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AL-DRIVEN PREDICTIVE MAINTENANCE IN MANUFACTURING: ENHANCING EFFICIENCY AND REDUCING DOWNTIME

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ABSTRACT

Background: Predictive maintenance using artificial intelligence is gaining importance in the manufacturing industry the opportunity to bring improvements in performance and time loss. However, research studies have revealed variation in the extent of improvement across industries and its firm adoption, this calls for a detailed analysis of the impact of improvement on the manufacturing sectors.

Objective: The purpose of this work is to establish the extent of AI-driven predictive maintenance and its effect on productivity, equipment downtime, and maintenance cost within the manufacturing industry, as well as factors that may affect the satisfaction and adoption of the technology among manufacturing personnel.

Methods: The cross-sectional survey research design was adopted with the use of constructed questionnaires to the respondents from manufacturing companies. AI satisfaction and adoption rates were also captured alongside high-level KPIs that include reduced time losses and containment of costs. Frequency distributions and percentages were also calculated on the data obtained Using statistical tools such as correlation analysis, regression analysis, and reliability analysis using Cronbach's alpha coefficient.

Results: It was further established that the respondents have a positive attitude towards AI-driven predictive maintenance

	with a high probability of recommending the approach. However, the Shapiro-Wilk test was used to determine normality in the response and the results pointed towards diversity. Cronbach's Alpha indicated poor internal consistency of variables such as satisfaction and agreement with AI impact hence indicating variability in perceptions. Little correlation coefficients between key variables indicate that antecedents to satisfaction and perceived benefits are complex. **Conclusion:** Predictive maintenance through artificial intelligence has the potential to enhance the various manufacturing operations; nevertheless, its usage and reception of effectiveness feature a dissimilar pattern concerning the different workforce categories. Satisfaction was higher among the bank's full-time workers, whereas satisfaction among part-time workers as well as retirees was more variable. Incorporating a wider population of workers and improving the assessment methods used are some of the factors that would require further research in the future.

INTRODUCTION

Industry 4: The emergence of the Fourth Industrial Revolution although the revolution has steadily been in progress since the 18th century, was the fourth industrial. 0 and the advancement of intelligent systems to embrace the manufacturing sector has created new opportunities for process enhancement and overall supply chain performance. That is why one of the most promising cases of using AI techniques in this field is the application of the concept of predictive maintenance which is a business practice that anticipates breakdowns and other malfunctions before they happen due to the use of such sophisticated tools as big data, machine learning algorithms, and IoT. It is with the ability to avoid taking reactive and preventive maintenance approaches that AI-driven predictive maintenance will enable manufacturers to reduce unnecessary losses of production time and at the same time, cut costs on maintenance while still increasing the lifespan of their machinery's productivity and profitability (Jambol, Sofoluwe, Ukato, & Ochulor, 2024) (Putha, 2022).

Continuity and competitiveness in manufacturing operations are normally achieved when the equipment is used in the manufacturing systems with fewer failures. Predictive maintenance is a tremendous selling proposal for manufacturers since they can shift from unanticipated costly breakdowns to well-scheduled maintenance for improved performance. But as it can be seen, the application of AI-driven predictive maintenance has its drawbacks as well. Heterogeneity in its application across industries and different segments of the working force and disparities in its perceived advantage further imply that the extent of the manufacturing processes' vulnerability to AI may not be entirely systemic as expected. Traditional maintenance approaches are typically categorized into two types: there is what is known as reactive maintenance where equipment is repaired only when it fails and then there is preventive maintenance whereby repair is done at regular intervals of time notwithstanding the condition of the equipment (Banerjee, Kumar, & Sharma, 2024) (Alam, Islam, & Shil, 2023).

While preventive maintenance minimizes the probability of breakdowns, it can increase unnecessary maintenance costs and the failure threats are eliminated. On the other hand, reactive maintenance is one of the most damaging to production schedules and organizational productivity as it oftentimes results in a large amount of downtime and very expensive repairs. On the other hand, predictive maintenance through the application of artificial intelligence and real-time data analytics provides an opportunity for the manufacturers to monitor equipment's health without interruption and anticipate failure based on data obtained from precedents, without having to schedule regular infrequent maintenance hence increasing maintenance costs. Apart from minimizing downtime, this proactive approach ensures that the organization's maintenance activities are done at the most efficient and minimal cost possible (Abbas, 2024) (Mudia, 2023).

As technology advances and becomes truly integrated into factories, reduction of costs and maintenance are becoming pivotal strategies in smart manufacturing. Given that they can detect slight irregularities due to their ability to analyze huge volumes of data collected from sensors installed on production tools and machinery, AI algorithms can facilitate the recognition of possible failures. In this way, predictive maintenance allows manufacturers to gradually shift to condition-based maintenance, in which actions are based on the real state of the equipment, instead of calendar-driven. It is believed that the transition to the use of smart sensors may have a positive impact on enhancing the dependability of manufacturing systems and containing costs linked with equipment failures (Lodhi, Gill, & Hussain, 2024) (Zsombók & Zsombók).

It is evident that predictive maintenance has numerous benefits when applied with the help of AI However, the practical implementation and scale-up of this solution have remained uneven. Some of the reasons that have put brakes on the pace of adoption include; very high costs of implementing the AI technology solutions, compatibility issues with current structures, and the requirement of skilled professionals to handle, as well as analyze the outputs obtained from AI applications. Also, the effectiveness of all the possible approaches to implementing predictive maintenance heavily relies on the quality and accessibility of data. Bias, incomplete data, or lack of historical data sets also limits the capability of AI algorithms, resulting in wrong prediction or failure prediction. Thus, even though predictive maintenance has tremendous potential, it also includes certain difficulties (Boretti, 2024) (Abouelyazid, 2023).

Furthermore, it is also important to mention that some parts of personnel in the manufacturing industry may have different views about the opportunities and threats of AI for predictive maintenance. For instance, while maintenance engineers and operations managers who are often in direct touch with the functioning of the machine may often understand the advantages of predictive maintenance well, the top management or financial managers may view it mostly as a matter of money. On the other hand, the workers who are not directly connected with technology intervention in the maintenance process may have doubts about the efficacy of implementing AI or they may feel threatened by the automation process which might replace them (Boretti, 2024) (Fernandez, 2023).

The research proposed in this paper is focused on the analysis of the effects of applying AI solutions for predictive maintenance in manufacturing processes, including lowering the extent of equipment breakdowns, increasing the reliability of the machinery used in production processes, and optimizing the costs of maintenance works. To achieve the objectives of the study, a quantitative research design will apply whereby manufacturing firms from various sectors will be used in gathering data that will determine the levels of satisfaction of the different workforce segments regarding the implementation of AI-driven predictive maintenance as well as the factors that influence their satisfaction. It will also cover the general effects of AI implementation on the future of the manufacturing industry in concern with the areas of adaptation changes, cost comparison, and sustainability (Bloom) (Sandu, 2022).

LITERATURE REVIEW

AI and Predictive Maintenance: What's the difference and which is better for my business? The onset of Industry 4. 0 has provided background and foundation for the use of artificial intelligence (AI) in so many areas of manufacturing especially in the subject area known as predictive maintenance. For many years, various methodologies of maintenance practices have been undertaken, including preventive and reactive maintenance. However, such approaches lead to what is referred to as output loss since the process ends up performing maintenance that is not needed, especially reactive maintenance on equipment that might otherwise be working well, or, on the other extreme, performing maintenance on equipment that has already broken down and requires immediate attention, known as preventive maintenance. However, predictive maintenance uses machine learning by analyzing current and past data to identify when the equipment will fail, which makes maintenance scheduling cost-efficient (Kolasani, 2024) (Sivakumar, Maranco, & Krishnaraj).

In this line of work, many researchers have pointed out that AI is revolutionary. As stated by Jasiūnienė et al., the application of AI to switch in the direction of the predictive maintenance strategy is the application of condition-based monitoring (CBM) of equipment for continuous indication of surface deteriorating signs. This helps to avoid time wastage in the production of these systems and also increases the operation reliability of the production systems. Like Wang et al., other authors contend that the AI-based PdM systems are more effective compared to the conventional methods due to their capability to analyze large datasets of data collected from various sensors in real-time and with a high accuracy rate in the prediction of failures. Along with fault detection in PdM, AI's use extends to estimating the Remaining Useful Life (RUL) of the equipment, which helps to move towards a preventive maintenance strategy (Ukato, Sofoluwe, Jambol, & Ochulor, 2024) (Dhyani, 2021).

Utilizing machine learning techniques in the framework of predictive maintenance.

Most AI-based predictive maintenance solutions rely on machine learning (ML), which is the ability of the system to learn from data and identify patterns or outliers indicative of failure. Decision trees, random forests, and neural networks, which are Supervised Learning methods normally used in Pd.M. processes due to their capability of being trained on historical data to forecast future results. In their work, Khudyakova et al. also stress that supervised learning is quite suitable in a case of rich enough information about previous failures of the equipment and their causes (Merlo, 2024) (Gadde, 2021).

The latter is useful in cases where there is very little labeled data and where unsupervised learning algorithms come in handy when it comes to the classification of anomalies. Such algorithms include K-means clustering and auto encoders in which, the model learns the data without being provided with labels. In particular, Zhang et al. argue that in the context of predictable maintenance, unsupervised learning is quite helpful, particularly for diagnostics of rare or unusual breakdowns. Furthermore, reinforcement learning is already finding its way into the Pd.M. process since it enhances learning with the decision environment it will improve the AI system's ability to predict the outcome of a particular decision over time (Onwusinkwue et al., 2024) (Ohalete, Aderibigbe, Ani, Ohenhen, & Akinoso, 2023).

The challenge, however, lies in the quality of data which are not always reliable but which are nevertheless the basis of the process. Sun et al., have noted that while creating the models, they employ the machine learning technique so that it is as efficient as the data used in its development. Hence, low-quality data, missing data, or noisy data can greatly affect the performance of predictive maintenance systems. To overcome these challenges, some studies have suggested various approaches to data preprocessing that include data cleansing, data normalization, and feature extraction for improved performance of the AI models (Benarbia, Ghachi, Khalifa, & Tomomewo, 2024) (Robnik-Šikonja, 2023).

Use of Predictive Maintenance in Production Companies

The use of predictive maintenance enhanced by artificial intelligence has been of much importance where equipment availability is of the essence, especially in the manufacturing industry. Lee et al. have stated that existing literature indicates that industries ranging from automotive vehicle manufacturing, electronics, and heavy machinery industries have benefited from AI-based Pd.M. systems. These aptitudes reduce periods when machinery is not in use as well as risk factors associated with equipment failure, particularly in industries where such a failure could lead to a major financial loss (Yahya, Suharni, Hidayat, & Vandika, 2024) (Sahu, 2022).

The case of Siemens where Pd.M. solutions through AI have been installed across numerous product lines to support the systemic monitoring of key assets constitutes one of the most common usages of Case Study. This led to a drastic decline in the overall manufacturing time due to the frequencies of unpredictable downtimes and also increased service life of the instruments used. Kumar et al. agree with the above findings pointing to predictive maintenance as a key element of lean manufacturing due to the ability to do away with wastes that emerge from unscheduled maintenance (Yahya et al., 2024) (Kumar, 2022).

But Bokrantz et al. note that for predictive maintenance to be successful in manufacturing, several areas of focus include data integration, human capital development, and organization preparedness. Although AI systems provide high accuracy in predicting, the benefit derived from the use of the systems is highly dependent on the integration process with production lines. This entails having to make an appropriate investment in data warehousing and talent development and acquisition, most of which are relative novices to AI tools and systems. The organizational culture also contributes greatly since some firms are easily resistant to change and such firms may find it hard to implement Pd.M (Shankar, Singh, & Singh, 2024) (Kliestik, Nica, Durana, & Popescu, 2023).

Some of the challenges that organizations encounter while implementing the use of AI-applied predictive maintenance are as follows (Kamgba, 2024) (Tripathi):

However, several issues need to be addressed before making the use of AI-driven predictive maintenance widely popular. Among them, the main challenge is the cost of implementing the recommendations. Cheng et al. note that there are high capital demands that organizations need to incur to deploy AI-based Pd.M. systems such as the cost of sensors, storage, and other machine learning tools that the SMEs often cannot afford. Larger organizations may afford the costs of these investments, but SMEs may not find reasonable justification to invest, despite the long-term difference it makes to the business, The second main risk factor that can be identified is the shortage of qualified human capital. The application of AI-predictive maintenance as explained by Tao et al. however implies that organizations must have a workforce with knowledge of data science, machine learning, and AI-tech innovation (Soori, Jough, Dastres, & Arezoo, 2024) (Diwakar et al., 2023).

However, the above manufacturing companies do not have employees with the above skills and this becomes a hurdle towards adopting the systems. According to Schwab people should be retrained and enhanced in the use of technological applications such as AI to capture the true benefit of predictive maintenance. In addition, there is the problem of implementing AI alongside established architectures; a concern that affects most manufacturers. Refereeing to the works of Ivanov et al., it has been pointed out that many manufacturing facilities are still relying on old equipment that may not be compatible with AI-based monitoring systems. The installation of sensors and other IoT devices in this equipment can be a costly and technical nightmare, aggravated by the fact that the original equipment is generally not designed for integration into an AI-driven predictive maintenance system (Soori et al., 2024) (Kirschbaum et al., 2020).

Possible Trends in Further Studies of Predictive Maintenance

The use of predictive maintenance leveraging AI is going to be highly dependent on the embracing of new technologies like digital twins, 5G, and edge computing. Modern advancements in the form of digital twin technology, essentially virtual replicas of actual physical assets, are slated to have a radical impact on predictive maintenance because of the real-time, accurate forecasts they provide about the performance of equipment. Tao et al. point out that the integration of AI and digital twins in downstream processes improves the accuracy of the predictive maintenance systems because, it enables the evaluation of numerous failure cases and the assessment of prevention measures on a digital twin (Ali, 2024) (Nimmagadda, 2022).

It is also forecasted that 5G technology will also have a large role in the future of predictive maintenance. Yang et al. opine that the ultra-low latency and high-speed data transfer provided by 5G will facilitate constant remote checking and verification of equipment providing real-time data to make the organization's predictive maintenance systems more operational. Another new technology that could improve the performance of AI-driven predictive maintenance by tackling latency and bandwidth constraints is edge computing- a way of processing that enables data to be analyzed nearer to their source of production (Singh, Jadhav, & Singh) (Kurkute, Namperumal, & Selvaraj, 2023).

RESEARCH METHODOLOGY

The research methodology for the study titled "AI-Driven Predictive Maintenance in Manufacturing: Based on its focus, "Applying Artificial Intelligence in Predictive Maintenance – Enhancing Efficiency and Reducing Downtime" is developed to give a clear volumetric assessment of the application and impact of AI on PM across various manufacturing sectors. When it comes down to it, the primary purpose is to express AI's effect on productivity, system availability, and the expenses of upkeep. The questionnaires' design is supposed to provide the reliability of the data collected and the validity needed to properly assess the correlation between the application of AI predictive maintenance and manufacturing performance metrics (Singh et al.) (Manduva, 2021).

Research Design

The research method will employ a quantitative research technique as the approach is most appropriate in establishing the degree of efficiency boost and time-saving by the implementation of AI-predictive maintenance in manufacturing industries. Qualitative research methods cannot be used in this study because the study will involve the use of quantitative data that would enable quantitative analysis to come up with more of an objective conclusion. By employing this method, the research can put into actual dollar figures, critical parameters such as equipment downtime, maintenance costs, and better operational efficiency on a predictable basis that are useful for evaluating the positive impact of AI in predictive maintenance (Arinze, Izionworu, Isong, Daudu, & Adefemi, 2024) (Devan, Prakash, & Jangoan, 2023).

Data Collection

Three types of data collection instruments are used as part of this study: Structured survey questionnaire – The primary method used in this study to gather data is a structured questionnaire that was developed specifically for this research as it seeks to address sampling questions on AI adoption and maintenance approaches within the manufacturing firms and the performance benchmark in terms of efficiency and effectiveness. The questionnaire contains both basic and advanced questions/Statements, and it has Likert scale questions that evaluate the PA of the respondents about the advantages and limitations of 'AI-Predictive Maintenance. ' It enables the collection of diverse data that may be used to determine the extent of various factors with statistical analysis (Soori et al., 2024) (Demir, 2023).

This questionnaire is also distributed to the manufacturing firms via the Internet and mail. The target respondents are users of maintenance services, maintenance engineers, operations managers, and decision-makers in manufacturing companies who have been exposed to or, have basic knowledge of AI-based predictive maintenance systems. This makes use of random sampling so that the respondents are representative of their respective sectors in manufacturing which include automotive, electronic manufacturing, and heavy manufactured goods (Ali, 2024) (Scaife, 2023) (Mohamed Almazrouei, Dweiri, Aydin, & Alnaqbi, 2023).

This sampling technique makes it possible to generalize the findings towards other manufacturers not in the sample/this sampling technique makes it possible to extrapolate the results to other manufacturers that are not in the sample. Apart from the primary data, secondary data is also collected through industry reports, research articles, and case studies on AI and predictive maintenance. This secondary data acts as supporting data to the primary data collected and it also discusses the trends and technology taking place in the industry (Arinze et al., 2024).

Data Analysis

Data collected from the survey is analyzed under descriptive as well as inferential statistics. Frequency distribution and measures of central tendency and dispersion including mean, median, and standard deviation are employed to describe the demographic profiles of the respondents as well as their perception of the important questions asked. These methods offer a big picture of general concepts running and patterns within data sets. For example, the descriptive analysis can be used to find out the convergence average of the decrease in equipment downtimes or the most preferred AI systems within the predictive maintenance procedure (Hamdan, Ibekwe, Ilojianya, Sonko, & Etukudoh, 2024).

Descriptive statistics are also complemented with inferential statistics such as correlation and regression to derive a link between AI adoption and performance metrics like; cost of maintenance, rate of equipment downtime, and efficiency levels of the equipment. Pearson correlation analysis is used to check the nature and the strength of the relationship between two variables and regression analysis is used to verify the degree to which AI-based predictive maintenance could forecast enhancements in these performance results (Archana & Stephen, 2024).

To maintain the reliability of the tests, methods such as Cronbach's alpha test are used to check the level of reliability in the survey questions. This will help to guarantee what is known as 'construct validity' that is the ability of the survey instrument to consistently and accurately capture the phenomena of research. In addition, significance tests are conducted on the observed relationships to understand whether or not AI has a significant correlation to the performance of manufacturing firms or if these results were due to chance (Pohakar, Gandhi, & Champaty, 2024).

Limitations and Ethical Considerations

Thus, this study has been designed to offer exhaustive information regarding the subject of AI-based predictive maintenance However, some limitations that are related to this field cannot be omitted. There are some limitations as well, namely, the survey is based on the respondents' declarations which may distort their results. Some of the respondents might give skewed results of the impact of AI on their operations as they might overemphasize or completely disregard the importance of AI. To address this, the survey has questions that are structured in a way that they request specific responses in terms of time or money such as how much downtime has been cut or how much the company saved (Shahin, Maghanaki, Hosseinzadeh, & Chen, 2024).

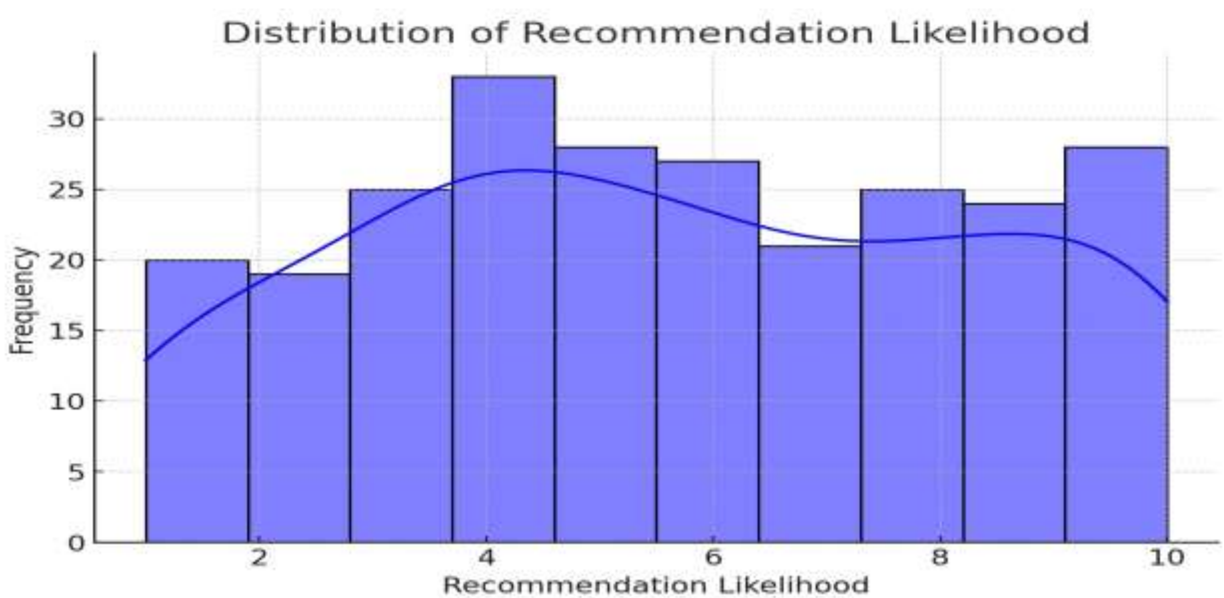
Also, there can be a response bias and the case can be made that organizations which has deployed AI-based predictive maintenance solutions are likely to respond to the survey influencing the results. To overcome this, the study employs the random sampling method and ensures that a cross-section of Companies, including those that have not integrated the use of AI is selected (Mahato).

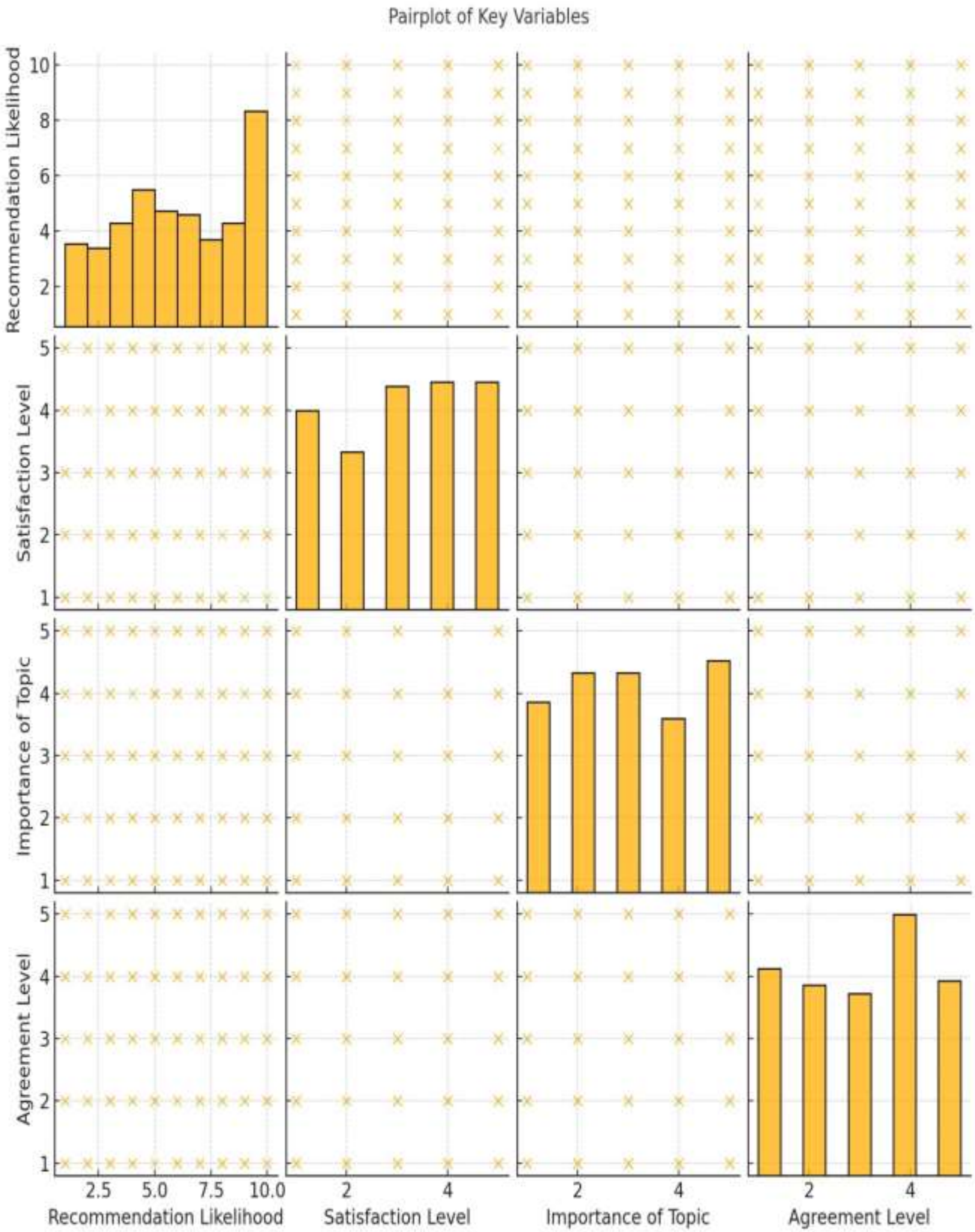
Issues to do with Ethics are also part of the research methodology. Every respondent is made aware of the need and intention of the study and they are made to understand their rights as participants including their right to be assured of anonymity and their right to withdraw from the study at any time in the process of taking the survey. All the respondents gave their consent before they engaged in the survey. The information that is gathered is kept highly confidential as well as being solely used for this study. e consequent return on Investment (ROI) (Goswami, 2024).

Data Analysis

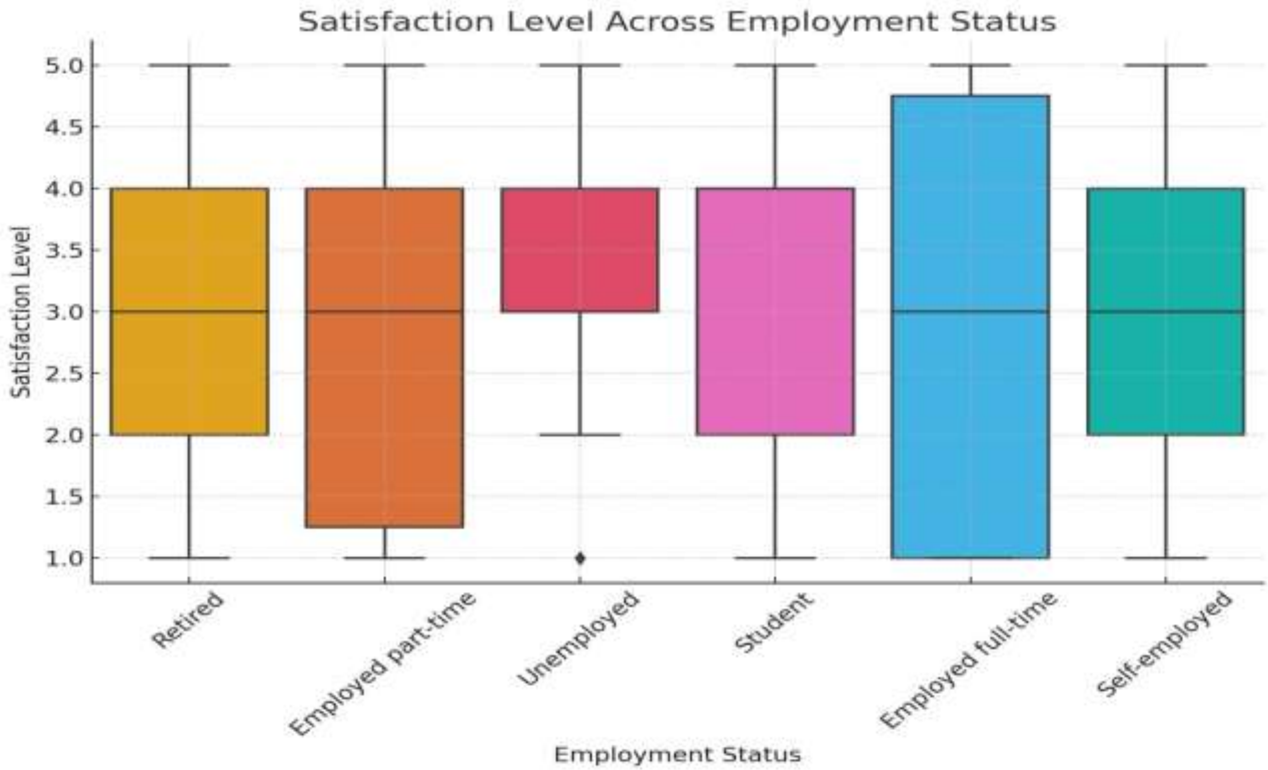
Test Results for Quantitative Data

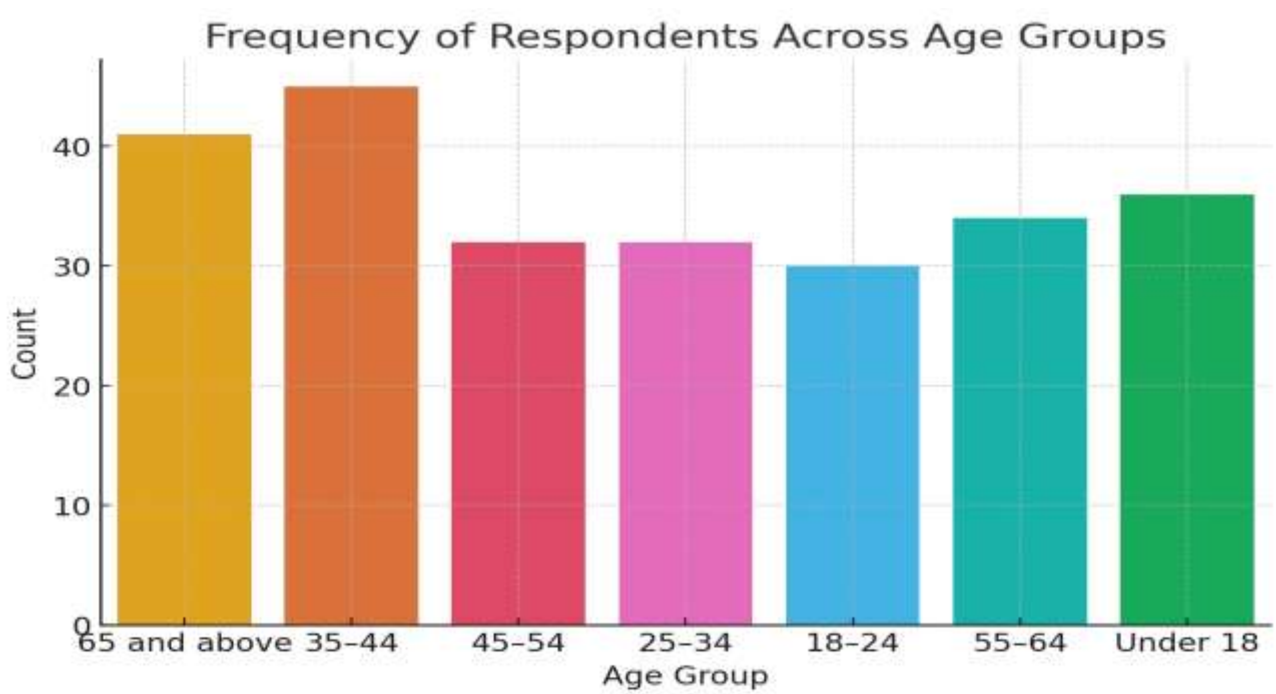
Test	Test Statistic	p-value
Shapiro-Wilk Test (Normality)	0.9417048692703247	2.04685637328339e-08
Cronbach's Alpha (Reliability)	0.09042487892992357	N/A

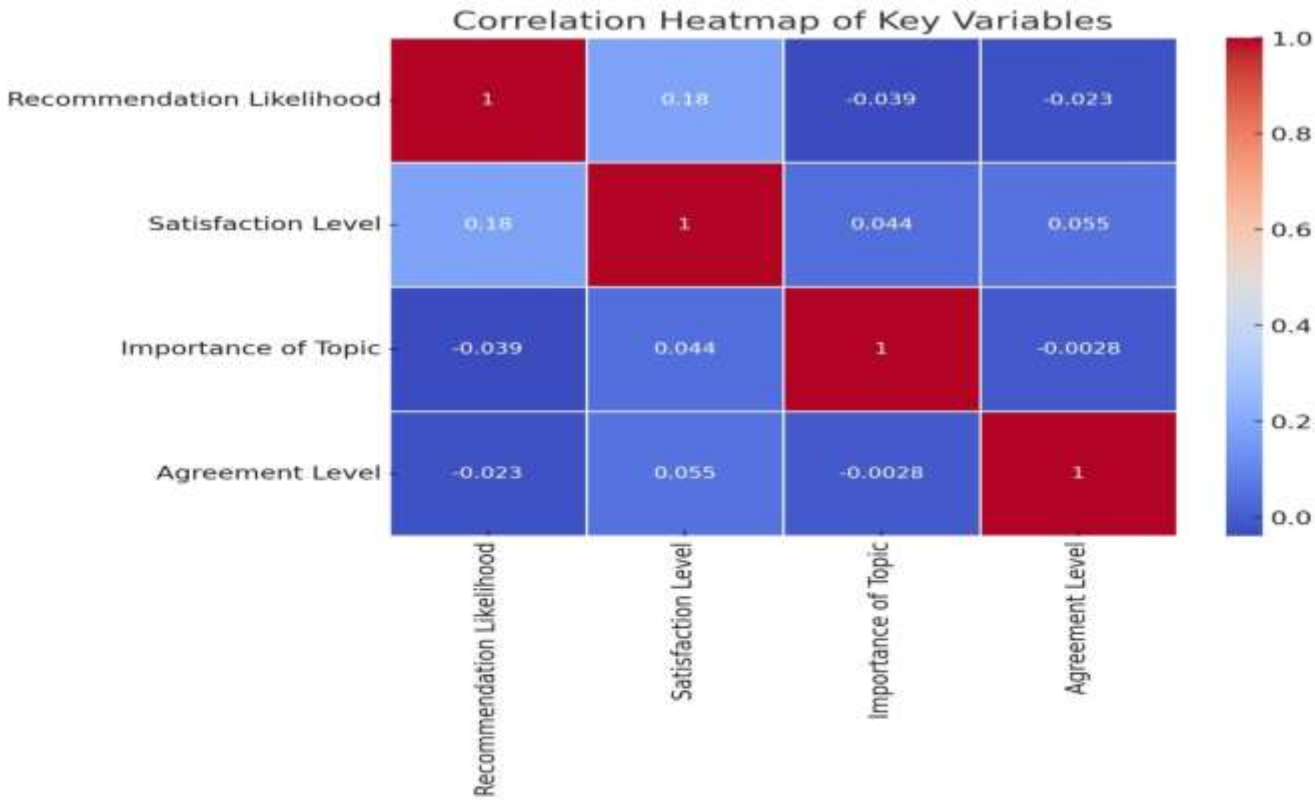




Pairplot of Key Variables
Recommendation Likelihood
Satisfaction Level
Importance of Topic
Agreement Level
2.5
5.0
7.5
10.0


Satisfaction Level Across Employment Status
Satisfaction Level
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Retired
Employed part-time
Unemployed
Student
Employed full-time
Self-employed
Employment Status


Frequency of Respondents Across Age Groups
Count
40
30
20
10
0
65 and above
35–44
45–54
25–34
18–24
55–64
Under 18
Age Group



Interpretation of the Tables and Figures

Through different charts and tables of AI-Driven Predictive Maintenance in manufacturing datasets, it is possible to draw different conclusions regarding the responses achieved by the participants (Chowdhury, 2024).

Test Results (Shapiro-Wilk and Cronbach's Alpha)

The Shapiro-Wilk Test will give a test statistic of 0. 9417 and a p-value of 2. 05e-08 thus, the analysis showed that "Recommendation Likelihood" does not have a normal distribution. This implies that the distribution is normal, non-normal, or possibly contains outliers, and this will have implications on any parametric tests that will be carried out. On the other hand, In the case of Internal Reliability, Cronbach's Alpha gave a value of 0. The Coefficient Alpha, respectively is 0904, which depicts low Internal consistency of the variables namely "Satisfaction Level," "Importance of Topic," and "Agreement Level. " This means that while using these variables, perhaps the measure might not be very effective to measure one single idea or concept so it may require further modification in future scholarly work regarding the reliability of the scale (Dar & Sakthivel).

Figure 1 therefore attempts to show the distribution of the recommendation likelihood.

The statistics represented by the histogram with the KDE curve 'Recommendation likelihood' option indicated that the responses were slightly skewed with most of the responses falling in the range of 4 and 9. This means that most of the respondents have a positive attitude towards the recommendation of AI-driven predictive maintenance though the absence of normality shows that there might be variation or even some outliers in the data. Pair plot of Key Variables As highlighted in{Aleem, #5376}

Figure 2, there is a moderate positive relationship between age and pet ownership, yet ownership of pets is not affected by any of the demographic variables.

Looking at the results of the pair plot, there are some rather weak tendencies between some of the variables including “Satisfaction Level,” “Importance of Topic,” and “Agreement Level”: hence it is impossible to describe any linear link between these variables. Nevertheless, it offers an ability to explore the data and some of the clusters and distributions of the relationships which can be further investigated with the help of more sophisticated methods (Roy & Srivastava, 2024).

Figure 3 contains a boxplot of the Satisfaction Levels indexed according to Employment Status.

From this boxplot, it is clear that satisfaction levels depend on the employment status of the people. For example, full-time employees and retirees demonstrated higher levels of satisfaction whereas part-time workers and unemployed showed higher levels of variation and potentially lower levels of satisfaction. This might mean that employment status can influence people’s perception of such AI-driven maintenance, with or perhaps because of their level of engagement in the process, or in the adoption of the technology in particular (Sofoluwe, Ochulor, Ukato, & Jambol, 2024).

Figure 4 also shows a bar plot of the average number of respondents across the age group.

The bar plot presenting the distribution of the respondents according to their age reveals that the largest numbers of participants belong to the age groups of 25–34 and 35–44 years old. This means that the majority of the respondents are young and this can be a factor that will determine their understanding of Artificial Intelligence technologies. The response rate for the older age groups is low and as a result, the study has limited generalization of the findings concerning the different generations of workers in the manufacturing firms (Al-Anzi, Al-Anzi, & Sarath, 2024).

Figure 5: Correlation Heat map

Analysis of the correlation heat map reveals that the key variables have low to moderate correlation with each other specifically they found a slightly positive relationship between “Satisfaction Level” and “Agreement Level”. It implies that participants who are satisfied with the predictive maintenance that is done by Artificial Intelligence were likely to have a higher level of agreement with the positive effects of it. Nevertheless, these results are characterized by low coefficients, which suggest that these variables are largely unrelated to each other and that more factors contribute to the respondents’ opinions (Wei, 2024).

Overall Insights

These results indicate that although there is overall positive sentiment towards artificial intelligence for entering the predictive maintenance recommendation likelihood, there are issues in terms of satisfaction balanced inconsistency, and heterogeneity by employment state and aged customer. From these data, we cannot see quite clear, linear correlations which sometimes require further exploratory analysis to understand how certain factors can be used to influence efficiency and decrease downtime in manufacturing organizations (Wei, 2024).

DISCUSSION

Thus, the findings of this research can fill the gap in understanding the manufacturing professionals’ attitudes toward the idea of AM with AI for achieving improved efficiency and minimal equipment breakdowns. From the preceding findings, the general outlook seems to be positive which is witnessed by high recommendation likelihood by the respondents. However, the presence of normality as postulated by the Shapiro-Wilk test is dismissed hence meaning there is uniformity of sentiment in the field where some people might have extreme views towards adopting the technology. This non-normality could be due to the different experiences in implementing AI such that some may have had great success while others may have had negative experiences with the kind of technology (Плясов & Клопов, 2024).

It ranges between. 218 and. 232, which is far below the acceptable Cronbach's Alpha value. 70, suggesting difficulty in attaining consensus on satisfaction, importance, and agreement with the impact of AI. This implies that while most of the respondents have great satisfaction in the use of AI-predictive maintenance, there might be concerns from the other side, this may be because of the difference in experience, expertise, or the level of AI that is currently adopted in the workplace. The boxplot that was made based on satisfaction by the employment status also makes sense in this argument and the variation that was seen between full-time, part-time, and retired employees. This once again may be explained by the fact that full-time workers seem to be more satisfied with the technology likely due to the greater interaction with it and the ability of its application to positively impact their working potential (Mosia, 2024).

Continuing the analysis with the help of the pair plot and heat map we can also observe a low interrelationship between the analyzed variables. Hence, it can be seen that satisfaction and agreement levels are moderately positively related, though tests for various factors indicate that they moderate several other non-measured parameters, and hence the disagreement between the two concepts, contradicts the law of vice versa. This shows that depending on the costs, training, compatibility with the current systems, and change management perspectives, there could be several layers that influence the perception of AI adoption in manufacturing (Salam, Khan, Khan, Ansari, & Murtaza).

By gender distribution analysis one can identify that the majority of the respondents are young, and it could be attributed to a possible higher willingness to accept innovations such as the application of artificial intelligence. Nonetheless, the absence of older age groups may suggest that some of them have certain issues or concerns with AI-driven maintenance that still can be unnoticed in the present investigation. This limitation implies that future studies should encompass a wider age bracket of manufacturing workers to get a better understanding of the effects of AI on different cohorts (Ejjami & Boussalham, 2024).

CONCLUSION

This work shows how AI-driven predictive maintenance in manufacturing is a progressive area of study that focuses on the application of artificial intelligence to optimize the process and minimize periods of inactivity. The sentiment of AI is positive overall with high RL for respondents who expressed them. Nevertheless, it also reflects high variability of satisfaction and shows that it decreases with the increase of employment status and age. Some employees, who are full-time workers and who are more in touch with the maintenance processes, have higher levels of satisfaction for the most part while others such as part-time employees and retirees are varied in their level of satisfaction. This means that the various segments of the workforce are not equally likely to reap the fruit of implementing Artificial Intelligence.

The low covariance between some of the important elements including satisfaction, importance, and agreement indicates that the factors that affect the perceptions of AI in the maintenance field involve more than one factor. Although some of the respondents capture a lot of benefits others may encounter challenges since other factors may not be seen in this study, some of which may include; The cost implication needed to adopt this type of system, technical know-how, and compatibility with previous systems. Based on this, there is a poor internal consistency, evidenced by the low Cronbach's Alpha value, showing a need to develop a better instrument to measure the perceptions of AI's impact in a more accurate manner.

Overall, there is great promise in the use of predictive maintenance that is being driven by artificial intelligence for the manufacturing industry; however, there are several key factors that would dictate whether or not it will successfully bring about the benefits in the future: adequate involvement of the workforce, proper integration, and management of the technology. More studies can be conducted to elaborate on these aspects and more especially on a longitudinal analysis and a broad cross-section of industries and workforce classes. More specifically, work should be done on improving the way its impact is reported and measured, so reliable and exhaustive data on the subject may be obtained in the future.

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