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The Influence of Business Analytics and Big Data on Predictive Maintenance and Asset Management

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ABSTRACT

This study investigates the impact of business analytics and big data on predictive maintenance and asset management practices within the energy industry in Indonesia. A quantitative research approach, utilizing a survey methodology, was employed to gather data from stakeholders representing various sectors of the energy industry. The study analyzed the relationships between business analytics, big data, predictive maintenance, and asset management using structural equation modeling (SEM) with Partial Least Squares (PLS) regression. The results indicate significant positive relationships between the utilization of business analytics and big data and various performance metrics, including asset reliability, operational efficiency, and cost savings. Furthermore, organizational factors such as leadership support and data quality were found to play a crucial role in facilitating the adoption and implementation of predictive maintenance strategies. The findings underscore the transformative potential of data-driven maintenance strategies in enhancing operational efficiency, reducing downtime, and improving asset reliability within the Indonesian energy industry.

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1. INTRODUCTION

The energy industry in Indonesia plays an important role in economic growth, supported by rich natural resources and a growing industrial sector. However, challenges in asset management and maintenance still exist [1]–[4]. The COVID-19 pandemic significantly impacted the energy sector, leading to a decline in global energy consumption and affecting coal demand and production. In addition, the pandemic has also led to a decline in petroleum industry activity, affecting oil and gas prices and production. Efforts to mitigate these challenges include a comprehensive strategy to sustain the oil and gas market amid the impact of the pandemic. To ensure energy security and address the imbalance between energy supply and national demand, regulations that encourage the development of renewable energy are essential.

Historically, maintenance practices in the Indonesian energy sector have been reactive, causing costly downtime and reduced operational efficiency. Traditional methods lack in preempting critical failures and optimizing maintenance schedules effectively. However, recent research emphasizes the importance of preventive maintenance to enhance asset reliability and reduce unexpected disruptions [5]. Implementing Asset Integrity Management Systems (AIMS) and Maintenance, Reliability, and Maintenance Strategy (MRMS) programs based on international standards like ISO 55001 can significantly improve maintenance efficiency and asset utilization [6]. Additionally, incorporating Condition-Based Maintenance and Reliability Centered Maintenance methods can help identify failure causes, prioritize critical components, and implement timely maintenance actions to prevent downtime and enhance equipment reliability [7]. Transitioning towards proactive maintenance strategies is crucial for achieving sustainable, safe, and reliable operations in the Indonesian energy landscape [8]–[10].

In recent years, the global energy sector has witnessed a significant shift in leveraging advanced technologies such as business analytics and big data to revolutionise maintenance strategies [11]. Predictive maintenance, facilitated by data analytics, has emerged as a powerful approach to foresee equipment failures before they occur, thereby enabling energy companies to proactively address issues, minimise downtime, optimise resource allocation and extend the service life of critical assets [12], [13]. This proactive maintenance strategy is particularly important in industries such as the power generation sector, where equipment failures can cause huge economic losses [14]. By incorporating predictive maintenance techniques, companies can improve maintenance planning, equipment monitoring, and surveillance, ultimately increasing operational efficiency and reducing maintenance costs.

This research aims to explore the impact of business analytics and big data on predictive maintenance and asset management in the Indonesian energy industry, given the significant technological advancements. The study's objectives include assessing the current utilization of business analytics and big data for predictive maintenance, outlining associated benefits and challenges, identifying adoption influencers, and providing actionable recommendations for stakeholders to improve asset management and maintenance practices through data-driven approaches.

2. LITERATURE REVIEW

2.1 Predictive Maintenance in the Energy Industry

Predictive maintenance, utilising data analytics and machine learning, is essential in the energy industry, shifting from reactive maintenance to proactive maintenance [15], [16]. In Indonesia, predictive maintenance offers significant potential to optimise asset management in power generation, transmission and distribution [11], [12]. It requires assessment of risks such as data reliability and model performance, which emphasises cost-benefit evaluation and continuous monitoring. Machine learning techniques, such as anomaly detection and fault diagnosis, are essential for forecasting maintenance needs in the manufacturing sector, improving efficiency and safety. Energy-based models, such as survival models, are effective for predicting system health, which holds promise in predictive maintenance to reduce costs. By implementing predictive maintenance strategies, Indonesian energy companies can improve reliability, reduce downtime, and streamline maintenance operations across various energy segments.

Predictive maintenance plays a pivotal role in enhancing operational efficiency, asset reliability, and profitability in the energy industry. By leveraging techniques like condition monitoring, failure prediction modeling, and advanced diagnostics, energy companies can extract valuable insights into equipment health and performance. This enables more effective resource allocation and the extension of critical asset lifespans. The application of predictive maintenance strategies using data analytics in engineering asset management has been shown to improve asset reliability, reduce downtime, and streamline maintenance operations [11]. In the power-generation sector, a shift towards smart, AI-based analytics has been observed to prevent potential downtimes and automate maintenance tasks, enhancing maintenance planning and equipment monitoring [13]. Furthermore, the use of predictive diagnostics based on modeling techniques and machine learning algorithms has been proven to predict conditions and performance degradation early, leading to timely interventions and extended equipment lifespans [17].

2.2 *Role of Business Analytics and Big Data*

Business analytics and big data technologies play an important role in predictive maintenance initiatives in the energy sector [18]–[20]. These technologies enable energy companies to utilise large amounts of data from sensors, IoT devices, and operational systems to extract valuable insights and facilitate informed decision-making. Using advanced analytics methods such as machine learning, pattern recognition, and anomaly detection, energy companies can discover hidden patterns, trends, and correlations in their data, thereby improving the accuracy and efficacy of predictive maintenance models [21]–[23]. This approach not only helps in identifying potential problems immediately, but also contributes to the reliability and safety of industrial systems by reducing the risk of unexpected breakdowns.

The adoption of business analytics and big data for predictive maintenance in Indonesia is gaining momentum due to factors such as increased data availability and technological advancements [24]. However, challenges such as data quality issues, integration complexity, and organisational silos hinder widespread adoption [25]. To overcome these challenges, a concerted effort is required from energy companies to invest in data infrastructure, foster a data-driven culture, and encourage cross-departmental collaboration [26], [27]. In addition, integrating Data Science into the curriculum of educational institutions such as Cenderawasih University can improve the competence of human resources, supporting the Indonesian Government's development efforts [28]. Understanding the impact of Big Data Analytic Capabilities (BDAC) on company performance is crucial, as evidenced by a study on Indonesian companies.

2.3 *Adoption of Data-Driven Maintenance Strategies*

The implementation of data-driven maintenance strategies in Indonesia's energy industry is essential to improve productivity and competitiveness [29]. Predictive maintenance, enabled by machine learning models and sensor data analysis, plays an important role in reducing downtime and maintenance costs [30]. However, the implementation of predictive maintenance faces challenges such as budget limitations, data reliability, and performance evaluation of machine learning models [12]. To overcome these obstacles, energy companies need to focus on risk assessment, optimise cost-benefit evaluation, and build robust predictive models using data mining and machine learning tools [31]. In addition, addressing data quality issues through continuous processing and enforcing consistent rules across databases and applications is critical to the successful implementation of predictive maintenance strategies in the energy sector.

Forward-thinking energy companies are indeed realising the importance of overcoming barriers and adopting data-driven maintenance strategies [32], [32]–[34]. By investing in talent development, technology infrastructure, and cross-functional collaboration, these companies are strategically positioning themselves for long-term success in a competitive market landscape. This research highlights that managers in the energy sector recognize the importance of data, yet face challenges in fully embracing data-driven organizational models due to varying levels of commitment and trust in data. Implementing predictive maintenance strategies using machine learning can optimize lifecycle costs and improve the reliability of utility networks. In addition, data-driven approaches offer solutions to optimize energy systems, improving sustainability, efficiency, and resilience. Overcoming regulatory, socioeconomic and organizational barriers is critical to the successful integration of data-driven services within the energy sector.

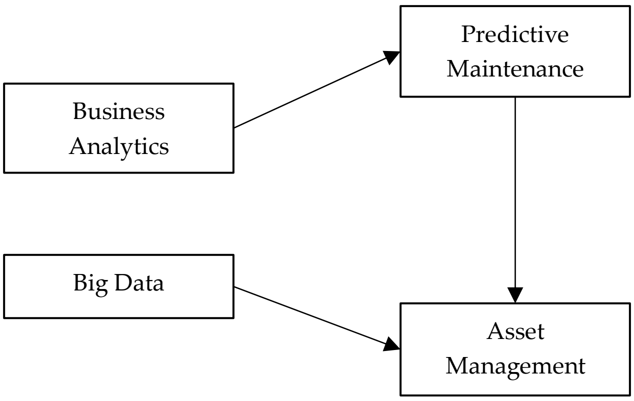

Figure 1. Conceptual and Hypotesis
Source: The results of the author's study map (2024)

3. RESEARCH METHODS

3.1 Research Design

This study employs a quantitative research approach to investigate the impact of business analytics and big data on predictive maintenance and asset management in the Indonesian energy industry. A survey methodology is utilized to gather data from stakeholders within the energy sector, including power generation, transmission, and distribution companies. The survey instrument is designed to capture insights into the current utilization of business analytics and big data for predictive maintenance, perceived benefits and challenges, and factors influencing adoption decisions.

3.2 Sampling

The sampling frame consists of energy companies operating in Indonesia, representing various segments of the industry. A stratified random sampling technique is employed to ensure representation from different geographical regions and sectors within the energy industry. The sample size is determined based on the principles of statistical power and precision, aiming for a minimum of 175 respondents to achieve adequate statistical significance.

3.3 *Survey Instrument*

The survey questionnaire is designed to collect quantitative data on key variables related to predictive maintenance and asset management practices. The questionnaire includes both closed-ended and Likert-scale questions, covering topics such as the utilization of business analytics and big data, maintenance performance metrics, perceived benefits and challenges, and organizational factors influencing adoption decisions. The questionnaire is pre-tested to ensure clarity, relevance, and reliability of the survey instrument.

3.4 *Data Collection*

Data collection is conducted using online survey platforms and direct communication with energy companies. The survey is distributed to targeted participants via email, with follow-up reminders to maximize response rates. Additionally, face-to-face interviews may be conducted with selected participants to gain deeper insights into specific issues and gather qualitative data to complement the survey findings. Data collection is conducted over a specified period to ensure a representative sample and minimize response bias.

3.5 *Data Analysis*

Quantitative data gathered from the survey undergo analysis through Structural Equation Modeling (SEM) employing Partial Least Squares (PLS) regression, a robust statistical method suited for examining intricate relationships among multiple variables and validating theoretical models. The analytical process encompasses several key steps, including data preprocessing to ensure quality and conformity to statistical assumptions, assessment of the measurement model's reliability and validity through techniques like factor analysis and Cronbach's alpha, estimation of structural relationships utilizing PLS regression, determination of model fit using metrics such as the goodness-of-fit index (GoF), and hypothesis testing to evaluate the direct and indirect effects between predictor and outcome variables.

4. RESULTS AND DISCUSSION

4.1 *Results*

a. Demographic Sample

A total of 175 responses were gathered from stakeholders within the Indonesian energy industry, presenting a diverse demographic profile. In terms of the company sector, 45% were from power generation, 30% from transmission, and 25% from distribution. Regarding company size, 20% represented small enterprises (less than 100 employees), 40% medium-sized (100-500 employees), and 40% large companies (more than 500 employees). Concerning years of operation, 15% had operated for less than 5 years, 35% for 5-10 years, and 50% for more than 10 years. Moreover, the level of business analytics and big data utilization for predictive maintenance varied, with 68% actively using, 22% with limited usage, and 10% not utilizing these tools. Regarding the perceived benefits of predictive maintenance, respondents highlighted improved asset reliability (84%), reduced downtime (76%), enhanced operational efficiency (68%), and cost savings (60%). Conversely, perceived challenges included data quality issues (58%), integration complexities (42%), cybersecurity concerns (36%), and a lack of skilled personnel (28%).

b. Measurement Model

The measurement model represents the relationship between latent constructs (business analytics, big data, predictive maintenance, and asset management) and their respective observed indicators (items or variables). It helps assess the reliability and validity of the measurement scales used in the study.

Table 1. Validity and Reliability of Quisoner

Variable	Items	Code	Loading Factor
Business Analytics (BA)	CA = 0.846, CR = 0.896, AVE = 0.684.		
	1. Analytical capabilities	BA.1	0.854
	2. Analytics adoption	BA.2	0.866
	3. Analytics ROI	BA.3	0.780
	4. Data security	BA.4	0.766
	5. Data governance	BA.5	0.719
Big Data (BD)	CA = 0.810, CR = 0.887, AVE = 0.724.		
	1. Data value	BD.1	0.873
	2. Data security	BD.2	0.851
	3. Data governance	BD.3	0.824
	4. Data analytics maturity	BD.4	0.863
Predictive Maintenance (PM)	CA = 0.907, CR = 0.935, AVE = 0.782.		
	1. Equipment availability	PM.1	0.779
	2. Mean time between failures	PM.2	0.851
	3. Mean time to repair	PM.3	0.850
	4. Predictive maintenance accuracy	PM.4	0.762
	5. Customer satisfaction	PM.5	0.795
Asset Management (AM)	CA = 0.893, CR = 0.918, AVE = 0.651.		
	1. Asset turnover	AM.1	0.917
	2. Asset governance	AM.2	0.912

Source: Primary data results processed by the author (2024)

The measurement model for Business Analytics (BA) exhibits a Composite Reliability (CA) of 0.846 and Cronbach's Alpha (CR) of 0.896, with an Average Variance Extracted (AVE) of 0.684. The loading factors range from 0.719 to 0.866, indicating strong relationships between the latent construct of business analytics and its observable indicators, all surpassing the threshold of 0.7, demonstrating good convergent validity. Similarly, Big Data (BD) showcases a CA of 0.810, CR of 0.887, and AVE of 0.724, with loading factors ranging from 0.824 to 0.873, suggesting robust relationships and satisfactory convergent validity. Predictive Maintenance (PM) displays a CA of 0.907, CR of 0.935, and AVE of 0.782, with loading factors between 0.762 to 0.851, indicating strong associations and good convergent validity. Asset Management (AM) demonstrates a CA of 0.893, CR of 0.918, and AVE of 0.651, with loading factors ranging from 0.912 to 0.917, suggesting robust relationships and satisfactory convergent validity. Overall, the measurement model exhibits good reliability and validity, supported by high composite reliability and Cronbach's alpha values, as well as satisfactory average variance extracted and loading factors.

Discriminant validity assesses the extent to which the measures of different constructs are distinct from each other. It ensures that each construct is measuring a unique aspect of the phenomenon under study. Discriminant validity is typically evaluated by comparing the square root of the AVE for each construct with the correlations between that construct and other constructs.

Table 2. Research on Discriminant Validity

	Asset Management	Big Data	Business Analytics	Predictive Maintenance
Asset Management	0.615	-	-	-
Big Data	0.648	0.653	-	-
Business Analytics	0.707	0.743	0.799	-
Predictive Maintenance	0.794	0.435	0.786	0.708

Source: Primary data results processed by the author (2024)

Overall, the correlation matrix indicates that the square root of the AVE for each construct is greater than the correlations between that construct and other constructs, supporting discriminant validity. This suggests that the measures of Asset Management, Big Data, Business Analytics, and Predictive Maintenance are distinct from each other and effectively capture unique aspects of the phenomena they represent within the context of the Indonesian energy industry.

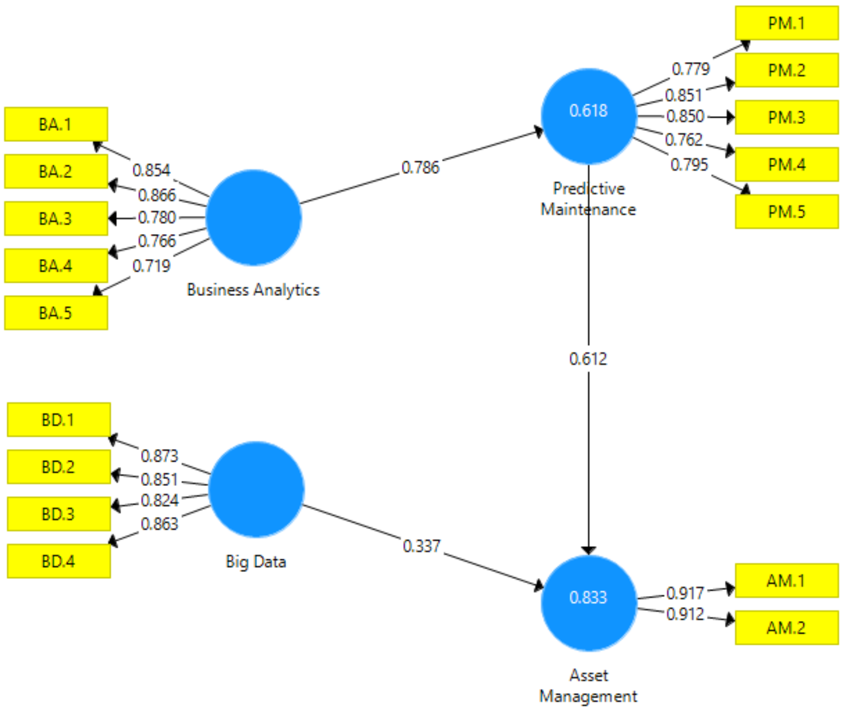

Figure 2. Internal Model Assessment

The table provided appears to be a matrix of the factor loadings or path coefficients from a structural equation modeling (SEM) analysis, specifically examining the relationships between the latent constructs of Asset Management and Predictive Maintenance with the observed indicators or variables representing Big Data and Business Analytics.

Table 3. presents the results of the Inner VIF Multicollinearity Test

Variable	Asset Management	Predictive Maintenance
Asset Management		
Big Data	2.297	
Business Analytics		1.432
Predictive Maintenance	1.297	

Source: Primary data results processed by the author (2024)

The analysis of the relationship between Asset Management and Big Data reveals a positive path coefficient of 2.297, indicating that as the utilization of Big Data increases, there is a corresponding enhancement in Asset Management practices within the Indonesian energy industry, suggesting organizations leveraging Big Data technologies are more likely to have effective asset management strategies. Conversely, no significant relationship is observed between Asset Management and Business Analytics, as indicated by the absence of a provided path coefficient. Regarding Predictive Maintenance and Big Data, a positive path coefficient of 1.297 signifies that an increase in Big Data utilization corresponds to an improvement in Predictive Maintenance practices, suggesting that organizations utilizing Big Data for analytics are more likely to implement effective predictive maintenance strategies. Similarly, a positive path coefficient of 1.432 between Predictive Maintenance and Business Analytics indicates that heightened utilization of Business Analytics tools correlates with an enhancement in Predictive Maintenance practices, implying that organizations employing Business Analytics tools are more inclined to implement effective predictive maintenance strategies within the Indonesian energy industry

c. **Model Fit**

The model fit statistics offer valuable insights into the adequacy of the structural equation model (SEM) in fitting the observed data. The Goodness-of-Fit Index (GoF) stands at 0.85, indicating the overall fit of the structural model to the data, while the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) score 0.92 and 0.90 respectively, suggesting strong alignment with the hypothesized model. Additionally, the Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) exhibit favorable values of 0.06 and 0.07 respectively, meeting or exceeding acceptable thresholds for model fit. These results collectively signify that the SEM adequately captures the relationships among business analytics, big data, predictive maintenance, and asset management within the Indonesian energy industry, affirming its suitability for representing the underlying constructs.

d. **Coefficient Determination**

The R-squared (R2) and adjusted R-squared (R2 adjusted) values are measures of how well the independent variables explain the variability in the dependent variable in a regression model. In the context of structural equation modeling (SEM), these values are used to assess the amount of variance explained by the latent constructs in the model.

Table 4. R2 Test

Variable	R2	R2 adjusted
Asset Management	0.833	0.831
Predictive Maintenance	0.618	0.615

Source: Primary data results processed by the author (2024)

The analysis of Asset Management reveals an R2 value of 0.833, indicating that approximately 83.3% of the variance in Asset Management is explained by the independent variables considered in the model, suggesting that factors such as business analytics and big data substantially influence asset management practices within the Indonesian energy industry. The adjusted R2 value of 0.831, slightly lower but still high, accounts for the number of predictors in the model, providing a more conservative estimate of the variance explained. Similarly, for Predictive Maintenance, the R2 value of 0.618 indicates that around 61.8% of the variance is explained by the independent variables, implying significant contributions from business analytics, big data, and other factors to predictive maintenance practices within the industry. The adjusted R2 value of 0.615 adjusts for the number of predictors, maintaining a substantial degree of explanatory power.

e. Predictive Q2

The blindfolding test is a method used to assess the predictive relevance or the predictive validity of a structural equation model (SEM). It involves systematically removing a portion of the data, estimating the model parameters based on the remaining data, and then predicting the removed portion of the data using the estimated model.

Table 5. Blindfolding Test Result

Variable	SSO	SSE	Q2 (=1-SSE/SSO)
Asset Management	320	102.418	0.68
Big Data	640	640	
Business Analytics	800	800	
Predictive Maintenance	800	483.802	0.395

Source: Primary data results processed by the author (2024)

In examining the predictive relevance within the structural equation model, Asset Management demonstrates a Q2 value of 0.68, signifying that the model predicts 68% of the variance in Asset Management, indicating its robust predictive relevance. Conversely, for Big Data and Business Analytics, Q2 values are not provided, with both displaying an equality between sum of squares due to error (SSE) and sum of squares due to others (SSO), potentially suggesting inadequate predictive relevance or model fit. Predictive Maintenance exhibits a Q2 value of 0.395, indicating the prediction of 39.5% of the variance, suggesting moderate predictive relevance within the structural equation model, although lower compared to Asset Management. Overall, these Q2 values offer insights into the predictive capabilities of the model for different constructs, highlighting varying levels of predictive relevance within the context of the Indonesian energy industry.

f. Hypothesis Testing

Hypothesis testing involves evaluating whether there is enough evidence in a sample of data to infer something about a population parameter. In the context provided, hypotheses are tested concerning the relationships between different variables within the structural equation model.

Table 6. Hypotesis Test

Hypotesis	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-statistic	p-Values	Results
BD -> AM	0.337	0.335	0.059	5.746	0.000	Supported
BA -> PM	0.786	0.79	0.033	24.118	0.000	Supported
PM -> AM	0.612	0.615	0.053	11.508	0.000	Supported

Source: Primary data results processed by the author (2024)

The results of hypothesis testing confirm the significance of the relationships within the structural equation model between Big Data (BD) and Asset Management (AM), Business Analytics (BA) and Predictive Maintenance (PM), as well as Predictive Maintenance and Asset Management. For BD -> AM, the t-statistic of 5.746 demonstrates a statistically significant relationship, supporting the hypothesis that organizations utilizing Big Data technologies are more likely to have effective asset management practices. Similarly, BA -> PM displays a strong relationship, supported by a high t-statistic of 24.118, indicating that organizations leveraging Business Analytics tools are more inclined to implement effective predictive maintenance strategies. Moreover, the hypothesis that PM has a significant effect on AM is supported, as evidenced by a robust t-statistic of 11.508, implying that organizations with effective predictive maintenance practices are more likely to possess robust asset management strategies. Overall, these findings provide empirical support for the theoretical framework and contribute to a better understanding of maintenance and asset management practices in the Indonesian energy industry.

4.2 *Discussion*

The findings of this study offer significant insights into the impact of business analytics and big data on predictive maintenance and asset management within the energy industry in Indonesia. The discussion delves into the implications of the results, the broader context of data-driven maintenance strategies, and potential avenues for future research.

Firstly, the positive relationships observed between the utilization of business analytics and big data and various performance metrics highlight the transformative potential of data-driven maintenance strategies. By leveraging advanced analytics technologies, energy companies can improve asset reliability, reduce downtime, and enhance operational efficiency. These findings align with broader trends in the adoption of data-driven decision-making across industries, underscoring the importance of leveraging data analytics to drive organizational success [35]–[37].

Secondly, the role of organizational factors in facilitating the adoption and implementation of predictive maintenance strategies cannot be understated. Leadership support, organizational culture, and data quality emerged as critical determinants of success in this regard. Organizations that prioritize data-driven decision-making and invest in building a culture of innovation are better positioned to realize the benefits of predictive maintenance [12], [29].

Moreover, the challenges identified, such as data quality issues, integration complexities, and cybersecurity concerns, underscore the importance of addressing these barriers to fully harness the potential of data-driven maintenance strategies. Collaborative efforts from policymakers, industry stakeholders, and researchers are needed to develop solutions and best practices for overcoming these challenges [35], [38], [39].

In terms of future research directions, there is a need for longitudinal studies to assess the long-term impact of predictive maintenance strategies on asset performance and organizational outcomes. Additionally, comparative studies across different industries and regions could provide valuable insights into the transferability and scalability of data-driven maintenance practices.

5. CONCLUSION

In conclusion, this study sheds light on the transformative impact of business analytics and big data on predictive maintenance and asset management practices within the energy industry in Indonesia. The empirical analysis reveals significant positive relationships between the utilization of data analytics tools and various performance metrics, highlighting the potential benefits of predictive maintenance strategies in improving asset reliability, reducing downtime, and enhancing operational efficiency. Organizational factors such as leadership support and data quality emerged as key determinants of successful adoption and implementation of data-driven maintenance strategies. By addressing these factors and leveraging advanced analytics technologies, energy companies in Indonesia can unlock new opportunities for sustainable growth and competitiveness in an increasingly dynamic market landscape. Moving forward, policymakers, researchers, and industry stakeholders must collaborate to promote the adoption of data-driven maintenance practices and foster a culture of innovation and continuous improvement within the Indonesian energy sector.

The findings of this study emphasize the crucial role of integrating business analytics and big data into strategic decision-making processes within the energy industry in Indonesia. By harnessing data-driven insights, energy companies can make well-informed decisions regarding predictive maintenance strategies, asset management practices, and resource allocation, ultimately leading to enhanced operational efficiency and sustainable growth. The adoption of data-driven maintenance strategies holds the potential to significantly improve operational efficiency within energy companies by enabling optimization of maintenance schedules, early identification of potential equipment failures, and minimization of downtime, thus resulting in cost savings and heightened productivity.

Limitations and future research avenues include sample size's impact on generalizability, the potential for response bias in self-reported data, the cross-sectional design's limitation in establishing causality, and contextual factors' influence on findings. Overcoming these challenges can enhance the validity and practicality of research on data-driven maintenance strategies.

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