

Review

Systematic Literature Review Predictive Maintenance Solutions for SMEs from the Last Decade

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Abstract: Today, small- and medium-sized enterprises (SMEs) play an important role in the economy of societies. Although environmental factors, such as COVID-19, as well as non-environmental factors, such as equipment failure, make these industries more vulnerable, they can be minimized by better understanding the concerns and threats these industries face. Only a few SMEs have the capacity to implement the innovative manufacturing technologies of Industry 4.0. The system must be highly adaptable to any equipment, have low costs, avoid the need of doing complex integrations and setups, and have future reliability due to the rapid growth of technology. The goal of this study was to provide an overview of past articles (2010–2020), highlighting the major expectations, requirements, and challenges for SMEs regarding the implementation of predictive maintenance (PdM). The proposed solutions to meet these expectations, requirements, and challenges are discussed. In general, in this study, we attempted to overcome the challenges and limitations of using smart manufacturing—PdM, in particular—in small- and medium-sized enterprises by summarizing the solutions offered in different industries and with various conditions. Moreover, this literature review enables managers and stakeholders of organizations to find solutions from previous studies for a specific category, with consideration for their expectations and needs. This can be significantly helpful for small- and medium-sized organizations to save time due to time-consuming maintenance processes.

Keywords: predictive maintenance; SMEs; expectations; requirements; challenges



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1. Introduction

Physical assets play a key role in fulfilling the needs of factories and companies. However, installation is highly automated and technically very complex, and, as a result, maintenance management has had to become more sophisticated to meet higher technical and commercial expectations. A wide variety of people work in very inefficient industrial environments [1]. In addition, much research has been conducted on the maintenance of machine repairs over the past several decades, with studies on different phases of maintenance, including run-to-failure or corrective maintenance, preventive or scheduled maintenance, and predictive maintenance. The extant literature [1–5], reports significant results for the performance of different phases of maintenance.

Figure 1 [5] gives an overview of the maintenance types. There are several maintenance strategies that can be identified according to their roles. Companies have to decide what kind of strategy works for them. In the case of run-to-failure (RTF), companies risk the failure of systems because they did not maintain them in advance. Preventive maintenance (PvM) can cause inefficient replacement of parts, often before the end of their service life. Effective and reliable maintenance strategy should improve the conditions of the equipment, reduce unexpected system failures, and minimize maintenance costs while maximizing the working time of system components. Regarding these factors, the predictive maintenance (PdM) strategy stands out amongst the others because it optimizes the utilization of equipment, maximizes operation time of system component, and reduces

risks from unexpected failures. PdM is related to the high degree of digitization and implementation of the industry 4.0 concept. Its advantages include maximizing the time of use and operation of equipment, delaying and/or reducing maintenance activities, and reducing material and labor costs [6].

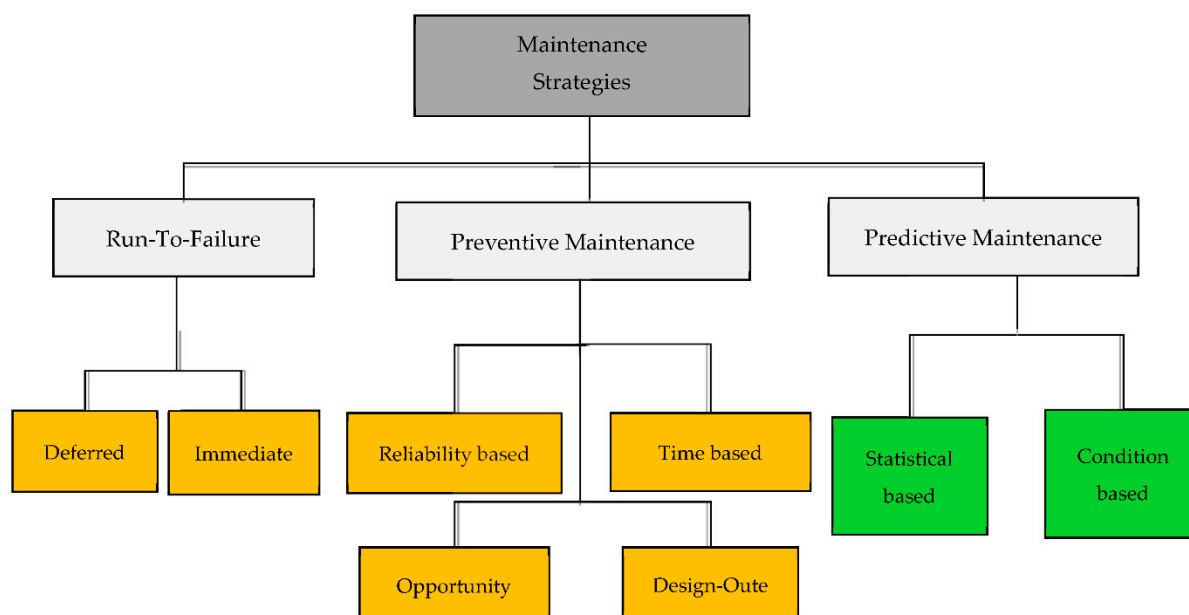


Figure 1. Classifications of maintenance strategies [5].

The European Union (EU) provides clear definitions of SMEs (small- and medium-sized enterprises) [7]; the categories of micro-, small-, and medium-sized enterprises consist of those with the following conditions:

- Has fewer than 250 employees
- Its annual turnover is less than EUR 50 million or its annual balance sheet is less than EUR 43 million total.

SMEs play an important role in the economy. The most important contribution of SMEs is in job creation. According to [7], they provide employment to two thirds of employees and thus contribute to the social stability of states. SMEs provide a creative and inspiring environment and thus support innovation and competitiveness.

Currently, according to Baglee et al. [8], SMEs generally use preventive or reactive maintenance strategies. As mentioned in their work, preventive refers to scheduling maintenance processes irrespective of the current state of the machine, whereas reactive refers to maintenance activities due to a change of state or anomaly.

Industry 4.0 is mainly offered by larger companies, and small and medium-sized companies are at risk of not being able to exploit this enormous potential. However, micro-, small-, and medium-sized companies provide about 45% of the value added of production and about 59% of employment and can, therefore, be considered the backbone of the European economy. Therefore, Industry 4.0 concepts should not only be conceived of and implemented in larger companies but also, and arguably more importantly, implementation solutions, approaches, concepts, and technology solutions for efficient implementation should be provided for SMEs [9].

Although efforts have been made to reduce the gap between large industries and SMEs in digital transformation, the main reasons for the slow pace still need to be addressed. Sassanelli et al. [10] identified in their literature review other major dimensions, including ecosystems, technology, business, skills, and data, that need to be considered by digital innovation hubs (DIHs) to support companies' digital transformations, especially SMEs. In addition, Sassanelli et al. [11] provided a roadmap for product lifecycle management (PLM)

for companies willing to approach digitization by integrated methodologies, evaluating a company by both digital and lean maturity. However, the prerequisites of each industry must also be considered in terms of expectations, requirements, and challenges. In Section 2, the research questions and methodology for reviewing these prerequisites are discussed.

2. Research Methodology

A systematic review of the literature (SLR) is a means of identifying, evaluating, and interpreting all available research related to a particular research question or a topic or phenomenon of interest. Individual studies that contribute to a systematic review are called preliminary studies. A systematic review is a kind of secondary study [12]. It is an evidence-based practice that combines all primary studies and their results [13].

The scope of a systematic review includes the aim of the study and collecting the primary knowledge about the subject of the study. As a result of an inquisitive study on the research conducted in the field, a set of research questions (RQs) was formulated. A search strategy was then developed, which provided the basis for collecting relevant research materials from the repositories. The most significant step was to refine the data gathered by defining the inclusion and exclusion criteria as well as analyzing the primary and secondary studies based on the guidelines for performing systematic literature reviews [14]. Figure 2 shows the research strategy used for the systematic literature review [15], following Denyer and Tranfield's [16] five steps for SR: question formulation or research questions, locating studies, study evaluation based on goals, analysis, and reporting by using the results. In Sections 2.1–2.3, the process of selecting the articles is explained in detail.

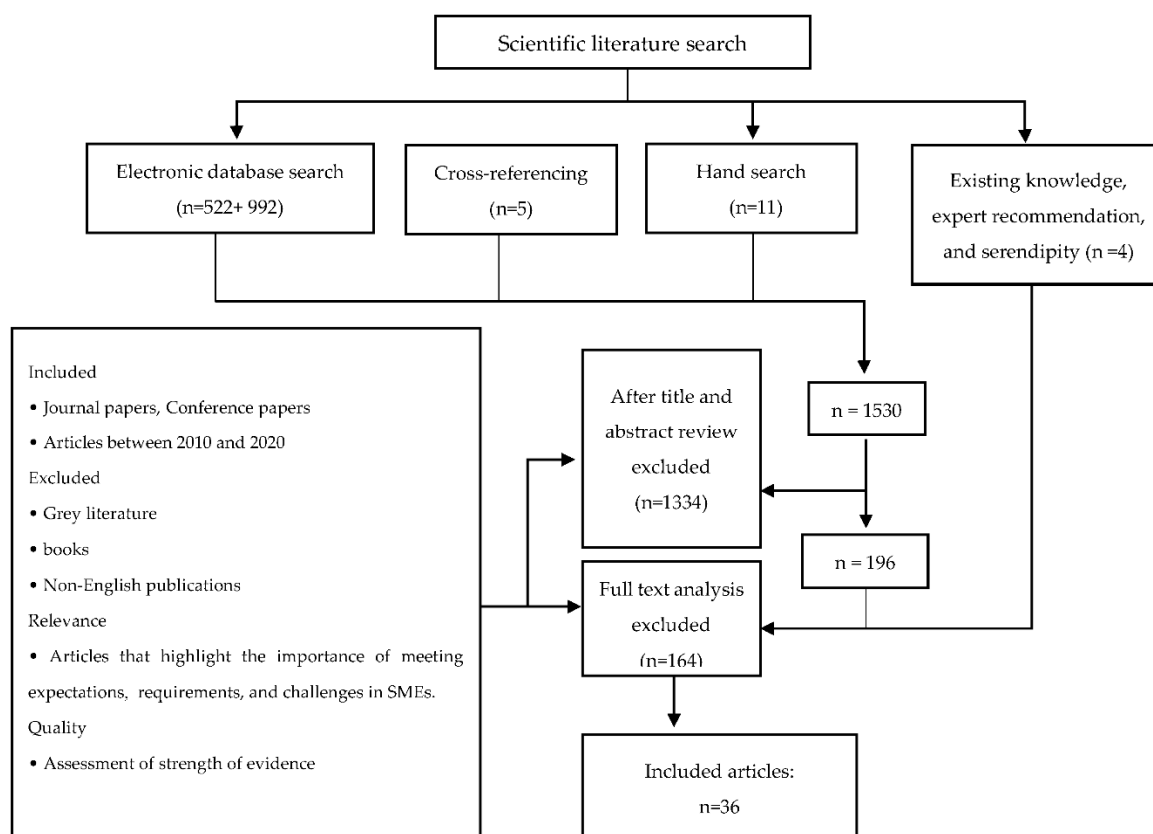


Figure 2. Research strategy (adapted from Smart et al. [15]).

2.1. Scope and Objective

The aim of this review was to evaluate and analyze the research conducted in the last decade on predictive maintenance based on Industry 4.0, with special consideration for small- and medium-sized enterprises. The main purpose, in addition to reviewing the

latest technologies used in the Internet of Things (IOT) in industries, was to address the challenges faced by small- and medium-sized enterprises (SMEs) in the field of information technology and, in particular, predictive maintenance (PdM). In this study, asking detailed questions determined those that can be answered in order to solve these challenges.

2.2. Research Questions (RQs)

Research questions help us to conduct research and analyze data effectively. The questions listed below are reviewed and answered in detail in Section 3.

- Q1. What are the most significant expectations and concerns of stakeholders in SMEs in regard to implementing PdM?
- Q2. What are the most important challenges SMEs are faced with regarding predictive maintenance?
- Q3. What equipment, facilities, and resources are required for PdM techniques in small- and medium-sized companies?
- Q4. How have recent studies provided an appropriate solution to implement predictive maintenance by considering the previous questions?

2.3. Search Strategy and Database

An advanced search strategy was used for mining the data sources to locate the pertinent publications. The Boolean operators “AND” and “OR” were used to arrange the keywords for forming the search string. To ensure the maximum retrieval of significant material, the search strategy was applied to a title, an abstract, and keywords.

According to the guidelines provided by Kitchenham [14], several data sources were searched to encompass the maximum possible information. Most computer science and engineering articles are in the IEEE and SPRINGER online libraries. The results of the publisher’s selection then led to the conclusion that if it is a Springer-publishing proceeding usually, it is LNCS (Lecture Note in Computer Science) and its sublecture notes such as LNAI. Similarly, there is LNEE (electrical engineering), and many other similar notes. These LNXX proceedings are indexed in Scopus. If it is IEEE, usually the papers will appear in IEEE Xplore (which is Scopus-indexed). Therefore, both are indexes in Scopus, which would be a significant parameter for guaranteeing the quality of studies. The following two sources were selected as the final search database:

- IEEE Xplore Digital Library (www.ieeeexplore.ieee.org, accessed on 28 April 2021)
- Springer (www.springerlink.com, accessed on 28 April 2021)

Moreover, search strings with different structures of filters were used for each of the data sources listed in Table 1, the results of which are presented and analyzed in Section 3.

Table 1. Search strings for selected data sources.

Categories	Data Source	Search String	Specific Filter
Group A	IEEE Springer Link	All Metadata: “Predictive Maintenance” in command search tab (under advanced search)	
Group B	IEEE Springer Link	All Metadata: “Predictive Maintenance” AND (“Machine Learning”) in command search tab (under advanced search)	
Group C	IEEE	All Metadata: Predictive Maintenance AND All Metadata: small enterprisesORAll Metadata: Predictive Maintenance AND All Metadata: SMEsORAll Metadata: Predictive Maintenance AND All Metadata: small companies	Date between 2010 and 2020
	Springer Link	“Predictive Maintenance” AND (“small enterprises” OR “SMEs” OR “small companies”) in command search tab (under advanced search)	

3. Early Results of SLR and RQs

The collected articles were statistically analyzed and categorized based on the previous method of extraction to be prepared for the final analysis. Then, the included articles were thoroughly assessed in regard to their specific categories (expectations, requirements, or challenges).

3.1. Article Extraction Process

Table 2 lists the publication types for the selected studies and primary studies retrieved from the repositories in different categories: Groups A, B, and C, which refer to research in the fields of predictive maintenance, predictive maintenance and machine learning, and, finally, predictive maintenance and SMEs, respectively, the latter of which is within the scope of this study,

Table 2. Overview of the selected primary studies in different groups.

Data Source	Group A	Group B	Group C
IEEE	2666	522	20
Springer Link	2524	992	176

The studies were also divided into the different categories of conference papers, journals, and books, the results of which are shown in Figures 3–5 for Groups A, B, and C, respectively.

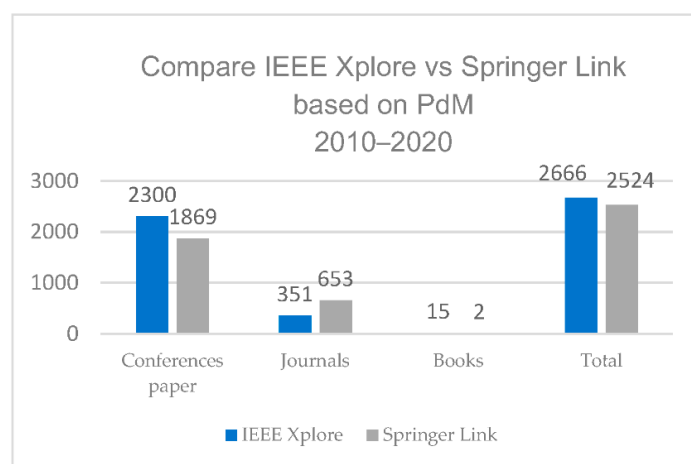


Figure 3. Compare IEEE Xplore vs. Springer Link studies based on PdM.

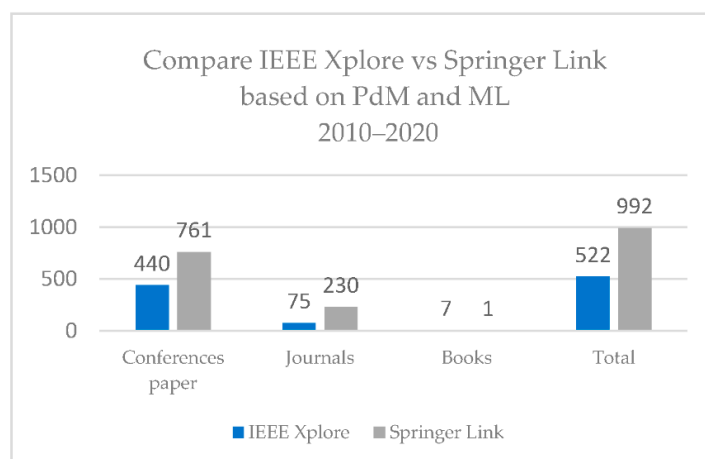


Figure 4. Compare IEEE Xplore vs. Springer Link Studies based on PdM and ML methods.

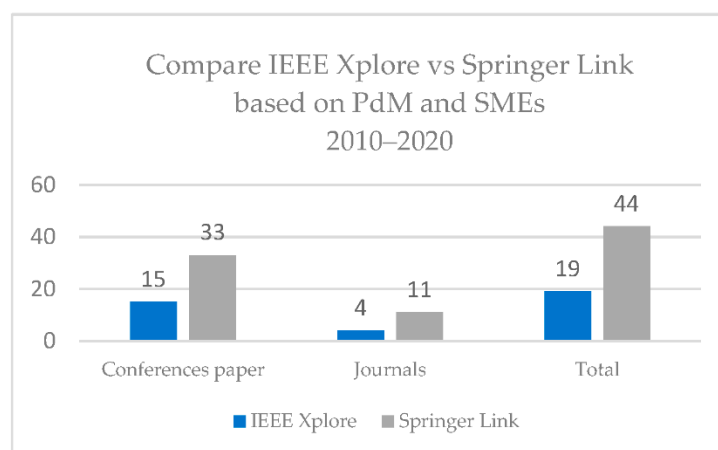


Figure 5. Compare IEEE Xplore vs. Springer Link studies based on PdM and SMEs.

Although the focus of this research was on project-oriented studies, considering the research articles, a total of 36 studies were extracted to answer the questions raised at the beginning of the review. These studies are the most relevant regarding maintenance and prediction as well as for instructions on how to apply this process in small industries.

Figure 6 depicts the processing pattern for the final selected studies. The template was inspired by the research questions in Section 2.2. In Section 3.2, we provide specific answers by summarizing the information from all the included studies. The expectations of managers and stakeholders of small- and medium-sized enterprises, the challenges that these companies face in establishing predictive maintenance, and the requirements related to facilities such as IT infrastructure or human resources were examined. The overlap of these three relevant factors largely determines the most effective solution, depending on the priorities of each organization. We attempted to extract these expectations, challenges, and requirements, and we propose solutions for several recent projects.

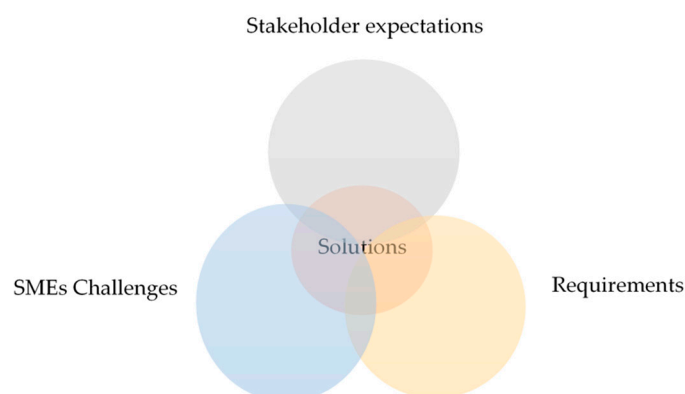


Figure 6. Study overlaps to achieve a solution for SMEs using PdM.

3.2. Stakeholder Expectations

To review the results of data analysis and articles and answer the research questions, we separated all the articles into three categories (expectations, requirements, and challenges). The results are summarized as follows:

Li et al. [17] presented an innovative structure for cognitive maintenance (CM) by using cyber-physical systems and also advanced artificial intelligence techniques. In their case, providing technical solutions to real-time online maintenance tasks was the most significant goal of the project. This approach was also considered previously; in 2015, Selvaraj et al. [18] searched for an enterprise management tool to apply to the predictive maintenance approach to integrate with the collaborative SME processes and real-time monitoring in order to enhance its predictive maintenance. This approach was also consid-

ered in India by [19], with the goal of keeping PdM in line with augmented reality, remote monitoring, and more in the automotive industry. Managers, especially managers of small- and medium-sized organizations, are concerned about financial issues. Sezer et al. [20] attempted to develop an Industry 4.0 architecture focused on predictive maintenance, integrating low-cost principles so as to be affordable to small manufacturing enterprises.

Jerrentrup [21] described the effect of digital transformation on SMEs considering the importance of these enterprises in Germany, as well as other countries, to achieve expected benefits or values, including cost reduction, flexibility, revenue enhancement, and quality improvement. In this regard, Hoffmann and Lasch [22] also provided a structured approach on how to implement a PdM strategy in industrial companies in order to reduce maintenance costs and resources. Although it is not reasonable to apply this strategy to every maintenance object in the company, they propose a roadmap for how to find an optimal mix of maintenance strategies and, therefore, to minimize maintenance costs. In addition, Adu-Amankwa et al. [23] focused on developing a cost model that assists SME machine shops in evaluating the benefits of adopting PdM techniques, using financial modeling and strategies that build on maximizing values. This was achieved by collecting and analyzing data from SME CNC machine shops in the UK that utilize PdM techniques and measure their impact on the performance cost. Regarding flexibility, in addition to Jerrentrup's [21] studies, Matt et al. [9] emphasized that the process of decomposition and mapping can be applied in the design of a production system in accordance with the concept of Industry 4.0. Such systems are flexible, reconfigurable, and highly innovative. In this way, they cover the expectations of managers.

In addition to the manager expectations and concerns mentioned above, which were repeated in numerous articles, highlighting their relevance, there are other expectations from the organization's stakeholders. Dobrotvorskiy et al. [24] noted that a graphical user interface maintenance management system is really critical for decision-making for users who are not skilled in IT. Regarding the subject of a user-friendly environment for a computerized maintenance management system (CMMS), Campos et al. [25] attempted to find a new way to dynamically interact with the physical environment, that is, the workplace, and support information systems, leading to faster responses to events and increased performance.

Finally, in many SMEs where predictive maintenance has been pre-established, one of the future concerns of managers is the acceptable performance of the intelligent system in detecting failures and anomalies. This was categorized as a challenge, and Xu et al. [26] attempted, in their study, to integrate the previous traditional model with new approaches to meet this expectation, that is, to improve the accuracy of the model prediction. Kiangala and Wang [27] reviewed an initial project to predictive maintenance on a conveyor motor in a bottling plant. The main expectation of this kind of SME was the decentralized monitoring system from which different modes can be controlled based on cloud-based reporting and it would be accessible via the Internet.

Large and small industries are always looking for technologies that will suffer the least amount of damage in the future. Baurina [28] justified the demand for the automation of technological processes at enterprises in Russia: 77% of large, and 42% of SMEs are ready to move to cloud technologies, in addition to which 34% of companies plan to increase their information technologies budgets. Additionally, he emphasized the specific circumstances of 2020 because COVID-19 has led companies to digitalize in the fields of predictive analytics, mobile maintenance and repair (M&R) and diagnostic systems, video surveillance and data processing systems, virtual data processing centers (DPCs) and systems of data storage, hybrid clouds, and technologies of digital doubles of the equipment. Gergin et al. [29] worked on a project that was initiated to identify the current situation of SMEs in Turkish industries. A comprehensive questionnaire was prepared to determine the expectations of the SMEs for an Industry 4.0 transformation. The results showed that preventative maintenance is the most used technology among other technologies in these

companies, but managers have ordered the use of automation and mobile systems along with predictive maintenance [30].

From another perspective, Shiling and Jianchao [31] provided the time series prediction model based on the grey system OBM(1,N), which is an optimization model based on motion generation to predict the decomposition of gas in the failure of high-voltage composite electrical appliances. A wide detection range, strong anti-interference ability, high output precision, and reliable repeatability were the most significant expectations of applying the grey system OBM (1,N).

3.3. SME Challenges

Industry 4.0 is a challenge for businesses in general, and SMEs in particular. The concepts and compatibility of Industry 4.0 for SMEs are only partially realized. Smaller SMEs are at higher risks that they will not be reimbursed for investment into digitization—at least in the short term [32]. One of the likely reasons for this obstacle is that the main idea for many SMEs is to ‘start from scratch’. However, SMEs often do not have a complete and correct assessment of their current state and lack an idea of the benefits of digitization in the future, which is another challenge [33]. Jerrentrup’s [21] study provides a comprehensive map of the challenges facing small industries in the deployment of Industry 4.0. We divided the challenges of the digitalization process in SMEs into five main categories: systems, structure, orientation, culture, and resources, each of which can have an effect on the other groups. Figure 7 shows examples of each the above groups.

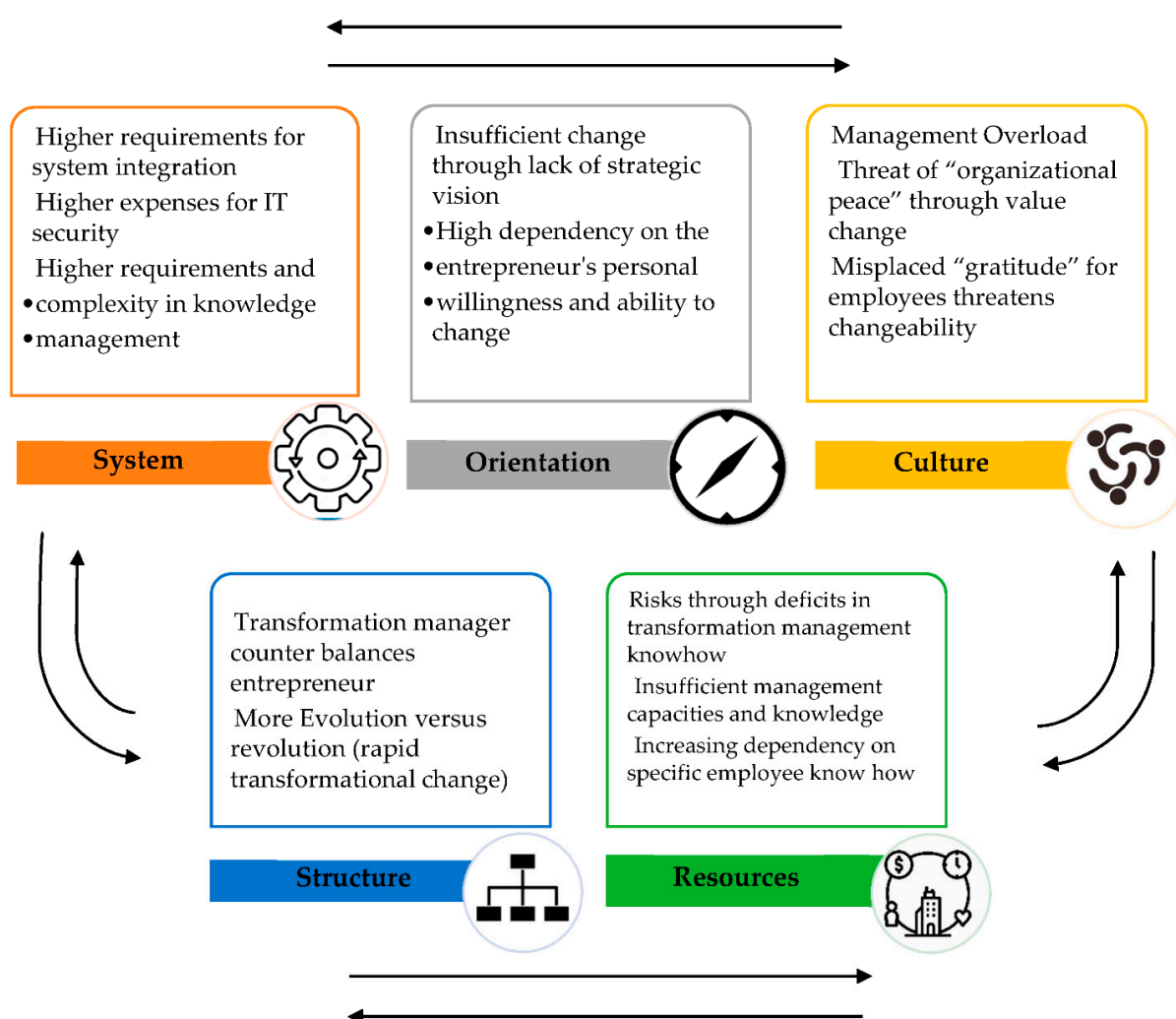


Figure 7. Challenges of the digitalization process in SMEs [21].

Other challenges discussed in the recent research, specifically on the subject of predictive maintenance, include investments and unclearly defined costs (based on a questionnaire in 2019 on Industry 4.0 regarding Serbian SMEs) [34], not enough opportunities for failure and small-sample learning tasks [17,35], a lack of highly qualified users [24], and the loss of specialists or the dependence of the system on them [36], forcing organizations to absorb increasingly more distant knowledge faster and with fewer opportunities for reuse [37]. This modeling and integration of large volumes of industrial data [38] are in contrast to small sample prediction problems [26]. Heinis et al. [39] completed an empirical study on 109 SMEs and large enterprises (LEs) in the electrical, metal, and machine industries which are located in Switzerland. Compared to SMEs, LEs showed higher levels of interest and engagement in IOT application development, such as PdM technologies. The limited human and financial resources, which prolong research and development activities, might explain this result.

In addition to the aforementioned, Kordon [40] emphasized that one of the biggest challenges is to achieve a smooth dialog between the two communities of business language and approach-specific language.

The environmental conditions of some industries also pose different challenges. Sezer et al. [20] faced sensor failure and high vibrations in sensitive environments, so there is a need to design highly durable and stable hardware as well as reliable prediction accuracy. Another example of this is the distance between the maintenance site and the relevant human sources. Actionable data may not be available at the right time and place or to the persons authorized to have access to it [25]. In addition, with the rapid spread of the Internet of Things, hackers can gain more access to wireless devices, e.g., sensors and cloud databases. The reliability of a complete system of sensors and cloud resources according to the importance of assets is high risk. Another problem is caused by the high heterogeneity of devices, which can cause a conflict with interoperability [41]. Although both Bluetooth and WLAN (wireless local area networks) are developing low-cost structures, so far, there are only very limited mechanisms to solve problems such as anti-interference, information security, and response times [42].

From a general point of view, Genenning [43] presented seven challenges for integrating an industrial cloud into the service systems of German small enterprises. These challenges, shown in Table 3, are divided into three categories: actors, information, and value proposition. See [43] for further details.

Table 3. Challenges of industrial cloud integration in service systems [43].

Actors	Interactions between the entities and stakeholders
	Adopt a philosophy in an integrated organization
	Adopt a strategy in an integrated organization
	Budget reclassification between units
Information	Acquire the required qualifications
Value Proposition	Requires a systematic process for service innovation by digital technology
	Implement a culture of failure in the organization

Finally, although PdM programs promise significant benefits, Adu-Amankwa et al. [23] mapped a summary of the additional responsibilities and challenges of PdM, including unreliable data or a calibration error, special training required and costs for system analysis, maintenance and security of data infrastructure, and significant investments in the acquisition cost.

3.4. Requirement

Considering the expectations and goals of small and medium industries in the establishment of Industry 4.0, especially predictive maintenance, there are also limitations

and challenges. Thus, we attempted to clarify the key roles of different requirements of different projects for researchers and executive engineers.

Olanrewaju and Abdul-Aziz [44] considered maintenance management from a new perspective. From their perspective, maintenance management requires a multidisciplinary approach, including technological, engineering, economical, commercial, and social views. Precisely, maintenance is a business. The maintenance department should be considered as a business unit.

Matt et al. [9] presented an explorative set of hypotheses of the requirements for implementing Industry 4.0 concepts into logistics processes in SMEs around the world, including the Northeastern United States, Central Europe, and Northern Thailand. The statements were assigned to ten general thematic clusters, which would be more specific in an enterprise: leanness and agility, real-time status, digitization, connectivity and network tracking, PPC and WMS, culture and people, security and safety, ease of use, transportation, automation.

Deployment requirements can be divided into two groups: hardware and visible or software and invisible. Li et al. [17], Selvaraj et al. [18], and Sezer [20] all expressed that PLCs, sensors, open platform communications (OPC), the industrial Internet of Things (IIOT), and sense HAT are among the most important devices and hardware that could help SMEs in data acquisition.

Moreover, Dobrotvorskiy et al. [24] mentioned that unified information flows in the workspace require connecting to a large number of databases, a homogeneous information structure, and information support. In this way, all stakeholders, systems, and data should thus be integrated via incremental steps so that adjustments can be made quickly [45]. Mascoloc et al. [46] verified the effectiveness of the complete DynaWeb solution by integrating the technological and information technology strands into business industries. They demonstrated the integration of 25 DynaWeb hardware and software components as well as services. The requirements for oil sensors included a power source (220 V per sensor), a computer for data gathering, and a connection to the lubrication system. In addition, to measure the oil, an outlet and inlet were required to connect to the lubrication system. Hydraulic fittings were used to connect the sensors to the conditional random fields (CRFs) system. In this case, the bypass was the most difficult problem to solve, because the oil tank was not easily accessible.

As Cerquitelli et al. [47] pointed out, there is a need for a coherent architecture for the implementation of effective predictive maintenance. The following functionalities are required to implement the platform and arrange an integrated architecture: communication broker, edge gateway, orchestration and registry, data storage, predictive analytics service, visualization, and scheduling. Based on all these architectural elements, we were able to develop a fog computing solution, which is presented in Section 4.

Finally, Yang [48] pointed out the significance of data collection through measurement parameters. He states that in order to monitor the performance of a system, it is essential to determine which system parameters should be measured, how to obtain these values and store them. They can be obtained by direct or indirect measurements. Some commonly used parameters in processing plants, depending on the type, are summarized as follows: flow rate, pressure, temperature, concentration, and liquid level.

3.5. Summary of Studies and RQ Answers

The three significant elements of this study, that is, stakeholder expectations, project implementation requirements, and the challenges faced by small- and medium-sized industries for predictive maintenance are based on the steps of PdM and are outlined in Figure 8. According to the PdM process, which includes the necessary phases for data production, preparation, analysis, validation, and visualization [49], data in the area of maintenance can be generated or extracted and then refined and validated.

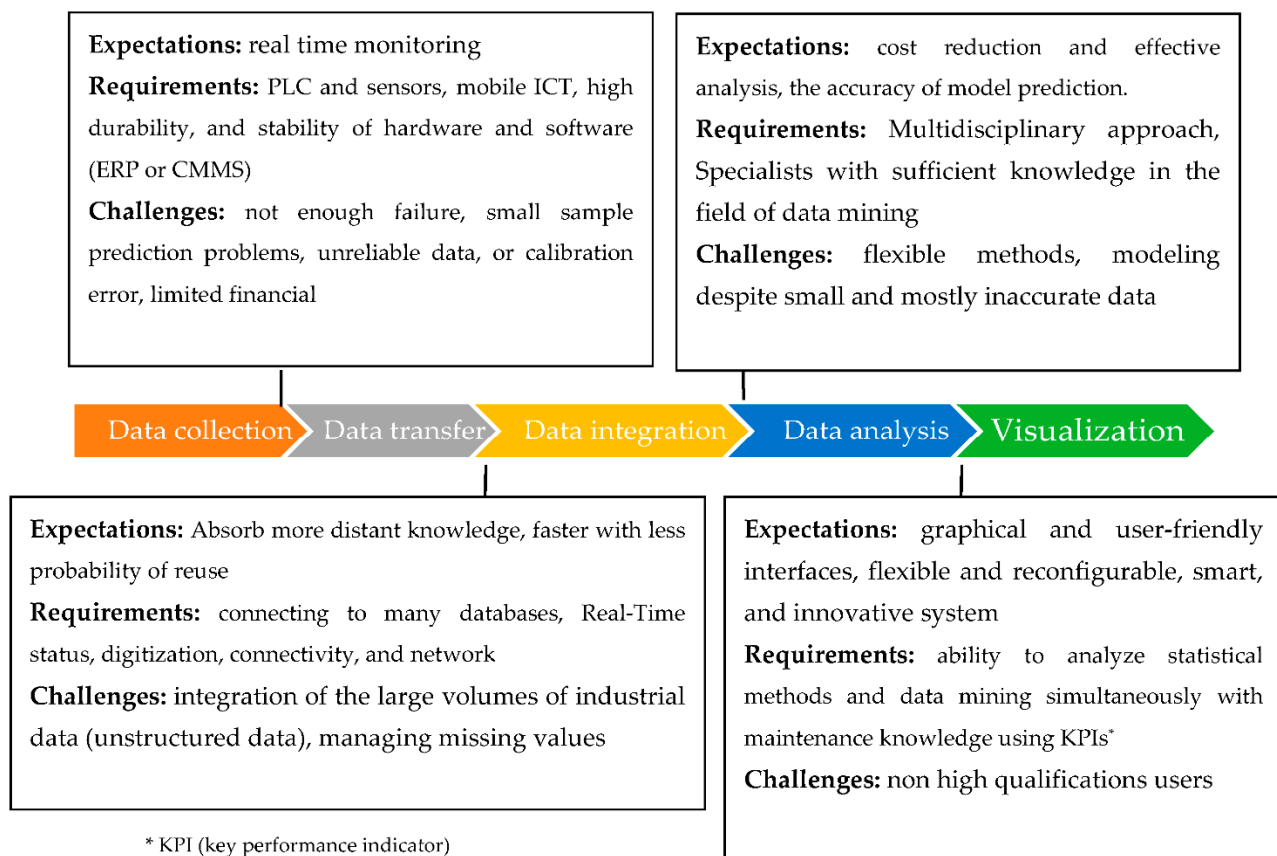


Figure 8. Expectations, requirements, and challenges in the field of predictive maintenance based on implementation phases.

The steps are summarized as follows:

1. **Data collection:** To obtain relevant data and manage its content. Data can be collected from a variety of sources, including sensors, RFID tags, people, and so on.
2. **Data transfer:** The collected data need to be transferred without affecting their content. Data are transferred from the source to the data management system.
3. **Data integration:** Combining data from different sources in a data warehouse using methods that ensure its quality.
4. **Data analysis:** Data analysis and extract information and knowledge to support decision making by managers.
5. **Visualization:** By visualizing the information required by the users or decision makers. Visualization can be statistical or reporting.

Based on the classification of the three parameters examined in previous studies, the answers to the research questions (Section 2.2) can be found in Figure 8, except for the solutions that studies have found so far in terms of solving challenges and meeting expectations based on existing requirements. In Section 4, the major solutions provided for the final research question are reviewed and discussed.

4. Discussion

The literature analysis provided some indications of potential solutions. In this section, the solutions proposed in previous studies are reviewed; these solutions will correspond with at least one of the three categories of expectations, requirements, and challenges.

Table 4 shows only a small portion of the solutions presented in some of the studies mentioned in Section 3. Smart services, such as ‘remote repair, diagnostics, and maintenance (RRDM)’ [50], that share manufacturing [51] enable a new way to solve the issues and concerns of managers in dealing with fast technologies of the future. Rastogi’s findings [52] also demonstrated that most SMEs aim to increase the remaining useful life (RUL) of the

system. In addition, we observed that that machine learning and deep learning techniques are most prevalent where predictive maintenance is concerned.

Table 4. Proposed solutions of the previous studies based on meeting the expectations, requirements, and challenges.

Solutions	Expectation	Requirement	Challenge
Deep belief network (DBN) method to predict backlash error [17]			X
Predictive virtual enterprise maintenance processes [18]	X		
Proposed single-board computer (the Raspberry Pi 3 Model B) and IIOT device (the Sense HAT) [20]			X
User-friendly interface and integrated platform (FGS2I4.0) [24]	X		X
A proposed toolkit for the implementation of Industry 4.0 [9]			X
Suggestion of the axiomatic design for the implementation of a specific solution for each enterprise [9]		X	
Cloud computing and IOT solutions [22]	X		X
Logistic regression and random forest (RF) for the design of predictive models in the Industry 4.0 environment [38]	X		X
Support of the top management, external knowledge, and the usage of benchmarks [21]	X		X
Wireless technologies and mobile systems [25]	X	X	X
Combination prediction method of power transformers based on the grey model [26]	X	X	X
Instant email notification system for every maintenance schedule generated [27]	X		
Human-level concept learning and hierarchical probabilistic learning [35]	X		
Titan software platform for integrating production environments with Industrial DevOp [45]	X		
Localization of knowledge [37]	X		

Our main aim in this study was to address the lack of research and evidence on what it means to mobilize knowledge when operating small- and medium-sized organizations. In this way, managers and stakeholders of small organizations who are concerned with meeting the needs of digitalization will be able to group their expectations, requirements, and challenges based on the research provided and take a similar approach within their industry. Although each organization has its own unique characteristics in terms of processes, resources, and requirements, this solution can be considered a parallel approach due to the time-consuming PdM projects.

5. Conclusions

This paper presents a literature review about the main factors that need to be considered for digitalization and Industry 4.0, especially for predictive maintenance to support SMEs. These factors were divided into parameters or elements of expectations, requirements, and challenges of small industries. The main aim of the research was to raise the awareness of each of these three dimensions of predictive maintenance, providing theoretical evidence and the application of solutions proposed for each dimension, which is one concern of relevant stakeholders.

There are various levels of equipment maintenance in different companies. Awareness of the enterprise's maintenance department requirements and challenges and the level of maintenance methods should be the first step in implementing PdM projects. Although each organization has its specific expectations, some of the main elements for small- and medium-sized enterprises in dealing with new and future technologies were mentioned. Among the expectations, needs, and challenges mentioned, there are many commonalities between small- and medium-sized companies that can be addressed by existing solutions.

6. Future Work

This study has provided only theoretical evidence for the selected parameters (expectations, requirements, and challenges) of SMEs regarding digitalization. So, the review of the theory related to the classification would lead the way to further studies to high-

light their relevance from a practical perspective. In future research, small and medium industries can be classified based on these parameters, and the identified solutions for these industries can be considered based on the set of best practices performed. In fact, if stakeholders are concerned about limited financial resources for digitalization, the proposed solution to access technology with limited resources can be considered. In addition, a more comprehensive review of other publishers not used in this study could significantly expand the range of solutions available for use in a variety of industries, for example, Elsevier and ACM Digital Library, which provide many studies regarding Industry 4.0 and predictive maintenance. In future research, the analysis of the studies of these two publishers in the field of predictive maintenance in small and medium-size industries can achieve more complete results and stakeholders will be given the opportunity to come up with a comprehensive plan of available solutions.

Author Contributions: S.H.D. conceptualized this paper and designed the research plan. She also performed the literature review and analyzed the SME case studies included in the sample. I.B. provided advice throughout the process and revised the manuscript. All authors approved the final version of the paper. All authors have read and agreed to the published version of the manuscript.

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