The Impact of Smart Maintenance Technologies on Production Efficiency: The Mediating Role of Predictive Analytics An applied studding in group of Industrial companies in Basrah

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Abstract

Aim: *The study aimed to analysis of the impact of using smart maintenance techniques on production efficiency in industrial companies. Evaluating the role of predictive analytics as a mediating factor in improving maintenance and production efficiency. Provide recommendations on how to make the most of smart maintenance technologies and predictive analytics.*

Methodology: *The study followed the descriptive analytical approach by applying the questionnaire tool to a sample of 100 employees of industrial companies that use smart maintenance technologies and predictive analytics.*

Findings: *The study highlights the significance of smart maintenance techniques in enhancing production performance by predicting faults, reducing repair time, and enhancing resource efficiency. Predictive analytics also contribute to this, reducing costs and coordinating between production and maintenance activities. However, the impact varies depending on the statement studied.*

Keywords*: Smart Maintenance Technologies, Production, Efficiency, Analytics*

Introduction

Companies operating in the industrial field seek to achieve excellence in the markets and provide products that meet the needs and desires of customers in terms of high quality and acceptable cost, thus achieving the goal of survival and growth in the world of business and achieving sustainable profits, and this cannot be achieved by owning outdated equipment and machines. Therefore, major companies thought about using advanced maintenance methods, as smart maintenance is one of the important methods to ensure the continued operation of equipment in the right ways, which began in Japan and then spread to the world in the past twenty years. Therefore, smart maintenance is a comprehensive method for dealing with equipment and emerged as a result of the necessity of integrated maintenance. With manufacturing operations in order to improve productivity and maintain equipment uptime (Fahd, 2023).

Statement of Problem

Production efficiency has become a critical concern for industrial firms due to the growing complexity of industrial production processes and the need to minimize unplanned failures. Maintenance systems are critical to an organization's ability to maintain operations and minimize unscheduled downtime. Based on contemporary technologies like artificial intelligence (AI) and the Internet of Things (IoT), smart maintenance solutions have emerged as a vital instrument for increasing maintenance productivity and decreasing downtime.

To get the most out of these new technologies and connect them with existing systems, businesses must overcome certain difficulties. In this situation, predictive analytics ,which depends on gathering and evaluating data from machinery , can be extremely helpful as a mediator by foreseeing problems before they arise and making suggestions for better maintenance.

Importance of Study

Predictive analytics plays a mediating function in this study's investigation of the relationship between production efficiency and smart maintenance technology. It is crucial to comprehend how smart maintenance solutions affect operational performance as more and more businesses use them. This study explores how proactive problem detection and resolution using predictive analytics incorporated in intelligent maintenance frameworks might improve production efficiency.

Question of Study

What is the impact of smart maintenance technologies on production efficiency, and how can predictive analytics play a Mediating role in improving this efficiency?

Hypotheses of Study

H01: There is an impact of smart maintenance techniques on production efficiency.

Objectives of Study

1. Analysis of the impact of using smart maintenance techniques on production efficiency in industrial companies.
2. Evaluating the role of predictive analytics as a mediating factor in improving maintenance and production efficiency.
3. Provide recommendations on how to make the most of smart maintenance technologies and predictive analytics.

Limits of Study

- Time limits: 2024

- Spatial boundaries: industrial companies that use smart maintenance technologies and predictive analytics in iraq- Basrah..
- Objective Frontiers: Identifying the impact of smart maintenance technologies on production efficiency through the mediating role of predictive analytics.

Review of literature

Study of (Kunju, khan, Naveed, Nida, & Anwar, 2021):

The fourth industrial revolution, or Industry 4.0, is a digital transformation of the production industries brought about by the quickly advancing fields of information and communication technology. In order to give the current production companies a boost by recommending areas and tasks with great potential, the goal of this research is to provide a conceptual insight into the impact of unique capabilities from the fourth industrial revolution on production and maintenance tasks. Methodology: Among the research techniques included in the study are a survey and a literature review. A semi-structured questionnaire was used to gather empirical data for the survey. This yielded more detailed and focused information on the research issues and gave a wide picture of the company's current production and maintenance situation. Results: The research indicates that the use of Industry 4.0 technology boosts output, quality, asset utilization, machine downtime in industries, and maintenance. Today, real-time location systems, cloud computing, mobile endpoints, sensor technology, and big data analysis are being used to enhance organizational competitiveness and streamline production procedures. The research also emphasizes the use of data collected during manufacturing for autonomous production control, predictive maintenance, and quality control. Moreover, I4.0 solutions give businesses greater asset efficiency at every level of the process, giving them better control over stocks and opportunity for operational optimization.

Study of (Bokrantz, Skoogh, Berlin, Wuest, & Stahre, 2020),

What effect do "smart maintenance" (or updated maintenance procedures) have on manufacturing facility performance? The challenge facing industrial maintenance management is providing data-driven answers to questions like these, particularly as the industry rapidly shifts to a digitally-pervasive industrial environment. Of light of this, the purpose of this paper the first of a two-paper series is to explore and respond to the query, "What is Smart Maintenance?" In order to develop Smart Maintenance, the authors used focus groups and interviews with over 110 specialists from over 20 different organizations, utilizing an empirical, inductive research technique. Our findings provide fresh paths for current and future maintenance research by examining our initial data through the prism of many general hypotheses. The first empirically based definition of smart maintenance and its four underlying dimensions data-driven decision-making, human capital resource, internal integration, and external integration—are described in this study along with the empirical findings and theoretical interpretations that went into creating it. Additionally, the idea structure is properly described and the connections between the underlying dimensions are established. By providing a clear understanding of the notion of Smart Maintenance, this study contributes to theory and management and helps practitioners and academics in the field of industrial maintenance management.

Study of (Lundgren, Bokrantz, & Skoogh, 2020):

By implementing Smart Maintenance, "an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies," this study aims to realize digitalized manufacturing and ensure robust, productive, and sustainable production systems. In order to simplify the implementation of smart maintenance, this study intends to assist industry practitioners in choosing performance indicators (PIs) to measure the effects of smart maintenance. 170 maintenance performance indicators were analyzed using intercoder reliability and negotiated agreement. The expected impacts of smart maintenance were used to systematically categorize the performance indicators. Conclusions: Businesses that alter their production and/or maintenance strategies (such as reorganizing their maintenance organization to focus on smart maintenance) must update their collection of performance indicators. To make the process of choosing PIs for Smart Maintenance easier, this study proposes 13 kinds of PIs. Based on an analysis of 170 PIs, the categories were created based on the expected outcomes of Smart Maintenance.

Theoretical background

Smart Maintenance Technologies:

Technologies that require diverse roles to be included in the implementation process (Giliyana, 2023).

Production Efficiency:

The point at which an economy or other entity can no longer produce more of a good without reducing the production level of another good is known as production efficiency (Kliment, et al., 2020).

Predictive Analytics:

The use of data to forecast future patterns and occurrences is known as predictive analytics. It forecasts possible situations using past data, which can aid in guiding strategic decisions (Kumar, 2018).

"How is maintenance going to change in this highly connected industrial environment?" was the comprehensive study topic posed by Roy et al. (2016) in light of the shift towards an industrial environment with ubiquitous digital technology. A growth in the quantity of proposed concepts is a normal and healthy outcome of the growing interest in this subject in both research and practice.

Generally speaking, this is a good indication that a field's theoretical and practical landscape is growing, which allows for the advancement of our understanding of what constitutes productive practices. However, as the number of concepts increases, so does the worry about issues brought on by unclear conceptions (Shaffer et al., 2016). Concept multiplication, or the existence of several similar ideas with distinct names but overlapping conceptual domains, is a common sign of unclear concepts (Podsakoff et al., 2016).

We can see that a wide range of maintenance ideas, recognized and employed by academics and professionals alike, are assumed to be appropriate for this new setting. In terms of scientific literature, these include, but are not limited to, the following: "Maintenance 4.0" (Kans et al., 2016), "E-maintenance" (Muller et al., 2008), "Prognostics and Health Management" (Lee et al., 2014), "Predictive Maintenance" (Carnero, 2005), and "Smart Maintenance" (Munzinger et al., 2009). When it comes to practice, the word "smart maintenance" is most frequently employed by professionals in our local Swedish manufacturing enterprises; this is also the case in other European nations (Akkermans et al., 2016).

Methodology and Sample.

This study follows the descriptive-analytical approach, as the descriptive-analytical approach relies on quantitative data collected using the study tool, analyzing it, and producing results and recommendations.

Study population

The study population consists of all employees in industrial companies that use smart maintenance and predictive analytics technologies, which number approximately 20 thousand employees.

The study sample

A purposive sample of the study population was selected from 10 companies, which consisted of 100 employees in industrial companies that use smart maintenance and predictive analytics technologies.

Study tool

An electronic questionnaire was designed consisting of three axes.

Validity of the study tool

The validity of the study tool was tested through the Pearson correlation coefficient, and the following table indicates the test results:

smart maintenance techniques	Correlation coefficient	predictive analytics	Correlation coefficient	production efficiency	Correlation coefficient
Phrase 1	0.785	Phrase 1	0.845	Phrase 1	0.765
Phrase 2	0.841	Phrase 2	0.765	Phrase 2	0.754
Phrase 3	0.832	Phrase 3	0.745	Phrase 3	0.841
Phrase 4	0.765	Phrase 4	0.768	Phrase 4	0.762
Phrase 5	0.743	Phrase 5	0.713	Phrase 5	0.736

The validity of the study tool was tested using the Pearson correlation coefficient, and the results showed that all statements in the three axes (first, second, and third) achieved high correlation coefficients with the axes to which they belong, with values ranging between 0.713 and 0.845.

These results indicate a high degree of validity for the tool used, as the different statements reflect the axes they were designed to measure consistently and accurately. High correlation values (greater than 0.7) highlight that the study tool is capable of measuring the target concepts with high efficiency and reliability, which enhances researchers' confidence in the results drawn from this tool.

Stability of the study tool

The reliability of the study tool was tested through Cronbach's alpha coefficient, the results of which the following table indicates:

	Number of phrases	Cronbach's alpha coefficient
smart maintenance techniques	**5 phrases**	**0.796**
predictive analytics	**5 phrases**	**0.782**
production efficiency	**5 phrases**	**0.765**
Overall Cronbach's alpha coefficient	**15 phrases**	**0.846**

The reliability of the study tool was tested using Cronbach's alpha coefficient, and the results showed that the reliability coefficients for all axes were high, reaching 0.796 for the first axis, 0.782 for the second axis, and 0.765 for the third axis. The overall Cronbach's alpha coefficient for the tool was 0.846 when calculated for all 15 statements. These values indicate a high degree of internal consistency of the tool, which means that the statements within each axis cohere well with each other, and that the tool is generally reliable and able to give consistent results. When reused in similar measurements. These results enhance the reliability of the instrument used in the research, ensuring the stability of the data collected.

Analysis of the results

Smart maintenance techniques

	Item	Mean	Standard Deviation
1	Intelligent maintenance technologies help predict equipment failures accurately.	3.7	1.4
2	Intelligent maintenance techniques reduce fault repair time.	4.1	1.0
3	Intelligent maintenance techniques contribute to maintaining equipment readiness and increasing the operating rate.	4.3	0.9
4	Intelligent maintenance technologies improve productivity by reducing downtime.	3.8	1.1
5	Smart maintenance techniques increase the efficiency of using available resources in the production process.	4.2	0.9

Statement 1: Intelligent maintenance technologies help in accurately predicting equipment failures. This indicates that study participants consider smart maintenance techniques to be moderately helpful in predicting equipment failures, as the mean is close to 4 (agreement) but there is a large diversity of opinions as shown by the high standard deviation (1.4).

Statement 2: Intelligent maintenance techniques reduce fault repair time. The arithmetic mean of 4.1 shows strong agreement among participants that smart maintenance technologies contribute to reducing fault repair time. A standard deviation of 1.0 indicates less diversity in opinions compared to the first statement, which enhances confidence in overall agreement.

Statement 3: Intelligent maintenance techniques contribute to maintaining equipment readiness and increasing operation rate. The arithmetic mean of 4.3 indicates a very strong agreement that smart maintenance techniques contribute to maintaining equipment readiness and increasing the operating rate. A low standard deviation (0.9) indicates broad agreement between participants.

Statement 4: Intelligent maintenance technologies improve productivity by reducing downtime. The arithmetic mean of 3.8 shows that participants tend to agree that smart maintenance technologies improve productivity by reducing downtime, but there is some variation in opinions as indicated by the standard deviation of 1.1.

Statement 5: Intelligent maintenance techniques increase the efficiency of using available resources in the production process. The arithmetic mean of 4.2 indicates strong agreement that smart maintenance techniques increase the efficiency of using available resources in the production process. The standard deviation of 0.9 reinforces this result by confirming broad agreement among participants.

Overall, study participants show strong agreement on the various benefits of smart maintenance technologies. The arithmetic means range between 3.7 and 4.3, indicating high levels of appreciation for the positive impact of these technologies on production efficiency. The standard deviations range between 0.9 and 1.4, which means that there is a relative difference in opinions, but the general agreement remains strong.

Predictive analytics

	Item	Mean	Standard Deviation
1	**Predictive analytics help predict future equipment failures.**	**4.7**	**0.6**
2	**Predictive analytics leads to more effective planning of maintenance activities.**	**4.5**	**0.8**
3	**Predictive analytics contribute to reducing maintenance costs and improving production performance.**	**4.1**	**1.0**
4	**Predictive analytics allows proactive decisions to be made to avoid potential failures.**	**4.0**	**0.8**
5	**Predictive analytics improves coordination between production and maintenance activities.**	**4.0**	**1.0**

Statement 1: Predictive analytics helps predict future equipment failures. The high arithmetic mean of 4.7 indicates very strong agreement among participants that predictive analytics helps predict future equipment failures. The low standard deviation (0.6) reinforces this result, indicating high homogeneity of opinions.

Statement 2: Predictive analytics leads to more effective planning of maintenance activities. The arithmetic mean of 4.5 shows that participants strongly agree that predictive analytics helps plan maintenance activities more effectively. A standard deviation of 0.8 indicates relative agreement between participants.

Statement 3: Predictive analytics reduces maintenance costs and improves production performance. The arithmetic mean of 4.1 shows that there is strong agreement that predictive analytics contributes to reducing maintenance costs and improving production performance. A standard deviation of 1.0 indicates that there is some variation in opinions.

Statement 4: Predictive analytics allows proactive decisions to be made to avoid potential failures. The arithmetic mean of 4.0 shows that participants largely agree that predictive analytics enables proactive decisions to avoid potential failures. A standard deviation of 0.8 indicates relative agreement between participants.

Statement 5: Predictive analytics improves coordination between production and maintenance activities. The arithmetic mean of 4.0 indicates strong agreement that predictive analytics improves the level of coordination between production and maintenance activities, but the standard deviation of 1.0 shows a relative difference in opinions.

Overall, the results indicate that study participants strongly believe in the significant benefits of predictive analytics in the context of maintenance and production. The arithmetic means range between 4.0 and 4.7, indicating a high appreciation for the positive impact of predictive analytics. Standard deviations range from 0.6 to 1.0, indicating a relative difference in opinions, but overall agreement remains strong.

Production efficiency

	Item	Mean	Standard Deviation
1	**Intelligent maintenance technologies and predictive analytics increase the operating rate of equipment.**	**3.9**	**1.1**
2	**Intelligent maintenance technologies and predictive analytics help reduce productive downtime.**	**3.7**	**1.2**
3	**Intelligent maintenance technologies and predictive analytics contribute to improving product quality.**	**3.3**	**1.3**
4	**Intelligent maintenance technologies and predictive analytics increase a company's overall productivity.**	**3.6**	**1.2**
5	**Intelligent maintenance technologies and predictive analytics bring productivity cost savings.**	**3.7**	**1.1**

Statement 1: Intelligent maintenance technologies and predictive analytics increase the operating rate of equipment. The arithmetic mean of 3.9 indicates that participants tend to agree that smart maintenance technologies and predictive analytics lead to increased operation rate of equipment. A standard deviation of 1.1 shows a moderate diversity of opinions.

Statement 2: Intelligent maintenance technologies and predictive analytics help reduce productive downtime. The arithmetic mean of 3.7 indicates moderate agreement that intelligent maintenance technologies and predictive analytics help reduce productive downtime. A standard deviation of 1.2 shows greater variation in opinions among participants.

Statement 3: Intelligent maintenance technologies and predictive analytics contribute to improving product quality. The arithmetic mean of 3.3 indicates that participants consider that smart maintenance technologies and predictive analytics contribute moderately to improving product quality. The standard deviation of 1.3 indicates a large discrepancy in opinions.

Statement 4: Intelligent maintenance technologies and predictive analytics increase a company's overall productivity. The arithmetic mean of 3.6 indicates moderate agreement that smart maintenance technologies and predictive analytics lead to increased overall company productivity. The standard deviation of 1.2 shows that there is a difference in opinions.

Statement 5: Intelligent maintenance technologies and predictive analytics bring productivity cost savings. The arithmetic mean of 3.7 indicates moderate agreement that smart maintenance technologies and predictive analytics achieve production cost savings. A standard deviation of 1.1 shows a moderate diversity of opinions.

The results show that participants moderately agree on the various benefits of smart maintenance technologies and predictive analytics in improving production efficiency. The means range from 3.3 to 3.9, indicating varying levels of appreciation for the positive impact of these technologies. Standard deviations range between 1.1 and 1.3, which indicates a relative diversity of opinions. Also, by increasing the operation rate of equipment, smart maintenance techniques and predictive analytics are significantly influential in increasing the operation rate. Also reduce production downtime as there is moderate agreement that these techniques help reduce downtime. Participants notice less impact in improving the quality of products. The results show moderate agreement on increased productivity. Participants believe that these techniques generate moderate financial savings.

Test of Hypothesis

H1: There is an impact of smart maintenance techniques on production efficiency.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.840[a]	.705	.703	.31177	1.851

a. Predictors: (Constant), smart maintenance techniques

b. Dependent Variable: production efficiency

The results of the statistical analysis indicate that there is a strong and noticeable impact of smart maintenance techniques on production efficiency, as the correlation coefficient (R) reached 0.840, indicating a strong and positive relationship between the two variables. The coefficient of determination (R Square) with a value of 0.705 also shows that about 70.5% of the changes in production efficiency can be explained by using smart maintenance techniques. The Durbin Watson value of 1.851 also shows that there is acceptable independence of the residuals, which enhances the credibility of the model. Based on these results, it can be concluded that the adoption of smart maintenance techniques contributes significantly to improving production efficiency.

Discussion

The first axis: smart maintenance techniques

Smart maintenance techniques help in accurately predicting equipment failures (3.7), reduce fault repair time (4.1), contribute to maintaining equipment readiness and increasing the operating rate (4.3), improve productivity by reducing downtime (3.8), and increase efficiency Resource utilization (4.2).

Study by (Kunju, khan, Naveed, Nida, & Anwar, 2021): Indicates that the use of Industry 4.0 technologies, including smart maintenance technologies, enhances production and quality and reduces machinery downtime. This is consistent with our results showing improvements in failure prediction, repair time, and increased operating efficiency.

(Bokrantz, Skoogh, Berlin, Wuest, & Stahre, 2020)study: Intelligent maintenance is defined as data-driven decision making and internal and external integration. These dimensions are consistent with our findings, where smart maintenance technologies enhance resource efficiency and improve productivity.

(Lundgren, Bokrantz, & Skoogh, 2020) study suggests that smart maintenance leads to robust and sustainable production systems, which is consistent with our findings of increased uptime and productivity.

The second axis: predictive analytics

Predictive analytics help predict future breakdowns (4.7), plan maintenance activities more effectively (4.5), reduce maintenance costs and improve production performance (4.1), make proactive decisions to avoid breakdowns (4.0), and improve coordination between production and maintenance activities (4.0).

(Kunju, khan, Naveed, Nida, & Anwar, 2021) study:

emphasizes the importance of predictive analytics in predictive maintenance and quality control, which is in line with our findings suggesting failure prediction and effective maintenance planning.
(Bokrantz, Skoogh, Berlin, Wuest, & Stahre, 2020) study supports that predictive analytics is part of intelligent, data-driven maintenance, enhancing performance efficiency as shown in our results.
(Lundgren, Bokrantz, & Skoogh, 2020) study: Calls for updating performance indicators to measure the impact of smart maintenance. Our results showing improved coordination and reduced costs are consistent with this framework.
The third axis: production efficiency
Intelligent maintenance technologies and predictive analytics increase equipment uptime (3.9), reduce production downtime (3.7), improve product quality (3.3), increase overall company productivity (3.6), and achieve production cost savings (3.7).
Study (Kunju, khan, Naveed, Nida, & Anwar, 2021): Indicates that Industry 4.0 technologies enhance production and quality. Our results are consistent with this point but indicate a smaller impact on product quality.
(Bokrantz, Skoogh, Berlin, Wuest, & Stahre, 2020) study: Supports findings indicating improvements in productivity and operating rate as part of intelligent maintenance.
(Lundgren, Bokrantz, & Skoogh, 2020) study: calls for measuring the impacts of smart maintenance through performance indicators. Our results of increased productivity and reduced costs support this approach.
The results of the hypothesis show that smart maintenance technologies have a strong and positive impact on production

efficiency, as evidenced by the high correlation coefficient and the coefficient of determination, which indicates that these technologies explain a large proportion of the changes in production efficiency. This indicates the importance of adopting these technologies in enhancing performance and productivity, as they can contribute to improving maintenance operations and reducing unexpected breakdowns. Moreover, these results reinforce the importance of investing in smart maintenance technologies as a strategic element for achieving operational efficiency and competitive advantage.

Overall, the results of our study show high agreement with previous literature regarding the many benefits of intelligent maintenance technologies and predictive analytics in enhancing production efficiency. These results underscore the importance of adopting these technologies to improve operational performance and reduce costs, while emphasizing the need to continuously measure these effects through appropriate performance indicators to ensure that the desired benefits are achieved.

Recommendations

1. Encouraging the use of smart maintenance technologies by offering suggestions to businesses on how to implement and grow the usage of these technologies, such as enhancing predictive maintenance and autonomous production control systems. suggesting the creation of guidance models to choose suitable technologies according to the manufacturing quality and size of the firm.
2. Enhancing predictive analytics through the suggestion of fresh uses for it in maintenance scheduling and raising output levels. In addition, talk about how better forecasting and fault

prediction may be accomplished by utilizing big data and artificial intelligence.

3. Key performance indicators that may be utilized to quantify the effects of predictive analytics and smart maintenance technologies on operational performance are identified. and make recommendations on how to create and upgrade the current performance indicators to accurately represent the anticipated advancements.

Conclusions

The results of the first axis confirm the importance of smart maintenance techniques in improving production performance by predicting faults, reducing repair time, maintaining equipment readiness, increasing the efficiency of resource use, and improving productivity in general.

The results of the second axis reinforce the importance of predictive analytics in improving maintenance efficiency, reducing costs, enhancing production performance, and coordinating between production and maintenance activities, which contributes to making proactive decisions and effective planning of maintenance activities.

The results of the third axis indicate that smart maintenance technologies and predictive analytics play an important role in improving production efficiency, but there is a noticeable variation in the extent of the impact of these technologies depending on the statement studied.

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Appendix

Questionnaire

The first axis: smart maintenance techniques

	Phrase	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1	Intelligent maintenance technologies help predict equipment failures accurately.					
2	Intelligent maintenance techniques reduce fault repair time.					
3	Intelligent maintenance techniques contribute to maintaining equipment readiness and increasing the operating rate.					
4	Intelligent maintenance technologies improve productivity by reducing downtime.					
5	Smart maintenance techniques increase the efficiency of using available resources in the production process.					

The second axis: predictive analytics

	Phrase	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1	Predictive analytics help predict future equipment failures.					
2	Predictive analytics leads to more effective planning of maintenance activities.					
3	Predictive analytics contribute to reducing maintenance costs and					

	improving production performance.					
4	Predictive analytics allows proactive decisions to be made to avoid potential failures.					
5	Predictive analytics improves coordination between production and maintenance activities.					

The third axis: production efficiency

	Phrase	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1	Intelligent maintenance technologies and predictive analytics increase the operating rate of equipment.					
2	Intelligent maintenance technologies and predictive analytics help reduce productive downtime.					
3	Intelligent maintenance technologies and predictive analytics contribute to improving product quality.					
4	Intelligent maintenance technologies and predictive analytics increase a					

	company's overall productivity.					
5	Intelligent maintenance technologies and predictive analytics bring productivity cost savings.					