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Maturity Level of Predictive Maintenance Application in Small and Medium-Sized Industries: Case of Morocco

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Abstract: In order to remain competitive in the long term and to push the company's efficiency to its limits, entrepreneurs are more and more open to the idea of integrating into Industry 4.0 aiming mainly at filling the important downtimes and the associated productivity losses by implementing predictive maintenance. This concept, common in developed countries, is much less widespread in Morocco and even less in small and medium-sized Moroccan companies. The objective of this article is to study the maturity level of predictive maintenance in Moroccan small and medium-sized enterprises, through a questionnaire validated by experts and made available to several companies. Valid data from 115 companies throughout the kingdom operating in different sectors were collected and processed by descriptive and factorial analysis under SPSS software. The results obtained show that only 33% of our sample were able to implement predictive maintenance, and that the expected benefits of this approach are the minimization of downtime at 96.5% and the increase in productivity at 94.8%, The main challenges observed are the lack of team motivation and a corporate culture unsuited to digitalization, which represents 42.277% of the total variance, lack of financial resources at 12.916% of the total variance and lack of data protection at 11.644% of the total variance. This analysis indicates that the level of maturity regarding the application of predictive maintenance in Moroccan small and medium-sized companies is low, these rates can be used to improve the root causes.

Keywords: Predictive maintenance, Benefits and challenges, Descriptive analysis, Factorial analysis, small and medium-sized Moroccan companies.

1. Introduction

Industrial maintenance is a black spot for companies, it is a challenge both economically and humanly [1]. However, maintenance has undergone a strong evolution in recent decades, with the objective of improving the performance and reliability of production tools and positively impacting productivity. The latest evolution represented by "predictive maintenance", aims to react as quickly as possible on the failing element once it has deteriorated, the principle requires the use of devices to measure the degradation in real time, which can be a vibration, a dimension, a geometry, a position, a pressure, a noise, a temperature, ... This relies mainly on the use of statistical tools for data processing and health analysis to predict a possible failure of the equipment [2]. Predictive maintenance is defined according to the standard NF EN 13306 X 60-319 as "conditional maintenance performed according to predictions extrapolated from the analysis and evaluation of significant parameters of the asset's degradation" [3]. In recent years, several companies in developed countries have successfully implemented predictive maintenance, several challenges have been encountered in its application [2, 4-7], and many benefits have been observed after its implementation [8-11]. All research in different countries has focused on large companies, and therefore we have no idea if predictive maintenance has already been applied in small or medium-sized Moroccan companies or ever, especially since these companies contribute a significant rate of national added value, so in our case we are interested in small and medium-sized companies in Africa, and specifically in Morocco. The objective of this article is to assess the maturity level of application of predictive maintenance in Moroccan industries and mainly in small and medium-sized Moroccan companies, and to identify the difficulties and challenges that hinder its application in order to have precise answers to our following questions:

What is the status of the deployment of predictive maintenance in Morocco? What benefits have been observed from its implementation? What are the barriers to its instauration?

The answers to these questions will serve as a basis to know the current status of the application of predictive maintenance in Morocco and the results can be taken into consideration in future studies.

2. Literature review

The 4th industrial revolution is known by its four pillars, Internet of Things (IoT), Industrial Internet of things (IIoT), Cloud-based Manufacturing (CBM) and Smart Manufacturing [12] and is currently called Industry 4.0 since its appearance in Germany in 2011, with the aim of digitizing information to ensure a flow of multiple information [13], through exchanges between machines (M2M) without the need for human intervention [14], via a bidirectional communication at very high speed between connected objects and the Cloud [15], where it will converge all these huge data in the Big Data [16], thus leading to automatic decision-making and autonomous actions [17]. In this sense, thanks to the integration of IoT and the analysis of data stored in Big Data and information technologies, it has become possible to monitor in real time the state of the system, giving rise to predictive maintenance [18], which is one of the most significant applications of IIoT, and which aims to use the actual operating status of equipment and systems in the plant to optimize its overall operation, through a condition-based preventive maintenance program that uses actual monitoring of mechanical condition, system efficiency, and other indicators to calculate the actual mean time to failure or loss of efficiency for each machine-train and plant system [19], and with IIoT, the results improve with data-driven information. This could result for many companies [20] in :

- Greater energy efficiency
- Cost benefits
- Improved product quality
- Effective decision-making capability
- Less system downtime

2.1 Benefits of predictive maintenance application

Although predictive maintenance is based on several different techniques, the objective is to list the benefits of implementing its application in industries, as shown in Table 1. In

Netherlands, [11] were able to explore the application of predictive maintenance in 13 industries, based on several techniques, and found the benefits of preventing serious incidents and minimizing downtime by determining the exact time of replacement of components in addition to the detection of anomalies and prediction of future behavior, this was also confirmed by a case study carried out by [9] in a metal industry in Portugal, which found improved efficiency and reliability of the system, preventing system failures and reducing maintenance costs .An Indian automotive company was also able to reduce downtime and increase productivity through rapid problem resolution and increase availability and support business continuity of its IT operations [21]. In a study by [10] in the automotive industry sector in Morocco, after at least 6 months of applying predictive maintenance, the plant was clearly able to reduce accidental downtime, improve data sharing, increase asset availability and improve retroactivity to analyze failures, which gave clear results on maintenance optimization. Note that in most cases, the decision to adapt predictive maintenance aims at an economic benefit that will minimize costs [8].

Table 1. *Predictive maintenance benefits*

No.	Benefits of Predictive maintenance	Country	Reference
1	-Prevention of serious incidents -Minimization of downtime -Prediction of future behavior	Netherlands	[11]
2	-Improved efficiency and reliability of the system -Prevention of system failures - Reducing maintenance costs	Portugal	[9]
3	-Reduction of accidental downtime -Improved data sharing -Growth in asset availability -Improved retroactivity to analyze failures	Morocco	[10]

2.2 Predictive maintenance barriers

Several benefits have been cited for the application of predictive maintenance, as to what several studies also focused on the difficulties encountered when applying predictive maintenance in different countries, three categories of challenges were structured by the study of [4] conducted in the global company Bosch , including:

1- The challenge related to the development of analytical solutions, where its major difficulty lies in the insufficient portability of analytical solutions in factories, processes and machines, resulting in significant implementation and maintenance costs.
2- The challenge of employee empowerment, where its major difficulty lies in the poor management of analytics software by business personnel as they have only limited basic knowledge of data analysis tools and techniques, which causes a drag on data-driven decision making and consequently slows down the development of a business culture based on new technologies and data analytics.
3- The governance challenge, where its major difficulty lies in the lack of advanced protection of enterprise data and the absence of policies on data ownership, which leads to economically risky use.

Similarly, in the study of [5] conducted on 9 companies, several difficulties were found in the application of predictive maintenance, including the lack of corporate culture towards data/evidence based decisions, the lack of skills and abilities of employees on digital technologies, intrinsic difficulty in establishing the return on investment for the digital transformation of maintenance. In the study of [2], it was identified as a major difficulty the inappropriate working conditions for the implementation of predictive maintenance, given that the traditional maintenance strategies are developed for a limited range of types of machines, this says that the company needs a radical change that requires a large investment to be able to adapt to new technologies. The study by [6], focuses on the human resources side and defines as a real barrier the communication and coordination between the staff, in addition to the lack of integration of the employees in the design of manufacturing systems control architectures, which leads to more or less critical failure state. The study of [7] has clearly defined that among the great challenges is the cost associated to the integration of an intelligent system in existing machines.

3. Research methodology

Given that in the literature review, we did not find many studies conducted in Morocco, we thought of establishing a questionnaire to rule on the current state of the application of predictive maintenance in our country-specially in small and medium-sized companies- and to evaluate the main obstacles and challenges that hinder the implementation of predictive maintenance, by adopting the research methodology in Figure 1. The questionnaire is a quantitative method that is applied to a sample that should allow statistical inferences [22]. This study is based on a representative sample of 115 small and medium-sized Moroccan companies.

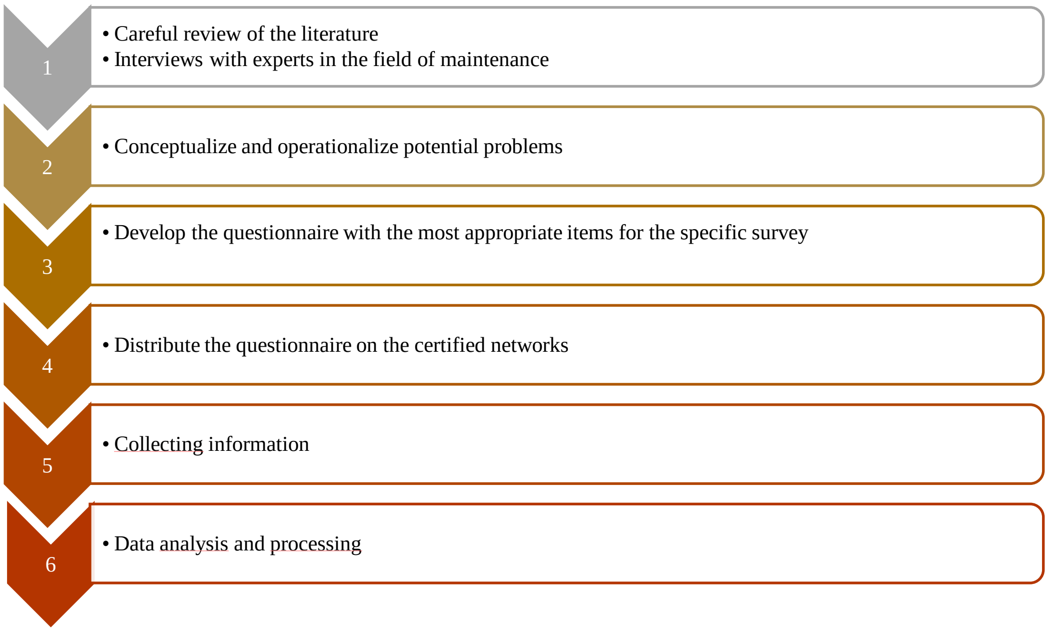

Figure 1. *Research methodology adopted*

1. The design of our questionnaire was based mainly on the review of the literature established beforehand, in addition to an interview with experts in the field of maintenance with an experience of more than 15 years in this service, namely: maintenance managers, infrastructure and means managers, operations managers, professors of higher education and coordinators / managers of spare parts stocks.
2. The interview allowed us to highlight the potential problems that companies may face, which served as input to our questionnaire and helped us to develop it further.
3. We designed the questionnaire according to several headings and sub-headings, with multiple choice, short answer, and multiple choice grid type questions, and timed an elementary time between 8 min and 12min of its completion by our experts in the final validation test.
4. The questionnaire was distributed to professional networks such as LinkedIn and by e-mail through Gmail after listing a large list of Moroccan companies.
5. The information was collected and visualized in a graphic format on Google Forms.
6. Statistical analysis and data processing were finally performed on SPSS software.

3.1 Questionnaire establishment

The questionnaire is composed of 5 sections:

- The first section simply describes the purpose of the study, the estimated time to complete the questionnaire and asks for the person's email to keep track.
- The second section deals with the person's personal information, i.e. level of education, number of years of experience and position held in the company.
- The third is about the company's information, its size, and field of activity, its date of creation, its location and its main customers.
- The fourth one aims at answering relevant questions about the status of predictive maintenance implementation in the company, the level of knowledge and application of maintenance optimization approaches, the level of need and expectation of the company regarding predictive maintenance as well as the level of subsidy.
- The fifth one allows to choose, through a multiple choice grid, the main barriers that slow down the application or the advancement of predictive maintenance within the companies.

3.2 Information collection

We chose to do a simple random sampling which is usually used for large populations, it is important to ensure a large enough sample size to adequately represent this population. A list of 2,800 Moroccan companies was made available to us, which we were able to filter all small and medium-sized companies, and we ended up with a total of 150 companies in various industries. The questionnaire was sent out in a general way on the professional network LinkedIn and eventually by e-mail in order to get as much information as possible quickly, while ensuring the representativeness of the sample. 132 companies were able to complete the questionnaire and only 115 companies were able to have 100% valid responses, which represents 76% of the target population.

3.3 Validity and reliability of the questionnaire

Among the issues of a study conducted by a questionnaire, we distinguish its reliability and validity. Reliability is a statistical measure of the degree of reproducibility of the data in a questionnaire, and validity refers to the effectiveness of the questionnaire in measuring what it is intended to measure [23]. A validity test was conducted with a group of experienced managers, all of whom found the layout of the questionnaire clear, and the majority of whom found the font size and length of the questionnaire appropriate. The questionnaire instructions were found to be easy to understand by 100% of the respondents, with a modification to the locking of the questions to make them mandatory.

In order to test the reliability of the 9 items presented which revolve around the difficulties encountered during the application of predictive maintenance by small and medium-sized Moroccan companies, we thought of carrying out an internal consistency between the items, two necessary elements are to be measured:

Cronbach's Alpha: which consists in measuring the homogeneity of the scale and of the different items of the scale between them, by calculating the value of Cronbach's alpha for all the Items and another measure which consists in removing one by one the Items.

The Cronbach's Alpha parameter is calculated as follows:

Equation 1:Cronbach's Alpha equation

$$\alpha = \left(\frac{k}{k-1}\right) x \left(1 - \frac{\sum_{i=1}^{k} \sigma_{yi}^2}{\sigma_x^2}\right) \tag{1}$$

Where:
k refers to the number of elements in the scale.
σ_{yi}^2 Refers to the variance associated with element i.
σ_x^2 Refers to the variance associated with the total observed scores.

Cronbach's alpha parameter varies between 0 and 1 and indicates good consistency if it is between 0,7 and 0,95, above 0,95 this indicates too much homogeneity which may indicate redundancy of the Items between them [24].

The second measure is the correlation between each Item and the total score of the questionnaire without this Item; if the correlation is > 0,6 and significant, this indicates that the correlation is significant [25].

Using SPSS V21.0, we obtained a value of 0,826 of Cronbach's Alpha test, which means that there is a good coherence between the items, in addition to the significant correlation between each item and therefore it is considered acceptable and can be used.

The order of classification of the items is important to collect relevant and exploitable data, so we opted for the Likert scale [26], defining a response grid from 1 to 5, of which 1= “Does not influence at all”, 2= “Does not influence”, 3= “Neutral”, 4=”Little influence” and 5= “Much influence”

3.4 Response Processing:

In the section entitled "Correspondent Information", the objective was to generate as much information as possible about the representative of the company studied, i.e. the position held, the years of experience and the level of training.

Descriptive analysis shows that 24,3% of our correspondents are maintenance managers, 21,7% are quality managers, 18,3% are continuous improvement managers, 13% are production managers, 11,3% represent technical managers and the rest are shared among several positions in the engineering department. Also, 91 correspondents have an engineering degree, 20 have a doctorate degree, 2 have a bachelor degree and 2 have a technician degree. Finally, 3 correspondents have a professional experience between 15 and 20 years, 4 have a professional experience between 10 and 14 years, 57 have a professional experience between 5 and 9 years and 51 have a professional experience of less than 5 years.

Our questionnaire was shared especially with all the Moroccan industries of small and medium-size in different sectors, showing that 61 of our correspondents work in the automotive industry sector, 22 in the food industry, 14 in the par-pharmaceutical industry, 3 in the wood and sawmill industry, 2 in the construction industry and 2 in each of the para-chemical and hygiene product industries. We notice that 8 companies have been in existence for less than 10 years, 5 companies for between 10 and 20 years, 16 companies for between 21 and 30 years, the vast majority, i.e. 65 companies, have been in existence for between 31 and 40 years and 21 companies have been in existence for more than 40 years. 36,52% of our population is located in the region of Tangier-Tetouan-Al Hoceima, 22,61% in the region of Settat-Casablanca, 21,74% in the region of Fez-Meknes, 13,04% in the region of Rabat-Sale-Kenitra, 5,22% in the region of Marrakech-Safi and only 0,87% in the eastern region of Morocco.

Table 2 defines 3 sectors of the main customers our correspondents work with, namely the private, public and semi-public sectors. The first frequency column "N" indicates the occurrence or number of participants associated with each specific valid value of the chosen variable. The second column gives the proportion of responses for each possible value, noting that 96,6% (i.e. 113/117x100) of all responses are attributed to the private sector, 0,9% to the public sector and 2,6% to the semi-public sector. The third column shows that we have 100% valid responses from our correspondents. The last column is less relevant when it is a dichotomous variable, the total is higher than 100% which is normal since each company can have clients from different sectors which means necessarily several answers. The dichotomous group is tabulated at value 1 which is coded under the value "Yes".

Table 2. *Sector of activity of the main customers*

Customer_sector Frequencies				
		Responses		Percent of Cases
		N	Percent	
Customer sector[a]	Private	113	96,6%	98,3%
	Public	1	0,9%	0,9%
	Semi_public	3	2,6%	2,6%
Total		117	100,0%	101,7%
a. Dichotomy group tabulated at value 1.				

4. Analysis and Discussion

In order to reach the objective of our research, we have made available to our correspondents a multitude of questions that will serve as a basis to evaluate the level of application of predictive maintenance in small and medium industries in Morocco, we will quote in the following, respectively each question, its result and its interpretation.

Question 1 "What are the performance improvement approaches adopted by your company? This multiple choice question has 5 possible answers: 1-TPM (Total Productive Maintenance), 2-PM (Predictive Maintenance), 3- Dependability, 4- FMEA (Failure Mode and Effect Analysis), 5- CMMS (Computerized Maintenance Management System). Grouping was performed for the 5 dichotomous variables and tabulated at value 1 which was coded under the value "Yes".

Table 3 shows that our correspondents can adopt several approaches at the same time, 95 companies adopt FMEA which represents a proportion of 24,5% among all possible values, 90 companies adopt TPM which in turn represents 23,3%, 84 companies adopt dependability represented by a proportion of 21,7%, 80 companies adopt CMMS represented by a proportion of 20,7%, and lastly, predictive maintenance adopted by only 38 companies and thus represents a proportion of 9,8% among all possible values.

Table 3. *Performance improvement approaches adapted by each company*

Performance_Improvement_Approach Frequencies				
		Responses		Percent of Cases
		N	Percent	
Performance_Improvement_Approach[a]	TPM	90	23,3%	78,3%
	PM	38	9,8%	33,0%
	Dependability	84	21,7%	73,0%
	FMEA	95	24,5%	82,6%
	CMMS	80	20,7%	69,6%
Total		387	100,0%	336,5%
a. Dichotomy group tabulated at value 1.				

It should be noted that several companies mentioned that their performance improvement initiatives are part of a quality management system certified according to a standard (ISO 9001 or IATF 16949), and that most of them follow key performance indicators (KPI) that are necessarily one or more parameters of the RMAS (Reliability-Maintenance-Availability-Security).

Since our study is mainly interested in the application of predictive maintenance, the second question is supposed to situate us in the state of progress of this approach within the company, by answering to: "What is your application level of predictive maintenance?" Only one answer is possible: 1- Applied approach, 2- Unplanned approach, 3- Planned approach, 4-Approach under deployment, 5-Abandoned approach.

Table 4 shows that 33% of the correspondents are already applying predictive maintenance, 38,3% of the correspondents have planned its application in the future, 20,9% have not yet applied it, 6,1% are in the process of deploying it and 1,7% have completely abandoned it.

Table 4. *Level of application of predictive maintenance by companies*

Application level of Predictive Maintenance					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	PM not planned	24	20,9	20,9	20,9
	PM planned	44	38,3	38,3	59,1
	PM being depolyed	7	6,1	6,1	65,2
	PM applied	38	33,0	33,0	98,3
	PM abandoned	2	1,7	1,7	100,0
	Total	115	100,0	100,0	

a. Dichotomy group tabulated at value 1

It was then useful to identify the priority index attributed by the company to this approach. The question is: "What priority index would you assign to the application of predictive maintenance?" Only one possible answer among these: 1- Low, 2-Medium, 3-High.

Table 5 shows that 50,4% of our correspondents have assigned a medium priority level to the application of predictive maintenance in their companies, 47,8% have defined a high priority and only 1,7% have defined a low priority.

Table 5. *Priority index assigned to the application of predictive maintenance company*

Predictive Maintenance Application Priority Index					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Medium	58	50,4	50,4	50,4
	High	55	47,8	47,8	98,3
	Low	2	1,7	1,7	100,0
	Total	115	100,0	100,0	

a. Dichotomy group tabulated at value 1.

For the companies that have already applied predictive maintenance, 86,84% of them have been applying it for less than 5 years and 13,16% have been applying it for 5 years up to 10 years. This shows that the application of predictive maintenance is recent in small and medium-sized companies in Morocco.

A short answer question was asked about the tool used to support the application of predictive maintenance, 61,50% mentioned having chosen an external support from a consulting firm and 38,50% had followed an external training.

Apart from filling in our questionnaire, we had the opportunity to talk to several company managers to find out what they expect from the application of predictive maintenance. Table 6 summarizes all these exchanges.

Although we provided our correspondents with 9 benefits of predictive maintenance on this multiple choice question, including B1 to B9 on Table 7, which constitute a group of dichotomous variables tabulated at the value 1= "yes".

The analysis showed that 96,5% of our correspondents expect predictive maintenance to minimize downtime, 94,8% expect it to increase their productivity, 82,6% expect an improvement in system efficiency and reliability and 78,3% expect a reduction in maintenance costs. B1 and B3 are the top 2 benefits expected by Moroccan companies. The total percentage of cases in the last column of Table 7 is normally greater than 100% since each respondent is allowed to choose up to 9 responses. The 717 represent the number of responses accumulated by all respondents.

Table 6. *Summary of oral exchanges with some company representatives*

Function of interlocutors	The expectations of PM	Sector of activity
35 Maintenance manager	-Cost reduction -Limitation of production losses and machine downtime -Increase in production volume -Reduction of unnecessary replacement product stocks -Improvement of the efficiency and performance of production units	Automotive, Parapharmaceutical, Agri-food
1 Plant director and 3 Technical managers	-Data reliability -prediction of the future behavior of the machine -Increase machine availability	Automotive
17 Quality manager	-Maintain the good functioning of the quality management system -Minimize downtime and replacement times -Increase effectiveness and efficiency -Reliable data sharing and analysis	Parapharmaceutical, Furniture, Agri-food, Building and public works
4 Continuous improvement managers	-Prevent critical incidents -Skills development and analytical capacity development -Fast decision-making -Improved machine availability	Automotive, Agri-food

Table 7. *Benefits of predictive maintenance*

Benefits_of_predictive_maintenance Frequencies				
		Responses	Percent of Cases	
		N	Percent	
Benefits of predictive maintenance[a]	B1: Minimization of downtime	111	15,5%	96,5%
	B2: Reduced maintenance costs	90	12,6%	78,3%
	B3: Increased productivity	109	15,2%	94,8%
	B4: Prevention of critical incidents	84	11,7%	73,0%
	B5: Improved efficiency and reliability of the system	95	13,2%	82,6%
	B6: Improved time to analyze failures	80	11,2%	69,6%
	B7: Reduction of spare product stocks	73	10,2%	63,5%
	B8: Prediction of future behavior	60	8,4%	52,2%
	B9: Improved data sharing	15	2,1%	13,0%
Total		717	100,0%	623,5%
a. Dichotomy group tabulated at value 1.				

Noting that with 96.5% highlighting reduced downtime and 94.8% noting increased productivity, predictive maintenance helps optimize operations and improve overall business efficiency. By reducing downtime, businesses can maintain consistent production and avoid revenue losses from unplanned breakdown. This results in better resource utilization and an increase in overall productivity. Additionally, by detecting potential issues before they become critical, predictive maintenance allows businesses to proactively plan repairs and interventions. This reduces maintenance costs and delays in production, which strengthens the competitiveness of companies in the market. By investing in predictive maintenance, Moroccan companies can improve their operational efficiency, reduce costs, increase productivity and remain competitive in the long term. It is a powerful way to stimulate economic growth and strengthen Morocco's position in the business world.

In order to generate several difficulties in the application of predictive maintenance and to be able to evaluate them, we put a long answer question to know what each of our correspondents think about the barriers that slow down the application of predictive maintenance. The answers were more or less similar between the correspondents, whose main ideas of the difficulties cited are as follows:

1- Lack of know-how, skills and expertise
2- Lack of financial resources/expensive monitoring equipment
3- Slow return on investment
4- Inadequate corporate culture for digitization
5- Lack of commitment and support from top management
6- Difficulty to make data-driven decisions
7- Lack of staff motivation
8- Lack of advanced enterprise data protection and lack of data ownership policies
9- Lack of methodology and formal procedures

Since the 9 difficulties reported through the questionnaire are consistent with those found in the literature, we adopted them as items that form the measurement scale to be able to analyze them through a matrix question using the Likert scale from 1 to 5 to measure the attitude of each individual, where 1=”Does not influence at all”, 2=”Does not influence”, 3=”No opinion”, 4=”Influences little”, 5=”Influences much”.

As on Table 8, for a scale composed of 5 items, we were able to obtain a Cronbach's Alpha value of 0,826 which is above the minimum threshold of 0,7 and therefore the internal consistency for this scale is satisfactory [27].

Table 8. *Cronbach's Alpha reliability test*

Cronbach’s Test	
Cronbach’s Alpha	N of Items
,826	9

The descriptive statistics on the Table 9 show that we have a number of 9 Items that represent the difficulties of the application of predictive maintenance, shared with N=115 correspondents, with a response scale ranging from 1 to 5, which means that the minimum value of this scale will be 9 and the maximum value is 45. This 5-point scale is considered as an interval scale [28], and can be interpreted according to the following 5 intervals:

I1: From 1 to 1.8 = "Does not influence at all", I2: from 1.81 to 2.6 = "Does not influence", I3: from 2.61 to 3.4 = "No opinion", I4: from 3.41 to 4.2= "Influences little", I5: from 4.21 to 5 = "Influences a lot".

Table 9 shows that our items were classified on 2 intervals, of which (D1, D2, D3, D4, D5, D6, D7, D9 belong to I5) and (D8 belongs to I4). Thus, the majority of correspondents evaluate as critical, with an average ranging from 4,23 to 4,54, the lack of know-how, skills and expertise, the lack of financial resources, the slow return on investment, the corporate culture unsuited to digitalization, the lack of commitment and support from top management, the difficulty of data-driven decision making, the lack of staff motivation, and the lack of methodology and formal procedures. These same correspondents rate as less critical, but with some influence, the lack of advanced enterprise data protection and the absence of data ownership policies, with an average of 4,15.

Table 9. *Descriptive statistics of the difficulties encountered*

Descriptive Statistcs					
	N	Minimum	Maximum	Mean	Std. Deviation
D1: Lack of know-how, skills and expertise	115	1	5	4,54	,798
D2: Lack of financial resources / Expensive monitoring equipment	115	1	5	4,23	,831
D3: Slow return on investment	115	1	5	4,31	,765
D4: Corporate culture unsuited to digitalization	115	1	5	4,24	,801
D5: Lack of commitment and support from management	115	1	5	4,30	,938
D6: Difficulty in data-driven decision-making	115	1	5	4,41	,805
D7: Lack of staff motivation	115	1	5	4,44	,752
D8: Lack of advanced corporate data protection and data ownership policies	115	1	5	4,15	,976
D9: Lack of methodology and formal procedures	115	1	5	4,30	,926
Valid N (Listwise)	115				

The next point aims to bring up the main challenges among the nine already mentioned before. The objective is to check the criteria of the principal component analysis (PCA), identifying if the collected data are factorable by the analysis of the correlation matrix, and calculating the KMO (Kaiser-Meyer-Olkin) index and finally the Bartlett's test of sphericity.

Note : Since Likert scales are always ordinal and therefore necessarily our variables have an ordinal measure, then our variables do not follow a normal distribution, so the data collected cannot be processed by parametric techniques requiring a normality condition such as the case of Shapiro-Wilk and Kolmogorov-Smirnov test. The non-parametric test recommended in this case is the Spearman or Pearson test represented on the correlation matrix in Appendix A, which shows that many variables are correlated and that their Pearson coefficients are greater than 0,3, so factorization is possible.

Table 10 shows a KMO index value of 0,810, which is a good result since it exceeds 0,8, this says that our variables share common factors and that component or factor analysis will be useful for our variables [29]. Bartlett's test of sphericity tests the hypothesis that our correlation matrix is an identity matrix. The significance level value is 0, indicating that factor analysis may be useful with our data when this value is less than 0,05, then it agrees that our variables are related and therefore useful for structure detection, so our correlation matrix is not an identity matrix.

Table 10. *Correlation statistics by KMO and Bartlett's test*

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,810
Bartlett's Test of Sphericity	Approx. Chi-Square	314,995
	df	36
	Sig.	,000

The conditions of use of PCA are respected, it is however possible to make the extraction of the principal components which will allow us to reduce the initial variables called metrics, in a small number of variables while keeping the maximum of information.

According to the Kaiser rule, only components with eigenvalues greater than 1 are retained. Table 11 of the total variance explained, shows 3 components with eigenvalues > 1 (3,805 and 1,162 and 1,048) and therefore the first 3 components are to be maintained, they concentrate more variance on the metric variables, this is why the 1st, 2nd and 3rd axes are those that give back the maximum information. In other words, they represent about 66,837% of the total variance among 9 Items. The 1st component has an eigenvalue of 3,805 and explains about 42,277% of the variance, the 2nd component has an eigenvalue of 1,162 and explains 12,916% of the variance and the 3rd component has an eigenvalue of 1,048 and explains 11,644% of the variance.

Table 11. *Extraction of principal components*

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,805	42,277	42,277	3,805	42,277	42,277
2	1,162	12,916	55,193	1,162	12,916	55,193
3	1,048	11,644	66,837	1,048	11,644	66,837
4	,711	7,897	74,734			
5	,575	6,389	81,123			
6	,542	6,023	87,146			
7	,441	4,894	92,041			
8	,398	4,422	96,463			
9	,318	3,537	100,000			

In order to facilitate the reading, we chose to use the Varimax rotation which allows to modify the components so that the axes are superimposed on representative and correlated factor sets. We considered the items with a value higher than 0,7 to make our study very representative.

Table 12 shows that Component 1 is mainly related to the lack of team motivation and corporate culture not adapted to digitalization, these factors can be classified in a group called "lack of managerial organization", whose main factor is the traditional monitoring of objectives by outdated means and tools such as a chain of emails, a spreadsheet, a slide, etc.. The team has no idea about the goal to be reached or the direction to be taken, no motivation system to increase staff satisfaction is in place.

Table 12. *Varimax rotation of the 3 components*

Rotated Component Matrix[a]			
	Component		
	1	2	3
D1: Lack of know-how, skills and expertise	,420	,573	,201
D2: Lack of financial resources / Expensive monitoring equipment	,061	,771	,322
D3: Slow return on investment	,149	,856	-,012
D4: Corporate culture unsuited to digitalization	,707	,157	,207
D5: Lack of commitment and support from management	,691	,052	,307
D6: Difficulty in data-driven decision-making	,626	,200	,425
D7: Lack of staff motivation	,830	,170	-,070
D8: Lack of advanced corporate data protection and data ownership policies	,206	,060	,852
D9: Lack of methodology and formal procedures	,177	,296	,805
Méthode de rotation : Varimax avec normalisation de Kaiser.[a]			
a. Rotation converged in 5 iterations.			

This first group represents 42.277% of the total variance, which is a high rate and requires focus to overcome this challenge. Component 2 is mainly explained by the slow return on investment and lack of financial resources, challenges that are also found in some large companies. Small and medium-sized Moroccan companies define a need for financial support from the state in order to evolve in their industries. This group 2, which we will call "lack of financial resources" represents 12.916% of the total variance. Component 3 is strongly explained by a lack of advanced protection of corporate data and the absence of policies on data ownership, this challenge is related to cyber security that is much less found in Moroccan SMEs. This group 3 that we will call "lack of data security" represents 11.644% of the total variance.

By adopting strategic measures, Moroccan small and medium-sized companies can overcome managerial organization, financial and data protection challenges, and promote the maturity of predictive maintenance in their organization. This will allow them to benefit from the advantages of this practice and remain competitive in the market. We therefore recommend the following strategic measures:

1. Seek external funding: Companies can explore external funding options such as grants, loans or partnerships to support the adoption of predictive maintenance. There are often government support programs or funding initiatives specifically designed to help SMEs adopt new technologies.
2. Training and Awareness: It is essential to train employees in the technical skills needed to implement predictive maintenance. Companies can organize internal training sessions or bring in external experts to impart the necessary knowledge. By making employees aware of the benefits of predictive maintenance, they will be more likely to support and adopt this practice.
3. Strategic Partnerships: Small and medium-sized businesses may consider partnering with larger companies or service providers specializing in predictive maintenance. This can help reduce costs and benefit from their expertise, while ensuring data protection through appropriate contractual agreements.
4. Implementation of data security protocols: Companies must have strict policies and procedures in place to protect data related to predictive maintenance. This may include implementing IT security measures, training employees on good data security practices and complying with data protection regulations.

However, the long-term sustainability of predictive maintenance initiatives in the context of small and medium-sized enterprises (SMEs) is one of the points to consider. It is important to take into account the resources available within the company. SMEs may have budgetary and personnel constraints, which may affect their ability to implement and maintain long-term predictive maintenance programs. It is therefore crucial to find solutions and partners that suit the needs and resources of the company. Second, staff training is essential. SMEs can invest in training their team to develop the skills needed to implement and manage predictive maintenance initiatives. This would ensure continuity and sustainability of efforts in the long term. Finally, regular evaluation of results and performance is important. SMEs can track and analyze data obtained through predictive maintenance to evaluate the effectiveness of their initiatives. This allows them to make adjustments and improvements over time, ensuring that initiatives remain sustainable and beneficial in the long term. It is also worth noting that SMEs can benefit from affordable and scalable technology solutions, tailored to their specific size and needs. This can help them implement predictive maintenance initiatives without compromising their long-term viability.

It is interesting to consider the policy implications and recommendations for government or industry initiatives aimed at supporting the implementation of predictive maintenance in small and medium-sized enterprises (SMEs). Governments can play a crucial role in encouraging and supporting SMEs to adopt predictive maintenance initiatives. This can be done through policies or incentive programs that provide benefits such as grants, tax credits or specialized training. Additionally, industry associations can also play a role in promoting predictive maintenance among SMEs. They can provide industry-specific resources, training and guidance to help businesses establish and maintain these initiatives.

Finally, global trends in the adoption of predictive maintenance show significant growth in recent years compared to Moroccan small and medium-sized enterprises. More and more companies are recognizing the benefits of predictive maintenance to optimize their operations. Key trends include increased use of the Internet of Things (IoT) to collect real-time data on equipment, enabling continuous monitoring and early detection of problems. Artificial intelligence and machine learning are also widely used to analyze data and predict potential failures. Another trend is the adoption of cloud-based solutions, which allow businesses to store and analyze large amounts of data without having to invest in expensive infrastructure. Collaboration between different departments of a company, such as maintenance, production and IT, has become essential to successfully implement predictive maintenance. These trends show that predictive maintenance is increasingly seen as an effective approach to improve equipment availability, reduce maintenance costs and optimize operational performance.

5. Conclusion

As a conclusion, this article aims to define the level of application of predictive maintenance in small and medium-sized Moroccan companies in different sectors and identify the major challenges that prevent its application. A literature review has been approached to generate the benefits and barriers of application of predictive maintenance in different countries and a questionnaire has been established only for small and medium-sized Moroccan companies, the study has been done on a sample of 115 companies, located on different cities of Morocco and represented by managers of different departments (Quality, maintenance, engineering, production ..) with a professional experience up to 20 years. It was found that the main benefits of the application of predictive maintenance are the reduction of downtime and the increase of productivity. The challenge assessment system used follows a Likert scale for more accuracy, the analysis of the main components was able to retain 3 components, which were grouped according to the factor of lack of managerial organization (Lack of team motivation and company culture unsuitable for digitalization) which accounts for 42, 277% of the total variance, lack of financial resources (slow return on investment and expensive equipment) which represents 12.916% of the total variance, and lack of enterprise data security (Lack of advanced enterprise data protection and lack of data ownership policies) which accounts for 11.644% of the total variance. For future study, it is recommended to focus on the main component 1, conduct surveys of these companies to trace the cause that prevents the integration of a staff motivation system and seek the voice towards the development of the internal culture of the SMEs.

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