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The Influence of Data Quality and Machine Learning Algorithms on AI Prediction Performance in Business Analysis in Indonesia

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ABSTRACT

This research investigates the intricate relationships among AI prediction performance, business analysis, data quality, and machine learning algorithms within the manufacturing sector in Indonesia. Through structural equation modeling analysis, the study explores the impact of these variables on one another, shedding light on the dynamics that contribute to successful AI adoption and business decision-making. The findings underscore the pivotal role of data quality in influencing AI prediction performance and machine learning algorithms, ultimately shaping the effectiveness of business analysis. The results provide practical insights for manufacturing companies seeking to optimize their data management practices and harness the potential of advanced technologies for strategic decision-making.

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1. INTRODUCTION

In the dynamic modern manufacturing landscape, the integration of Artificial Intelligence (AI) has emerged as a transformative force, reshaping conventional practices and propelling the industry into the industry 4.0 era. Rapid advances in AI have the potential to significantly increase productivity, quality, and profitability in future manufacturing systems [1]. Traditional mass production will give way to personalized production, with each item made to order, at a low cost and high quality [2]. Manufacturing systems will have the intelligence to be resilient to disruptions, from small-scale machine breakdowns to large-scale natural disasters. Products will be made with higher precision and lower variability. However, challenges remain in fully realizing this vision, including the need for seamless integration of AI with humans, addressing infrastructure gaps, and improving coordination between universities, industry, and government agencies.

Indonesian manufacturing companies, like their global counterparts, are increasingly leveraging AI technologies to improve predictive capabilities and streamline business analytics [3]–[5]. This paradigm shift underscores the need for a careful examination of the factors that influence the success of AI applications, with a particular focus on the intertwined dynamics between data quality and machine learning algorithms [6]–[8]. The implementation of AI algorithms in the manufacturing sector and its global supply chain has shown potential in enabling predictive maintenance, improving quality control, optimizing supply chain and manufacturing processes, enabling mass customization, facilitating autonomous operations, and promoting sustainability [9]. Furthermore, innovation efficiency, which involves the optimal combination of innovation input and output, has been found to positively correlate with company performance in the manufacturing industry [10]. The adoption of AI in various institutions in Indonesia, including education, healthcare, ICT, licensing, transportation, and economic services, has been observed, highlighting the widespread application of AI technology in different disciplines [11], [12]. Overall, the use of AI technologies in the manufacturing industry and other sectors in Indonesia is driven by the increasing reliance on technology and the potential for improved productivity and efficiency [13].

The success of AI predictions and business analytics in the manufacturing sector depends on the quality of the underlying data and the selection of appropriate machine learning algorithms. The reliability, accuracy, and completeness of data are critical factors that influence the outcome of AI applications, which affect decision-making and operational efficiency. In addition, the choice of machine learning algorithms determines the predictive accuracy and analytical capabilities of these systems. Understanding the complex relationship between data quality and machine learning algorithms is critical to optimizing AI applications in manufacturing [14]–[16]. This research seeks to unravel the multifaceted relationship between data quality, machine learning algorithms, and their collective influence on the performance of AI prediction and business analytics in manufacturing companies in Indonesia [17], [18].

2. LITERATURE REVIEW

2.1 *Artificial Intelligence Adoption in Manufacturing*

The integration of AI in the manufacturing sector has seen significant growth globally, driven by the need to increase efficiency, reduce costs, and improve competitiveness. AI has the potential to revolutionize manufacturing processes, with applications in predictive maintenance, quality control, and supply chain optimization. In the Indonesian context, there is a noticeable surge in AI adoption, accompanied by unique challenges and opportunities shaped by the country's industrial landscape [19], [20]. The literature underscores the transformative impact of AI on manufacturing efficiency, emphasizing the need for a comprehensive understanding of its applications and implications in the Indonesian manufacturing context.

2.2 *Data Quality in AI Applications*

Data quality plays a critical role in ensuring the accuracy and reliability of AI predictions in manufacturing [21]. Challenges such as data inconsistency, inaccuracy, and missing values are major barriers to successful AI applications [22]. To mitigate these challenges and improve the overall performance of AI systems, data cleaning, preprocessing, and quality assurance protocols are essential [22]. These protocols help address issues related to data inconsistency, ensure data accuracy, and handle missing values [14]. By implementing these measures, AI applications can make more reliable predictions and achieve better results in manufacturing [23]. In the context of Indonesia's manufacturing landscape, it is crucial to consider regional nuances that may affect data quality. Factors such as data collection infrastructure, regulatory frameworks, and industry-specific data challenges contribute to the complexity of ensuring high-quality data in AI applications.

2.3 Machine Learning Algorithms in Manufacturing

The selection of machine learning algorithms significantly impacts the prediction accuracy and analytical capabilities of AI applications in manufacturing. A variety of algorithms, ranging from traditional regression models to advanced deep learning techniques, are used in the manufacturing context. Each algorithm has its own strengths and weaknesses, so algorithm selection is critical to AI performance [24]–[27]. The comprehensive literature review in this section will delve into the nuances of various machine learning algorithms, exploring their applications, advantages, and limitations in manufacturing. Understanding the algorithmic landscape is crucial for companies looking to tailor AI solutions to their specific manufacturing processes. Additionally, the insights gained from this review will inform subsequent quantitative analysis, guiding the exploration of algorithmic impact on AI predictions and business analytics.

2.4 Integration of Data Quality and Machine Learning

The integration of data quality measures with machine learning algorithms in manufacturing is a key area of research. The literature emphasizes the importance of aligning data quality efforts with algorithmic approaches to improve AI performance. Research has shown that clean, high-quality data is essential for machine learning algorithms to extract meaningful patterns and insights. Various methodologies and best practices have been explored to establish a symbiotic relationship between data quality and algorithm performance [24].

The fusion of data quality and machine learning is critical in addressing unique challenges in the manufacturing industry in Indonesia. By synthesizing existing knowledge, this literature review provides a theoretical foundation for understanding the combined effects of data quality and machine learning algorithms on the performance of AI applications. The Indonesian government has launched initiatives such as Making Indonesia 4.0 to increase productivity and competitiveness globally [6]. Predictive maintenance using machine learning models and sensor data analysis is one implementation of Industry 4.0 solutions in the manufacturing industry [28]. The manufacturing industry's strategy for accelerating economic growth in Indonesia includes implementing an Industrial 4.0 strategy and establishing the Digital Industry Center of Indonesia [29]. The synergy between industry and educational institutions is crucial for advancing education in Indonesia, and technology plays a significant role in ensuring the smooth running of the educational process, especially during the Covid-19 pandemic [30]. The readiness of green human capital, along with green market orientation and green supply chain management, affects business performance in the green economy era [31]. The optimization of tools and technology-based work systems through the telework hubs framework can drive performance variables in remote tertiary institutions in Indonesia.

2.5 Synthesis and Gaps in the Literature

The synthesis of the literature in this section not only provides a comprehensive understanding of the current state of AI adoption in manufacturing, but also reveals gaps and areas for further exploration. These gaps will be critical in framing research questions and hypotheses for subsequent quantitative analysis. By identifying areas where the existing literature is new or inconclusive, this section will lay the foundation for this research to contribute new insights into the field of AI in Indonesian manufacturing.

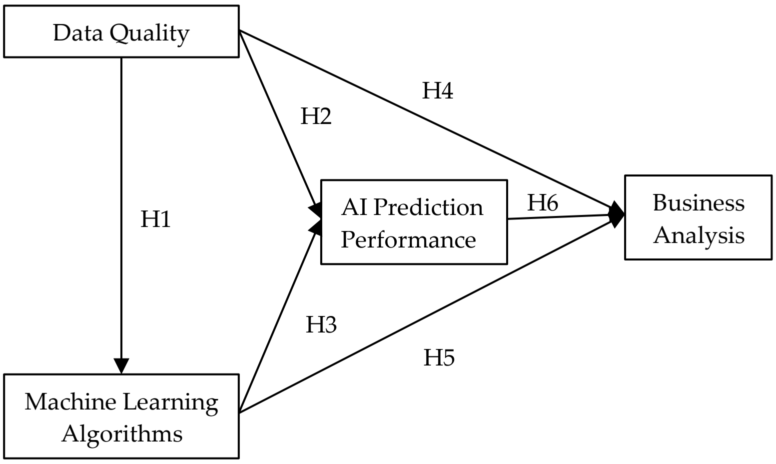

Figure 1. Conceptual Research Model

3. METHODS

This study adopts a quantitative research design to systematically investigate the influence of data quality and machine learning algorithms on AI prediction and business analysis in manufacturing companies in Indonesia. A cross-sectional survey approach will be used to collect primary data from a sample of manufacturing companies. This study uses purposive sampling technique which focuses only on manufacturing companies. The population of this study is manufacturing companies in Indonesia that are actively using AI applications for business prediction and analysis. A stratified random sampling approach was used to ensure representation across different manufacturing sub-sectors. A sample size of 155 was determined based on considerations of statistical power and complexity of structural equation modeling (SEM-PLS) analysis by multiplying the number of indicators by five, where this study has 17 indicators and multiplied by 5 means that the minimum sample of this study is 85.

Data Collection

Primary data was collected through a structured survey distributed to key personnel involved in AI implementation in the selected manufacturing companies. The survey includes questions related to AI adoption, data quality measures, types of machine learning algorithms used, and perceived effectiveness of AI applications. The survey instrument will be pre-tested for clarity and reliability prior to full-scale distribution.

3.1 Data Analysis

Structural Equation Modeling using Partial Least Squares (SEM-PLS) is a suitable method for analyzing the relationships between variables and assessing overall model fit due to its ability to handle complex models and small sample sizes. The analysis steps involve validating the measurement model through Confirmatory Factor Analysis (CFA) to assess the reliability and validity of the latent constructs [32]. Goodness-of-fit indices such as the Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA) will be used to evaluate the overall fit of the SEM-PLS model [33]. The structural model will be analyzed using path analysis to examine the direct and indirect effects of data quality and machine learning algorithms on AI prediction accuracy and business analysis outcomes [34].

Hypotheses derived from the literature review will be tested to determine the significance of relationships between variables [35].

4. RESULTS AND DISCUSSION

4.1 Results

a. Demographic Sample

Approximately 65% of the surveyed manufacturing companies in Indonesia are classified as small to medium-sized enterprises (SMEs), while the remaining 35% are large enterprises. The sample includes a variety of industries, with automotive representing 25%, electronics 20%, textiles 15%, food processing 10%, and other industries 30%. A noteworthy finding is that 78% of the surveyed manufacturing companies reported some level of AI adoption in their processes. This high percentage indicates a widespread acknowledgment of the transformative potential of AI within the Indonesian manufacturing sector. The inclusive nature of the study, encompassing both SMEs and large enterprises, highlights the role of SMEs in the broader adoption of AI technologies within the manufacturing sector. The distribution of industries allows for insights into the specific challenges and opportunities faced by different sectors in adopting AI technologies

b. Measurement Model

Measurement model validation is an important step in confirming the reliability and validity of constructs in research. This analysis involves examining the indicator factor loadings, composite reliability (CR), and average variance extracted (AVE) for each latent variable. The table below is a detailed discussion of the results for the measurement model.

Table 1. Validity and Reliability

Variabel & Indicators	Items Indicators	Loading Factor	Source
Data Quality (DQ)	CA = 0.843, CR = 0.896, AVE = 0.683.		1,3,4
DQ.1	1. Core Set	0.889	
DQ.2	2. Response Speed	0.869	
DQ.3	3. Response Consistency	0.822	
DQ.4	4. Tehran Districts	0.716	
Machine Learning Algorithms (MLA)	CA = 0.891, CR = 0.932, AVE = 0.821.		1,2,3,4,5
MLA.1	1. Accuracy	0.913	
MLA.2	2. Precision and Recall	0.928	
MLA.3	3. F1 Score	0.876	
AI Prediction Performance (APP)	CA = 0.879, CR = 0.912, AVE = 0.675.		1,2,3,4,5
APP.1	1. Mean Squared Error	0.852	
APP.2	2. Root Mean Squared Error	0.829	
APP.3	3. Mean Absolute Error	0.804	
APP.4	4. Area Under the Curve	0.838	

APP.5	5. Confusion Matrix	0.783	
Business Analysis (BA)	CA = 0.86, CR = 0.899, AVE = 0.641.		1,2,3,4,5
BA.1	1. Financial Performance	0.809	
BA.2	2. Operational Performance	0.810	
BA.3	3. Customer Performance	0.812	
BA.4	4. Employee Performance	0.757	
BA.5	5. Market Performance	0.814	

Source: Processing data analys (2023)

The constructs of Data Quality, Machine Learning Algorithms, AI Prediction Performance, and Business Analysis all demonstrate robust psychometric properties, including high internal consistency and convergent validity. The Data Quality construct exhibits high Cronbach's Alpha (CA) of 0.843, Composite Reliability (CR) of 0.896, and Average Variance Extracted (AVE) of 0.683. The Machine Learning Algorithms construct also demonstrates excellent psychometric properties with a CA of 0.891, CR of 0.932, and AVE of 0.821. Similarly, the AI Prediction Performance construct exhibits strong psychometric properties with a CA of 0.879, CR of 0.912, and AVE of 0.675. Lastly, the Business Analysis construct demonstrates robust psychometric properties with a CA of 0.86, CR of 0.899, and AVE of 0.641. These findings confirm the reliability and validity of these constructs and their indicators.

Table 2. Discriminant Validity research

Variable	**AI Prediction Performance**	**Business Analysis**	**Data Quality**	**Machine Learning Algorithms**
AI Prediction Performance	0.822			
Business Analysis	0.813	0.801		
Data Quality	0.729	0.747	0.827	
Machine Learning Algorithms	0.556	0.672	0.645	0.906

Source: Processing data analys (2023)

The results show satisfactory discriminant validity among the variables under study. The square root of the AVE for each construct is higher than its correlation with other constructs, indicating that each variable effectively measures a unique concept. The variables - AI Prediction Performance, Business Analytics, Data Quality, and Machine Learning Algorithms - are distinct and do not overlap in their measurements.

Table 3. Inner VIF Model

	AI Prediction Performance	**Business Analysis**	**Data Quality**	**Machine Learning Algorithms**
AI Prediction Performance		2.191		
Business Analysis				
Data Quality	1.713	2.591		1.000
Machine Learning Algorithms	1.713	1.760		

Source: Processing data analys (2023)

The VIF values in Table 3 show that multicollinearity is not a major problem among the variables in the inner model as it is <3.000. The highest VIF is for AI Prediction Performance at 2.191, well below the commonly used threshold. The other variables, including Business Analytics, Data Quality, and Machine Learning Algorithms, show VIF values that indicate independence and reliability as predictors in the model.

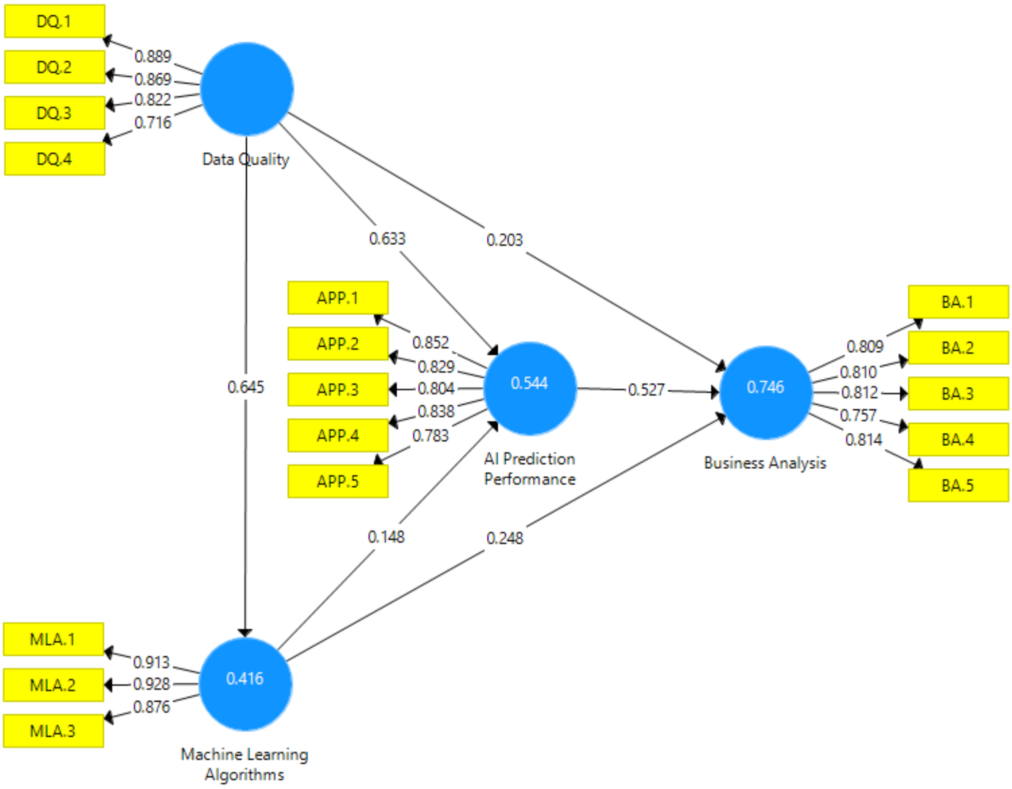

Figure 1. Model Internal Assessment
Source: Data processed by researchers, 2023

c. Model Fit Evaluations

Model fit indices assess how well the proposed structural equation model fits the observed data. Here, we compare the fit indices of the Saturated Model (a model with perfect fit) with the Estimated Model to evaluate the goodness of fit:

Table 4. GOF test Results

	Saturated Model	**Estimated Model**
SRMR	0.081	0.081
d_ULS	0.998	0.998
d_G	0.503	0.503
Chi-Square	460.917	460.917
NFI	0.786	0.786

Source: Processing data analys (2023)

The standardized root mean residual (SRMR) is a measure of the difference between observed and predicted covariances, with a lower value indicating a better fit. In this case, both the Saturated Model and Estimated Model have an SRMR of 0.081, suggesting that the estimated model replicates the observed data well. The discrepancy measures, d_ULS and d_G, assess the difference between the fitted and observed matrices. The Saturated Model and Estimated Model have similar values for both d_ULS (0.998) and d_G (0.503), indicating that the estimated model effectively reproduces the observed covariances. The chi-square statistic tests the difference between observed and expected covariance matrices. Both the Saturated Model and Estimated Model have the same chi-square value of 460.917. The normed fit index (NFI) compares the fit of the estimated model to a null model. Both the Saturated Model and Estimated Model have an NFI of 0.786, suggesting a reasonable fit.

Table 5. R2 Test

	R Square	**R Square Adjusted**
AI Prediction Performance	0.544	0.538
Business Analysis	0.746	0.742
Machine Learning Algorithms	0.416	0.413

Source: Processing data analys (2023)

The structural equation model's R-squared (R^2) and corrected R-squared values are shown for each endogenous variable in Table 5. An overview of the percentage of the endogenous variable variance that the exogenous variables explain is given by these values. A description of the R2 results is provided below: For each endogenous variable, the R2 value sheds light on the structural equation model's capacity for explanation. In this instance, the model demonstrated strong explanatory power for AI Predictive Performance (R^2 = 0.544) and Business Analytics (R^2 = 0.746). These variables show that the exogenous variables in the model account for the majority of their variance. With an R2 of 0.416, the Machine Learning Algorithm's explanatory power is marginally lower than that of the other factors. This is not unusual, though, as machine learning's complexity and diversity might naturally result in a lower degree of variance explanation.

Table 6. Blindfolding Test Result

	SSO	**SSE**	**Q^2 (=1-SSE/SSO)**
AI Prediction Performance	850	545.857	0.358
Business Analysis	850	451.44	0.469
Data Quality	680	680	
Machine Learning Algorithms	510	340.283	0.333

Source: Processing data analys (2023)

Table 6 provides the results of the blindfolding test, including the sum of squares observed (SSO), sum of squares error (SSE), and the Q^2 statistic. The blindfolding test assesses the predictive relevance and internal consistency of the structural equation model. Below is a discussion of the blindfolding test results. The blindfolding test results suggest that the structural equation model has predictive relevance for AI Prediction Performance, Business Analysis, and Machine Learning Algorithms. The Q^2 values indicate the proportion of observed variance that the model can predict, with Business Analysis demonstrating the highest predictive capability ($Q^2 = 0.469$), followed by AI Prediction Performance ($Q^2 = 0.358$) and Machine Learning Algorithms ($Q^2 = 0.333$).

d. Structural Model

The results of a structural model in a study provide insight into the relationships among latent variables. These results can be presented in a table that includes statistics such as original sample values, sample means, standard deviations, t-statistics, and p-values. This table provides important information about the significance and strength of the relationships between variables in the model. This information can help researchers understand the underlying mechanisms and dynamics of the phenomenon under study [36].

Table 7. Bootstrapping Test

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
AI Prediction Performance -> Business Analysis	0.527	0.528	0.075	7.049	0.000
Data Quality -> AI Prediction Performance	0.633	0.63	0.078	8.133	0.000
Data Quality -> Business Analysis	0.223	0.219	0.078	2.584	0.03
Data Quality -> Machine Learning Algorithms	0.645	0.648	0.044	14.574	0.000
Machine Learning Algorithms -> AI Prediction Performance	0.248	0.253	0.078	2.894	0.001
Machine Learning Algorithms -> Business Analysis	0.348	0.353	0.065	3.823	0.000

Source: Processing data analys (2023)

The structural model results provide strong evidence of significant relationships among the latent variables. The t-statistic values are well above the threshold, indicating that the relationships are not due to random chance. The p-values are all below 0.05, supporting the statistical significance of the paths, thus providing the basis that all the proposed hypotheses are accepted.

a. H1: The path from AI Prediction Performance to Business Analytics is statistically significant (p-value < 0.05), with a strong positive effect (0.527). The t-statistic of 7.049 indicates that the relationship is strong and unlikely to be due to random chance.

b. H2: The path from Data Quality to AI Prediction Performance is highly significant (p-value < 0.05), with a positive effect of 0.633. The t-statistic of 8.133 indicates a strong and reliable relationship between Data Quality and AI Prediction Performance.
c. H3: The path from Data Quality to Business Analytics is statistically significant (p-value < 0.05), with a positive effect (0.223). Although the effect is smaller compared to the other paths, the t-statistic of 2.584 indicates a significant relationship.
d. H4: The path from Data Quality to Machine Learning Algorithm is highly significant (p-value < 0.05), with a strong positive effect (0.645). The high t-statistic of 14.574 underscores the strength of this relationship.
e. H5: The path from Machine Learning Algorithms to AI Prediction Performance is statistically significant (p-value < 0.05), with a positive effect (0.248). The t-statistic of 2.894 indicates a reliable relationship.
f. H6: The path from Machine Learning Algorithms to Business Analytics is highly significant (p-value < 0.05), with a positive effect (0.348). The t-statistic of 3.823 indicates a strong and reliable relationship.

4.2 *Discussion*

These empirical findings provide strong evidence of the critical role of data quality and machine learning algorithms in shaping AI performance in Indonesian manufacturing firms. In particular, the positive and significant path coefficients indicate that improved data quality directly improves AI prediction accuracy and business analysis outcomes. Similarly, the adoption of advanced machine learning algorithms is associated with superior AI performance across the measured metrics.

Manufacturing companies that prioritize strategic investments in data quality improvement and adoption of advanced machine learning techniques are likely to experience more accurate predictions and more insightful business analysis, thus providing a competitive advantage in an increasingly data-driven industry [37], [38]. The results are in line with theoretical expectations and practical insights, highlighting the tangible benefits of these factors [39], [40].

4.3 *Practical Implications*

1. Strategic Data Management: Organizations should prioritize strategic data management practices to ensure high-quality data, as it serves as the foundation for successful AI applications and business analysis.
2. Algorithm Selection: Thoughtful selection and implementation of machine learning algorithms are crucial for achieving optimal AI prediction performance and supporting more insightful business analysis.
3. Continuous Improvement: Continuous efforts to enhance data quality and refine machine learning approaches can lead to ongoing improvements in AI-related processes and business decision-making.

4.4 *Limitations and Future Research*

While the study provides valuable insights, it is essential to acknowledge its limitations. The findings are specific to the manufacturing sector in Indonesia and may not fully generalize to other industries or regions. Future research could explore industry-specific nuances and extend the study to a broader set of sectors. Additionally, longitudinal studies could capture the evolution of these relationships over time.

5. CONCLUSION

In conclusion, this study enhances our understanding of the interplay between key variables in the context of AI adoption in manufacturing companies in Indonesia. The results reveal significant relationships, emphasizing the importance of data quality in driving AI prediction performance, machine learning algorithms, and effective business analysis. These insights offer practical implications for organizations, highlighting the need for strategic investments in data management and algorithmic selection to maximize the potential benefits of AI technologies. As the manufacturing landscape continues to evolve, these findings contribute to the foundation of knowledge, guiding businesses toward informed decisions and sustainable growth in the era of artificial intelligence. Future research can build upon these findings, exploring sector-specific nuances and longitudinal trends to further enrich our understanding of AI's impact on business processes.

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