for analysis.
5.	Data integrity and quality check.	• Include validation steps to identify inconsistent or incomplete data before proceeding to analysis.

- Phase 3: Application of Machine Learning: Machine learning models are developed and applied to predict failures based on historical and real-time data (Table 6). Although machine learning algorithms play an essential role in the proposed model, their applicability depends directly on the specific characteristics of each case, namely the type of data collected in the previous phase. Factors such as the type of data (structured or unstructured), volume of data available, objective of the algorithm (classification, prediction, or clustering) and computational capacity are decisive for the selection of the appropriate method. Therefore, the model foresees a detailed prior assessment to ensure that the chosen algorithm is compatible with the conditions of the business environment and the objectives of the automation process.

Table 6. Assessment criteria and description for Phase 3: Application of Machine Learning.

Phase 3: Application of Machine Learning		
	Assessment Criteria	**Description**
6.	Selection of the machine learning algorithm that best fits the data.	• Choose an algorithm (e.g., regression, neural networks, decision trees) based on the data characteristics and prediction goals.
7.	Development of the machine learning script.	• Implement and train the selected model, adjusting its hyperparameters to maximize accuracy and minimize errors.
8.	Forecast results generated by the machine learning script.	• Produce predictions about failures, anomalies, or maintenance patterns based on historical and real-time data.

- Phase 4: Integration of Results with RPA: Predictive results are integrated into operations through RPA bots, automating data analysis and anomaly detection (Table 7). The implementation of control automation processes in the proposed model requires the existence of an infrastructure that allows for automated interventions. These processes are more easily applicable in robust infrastructures, such as cloud-based solutions, which offer greater resilience and real-time responsiveness. For on-premise environments, the application of these processes may be limited due to resource constraints. However, when implemented, these mechanisms ensure the continuity of operations and the safe execution of machine learning algorithms, allowing the system to not only predict possible failures but also perform automatic corrections without compromising the integrity of business processes. In the specific case of this model, control automation processes can be applied given that there are platforms where automation intervention is required to collect data and subsequently organize structured data for the later application of machine learning algorithms.

Table 7. Assessment criteria and description for Phase 4: Integration of Results with RPA.

Phase 4: Integration of Results with RPA		
	Assessment Criteria	**Description**
9.	Forecast data collection through RPA.	• Deploy RPA bots to monitor and extract predictions directly from the machine learning model.
10.	Data analysis through RPA.	• Automatically cross-reference forecast data with the patterns stipulated by the company.
11.	Are there data points outside the company's stipulated average values?	• Automatically identify deviations or anomalies that could indicate imminent failures or maintenance needs.

- Phase 5: Action and Feedback: predictions are transformed into corrective actions by sending automated alerts, executing maintenance, and gathering feedback to improve the models (Table 8).
- Phase 6: Continuous Learning and Sustainability: continuous improvement is ensured through performance metrics, team training, and regular reviews, promoting sustainability and operational efficiency (Table 9).

Table 8. Assessment criteria and description for Phase 5: Action and Feedback.

Phase 5: Action and Feedback		
	Assessment Criteria	**Description**
12.	Sending alerts to the responsible department through RPA.	• Automatically send notifications to the responsible team when deviations or failures are detected.
13.	Maintenance execution.	• Ensure corrective actions are taken based on forecasts and alerts issued.
14.	Feedback through evaluation of the received alerts for usefulness.	• Assess the generated alerts to verify if they were accurate, relevant, and helped avoid issues.
15.	Record this evaluation for machine learning algorithm learning.	• Update the machine learning model with the feedback received, enabling continuous learning and improved accuracy.

Table 9. Assessment criteria and description for Phase 6: Continuous Learning and Sustainability.

Phase 6: Continuous Learning and Sustainability		
	Assessment Criteria	**Description**
16.	Operational efficiency and sustainability through metrics calculations.	• Calculate metrics such as mean time to repair (MTTR), mean time between failures (MTBF), and sustainability indicators like reduced energy consumption and emissions.
17.	Training and adaptation of teams for the predictive maintenance system.	• Train staff to interpret the results and interact with the system, ensuring all teams align with the new approach.
18.	Periodic review of system performance.	• Establish regular reviews to assess the performance of RPA bots, the accuracy of machine learning models, and the overall impact on the production process.

The model allows each phase to be tailored according to the available technological infrastructure and the needs of the organization. For instance, different ML algorithms can be selected in Phase 3 depending on the data types and failure patterns being addressed, and RPA tools can be integrated in various ways depending on the organization's existing platforms.

The proposed model, SIRPM, was designed as an innovative solution to meet the predictive maintenance needs of organizations facing challenges in adopting Industry 4.0 technologies. We recognize that I4 principles prioritize the centralization and control of cloud-based processes, but many organizations are not yet fully prepared for this transition. In response, SIRPM was designed to function as a strategic transition stage, enabling a gradual evolution towards the full adoption of cloud-based I4 without compromising efficiency and sustainability objectives in the short term.

Therefore, we detail how the model was designed to function as a transition stage as follows:

- Data collection based on Industry 4.0 guidelines: Data collection in SIRPM is performed through smart sensors, aligned with I4 principles, such as connectivity and interoperability. These sensors generate data that can be stored locally, in the cloud or in hybrid infrastructures, depending on the organization's technological maturity.

- Cloud-based storage and control: The model prioritizes cloud solutions to ensure resilience, scalability, and access to advanced machine learning (ML) tools. However, it is adaptable, allowing for initial control in on-premise infrastructures and a progressive evolution to cloud solutions as organizations advance in the process of technological modernization.
- Implementation of machine learning logic: The ML logic in SIRPM is designed to be implemented both in the cloud and on-premise, in a scalable and flexible way. In the context of I4, cloud technologies offer access to advanced ML libraries and robust computational capabilities, overcoming internal limitations that many companies still face.
- Mobility and accessibility in infrastructure: The hybrid architecture of the model ensures that even without a complete migration to the cloud, organizations can enjoy the benefits of connectivity and mobility, essential for I4. For example, the automation of data collection and processing by RPA can be achieved locally but with interfaces ready for future integration into cloud-based solutions, promoting a continuous flow of information between machines, systems, and people.
- Structured transition to cloud-based Industry 4.0: The model prepares the technological environment of organizations for a continuous and sustainable evolution towards the principles of I4. Each phase of SIRPM, from data collection to the analysis and integration of results, is designed to be fully compatible with cloud infrastructures, ensuring a harmonious and efficient transition.

SIRPM combines flexibility and innovation to meet the immediate needs of predictive maintenance while offering a structured path to digital transformation based on Industry 4.0.

The functioning of the SIRPM model will be detailed step by step in the following phases:

The SIRPM model provides a flexible, structured approach for integrating RPA and ML into predictive maintenance systems. It emphasizes the sustainable application of these technologies while ensuring interoperability with existing systems. The flexibility embedded in the model allows it to be adapted to different organizational contexts, ensuring a responsible and efficient approach to predictive maintenance.

By following the defined criteria for each phase, the integration of RPA and ML will align with best practices for sustainability and operational efficiency while allowing organizations to customize technology choices based on their specific needs.

4.2. Characteristics and Benefits of the Model (SIRPM)

The SIRPM model presents characteristics (Table 10) and benefits (Table 11) that make it a robust and well-suited solution for predictive maintenance systems in industrial environments.

This section highlights the main technical features and the advantages associated with its implementation.

The SIRPM model offers an ideal balance between automation, intelligence, and flexibility, enabling companies to maximize productivity while minimizing costs and environmental impacts. The modular structure and continuous learning make the model a long-term solution for companies seeking innovation and sustainability in managing their industrial assets.

Below, the comparative Table 12 is presented between the existing studies and the proposed model (SIRPM).

Table 10. Model (SIRPM) characteristics.

Model (SIRPM) Characteristics		
Characteristics		**Description**
1.	Integration of Advanced Technologies	• Combines robotic process automation (RPA), machine learning (ML), and the IoT. • Enables continuous data flow between sensors, analysis platforms, and operational teams.
2.	Intelligent Automation	• Automates data collection, processing, analysis, and execution of maintenance-related actions. • Reduces manual intervention, minimizing human errors.
3.	Continuous Learning	• The machine learning model is continuously updated with maintenance feedback, becoming more efficient and accurate over time.
4.	Modular Configuration	• Clearly divided into phases that can be implemented gradually, depending on the company's needs. • Supports different algorithms and sensors, ensuring flexibility for integration with existing systems.
5.	Real-Time Monitoring	• Allows real-time data analysis for anomaly detection and immediate alert generation.
6.	Sustainability and Energy Efficiency	• Promotes waste reduction and resource optimization through detailed predictive analyses.

Table 11. Model (SIRPM) benefits.

Model (SIRPM) Benefits		
Benefits		**Description**
1.	Increased Operational Efficiency	• Minimizes unplanned downtime through proactive predictive maintenance. • Enhances productivity with faster and more precise interventions.
2.	Cost Reduction	• Prevents catastrophic failures and extends the equipment's lifespan. • Optimizes human and material resources based on reliable forecasts.
3.	Data-Driven Decision-Making	• Generates detailed insights to improve asset management. • Provides structured data that can be used to create performance metrics and strategic reports.
4.	Corporate Sustainability	• Reduces energy consumption and minimizes waste, contributing to environmental goals. • Helps meet regulations related to industrial sustainability.
5.	Continuous Improvement and Adaptation	• Feedback from alerts allows for an evaluation of their usefulness, adjusting the system as needed. • Machine learning capability ensures the system stays updated with changes in the operational environment.
6.	Team Empowerment	• Promotes adaptation of operational teams to modern technologies, increasing their efficiency and technical knowledge.
7.	Scalability and Flexibility	• Can be expanded to other areas or sectors of the company with similar needs. • Supports a wide range of industries, from manufacturing to logistics and energy.

Table 12. Comparative analysis between the existing studies and the proposed SIRPM model.

	Technology Integration (RPA, Machine Learning, IoT)	Method/ Algorithm	Intelligent Automation	Continuous Learning	Flexibility and Scalability	Real-Time Monitoring	Energy Efficiency and Sustainability
[26] Zhang, X.; Liu, T.; Wang, H. (2020)	Deep Learning	Artificial Neural Networks (ANNs)			Moderate		
[27] Zhang, W.; Yang, D.; Wang, H. (2019)	Deep Learning	Artificial Neural Networks (ANNs)			Moderate		
[28] Vasiliadis, L.; Manitsaris, S.;Kapsalis, A. (2021)	RPA	Rule-Based Automation, UI Automation	x		High		
[29] Lubis, L.; Sembiring, D. (2023)	RPA	Rule-Based Automation, UI Automation	x		High		
[30] Martínez-Gomez, J.; Martínez, P.; Ramos, F. (2021)	Machine Learning	Random Forest, Decision Trees, SVM		x	Moderate		
[31] Singh, R.; Singh, A.; Pandey, P. (2020)	Machine Learning	Random Forest, Decision Trees, SVM		x	Moderate		
[32] Pech, M.; Vrchota, J.; Bednář, J. (2021)	Machine Learning, IoT	Random Forest, KNN, SVM		x	Moderate	Limited	
[33] Santos, G.; Oliveira, J.; Silva, P. (2021)	RPA	Rule-Based Automation, UI Automation			High		
[34] Chen, W.; Liu, Z.; Yang, F. (2020)	Machine Learning	Random Forest, Decision Trees		x	Moderate		
[35] Anwar, A.; Mohd Ali, N.; Ali, I. (2020)	Machine Learning	Random Forest, Decision Trees		x	Moderate		
[36] Ribeiro, J., Lima, R., Eckhardt, T., & Paiva, S. (2020)	RPA, AI	Rule-Based Automation	x	x	Moderate	x	Moderate
[37] Kumar, P., Khalid, S., & Kim, H. (2023)	Machine Learning	ANN		x	Moderate	Moderate	
[38] Kumar, R.; Nair, R. (2021)	Machine Learning	Random Forest, Decision Trees, SVM		x	Moderate	Limited	
[39] Balaraman, K.; Palaniappan, S.; Zhuang, J. (2021)	Machine Learning	Random Forest, Decision Trees			Moderate		
[40] Zonta, T.; Costa, C.; Righi, R.; Lima, M.; Da Trindade, E.; Li, G. (2020)	AI, IoT	Genetic Algorithms		x	Moderate	x	
[41] Lee, J.; Davari, H.; Singh, J. (2021)	AI	Reinforcement Learning Algorithms, Search Algorithms	x		High	x	x
[42] Ribeiro, P.; Silva, F.; Rocha, A. (2021)	AI, IoT	Genetic Algorithms		x	Moderate	x	Moderate

Table 12. *Cont.*

	Technology Integration (RPA, Machine Learning, IoT)	Method/ Algorithm	Intelligent Automation	Continuous Learning	Flexibility and Scalability	Real-Time Monitoring	Energy Efficiency and Sustainability
[43] Sharma, N.; Garg, H.; Arora, A. (2021)	Machine Learning	Random Forest, SVM		x	Moderate		
[44] Çınar, Z.; Nuhu, A.; Zeeshan, Q.; Korhan, O.; Asmael, M.; Safaei, B. (2020)	AI	Bayesian Networks	x		Moderate	x	
[45] Abidi, M.; Mohammed, M.; Alkhalefah, H. (2022)	Machine Learning	Random Forest, Decision Trees		x	Moderate	Limited	
[46] Sobczak, A.; Ziora, L. (2021)	RPA	Rule-Based Automation	x		High		Moderate
[47] Cheng, Y.; Zhou, J.; Zhao, Y. (2020)	AI	Search Algorithms, Dynamic Programming			Moderate	x	
[48] Alves, S.; Silva, J.; Lima, J. (2021)	RPA	Rule-Based Automation			High		
[49] Patil, A.; Nair, M.; Thomas, S. (2021)	IoT, Machine Learning	Random Forest, Decision Trees, KNN		x	Moderate	Moderate	
[50] Teoh, Y.; Gill, S.; Parlikad, A. (2021)	Machine Learning	Random Forest, Decision Trees		x	Moderate		
[51] Meyer, D.; Redi, J.; Smith, T. (2021)	AI	Reinforcement Learning Algorithms			Moderate		
[52] Kliestik, T.; Nica, E.; Durana, P.; Popescu, G. (2023)	AI, IoT	Reinforcement Learning Algorithms		x	Moderate	x	Moderate
[53] E-Fatima, K.; Khandan, R.; Hosseinian-Far, A.; Sarwar, D. (2023)	RPA	Rule-Based Automation, UI Automation			High		
[54] Ruiz-Sarmiento, J.; Monroy, J.; Moreno, F.; Galindo, C.; Bonelo, J.; Jiménez, J. (2020)	Machine Learning	Random Forest, Decision Trees		x	Moderate		
[55] Wang, H., Zhang, W., Yang, D.; Xiang, Y. (2023).	Deep Learning, IoT	Deep Neural Networks (DNNs)	x	x	High	x	x
[56] Patrício, L.; Varela, L.; Silveira, Z. (2024)	RPA, AI	Rule-Based Automation, UI Automation	x		High	x	Moderate
[57] Costa, C.R.S.; Patrício, L.; Ferreira, P.; Varela, L.R. (2023)	RPA	Rule-Based Automation	x		High	x	Moderate
[58] Patrício, L.; Costa, C.R.S.;Fernandes, L.P.; Varela, M.L.R. (2023)	RPA	Rule-Based Automation	x		High	x	Moderate

Table 12. *Cont.*

	Technology Integration (RPA, Machine Learning, IoT)	Method/ Algorithm	Intelligent Automation	Continuous Learning	Flexibility and Scalability	Real-Time Monitoring	Energy Efficiency and Sustainability
[59] Patrício, L.; Avila, P.; Varela, L.; Cruz-Cunha, M.M.; Ferreira, L.P.;Bastos, J.; Castro, H.; Silva, J. (2023)	RPA	Rule-Based Automation	x		High	x	Moderate
[60] Patrício, L.; Costa, C.R.S.; Varela, L.; Cruz-Cunha, M.M. (2024)	RPA	Rule-Based Automation	x		High	x	Moderate
[61] Daase, C., Pandey, A., Staegemann, D.; Turowski, K. (2023)	RPA	Rule-Based Automation	x		High	x	Moderate
[62] Patrício, L.; Costa, L.; Varela, L.; Ávila, P. (2023)	RPA	Rule-Based Automation	x		High	x	Moderate
[This work]	RPA, Machine Learning	Rule-Based Automation, Decision Trees	x	x	High	x	High

The comparative analysis between existing studies and the proposed SIRPM model clearly demonstrates the distinct advantages that our model offers. Table 12 shows that while many previous models integrate technologies such as machine learning, the IoT, or RPA in isolation or with varying levels of automation, the SIRPM model stands out for its advanced combination of RPA and machine learning, providing intelligent automation and continuous learning. In addition, SIRPM stands out for its flexibility and scalability, allowing for efficient adaptations and expansions according to the company's needs. This integration results in more accurate and effective real-time monitoring in addition to an improvement in energy efficiency and sustainability, aspects that are often addressed in a limited way in existing models. Artificial intelligence (AI) is a broad field encompassing techniques to simulate human intelligence in machines. Machine learning (ML) is a subset of AI focused on systems capable of learning and improving from data without the need for explicit programming. Deep learning (DL), in turn, represents an advanced approach within ML, utilizing deep neural networks to solve complex problems such as pattern recognition in large volumes of data. In this model, ML is primarily used to identify patterns and predict failures, while DL can be applied to the analysis of complex data, such as images or time series. Although DL is a promising field, the decision was made to adopt ML due to the nature of the problem and the available data. DL is particularly effective in contexts where large volumes of unstructured data, such as images or videos, are common. However, in the present study, the amount of tabular data available for analysis does not justify the use of DL models, which require considerable computational resources. ML, on the other hand, offers an efficient, accessible, and suitable approach to address predictive maintenance, providing satisfactory performance with a more agile implementation.

The distinction between AI, ML, and DL, as presented in Table 12, can be observed based on the approaches adopted in studies related to artificial intelligence as follows:

- AI (artificial intelligence) encompasses various techniques to simulate human intelligence. Several articles mentioned in Table 12 utilize AI through diverse approaches, including machine learning algorithms, genetic algorithms, and dynamic programming.

- ML (machine learning), a subset of AI, focuses on systems that learn from data. Articles that explicitly use ML techniques, such as reinforcement learning algorithms, search algorithms, and Bayesian networks, aim to identify patterns and make predictions based on data.
- DL (deep learning) represents an advanced approach within ML, utilizing deep neural networks. The use of deep neural networks is more relevant in contexts involving large volumes of unstructured data, such as images or videos, which are not directly addressed in the studies in the table.

Thus, the differentiation is clear: AI encompasses various approaches, ML is a subset of AI that focuses on learning from data and is the most widely used in the studies presented, while DL is a more advanced and specific form of ML, typically applied to unstructured and more complex data. Shown below, it is possible to analyze each of the articles in terms of their description regarding their function and technological application.

- [26] Deep learning in predictive maintenance, which is used to predict failures in industrial equipment, helping to optimize processes and reduce maintenance costs.
- [27] Deep learning in predictive maintenance employs deep learning models to analyze data and predict failures in industrial systems, increasing efficiency and sustainability.
- [28] RPA in business process optimization involves the automation of business processes to increase efficiency, reduce errors, and contribute to organizational sustainability.
- [29] RPA in digital transformation, which is used to improve business process efficiency, reducing manual errors and accelerating digital transformation.
- [30] Machine learning in predictive maintenance uses machine learning algorithms to predict failures in industrial systems, helping to reduce costs and increase operational efficiency.
- [31] Machine learning in predictive maintenance employs machine learning models for predictive maintenance strategies, increasing productivity and minimizing downtime.
- [32] Technologies for smart manufacturing and predictive maintenance integrates AI and machine learning technologies to predict failures and improve sustainability in manufacturing.
- [33] RPA in Industry 4.0: RPA implementation for the automation of industrial processes, promoting efficiency and sustainability in the sector.
- [34] Machine learning in predictive maintenance uses machine learning techniques to predict failures in industrial systems, reducing costs and increasing operational efficiency.
- [35] Machine learning in predictive maintenance applies machine learning algorithms to optimize manufacturing operations and reduce unexpected failures.
- [36] RPA and AI in Industry 4.0 combines RPA and AI for the intelligent automation of industrial processes, optimizing operations and promoting sustainability.
- [37] Deep learning for the predictive maintenance of industrial robots uses deep neural networks to predict failures and optimize the maintenance of industrial robots.
- [38] Data-driven algorithms for predictive maintenance applies machine learning algorithms to optimize predictive maintenance strategies and reduce costs.
- [39] Sustainable technologies in Industry 4.0 integrates technologies to improve maintenance and reduce environmental impacts in industrial processes.
- [40] Machine learning in predictive maintenance uses machine learning to improve efficiency and predict failures in industrial systems, promoting sustainability.

- [41] Predictive maintenance and sustainability: the application of predictive maintenance to reduce environmental impacts and improve sustainability in industrial systems.
- [42] AI and the IoT for predictive maintenance integrates AI and the IoT to optimize predictive maintenance, contributing to sustainability and operational efficiency.
- [43] Machine learning in predictive maintenance uses machine learning to predict failures and optimize maintenance, ensuring greater efficiency in the industrial environment.
- [44] Industrial AI and predictive maintenance applies AI to predict failures and optimize processes, promoting sustainability in manufacturing.
- [45] Predictive maintenance and AI uses AI to optimize predictive maintenance, improving production and promoting more sustainable industrial practices.
- [46] RPA and sustainability in Industry 4.0: RPA as a tool to improve sustainability and efficiency in industrial processes.
- [47] AI and predictive maintenance: the application of AI for predictive maintenance in industrial environments, improving the efficiency and sustainability of processes.
- [48] RPA in sustainability in supply chains: RPA for process automation in supply chains, aiming at sustainability and operational efficiency.
- [49] The IoT and machine learning for predictive maintenance integrates the IoT and machine learning to optimize the maintenance of industrial systems and reduce failures.
- [50] Smart predictive maintenance with AI and machine learning applies AI and machine learning to improve predictive maintenance in industrial environments.
- [51] Predictive maintenance and environmental impact uses predictive maintenance to reduce the environmental impact of industrial processes and promote sustainable practices.
- [52] Integration of AI and the IoT for predictive maintenance combines AI and the IoT to optimize maintenance and ensure sustainability in industrial systems.
- [53] Sustainable RPA: the implementation of sustainable RPA in industrial processes, promoting efficiency and reducing environmental impact.
- [54] Machine learning for predictive maintenance in Industry 4.0 uses machine learning to optimize maintenance and improve the efficiency of industrial systems.
- [55] Deep learning for predictive maintenance applies deep learning to optimize maintenance and predict failures in industrial systems.
- [56] The integration of AI and RPA proposes a sustainable model for integrating AI and RPA in industrial processes, optimizing operations and promoting sustainability.
- [57] RPA and energy efficiency: RPA used to optimize industrial processes, improving energy efficiency and reducing consumption.
- [58] Framework for RPA implementation: development of a framework for RPA project implementation and control, focusing on sustainability and operational efficiency.
- [59] Decision models for sustainable RPA implementation: review of decision models for the sustainable implementation of RPA, aiming for optimization and reduction in environmental impacts.
- [60] Sustainable RPA implementation in healthcare administrative services: analysis of RPA implementation in healthcare, focusing on sustainability and efficiency.
- [61] Universal model for sustainable RPA implementation: proposal of a universal model for sustainable RPA implementation, promoting efficiency and sustainability.
- [62] Sustainable RPA implementation: development of a mathematical model for the sustainable implementation of RPA across different industrial contexts.

The IoT plays a crucial role in real-time data collection and transmission. Many of the solutions highlighted in Table 12 adopt wireless technologies due to their efficiency and mobility. However, in specific cases, wired networks may be employed depending on security and bandwidth requirements. Table 12 illustrates a combination of technologies such as RPA, machine learning, the IoT, and AI, with a focus on intelligent automation and energy efficiency, among other aspects. The interaction between the IoT and technologies such as RPA and machine learning is noteworthy, especially in the development of smart solutions for automation and monitoring. The IoT, by integrating connected devices, facilitates data collection and communication between systems, allowing for the application of machine learning algorithms for predictive analysis and process optimization. Regarding IoT solutions, the table reveals that it is often associated with machine learning technologies, especially in contexts involving techniques such as random forest, decision trees, and support vector machines (SVMs), applied to process data collected from IoT devices. These systems may include both wired and wireless solutions, depending on the context's needs.

Wireless solutions (greater mobility and efficiency): These solutions are predominantly used in IoT technologies, being more common in environments that require greater flexibility and mobility. Examples include wireless sensor networks and IoT devices connected via Wi-Fi or 5G, offering freedom of movement and ease of implementation. Wired solutions: These are applied in scenarios requiring more stable communication and higher bandwidth, such as industrial installations or local area networks (LANs). Wired IoT devices are typically used when more reliable and secure connections are needed. In the case of IoT solutions associated with technologies such as RPA and machine learning, the trend is towards wireless systems. This choice is characteristic of scenarios that require greater mobility and efficiency, as wireless technologies offer greater flexibility and ease of implementation, especially in dynamic and scalable environments. Technologies such as Wi-Fi, Bluetooth, Zigbee, LoRa, and 5G are frequently used in IoT devices to ensure efficient communication without the need for complex physical infrastructure. These technologies enable real-time data collection and remote monitoring, which is crucial for applications in intelligent automation and sustainability, as evidenced in the table. While wired solutions (such as Ethernet or industrial cables) provide greater stability and bandwidth, they are less common in IoT solutions geared towards mobility and efficiency. Wired solutions are more frequently adopted in specific environments requiring greater reliability and security, such as complex industrial installations. The IoT, in most cases mentioned in the table, is associated with wireless solutions, offering greater mobility, flexibility, and efficiency.

The SIRPM model positions itself as a robust and innovative solution in the field of predictive maintenance. It offers a set of features and benefits that provide greater operational efficiency, cost reduction, and better data-driven decision-making. The integration of advanced technologies such as RPA, machine learning, and the IoT results in a system capable of continuously adapting to changes, ensuring sustainability and reducing environmental impacts, in addition to promoting the training of operational teams.

In the context of the proposed model, scalability is an essential characteristic to assess the system's ability to handle increases in demand without compromising its efficiency. Limited scalability refers to a system that can only support small expansions, requiring significant infrastructure changes to handle a significant increase in load. Moderate scalability, on the other hand, allows for some degree of adjustment but still requires modifications to accommodate substantial increases in demand. High scalability indicates that the system is capable of supporting large expansions without the need for structural changes, maintaining efficiency and performance without interruptions, regardless of the workload.

With regard to energy efficiency, this is defined as the system's ability to perform its functions with minimum energy consumption, optimizing the use of resources and thus reducing operating costs. Energy efficiency not only seeks to minimize the need for energy but also to ensure that the system operates sustainably. When integrated with sustainability, energy efficiency gains an additional dimension, promoting a reduction in the environmental impact of operations. This involves using technologies that not only reduce energy consumption but also favor renewable sources and practices that minimize the waste of resources. Thus, energy efficiency and sustainability are directly associated with the implementation of solutions that ensure both system performance and environmental responsibility, aligning with responsible business practices and the adoption of green technologies in the automation process.

The main advantages of the SIRPM model in relation to existing models are as follows:

1. Advanced technology integration (RPA, machine learning): it offers a robust and comprehensive combination of technologies, providing greater effectiveness and a continuous flow of data between sensors, analysis platforms, and operational teams.
2. Intelligent automation: it minimizes human intervention, reducing errors and making the process more efficient and secure.
3. Continuous learning: the machine learning system continuously adapts based on operational feedback, enhancing the accuracy of predictions and decision-making over time.
4. Flexibility and scalability: the model is modular and can be implemented gradually according to the specific needs of the company, allowing for expansion into other sectors or areas of the organization.
5. Real-time monitoring: immediate anomaly detection and real-time alert generation facilitate a quick response to failures, reducing unplanned downtime.
6. Energy efficiency and sustainability: the model promotes resource optimization and waste reduction, aligning with environmental goals and corporate sustainability regulations.

These features not only make the SIRPM more effective but also ensure it is a long-term solution for companies seeking innovation, cost reduction, and sustainability in the management of their industrial assets.

5. Case Study

5.1. Case Study Presentation

Alpha is a small family-owned business located in an industrial area of a Portuguese city. Its primary activity involves the production of cardboard packaging for the food sector, with a particular focus on manufacturing boxes for the transportation and storage of fresh food. The company operates a production line consisting of several automated machines, yet it has faced recurring issues with machine breakdowns, resulting in frequent production stoppages.

Alpha employs a total of 11 staff members, distributed as follows:

- Management (one person): The owner of the company is responsible for overall management and supervision. While actively involved in the factory operations, he makes strategic decisions and handles administrative matters.

Administrative Department (three people):

- One financial manager oversees the company's finances and cash flow, ensuring that production remains within a controlled budget.
- One production planning engineer is responsible for planning production schedules, ensuring orders are met on time and that machines operate within the designated hours.
- One marketing manager is focused on brand promotion and customer relations, ensuring client retention and the acquisition of new business.

Production Department (six people):

- One production manager (production supervisor) oversees the production line, ensuring smooth operations during the work shift.

- Two machine operators operate the machines that produce the packaging, ensuring the production process follows technical specifications and that materials are available.
- One maintenance technician (responsible for basic maintenance) is responsible for performing minor repairs and adjustments to the machines when simple failures occur, such as part replacements or calibration adjustments. However, they did not perform systematic predictive or preventive maintenance.
- Two production support workers (packers and auxiliary operators) assist with packaging finished products and keeping the production process organized, moving boxes and materials.

Logistics Department (one person):

- One driver/logistics manager is responsible for the distribution of packaging to customers and suppliers, as well as managing the flow of materials within the factory.

Although Alpha had a functional structure and smooth operations, it faced significant challenges related to machine maintenance. Breakdowns were frequent, particularly with some of the older machines, which experienced unexpected downtimes. The core issue was the lack of predictive maintenance; only mandatory maintenance was carried out, scheduled by the external maintenance company with which the business had a contract.

The production manager, together with the maintenance technician, handled the simpler faults, but machine stoppages still occurred unexpectedly. When more severe breakdowns took place, factory production would be interrupted, resulting in order delays, loss of efficiency, and increased costs due to the need for urgent repairs. Without a real-time monitoring system, the factory was vulnerable to unforeseen failures, which led to prolonged periods of inactivity, affecting the company's ability to meet delivery deadlines.

This situation became unsustainable, prompting the owner, along with the production manager and the production planning engineer, to consider implementing a more advanced system to address the breakdowns. The inability to predict or even anticipate failures before they caused production stoppages was negatively impacting both internal operations and relationships with customers. As a result, the need arose to seek more effective solutions to optimize the factory's operation and reduce the costs associated with unexpected failures.

At this point, the company began exploring technological solutions that could improve production efficiency and machine reliability, leading them to investigate options such as real-time monitoring systems, predictive maintenance, and the use of modern tools to assist in early fault detection and maintenance optimization.

This process of adaptation and technological modernization marked the first step for Alpha in overcoming its maintenance challenges and ensuring a more efficient and sustainable future for its operations.

The implementation of SIRPM in the case study was based on RPA processes optimized for the collection, processing, and analysis of operational data from industrial equipment. These automated processes were implemented in virtual machines (VMs) configured in a hybrid cloud environment. RPA software (Uipath 2022.4.1) licenses were installed directly on the VMs, where the robots executed the automations necessary to interact with platforms to access the databases.

IoT sensors were strategically positioned on the machines to monitor critical variables such as temperature, vibration, and pressure.

The data collected by the sensors were transmitted via LTE and Wi-Fi-based telecommunications networks to IoT gateways. These gateways played a crucial role in efficiently aggregating and transmitting this information to the central operations system. This connectivity architecture was designed to ensure low latency and high reliability in real-time data flow, essential characteristics for predictive maintenance and industrial automation systems.

Similar IoT architectures using LTE and Wi-Fi networks have been widely used in industrial and automation systems. For example, studies such as [63,64] discuss the use of IoT gateways for efficient communication in high-data-density scenarios, while [65] explores the advantages of LTE in real-time applications, especially in critical environments.

Furthermore, hybrid cloud solutions, as described in [66], were considered in the system design, enabling effective integration between IoT gateways and centralized databases. The adoption of such an approach has shown promising results in balancing the scalability, security, and reliability of the system, being essential for the continuous transmission and processing of the collected data.

The data collected by the RPA robots were processed, which guaranteed consistency and suitability of the data for analysis. The information was then sent to the predictive maintenance model, which used machine learning-based algorithms to identify patterns and predict possible failures.

5.2. Application of the Model to the Case Study

To address Alpha's recurring machine breakdowns and maintenance inefficiencies, the SIRPM model is applied to optimize predictive maintenance through the integration of robotic process automation (RPA) and machine learning (ML). Below is the step-by-step implementation tailored to Alpha's context.

- Phase 1: Infrastructure Assessment

The evaluation of Alpha's infrastructure confirms the readiness for data collection and connectivity.

Assessment Outcomes:

1. Smart sensors: install IoT-enabled sensors on critical machines to collect data on temperature, vibration, and pressure.
2. Connectivity: ensure a robust connection between sensors and a central data platform using Wi-Fi or industrial connectors for reliable real-time data flow.

- Phase 2: Automation of Data Collection and Processing

Automation is introduced to handle data collection, preprocessing, and validation.

Actions Implemented:

3. Deploy RPA bots to collect data directly from the installed sensors and Alpha's existing systems.
4. Automate preprocessing tasks like cleaning and normalizing data to make it analysis-ready. The preprocessing of the captured data was carried out in several steps to ensure its quality and usability. Initially, missing values were filled using linear interpolation to preserve data integrity. Then, outliers were identified and removed based on statistical metrics such as standard deviation. The data were then normalized, facilitating the predictive analysis and training of machine learning models. This transformation was essential to ensure comparability between different variables and reduce potential biases during analysis.
5. Validate data quality, ensuring only consistent and complete data are processed. Data quality validation is ensured through a rigorous pre-processing process, where automated actions are performed to ensure that the data collected from the sensors are consistent and complete. Initially, missing values are filled with linear interpolation, maintaining data integrity. Outliers are identified and removed based on statistical metrics, such as standard deviation, to avoid bias in the analyses. The data are then normalized to ensure comparability between different variables, facilitating the training of machine learning models. The final quality of the data is validated by automated checks, where it is compared with reference values and machine operating

conditions. Inconsistent data or data outside the expected parameters are flagged or discarded, ensuring that only valid data ready for analysis are used, guaranteeing the effectiveness of predictive analysis and the accuracy of decisions based on these data. For data validation, the following steps were performed:

  - Rigorous pre-processing: automated actions were implemented to ensure the consistency and completeness of sensor-collected data.
  - Filling of missing values: linear interpolation was used to maintain data integrity.
  - Outlier identification and removal: outliers were detected and eliminated based on statistical metrics, such as standard deviation, to avoid bias in the analyses.
  - Data normalization: variables were normalized to ensure comparability, facilitating the training of machine learning models.
  - Automated quality checks: data were compared against reference values and machine operating conditions to verify its validity.
  - Flagging or discarding inconsistent data: data outside expected parameters were either flagged or discarded, ensuring only valid data were used for analysis.
  - This process ensures effective predictive analysis and enhances the accuracy of decisions based on the validated data.

- Phase 3: Application of Machine Learning

Predictive models are developed and trained to forecast failures.
Steps Executed:

6. Algorithm selection: use decision trees for initial predictions due to the small dataset and ease of interpretation.
7. Develop and train ML models.
8. Generate failure forecasts, identifying patterns indicative of imminent breakdowns.

- Phase 4: Integration of Results with RPA

The ML model outputs are integrated into Alpha's operations through automation.
Integration Details:

9. Use RPA bots to extract ML predictions in real time.
10. Automate the cross-referencing of predictions with Alpha's operational norms, identifying deviations.
11. Highlight anomalies, enabling the identification of potential failures before they disrupt production.

- Phase 5: Action and Feedback

Proactive measures are taken based on predictions, and feedback loops are created to enhance system performance.
Implemented Measures:

12. Automatically send alerts to the responsible department through RPA upon detecting deviations or failures.
13. Execute maintenance, ensuring corrective actions are taken based on forecasts and alerts issued.
14. Collect feedback on the usefulness of the received alerts, assessing whether they were accurate, relevant, and helped prevent issues.
15. Record this evaluation for machine learning algorithm learning, updating the model with the feedback received, enabling continuous learning and improved accuracy.

- Phase 6: Continuous Learning and Sustainability

Alpha ensures sustained efficiency through ongoing improvement and team adaptation.

Sustainability Measures:

16. Operational efficiency and sustainability through the calculation of key metrics, such as mean time to repair (MTTR), mean time between failures (MTBF), and sustainability indicators, such as reduced energy consumption and emissions.
17. Training and adaptation of teams for the predictive maintenance system, ensuring all teams are trained to interpret results and interact with the system.
18. Periodic review of system performance, conducting regular assessments of RPA bots, the accuracy of machine learning models, and the overall impact on the production process.

The application of the SIRPM model at Alpha demonstrated the feasibility and effectiveness of the sustainable integration of RPA and ML into predictive maintenance systems, addressing the challenges faced by the company in a structured way.

In the implementation of the SIRPM model, IoT sensors were strategically positioned on machines to monitor critical variables such as temperature, vibration, and pressure. These sensors were intended to identify operational anomalies and prevent failures by sending the collected data via LTE and Wi-Fi telecommunications networks to IoT gateways. The gateways aggregated the information and transmitted it to the central operations system, ensuring a real-time data flow with low latency and high reliability.

An RPA robot, installed on a virtual machine configured in a hybrid cloud environment, was periodically executed to access the collected data. This robot extracted the information from the central system and stored it in a SQL database.

Data processing and next-value predictions were performed using machine learning algorithms implemented in a secure virtualized environment. This environment, developed with Python, integrated libraries such as Pandas, NumPy, and Scikit-learn for data manipulation, mathematical operations, and predictive modeling.

A second RPA robot was automatically triggered, analyzed the value, and if the predicted value was outside the defined reference range, the robot generated an alert. This alert was sent via email to the maintenance team, allowing for a proactive response and mitigation of potential failures before they compromised operations.

This integrated architecture, using IoT sensors, RPA, and machine learning, was designed to optimize the collection, processing, and analysis of operational data, ensuring greater efficiency and reliability in machine monitoring.

Data processing and forecast generation were performed by a computational service configured to integrate data from the SQL database and execute machine learning algorithms, using an architecture based on Python libraries. This service is designed to interact directly with the maintenance management system, offering real-time forecasts.

Additional Process Description:

1. Integrated Computing Service:

An automated service was deployed in a virtualized environment to access the data collected and stored in the SQL database. This service has been configured to perform the following:

- Connect to the SQL database through ODBC drivers, ensuring compatibility and security in data transmission.
- Execute pre-defined workflows that include the preprocessing, normalization, and application of machine learning algorithms.

2. Interfaces Used:

- Database interface: the service used structured queries to extract data from the SQL database, handling large volumes of records and applying filters for the most recent data (last 24 h).
- Results interface: after generating the forecasts, the predicted values were automatically inserted into a dedicated table within the same SQL database, allowing for tracking and integration with the alert system.

3. Controls and Automation:
   - The service has been scheduled to automatically run tasks at regular (hourly) intervals using scheduling tools within the server operating system.
   - Machine learning algorithms were implemented in a secure virtualized environment designed to ensure system integrity during data processing and analysis.
4. Interaction with the Alert System:
   - After processing and predictive analysis, the service would forward the results to a second automated system (controlled by RPA). This system checked whether values were outside pre-defined limits and, if they were, triggered automatic notifications to the maintenance team.
5. Libraries Used:
   - Pandas and NumPy: data manipulation, normalization, and mathematical operations.
   - Scikit-learn: decision tree model training and inference (CART).
   - SQLAlchemy: integrating and managing SQL database connections.

In Figure 3, a schematic diagram is presented, illustrating the integrated sequencing of the operational flow of the model applied in the company. This diagram will visually represent the step-by-step process, from the data collection via IoT sensors to the RPA robots' data extraction, processing, predictive analysis, and the final alert generation in case of anomalies, showcasing the seamless interaction between technologies in the predictive maintenance process.

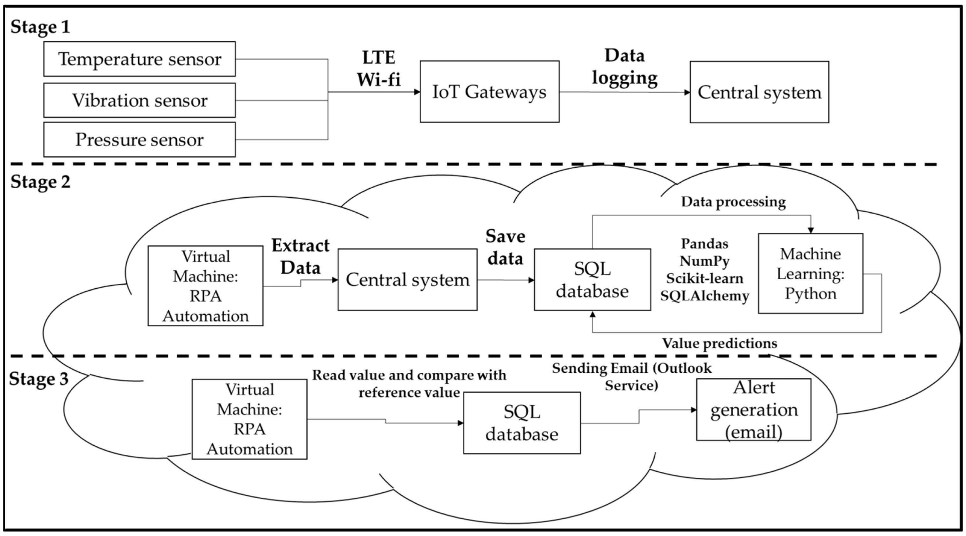

Figure 3. Schematic diagram of the operational flow of the predictive maintenance model applied to the company.

5.3. Detailed Description of the SIRPM Model

The SIRPM model was implemented at Alpha Company to optimize predictive maintenance for critical machinery using robotic process automation (RPA) and machine learning (ML) technologies.

Investigation duration: 12 months, including data collection, model training, and implementation.

Working hours in Portugal: 8 h/day.

Work shifts per day: two shifts of 8 h, totaling 16 h daily.

The following sections detail the implementation process, technologies used, and results obtained:

- Phase 1: Infrastructure Assessment

To ensure the feasibility of the SIRPM model, the process began with an evaluation of the company's infrastructure, examining its ability to connect sensors and integrate necessary platforms. Alpha's infrastructure supported real-time data collection, enabling the installation of IoT sensors on selected machines.

Machines Analyzed:

- ○ Paper cutter—vibration sensor to monitor mechanical wear.
- ○ Hydraulic press—pressure sensor to detect variations in hydraulic fluid.
- ○ Flexographic printer—temperature sensor to predict overheating.

- Phase 2: Data Collection and Processing

During this phase, data collection was automated via smart sensors to ensure real-time information retrieval.

Technologies Used:

- ○ RPA: UiPath was employed to automate data collection from sensors connected to the machines. RPA (robotic process automation) was used to automate the collection of data from sensors connected to industrial machines. The tool chosen was UiPath, which was configured on a virtual machine in the hybrid cloud environment. In this environment, RPA robots were programmed to interact with the machines' control systems and extract real-time data, such as vibration, pressure, and temperature values. UiPath was programmed to perform automatic logins to the machines' monitoring systems, access the sensor data, and organize it in a structured way. After collection, the RPA sent the data to a SQL database, where it was stored for later analysis. The programming was performed using the UiPath Studio graphical interface, which allows you to create automated flows through specific activities for each task, such as logging in, extracting, and sending data.
- ○ Python: Used for pre-processing and normalization, ensuring consistency and readiness for analysis. Python was used to access data from the SQL database using SQLAlchemy, clean missing values, and normalize variables for predictive analysis, with libraries like Pandas, NumPy, and Scikit-learn. Python was also used to feed a machine learning-based predictive model, which identified patterns and predicted possible machine failures. The Python scripts were executed on virtual machines within the same cloud environment, enabling integration with the data collected by the RPA, ensuring the continuity of the automated predictive maintenance process.

Data collection (Table 13) was conducted over five months, with historical data stored on local servers and in the cloud for subsequent analysis.

The data presented in this table correspond to the monthly averages of the data collected throughout the year. To build the model, the data recorded every hour by the sensors were used. However, to facilitate visualization and analysis in this work, it was decided to present the accumulated average values of each month, allowing for a clearer and more concise interpretation of the information throughout the analyzed period.

Table 13. Historical data summary (first 5 months).

Month	Average Vibration (Cutter) (mm/s)	Average Pressure (Press) (bar)	Average Temperature (Printer) (°C)
1	1.2	150	75
2	1.3	145	78
3	1.4	140	80
4	1.5	138	82
5	1.3	142	77

- Phase 3: Machine Learning Model Training

With the historical dataset ready, the machine learning (ML) model was trained. Decision trees (CART) were chosen for their simplicity and interpretability, especially given the limited data volume.

Training Process:

- Data cleaning: removal of inconsistencies and handling of missing values.
- Normalization: scaling data to ensure comparability and training accuracy.
- Data splitting: 80% of the data was used for training, with 20% reserved for model validation.

The CART algorithm (classification and regression trees) was configured to identify failure patterns from the collected data. Decision trees are a widely used machine learning model that seeks to predict a value or class by constructing a hierarchical structure of decisions, represented by nodes. Each internal node of the tree corresponds to a condition on an attribute of the data, and the leaves contain the final prediction (value or class). The decision tree algorithm performs a series of divisions on the data based on criteria such as the Gini index or the mean squared error, aiming to optimize the homogeneity of the data in each subset generated. In the context of the SIRPM model, the regression tree (CART for regression) was chosen due to the objective of predicting continuous values, such as the time to failure in machines or the severity of component wear, rather than simply classifying a failure condition. The choice for regression was justified by the nature of the data collected (such as vibration, pressure, and temperature of machines), which are continuous numerical values, and the desired prediction was of a quantitative value, representing the probability or time to failure. The regression tree model was trained using historical machine data, after data cleaning and normalization, to accurately predict the occurrence of imminent failures, providing a continuous value that could be used to make preventive maintenance decisions. This approach was applied to the machine learning model with the CART algorithm training, using 80% of the data for training and 20% for validation in order to assess the accuracy of the model before its integration with the RPA system for automatic alert and maintenance actions.

- Phase 4: Predictive Model Implementation with RPA Integration

From the seventh month, the predictive machine learning model was integrated with the automated RPA system. The RPA bot (UiPath) was programmed to collect sensor data hourly, processing the last 24 h of information. The process involved the following:

1. The RPA bot collected data and stored it in a SQL database.
2. A Python script executed the machine learning algorithm, reading SQL table values, making predictions, and saving results in a new table.
3. A secondary RPA script analyzed predicted values. If anomalies were detected, it generated automated email alerts to the maintenance team, specifying the affected machine and identified value.

Automated Workflow:

1. Data collection: sensors provided data stored in the SQL database.
2. Data processing: the ML model analyzed patterns and made predictions.
3. Alerts: anomalous values triggered automatic email notifications to the maintenance team.

Technologies Used:

- UiPath: for data collection and alert automation.
- Python (scikit-learn): for developing the machine learning model, leveraging libraries such as Pandas, NumPy, and matplotlib for data analysis and visualization.

The identification of alert values for each type of sensor in Alpha machines was based on the typical reference values mentioned by the company, with the aim of monitoring machine performance and anticipating imminent failures. The reference values for each sensor were defined to ensure efficient operation of the equipment and minimize failures during the manufacturing process. Below, we explain how alerts were identified for vibration, pressure, and temperature sensors, based on the standard values and established limits.

- Vibration sensor (paper cutter): Excessive vibration is one of the first signs of mechanical wear or misalignment of machine parts. The ideal vibration range for the paper cutter was defined between 1.0 and 1.3 mm/s, considering normal machine operation. When vibration exceeded 1.5 mm/s, this indicated a possible imminent mechanical failure, such as a misalignment of parts or excessive wear, which could compromise machine operation. On the other hand, if the vibration fell below 1.0 mm/s, this could indicate that the machine's moving components were having little interaction or contact, which could also cause operational problems. These values were used as a basis for triggering automatic alerts so that the maintenance team could investigate potential failures before they occurred.
- Pressure sensor (hydraulic press): The pressure of the hydraulic fluid in the hydraulic press is essential to ensure that the pressing process occurs correctly and with quality. The ideal pressure range was established between 145 and 150 bar, with values outside this range indicating potential problems. If the pressure rose above 155 bar, this could signal failures in the pressure control system or even blockages in the hydraulic line, which would affect the quality of the packaging formation. On the other hand, pressures below 140 bar indicated that the hydraulic pressure was below what was necessary, which would impair the efficiency of the process and could cause failures in the pressing process. These alert values helped to anticipate the necessary maintenance, avoiding failures during operation.
- Temperature sensor (flexographic printer): The temperature of the printheads is crucial to ensuring print quality and the efficiency of the flexographic printer's operation. The ideal temperature range was defined as between 75 and 80 °C, with upper and lower limits to alert for failures in the cooling or heating system. If the temperature rose above 85 °C, this could indicate failures in the cooling system, which would result in overheating and possible damage to the printheads. Temperatures below 70 °C, on the other hand, indicated failures in the heating system, compromising print quality. These alerts were essential to avoid damage to the equipment and ensure the continuity of the production process.

These reference values and alerts were fundamental to the predictive maintenance system implemented by Alpha. Using the data collected by the sensors, the system was able to quickly identify when values were outside the ideal range, generating automatic alerts for the maintenance team. This allowed preventative maintenance to be carried out before serious failures occurred, improving operational efficiency and reducing machine downtime.

- Phase 5: Proactive Action and Feedback

When the model predicted an imminent failure, RPA automatically alerted the responsible teams, prompting corrective actions such as adjustments or repairs.

Implemented Actions:

- ○ Automated email alerts to the maintenance team.
- ○ Execution of corrective maintenance and preventive adjustments.
- ○ Feedback collection on alert effectiveness and prediction accuracy.

The proactive measures' outcomes were monitored to refine the model using intervention feedback, thereby improving machine learning predictions.

- Phase 6: Sustainability and Continuous Improvement

To ensure the model's sustainability and continued efficiency, key performance indicators such as the MTTR (mean time to repair) and MTBF (mean time between failures) were calculated, alongside sustainability metrics related to energy consumption and emissions reduction.

Continuous Monitoring:

- ○ The machine learning model's performance was periodically reviewed.
- ○ The RPA system was adjusted as needed for accuracy and efficient integration.
- ○ Continuous staff training ensured adaptation to the new predictive maintenance methodology.

The machine learning model implemented in this study is a post-processing approach. The decision tree (DT) model was executed periodically at hourly intervals to process the data collected by the RPA system. This process was essential for generating failure predictions in the monitored systems based on the selected critical variables, such as T (temperature), V (velocity), and P (pressure). These variables were chosen for their significance to machinery performance, enabling precise analysis and the anticipation of potential failures.

The regressor employed in the decision tree model was a regression algorithm based on decision trees. The model's outputs, namely the failure predictions, directly influence the RPA processes of the machinery. When a failure is predicted, the RPA system triggers alerts to notify the maintenance team of potential intervention needs.

The integration process between the machine learning model and the RPA system follows a continuous monitoring cycle, during which the performance of the model is periodically reviewed. With each adjustment or enhancement made to the ML model, the RPA system is updated to ensure the accuracy and efficiency of the integration.

The MTBF (mean time between failures) is a metric that measures the average time between failures of a piece of equipment or system during its operation. The higher the MTBF, the better the system's reliability.

The formula for calculating the MTBF is

$$\text{MTBF} = (\text{Total Operating Time})/(\text{Number of Failures});$$

where

- Total Operating Time is the time during which the system or equipment is running without failures.
- Number of Failures is the number of failures that occur during the considered time period.

The MTTR (mean time to repair) is a metric that measures the average time required to repair a piece of equipment after a failure. The lower the MTTR, the faster the equipment is repaired and returned to operation.

The formula for calculating the MTTR is

$$\text{MTTR} = (\text{Total Downtime})/(\text{Number of Failures});$$

where

- Total Downtime is the total time during which the system or equipment was out of operation due to failures.
- Number of Failures is the number of failures that occur during the considered time period.

In the present study, calculations based on specific formulas were used to evaluate percentage reductions in different cost categories related to maintenance and operations. These calculations were performed based on the values provided by the company, with the following formulas applied:

- The formula for calculating REDUCTION_Average Repair Costs is

$$\text{REDUCTION\_Average Repair Costs \%} = [1 - [(\text{AFTER\_ Average Repair Costs})/(\text{BEFORE\_ Average Repair Costs})]] \times 100;$$

- The formula for calculating REDUCTION_ Total Maintenance Costs is

$$\text{REDUCTION\_ Total Maintenance Costs \%} = [1 - [(\text{AFTER\_ Total Maintenance Costs})/(\text{BEFORE\_ Total Maintenance Costs})]] \times 100;$$

- The formula for calculating REDUCTION_ Unplanned Downtime Costs is

$$\text{REDUCTION\_ Unplanned Downtime Costs \%} = [1 - [(\text{AFTER\_Unplanned Downtime Costs})/(\text{BEFORE\_ Unplanned Downtime Costs})]] \times 100;$$

- The formula for calculating REDUCTION_ Total Operational Costs is

$$\text{REDUCTION\_ Total Operational Costs \%} = [1 - [(\text{AFTER\_ Total Operational Costs})/(\text{BEFORE\_ Total Operational Costs})]] \times 100;$$

The first formula measures the percentage reduction in total operational costs over the analyzed period, reflecting the overall impact of the implemented strategies. The second formula calculates the reduction in costs associated with unplanned downtime, highlighting improvements in operational efficiency. The third formula evaluates the percentage decrease in total maintenance costs, offering a clear view of the cost-saving measures implemented. Lastly, the formula for average repair costs measures the percentage reduction by comparing the values before and after the improvements, showcasing the effectiveness of the interventions.

Regarding sustainability metrics, the company identified and monitored five main criteria, namely energy consumption, CO_2 emissions, waste produced, use of materials, and recycling rate. For each of these criteria, historical values were provided before and after the model was implemented. The percentage reduction was calculated based on the difference between the values before and after implementation, where the value obtained after implementation was divided by the previous value, subtracted from one and multiplied by 100. These calculations allow us to accurately measure the improvement in terms of sustainability. Energy consumption and CO_2 emissions are crucial to assessing a company's environmental impact, and reducing these indicators is directly related to reducing the carbon footprint. The waste produced and the use of materials reflect the efficiency in the use of natural resources, while the recycling rate indicates the company's commitment to sustainability in waste management. These values were tracked by the company, allowing for a detailed analysis of the environmental gains resulting from the implementation of the model.

$$\text{REDUCTION \%} = [1 - [(\text{AFTER Implementation})/(\text{BEFORE Implementation})]] \times 100;$$

6. Analysis of Results and Discussion

6.1. Analysis of Results

In this chapter, the results obtained after implementing the model will be presented and analyzed. To this end, we will present data from one month of implementation, which was during month 8 of operation. During this period, the factory was in operation for 22 business days, and on each of these days, 16 daily predictions were generated for each sensor installed on the monitored machines. These predictions were made based on data from the last 24 h of operation using a machine learning model, specifically decision trees, which was executed every hour. The model considered critical variables such as the vibration, pressure, and temperature of each machine.

For each sensor, the execution of the model generated a single prediction for the next hour of operation, based on the most recent historical data. In practical terms, the prediction generated for the "next hour" was based on information from the last 24 h and the model's learning history.

Over the 22 business days of operation, the model generated a total of 352 predictions, distributed among the three types of sensors, namely vibration, pressure, and temperature sensors. To facilitate analysis, the results are presented through three distinct graphs, each corresponding to a type of sensor as follows: vibration (Figure 4), pressure (Figure 5), and temperature (Figure 6), allowing for a clear visualization of the fluctuations in the predictions and the comparison of the predicted failures throughout the month.

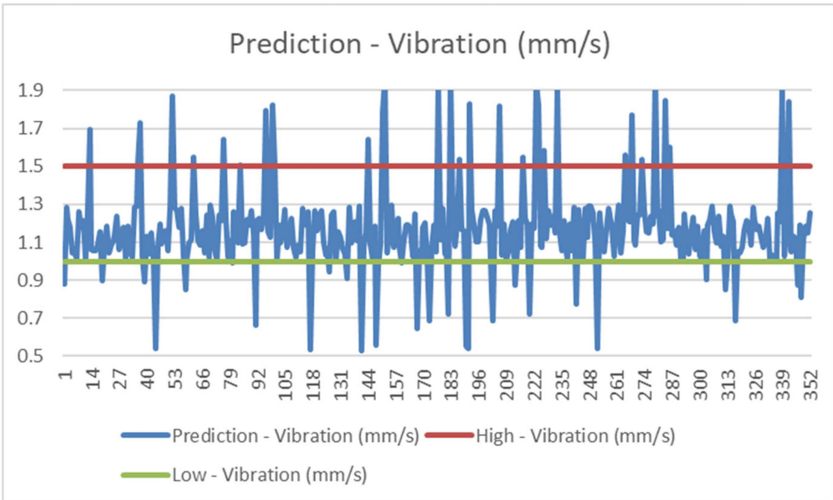

Figure 4. Prediction—vibration (mm/s).

When the predicted values for the vibration, pressure, and temperature sensors exceeded the established upper or lower limits, an automatic alert was generated for the maintenance team. These limits were defined as follows: for vibration, the maximum and minimum values were 1.5 mm/s and 1 mm/s, respectively; for pressure, the limits were 155 bar (maximum) and 140 bar (minimum); and for temperature, the established limits were 85 °C (maximum) and 70 °C (minimum).

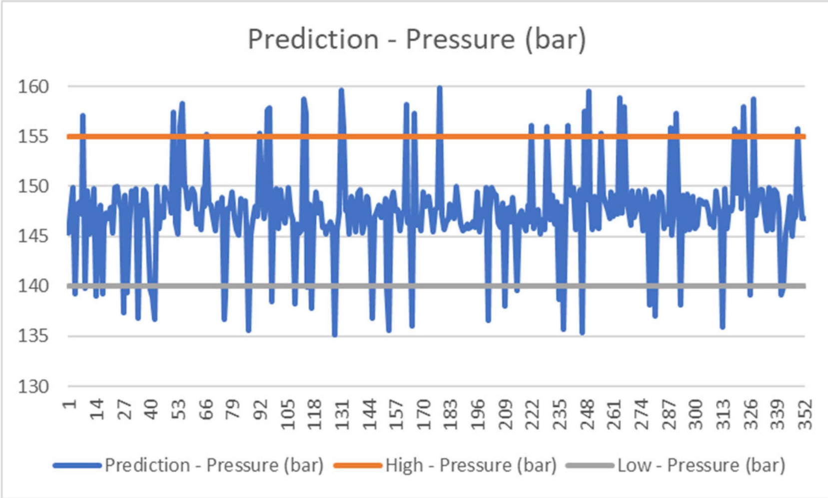

Figure 5. Prediction—pressure (bar).

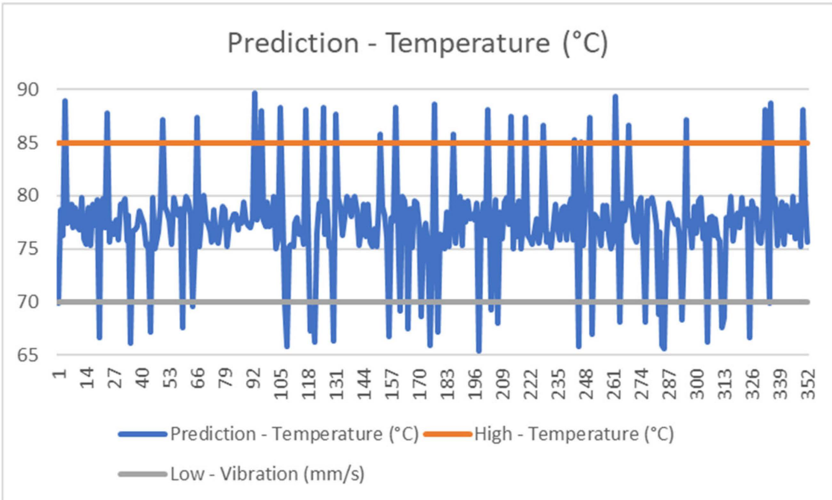

Figure 6. Prediction—temperature (°C).

Whenever the predicted values for any of these parameters exceeded the limits, an alert was triggered, allowing the maintenance team to be immediately notified. This approach was crucial in preventing unexpected failures, as it allowed the team to monitor the machine proactively, identifying potential problems and carrying out the necessary maintenance before they could result in unforeseen downtime or serious damage to the machines.

The implementation of the SIRPM model at Alpha resulted in significant improvements in both operational efficiency and sustainability. The analysis presents the key performance indicators (KPIs) before and after the adoption of the model during the 6-month operating period between months 7 and 12. This analysis highlights the effectiveness of the predictive maintenance system and its impact on cost reduction, resource optimization, and environmental sustainability.

The effects of the SIRPM model on maintenance performance are evident when comparing the key indicators before and after its implementation. These indicators clearly demonstrate the operational benefits achieved with the predictive maintenance system, which combines RPA and machine learning.

For the analysis, the values were compared with the historical maintenance data from the previous year, which were provided by the company.

The impact of the SIRPM model on maintenance performance can be clearly seen in the comparison of key metrics before and after its adoption. These metrics show the operational benefits achieved through the predictive maintenance system, which integrates RPA and machine learning (Table 14).

Table 14. Maintenance performance improvements.

Metric	Before Implementation	After Implementation	Improvement
Mean Time Between Failures (MTBF)	23.47 h/events	70.4 h/events	+100%
Mean Time to Repair (MTTR)	12 h	4 h	−67%
Unplanned Downtime Events	15 events/month	5 events/month	−66.67%
Failure Prediction Accuracy	+60%	+90%	+50%

The formula for calculating MTBF is

$$\text{MTBF} = (\text{Total Operating Time})/(\text{Number of Failures});$$

Before the implementation of improvements, the company operated with an average of 15 failures per month. Considering that the monthly operation is 352 h (22 working days × 16 working hours per day), the MTBF calculation before implementation was

$$\text{MTBF (before)} = (352\ \text{h})/(15\ \text{events/month}) = 23.47\ \text{h/events}$$

This means that on average, failures occurred every 23.47 h of operation.

After implementing the improvements, the number of failures was reduced to five failures per month. The MTBF calculation after implementation was

$$\text{MTBF (after)} = (352\ \text{h})/(5\ \text{events/month}) = 70.4\ \text{h/events}$$

In other words, with the reduction in the number of failures, the system began to operate for an average of 70.4 h between failures, representing a +100% improvement in the MTBF.

The MTTR is

$$\text{MTTR} = (\text{Total Downtime})/(\text{Number of Failures});$$

Before the improvements were implemented, the average time to repair a failure was 12 h. With 15 events per month, the total monthly downtime was

$$\text{Total Idle Time (before)} = 12\ \text{h/events} \times 15\ \text{h/events} = 180\ \text{h/month}$$

After implementation, the average repair time was reduced to 4 h per failure, with five failures per month. The total monthly downtime was

$$\text{Total Idle Time (after)} = 4\ \text{h/events} \times 5\ \text{h/events} = 20\ \text{h/month}$$

This results in a significant improvement in repair time, with a −67% reduction in the MTTR.

Failure prediction accuracy was provided directly as a business performance metric, with no additional calculation required. Prior to the implementation of the improvements, failure prediction accuracy was 60%, meaning that 60% of failures were correctly anticipated. After the implementation of the improvements, this accuracy increased to 90%, representing a significant increase in the ability to predict failures before they occur. The +50% improvement is a value provided by the business, reflecting improvements in failure monitoring and prediction practices and technologies, allowing for a more effective anticipation of failure events and, consequently, more reliable operation.

The predictive capabilities of the SIRPM model not only improved maintenance performance but also resulted in considerable cost savings (Table 15). By preventing catastrophic failures and reducing the need for emergency repairs, the model led to substantial reductions in repair and operational costs.

Table 15. Cost reduction.

Cost Category	Before Implementation	After Implementation	Reduction
Average Repair Costs	EUR 2500 per incident	EUR 1200 per incident	−52%
Total Maintenance Costs	EUR 4000/month	EUR 2500/month	−37.5%
Unplanned Downtime Costs	EUR 3500/month	EUR 1000/month	−71.4%
Total Operational Costs	EUR 30,000/month	EUR 25,000/month	−16.67%

As illustrated, the average repair costs decreased by 52%, from EUR 2500 to EUR 1200 per incident. This reduction reflects the ability of the predictive maintenance system to identify potential issues early, allowing for less costly repairs. The total maintenance costs also saw a 37.5% reduction, from EUR 4000 to EUR 2500 per month. Furthermore, unplanned downtime costs were significantly lowered by 71.4%, from EUR 3500 to EUR 1000 per month. This resulted in an overall decrease in total operational costs of 16.67%, from EUR 30,000 to EUR 25,000 per month.

The cost reduction figures presented in Table 15 were provided by the company and represent average costs for the period before and after the implementation of the predictive maintenance model based on a study conducted over a period of 6 months. These costs reflect the average expenditure on repairs and maintenance during this period, both before and after the implementation of the new system. With the ability to predict failures before they occur, interventions could be planned in advance, resulting in a significant reduction in unexpected failures and the costs associated with these failures. This contributed to a decrease in repair costs, maintenance costs, and unplanned downtime costs, as shown in the table, evidencing the effectiveness of the system in improving operational cost management.

In addition to operational and cost-related improvements, the SIRPM model contributed to significant sustainability gains. By improving operational efficiency and reducing waste, energy consumption, and emissions, the model helped Alpha achieve its environmental goals (Table 16).

Table 16. Environmental and sustainability improvements.

Environmental Metric	Before Implementation	After Implementation	Improvement
Energy Consumption	10,000 kWh/month	7500 kWh/month	−25%
CO_2 Emissions	5000 kg/month	3000 kg/month	−40%
Waste Produced	500 kg/month	350 kg/month	−30%
Material Usage	8000 kg/month	6500 kg/month	−18.75%
Recycling Rate	70%	85%	+21.43%

The energy consumption was reduced by 25%, from 10,000 kWh to 7500 kWh per month, as a result of a more efficient use of equipment and fewer unplanned downtimes. CO_2 emissions saw a reduction of 40%, from 5000 kg to 3000 kg per month, contributing to a lower environmental footprint. Similarly, waste produced decreased by 30%, from 500 kg to 350 kg per month, while material usage was reduced by 18.75%, from 8000 kg to 6500 kg per month. The recycling rate also improved, rising by 21.43%, from 70% to 85%, reflecting better resource management and sustainability practices.

The values presented in Table 16 regarding environmental and sustainability improvements were provided by the company, based on data collected during a period of 6 months, before and after the implementation of the predictive maintenance model (SIRPM). These values reflect the average of the environmental indicators during this study period and were used to compare the results before and after the application of the model.

Energy and CO_2 emissions reduction can be analyzed against recognized standards such as those defined by ISO 50001 (energy management system) [67], which provide essential guidelines for companies to manage energy efficiently and reduce environmental impacts. These standards are widely adopted by companies worldwide to promote continuous improvement in energy and environmental performance.

- ISO 50001 focuses on the continuous improvement of energy performance, with the main goal of reducing energy consumption. The standard suggests a reduction of 5% to 10% per year in companies that implement energy management systems [68]. The 25% reduction in energy consumption observed at Alpha significantly exceeds the standard's objectives, demonstrating excellent performance in terms of energy efficiency.

The cost reductions and efficiency improvements also translated into stronger financial performance for Alpha, demonstrating the long-term economic benefits of adopting predictive maintenance technologies (Table 17).

Table 17. Financial impact.

Financial Metric	Before Implementation	After Implementation	Improvement
Profit Margin	5%	12%	+7%

As seen in the table, the profit margin increased from 5% to 12%, reflecting the overall financial benefit of reduced maintenance and operational costs. This increase in profitability highlights the effectiveness of the SIRPM model in not only enhancing operational efficiency but also contributing to the company's financial growth.

The calculations and surveys performed to measure improvements in maintenance performance, energy consumption, and emissions were based on manual records from the maintenance team before and after the implementation of the SIRPM model. During the period in which the model was not applied, the maintenance team recorded all failures, repair times, downtime events, and energy consumption manually, using spreadsheets and daily reports to monitor equipment performance and operations. With the implementation of the predictive model, the team began to compare the data from each month with the records from the previous year, now with the adoption of the predictive system, which included greater accuracy in failure predictions, optimization of repair time, and better energy management practices. The comparison between the periods before and after the application of the model allowed for the quantification of improvements in terms of reduced operating costs, maintenance efficiency, and sustainability, such as energy consumption and CO_2 emissions, validating the positive impacts of the adopted solution.

6.2. Discussion

The implementation of the SIRPM (smart integrated predictive maintenance) model at Alpha represents a significant advancement in both operational efficiency and sustainability. The results clearly demonstrate the effectiveness of the predictive maintenance system, which integrates RPA (robotic process automation) and machine learning, contributing to improvements across multiple dimensions, such as maintenance performance, cost efficiency, sustainability, and overall financial outcomes. These findings are not only relevant to Alpha but also offer valuable perceptions for broader applications across various industries.

The analysis of the key performance indicators (KPIs) revealed substantial improvements in operational performance. Notably, the mean time between failures (MTBF) more than doubled, from 23.47 h per event to 70.4 h per event, representing a 100% improvement. This increase in the MTBF highlights the enhanced reliability of the machinery, allowing Alpha to reduce unplanned downtime and improve overall productivity. Furthermore, the mean time to repair (MTTR) saw a remarkable reduction of 67%, from 12 h to 4 h, reflecting more efficient and faster response times from the maintenance team.

These improvements are directly attributable to the predictive capabilities of the SIRPM model, which allowed Alpha to anticipate and address failures before they occurred. The increased prediction accuracy, from 60% to 90%, demonstrates the effectiveness of machine learning in improving failure detection and proactive maintenance strategies. This reduced downtime and repair time, ultimately enhancing operational performance and reducing costs.

The financial benefits of implementing the SIRPM model are equally impressive. The reduction in average repair costs by 52%, from EUR 2500 to EUR 1200 per incident, and the 37.5% reduction in total maintenance costs, from EUR 4000 to EUR 2500 per month, clearly demonstrate the cost-saving potential of predictive maintenance. The model enabled the company to reduce unplanned downtime costs by 71.4%, from EUR 3500 to EUR 1000 per month, leading to a substantial decrease in total operational costs, down by 16.67%, from EUR 30,000 to EUR 25,000 per month. These reductions were driven by the model's ability to identify potential failures early, allowing for less expensive and more planned repairs rather than emergency interventions.

Additionally, the predictive maintenance model led to a more efficient allocation of resources. By reducing the need for emergency repairs and minimizing unplanned downtime, Alpha was able to better manage its workforce, repair materials, and energy resources, ultimately leading to reduced operational costs and improved profitability.

The environmental impact of the SIRPM model was also substantial. The reduction in energy consumption by 25%, from 10,000 kWh to 7500 kWh per month, can be attributed to the more efficient use of machinery and reduced downtime. Similarly, CO_2 emissions decreased by 40%, from 5000 kg to 3000 kg per month, and waste production decreased by 30%, from 500 kg to 350 kg per month. The improvement in material usage, which dropped by 18.75%, from 8000 kg to 6500 kg per month, reflects better resource management practices. The recycling rate also saw an improvement, rising by 21.43%, from 70% to 85%, indicating a stronger commitment to sustainability and efficient resource use.

These environmental improvements align with global sustainability standards, such as ISO 50001, which focuses on continuous energy performance improvement. The 25% reduction in energy consumption exceeds the standard's typical targets of 5–10% annual reductions, demonstrating Alpha's leadership in energy efficiency.

The implementation of the SIRPM model had a positive effect on Alpha's workforce. Employees were provided with training to operate new technologies, which enhanced their technical skills and empowered them to make more data-driven decisions. This upskilling not only increased employees' engagement with the system but also fostered a culture of continuous learning and improvement. As employees became more adept at using the predictive maintenance system, they were able to contribute more effectively to proactive maintenance efforts, resulting in greater operational ownership and improved team collaboration.

The workforce's enhanced technical capabilities also contributed to greater job satisfaction, as employees were more involved in the decision-making process and better equipped to handle emerging challenges. The shift towards a more data-driven and proactive maintenance culture strengthened the overall performance of the maintenance team, ensuring a more responsive and efficient operation.

One of the key strengths of the SIRPM model lies in its broad applicability across various industries. While the results presented here are specific to Alpha, the core principles of the model—predictive maintenance, RPA integration, and machine learning—can be adapted to suit the needs of other sectors. For example, industries such as manufacturing, energy, transportation, and healthcare can benefit from implementing similar predictive maintenance strategies. In manufacturing, the model could enhance machinery uptime and reduce production delays. In the energy sector, it could help optimize the performance of power plants and reduce the risk of equipment failures that lead to costly outages.

Additionally, in the transportation industry, predictive maintenance could improve fleet management by identifying potential issues in vehicles or aircraft before they lead to operational disruptions. In healthcare, the model could be used to predict equipment failures in critical systems, such as medical imaging devices or patient monitoring systems, ensuring that equipment is always available and operational when needed.

The scalability and flexibility of the SIRPM model make it a highly practical solution for businesses across different sectors. The ability to customize the model based on the unique needs of each industry ensures that the system can deliver optimal results regardless of the context.

The results from the implementation of the SIRPM model at Alpha demonstrate the profound impact that predictive maintenance can have on operational efficiency, cost savings, environmental sustainability, and workforce development. By integrating RPA and machine learning, Alpha was able to achieve significant improvements in machine reliability, downtime reduction, and resource optimization, all of which contributed to enhanced financial performance and sustainability goals.

The model's applicability to other industries further emphasizes its potential to drive similar improvements in diverse sectors, offering a cost-effective and scalable solution for companies looking to enhance operational efficiency and reduce their environmental footprint. As industries continue to embrace the digital transformation, predictive maintenance systems like the SIRPM model will play a pivotal role in shaping the future of operations management, sustainability practices, and overall business performance.

While the results presented in this study are specific to Alpha, the SIRPM model demonstrates broad applicability across various industries, given its modular and adaptable nature. The integration of RPA and machine learning allows for a flexible solution that can be customized to the specific needs of diverse sectors. Industries such as manufacturing, energy, transportation, and healthcare are prime candidates for adopting similar predictive maintenance strategies. For example, in manufacturing, the model can enhance machinery uptime, reduce production delays, and lower maintenance costs. In the energy sector, it can optimize the performance of power plants and prevent costly outages caused by equipment failure. In transportation, predictive maintenance can improve fleet management by identifying potential issues in vehicles or aircraft before they result in operational disruptions. Similarly, in healthcare, the model can help prevent critical failures in medical devices, ensuring their availability when needed.

The scalability of the SIRPM model and its proven results in different contexts make it an ideal solution for businesses seeking to improve operational efficiency and sustainability. Further research into its application in other industries could help identify sector-specific modifications or enhancements that would optimize performance.

7. Conclusions

The primary aim of this study was to investigate how the implementation of a predictive maintenance model, based on robotic process automation (RPA) and machine learning (ML), could enhance efficiency and reduce operational costs within a company like Alpha, which faces recurrent equipment failure issues. The research demonstrated that by adopting this model, the company was able to anticipate failures before they led to unexpected downtime, thereby increasing equipment reliability and optimizing production.

The PICO methodology (Population, Intervention, Comparison, and Outcome) played a crucial role in the development of the predictive maintenance model. The target population was Alpha, while the intervention involved the implementation of an integrated predictive maintenance system using RPA and ML. A comparison was made between pre- and post-implementation scenarios to identify improvements in the company's operational and financial processes. This methodology provided a clear structure for the study, enabling an accurate assessment of the intervention's effects and offering valuable visions into the applicability of the model for other small businesses. The PICO methodology provided a clear structure for the study, allowing for the identification of significant outcomes related to the implementation of the SIRPM model. However, there were limitations in the scope of the data available for analysis. Specifically, the dataset used in the study was limited to a single company, Alpha, and did not account for potential variations in industry-specific factors that may influence the model's effectiveness. Future studies should aim to incorporate larger, more diverse datasets to improve the generalizability of the findings and allow for a more comprehensive understanding of the model's applicability across different sectors.

The synthesis of results had a significant impact on the development of the integrated RPA and ML predictive maintenance system (SIRPM), highlighting key trends and gaps that guided the proposal for a sustainable integration of RPA and ML technologies in predictive maintenance systems. The analysis revealed a strong focus on predictive maintenance and machine learning, with an increasing emphasis on sustainable contributions, suggesting that the model should align these technologies to optimize industrial processes while promoting environmental, social, and economic sustainability. Despite the promising results observed in this study, several limitations must be acknowledged. The scope of the study was confined to a single company, which means that the results cannot be generalized across all sectors or industries without further validation. In addition, while the study demonstrated improvements in predictive maintenance, the long-term effects of implementing the SIRPM model need further investigation to assess sustainability and continued performance. As a result, the SIRPM model was developed to combine these technologies in a modular and scalable way, fostering operational efficiency and offering a structured pathway for continuous implementation and adaptation.

The results showed substantial improvements as follows:

- A 100% increase in the mean time between failures (MTBF), from 23.47 h per event to 70.4 h per event.
- A 67% reduction in the mean time to repair (MTTR), from 12 h to 4 h.
- A 66.67% decrease in the number of unplanned downtime events, from fifteen to five events per month.
- A reduction in operational costs, with a 37.5% decrease in maintenance costs and a 71.4% reduction in costs related to unplanned downtime.
- Environmental gains, including a 25% reduction in energy consumption and a 40% decrease in CO_2 emissions.

These results demonstrate that the application of RPA and ML in the predictive maintenance system was effective in reducing failures and improving operational efficiency.

Among the main advantages of the SIRPM model are the following:

1. Advanced technology integration: the combination of RPA and machine learning improves the system's effectiveness, providing a continuous data flow between sensors, analysis platforms, and operational teams, enhancing failure predictions and response times.
2. Intelligent automation: automation reduces human intervention, minimizing errors and increasing the efficiency and safety of processes.
3. Continuous learning: the machine learning system adapts over time, improving predictions and decision-making.
4. Flexibility and scalability: the model is modular and can be gradually implemented, allowing for expansion into other areas of the company.
5. Real-time monitoring: the detection of anomalies and the generation of real-time alerts facilitate quick responses to failures, reducing unplanned downtime.
6. Energy efficiency and sustainability: the model promotes resource optimization and waste reduction, aligning with environmental goals and corporate sustainability standards.

These features not only make the SIRPM model more effective but also ensure its long-term viability as a solution for companies seeking innovation, cost reduction, and sustainability in the management of their industrial assets. The reduction in operational costs, improvement in energy efficiency, and positive environmental impact, alongside team development, make the model a key element for digital and sustainable transformation in small and medium-sized enterprises.

The SIRPM model also stands out for addressing sustainability in the following three main dimensions:

- Social: It promotes a better allocation of human resources by reducing repetitive and hazardous tasks while empowering teams with new digital skills. Additionally, it contributes to improved working conditions and enhanced operational safety.
- Environmental: the model contributes to waste reduction, decreased CO_2 emissions, and lower energy consumption, aligning with global environmental preservation goals.
- Economic: the reduction in operational costs and increased productivity result in greater competitiveness for companies while ensuring long-term financial returns.

The central research question was comprehensively addressed in this study. The results showed that the integration of RPA and ML is an effective approach to optimizing predictive maintenance systems. This combination allowed for substantial improvements in fault prediction, as evidenced by the significant increase in the MTBF, as well as reductions in the MTTR and unplanned downtime events. These improvements translated into greater operational efficiency, with tangible benefits in terms of reduced operational costs and increased productivity. Additionally, the developed model incorporated sustainability principles.

These findings demonstrate that the predictive maintenance model based on RPA and ML is effective in addressing the central research question, showcasing its potential to transform the management of industrial maintenance in small and medium-sized businesses. The SIRPM model not only promoted operational efficiency but also offered sustainable solutions aligned with contemporary business needs. The validity of the hypotheses reinforces the importance of integrating advanced technologies to foster more efficient and responsible industrial management.

The investigation validated both hypotheses, showing the following:

- H1: The combined application of RPA and ML significantly enhanced the ability to anticipate failures. This improvement was evident in the increase in the MTBF (+100%), the reduction in the MTTR (−67%), and the decrease in unplanned downtime events (−66.67%). These advances resulted in more efficient maintenance management and a 37.5% reduction in operational costs.
- H2: The research revealed positive impacts in all sustainability dimensions. Environmentally, there was a 25% reduction in energy consumption and a 40% decrease in CO_2 emissions. Socially, the model promoted team empowerment, with greater safety and efficiency in operations. Economically, the benefits included increased productivity and significant reductions in costs associated with unplanned failures.

The study validated both hypotheses, demonstrating that the integration of RPA and ML improves fault prediction accuracy, significantly reducing downtime and promoting sustainable benefits. However, the study identified limitations, such as the need for ongoing team training.

Future research could explore the following:

- Expanding the model with larger datasets.
- Integrating emerging technologies, such as big data and artificial intelligence, to increase prediction accuracy.
- Investigating the cultural adaptation and training of teams, which are crucial for the long-term acceptance and effective use of new technologies.

In conclusion, the application of the predictive maintenance model based on RPA and ML at Alpha was effective in resolving recurrent equipment failure issues, improving operational efficiency. The PICO methodology structured the research clearly, allowing for a robust evaluation of the impact of the intervention. The results demonstrate that the adoption of advanced technologies can transform maintenance management in small businesses, delivering significant benefits at the operational, financial, and environmental levels.

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