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Impact of HR Management on AI Implementation and Data Protection in Indonesian Manufacturing

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ABSTRACT

This study aims to analyze the influence of Human Resource Management (HRM) strategies on the implementation of Artificial Intelligence (AI) in industrial forecasting and data protection within the cybersecurity era in Indonesian manufacturing companies. **A quantitative approach** was used with a **survey method** to collect data from 96 employees of manufacturing companies in Indonesia, determined by the Lemeshow formula. The **findings** show that HRM strategy has a positive and significant effect on industrial forecasting, with a t-statistic of 48.639 $>$ 1.984 and a P-value of 0.000 $<$ 0.05. Furthermore, HRM strategy significantly affects data protection, with a t-statistic of 27.927 $>$ 1.984 and a P-value of 0.000 $<$ 0.05. Industrial forecasting positively influences AI implementation, with a t-statistic of 27.927 $>$ 1.984 and a P-value of 0.000 $<$ 0.05, while data protection also positively affects AI implementation, supported by a t-statistic of 2.457 $>$ 1.984 and a P-value of 0.014 $<$ 0.05. Additionally, HRM strategy significantly influences AI implementation, with a t-statistic of 6.020 $>$ 1.984 and a P-value of 0.000 $<$ 0.05. Finally, HRM strategy positively impacts AI implementation through data protection, indicated by a t-statistic of 2.421 $>$ 1.984 and a P-value of 0.016 $<$ 0.05. In **conclusion**, this study highlights the importance of HRM strategies in enhancing AI implementation and cybersecurity in Indonesian manufacturing companies, underscoring the need for integrating HR strategies with AI and data protection systems to optimize operational efficiency and safeguard against cyber threats.

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1. INTRODUCTION

The industrial world has undergone significant changes due to the rapid growth of digital technology, particularly in the context of the Industrial Revolution 4.0 [1]. The application of AI, or AI, is one of the greatest technological advancements. AI is now crucial for various production and operational systems, particularly in manufacturing companies seeking to improve efficiency, productivity, and product quality [2]. However, to implement AI, organizations also need to prepare their Human Resources (HR).

While AI offers many opportunities, it also poses significant challenges in cybersecurity. Increasingly complex and sophisticated cyberattacks put connected digital systems at real risk [3]. Therefore, companies must not only utilize advanced technology but also ensure that every employee has the awareness, capabilities, and skills necessary to maintain the security of the company's digital systems. HRM strategies are a crucial component that cannot be overlooked in this situation [4].

An adaptive and proactive HR strategy plays a crucial role in preparing competent HR in technology, including AI and cyber risk management [5]. This encompasses workforce needs planning, digital competency development, cybersecurity training, and the creation of an agile, technology-driven work culture. Therefore, the implementation of AI depends heavily on how businesses manage and develop their HR to navigate the challenges of the digital era [6].

This study is closely aligned with the Sustainable Development Goals (SDGs), particularly SDGs 8 (Decent Work and Economic Growth) and SDGs 9 (Industry, Innovation, and Infrastructure) [7]. By emphasizing the role of HRM strategies in preparing a skilled, digitally competent workforce, this research supports SDGs 8 through the promotion of decent work, productivity enhancement, and sustainable economic growth in the manufacturing sector. At the same time, the integration of AI, industrial forecasting, and data protection frameworks reflects SDGs 9 by strengthening industrial innovation, technological infrastructure, and resilient manufacturing systems in Indonesia. Effective HR strategies thus serve as a critical enabler for sustainable industrial transformation in the era of cybersecurity and Industry 4.0 [8].

In today's digital manufacturing industry, digital systems and data are increasingly dependent on strategic decision-making, supply chains, and production processes [9]. Data-driven industrial forecasting, also known as industrial forecasting, has become crucial in the Fourth Industrial Revolution (Industry 4.0) [10], enabling policy-making, operational efficiency, and market demand prediction [11]. On the other hand, this increased reliance on data brings new challenges. One of these is increasingly complex cybersecurity threats, which have the potential to threaten business continuity.

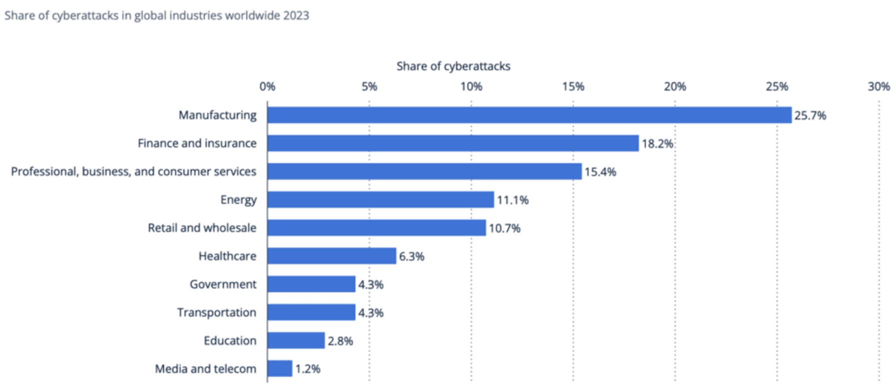

Figure 1. Distribution of cyber attacks across industries worldwide in 2023

As shown in Figure 1, the manufacturing industry is the most vulnerable sector to cyberattacks, with 25.7% of the total cyber incidents targeting this sector. The finance and insurance sector follows with 18.2%, while the professional, business, and consumer services sector accounts for 15.4%, and the energy sector stands at 11.1%. Additionally, the retail and wholesale sector faces 10.7% of cyberattacks. On the other hand, the education sector is least affected, with only 2.8% of attacks, and the media and telecom sector experiences the fewest incidents at 1.2%. This data highlights the significant risks faced by the manufacturing industry due to increasing reliance on IT systems, digitalization, AI integration, and automation [12].

As manufacturing becomes more dependent on technology, it opens up greater opportunities for cyberattacks, including ransomware, data theft, production system sabotage, and supply chain disruptions [13]. Many companies in the sector lack up-to-date data protection and cybersecurity policies, with poorly trained personnel and inadequate infrastructure being primary contributors to these vulnerabilities [14]. Manufacturing companies in Indonesia urgently need to safeguard their strategic data from internal and external threats, while optimizing the use of this data for industrial forecasting. In this context, HRM strategies play a crucial role in strengthening data security and forecasting capabilities [15].

A robust HR strategy is essential for addressing these challenges. It involves digital competency planning, cybersecurity training, and cultivating a data-aware culture [16]. Employing skilled, tech-savvy personnel can help businesses manage data more securely, improve forecasting accuracy, and adapt to dynamic industry changes. However, many Indonesian manufacturing companies have yet to integrate HR management fully into their data security policies and forecasting systems [17]. These companies often focus solely on technology, neglecting the mental readiness, skills, and work culture of their employees, which can hinder the development of secure, responsive, and predictive systems in the face of global challenges [18]. This study aims to explore how HR strategies impact industrial forecasting and data protection in the Indonesian manufacturing sector, particularly in the context of cybersecurity and AI.

2. LITERATURE REVIEW

2.1. Human Resource Management (HRM) Strategy

According to [19], HRM is the science and art of managing relationships and roles of workers effectively and efficiently to help achieve the goals of the company, employees, and society. [20] defines HRM as the recruitment, selection, development, maintenance, and use of HR to achieve both individual and organizational goals. [21] states that HRM is the management and utilization of resources that exist in individuals. Furthermore, [22] identifies the HR indicators as Work tasks, Work quality, Quantity, Timeliness, and Cost effectiveness.

2.2. Application of Artificial Intelligence (AI)

AI is a representation of knowledge closely linked to computer-based technology, enabling computers to perform tasks with capabilities similar to human abilities [23]. According to [24], AI can function as a mobile assistant, resembling a robot, but it exists as a virtual display within a computer system. This technology allows for the automation of processes and the completion of activities that would typically require human intelligence.

Additionally, [25] define AI as a technology that enables machines to simulate human behavior. [26] describe AI as having four key dimensions, mechanical intelligence, analytical intelligence, intuitive intelligence, and empathetic intelligence. These dimensions represent the different aspects of AI that allow machines to mimic human cognitive and emotional responses, making AI a versatile and evolving field in modern technology [27].

2.3. Industry Forecasting

According to [28] “Forecasting in industry helps organizations to prepare for future business conditions and make informed strategic decisions.” (Forecasting in industry helps organizations to prepare for future business conditions and make informed strategic decisions.) and according to [29] “Forecasting is a prediction or forecast of future events as a basis for decision making.” Furthermore, according to [30] “Forecasting is the process of predicting the future based on past and present data trends.” (Forecasting is the process of predicting the future based on past and present data trends.)

Meanwhile, [30] industry forecasting indicators are, historical sales trends, economic growth, market and consumer demand, level of technology and innovation, government regulations and industrial policies, competitive conditions, production capacity and supply chain.

2.4. Data Protection

According to [31], data is defined as true and real information that can be used as a basis for study. The Personal Data Protection Bill in Article 1 Paragraph defines personal data as any data about a person whether identified and identifiable individually or combined with other information either directly or indirectly through electronic or non-electronic systems [32]. This legal definition highlights the importance of protecting personal data in both digital and non-digital contexts. Data security refers to efforts to protect and guarantee three crucial aspects in the cyber world which are data confidentiality, data integrity, and data availability [33]. These aspects form the foundation of cybersecurity measures aimed at ensuring that data remains protected from unauthorized access, alteration, and loss.

[34] describes information security as protecting information from all potential threats to ensure business continuity, minimize risks, and maximize returns on investment and business opportunities. [35] further emphasizes that information security involves protecting data from threats to its integrity while ensuring business continuity, mitigating risks, and maximizing returns. [36] identifies two key dimensions of data security

and protection which are security guarantee and data confidentiality, both of which are vital for safeguarding valuable information.

2.5. Cyber Security

According to [35], cybersecurity is the effort made to protect computer systems from various threats or unauthorized access. Cybersecurity typically involves the tools, policies, and security concepts used to protect organizational or national assets and minimize the risk of computer attacks. According to [37], cybersecurity is a crucial concern in the modern era, especially for those focused on business. Everyone developing applications needs to understand the concept of cybersecurity to ensure a safe and secure business environment [38].

3. RESEARCH METHODS

This quantitative research uses a descriptive and associative approach. This study was conducted to analyze the influence of HRM Strategy on the Implementation of AI in Industrial Forecasting and Data Protection in the Cybersecurity Era in Indonesian Manufacturing Companies.

The data collection method for this study used a survey research method. The data analysis technique used Smart PLS 3.0. The population and sample in this study were employees of a manufacturing company in Indonesia. In determining the sample, the Lemeshow formula was used, this is because the population size is unknown or infinite. The following is the Lemeshow formula [39]:

$$n = \frac{z^2 \cdot 1 - \alpha/2 \cdot P \cdot (1 - P)}{d^2} \tag{1}$$

Information:

- n = Number of samples
- z = z score at 95% confidence = 1.96
- P = maximum estimate = 0.5
- d = alpha (0.10) or sampling error = 10%

Using the formula above, the number of samples to be taken is:

$$n = \frac{1.962 \cdot 0.5 \cdot (1 - 0.5)}{0.12^2}$$

$$n = \frac{3.8416 \cdot 0.25}{0.01}$$

$$n = 96.04 = 96 \text{ respondents.}$$

Based on the calculation using the formula above, the sample size required for the study is 96.04, which rounds to 96 respondents. This sample size is determined by applying a 95% confidence level, a maximum estimate of 0.5, and a sampling error of 10%. By using these values, the researcher ensures that the sample is representative of the population and the results will be statistically significant within the desired margin of error. Therefore, 96 respondents will be selected for the study, ensuring that the findings are reliable and accurate for the intended analysis.

3.1. Data Collection Techniques

In the Data Collection Techniques section, the study utilized a survey method to gather data. This approach involved distributing a questionnaire, which consists of a list of questions aimed at the respondents. The survey method allows for efficient data collection from a sample of the population, ensuring that the responses obtained reflect the opinions and experiences of the respondents relevant to the research topic. The use of questionnaires is particularly beneficial in gathering quantitative data that can be analyzed statistically to draw meaningful conclusions.

3.2. Data Analysis Techniques

For the Data Analysis Techniques, the study employed PLS software version 3.0 (Partial Least Squares), which is a variant-based structural equation model (SEM) [40]. PLS-SEM is an advanced statistical technique that allows researchers to simultaneously test both measurement models and structural models, making it a powerful tool for understanding the relationships between variables [41]. By using PLS-SEM, the study is able to analyze complex data structures and test hypotheses with a high degree of accuracy, providing valuable insights into the research questions posed [42].

3.2.1. Measurement Model (Outer Model)

A measurement model (outer model) was used to test the validity and reliability of the research instrument. This study used convergent and discriminant validity to test the validity. Convergent validity is assessed through the measurement model, with indicator reflection assessed based on the correlation between the component score/item score and the construct score calculated using PLS [43]. If the correlation is greater than 0.70 with the construct being measured, the individual reflection measure is considered high. For initial research, measurements with an outer loading value of 0.5-0.6 are considered sufficient. [44] explains that in assessing discriminant validity with other methods, it is necessary to compare the square root of Average Variance Extracted (AVE) value. The recommended composite reliability value must be above 0.6. The AVE formula according to [44] is:

$$AVE = \lambda_1^2 + \lambda_2^2 + \text{ivar}(\epsilon i) \tag{2}$$

The equation 2 explains the calculation of AVE, which is used to measure convergent validity in the measurement model. AVE assesses how much variance in the indicators is explained by the construct, relative to the total variance in the indicator. A higher AVE value indicates that the indicators used in the model explain more variance, meaning the model has better validity [45]. Therefore, the recommended threshold for AVE to meet the convergent validity assumption is greater than 0.6, meaning that the variance explained by the indicators exceeds 60%. Additionally, to ensure the reliability of the model, the composite reliability value must also be greater than 0.6, indicating the internal consistency of the measurement used in this study.

3.2.2. Structural Model (Inner Model)

Structural models are used to predict causal relationships between latent variables. Structural models are evaluated by examining the percentage of variance explained by the R^2 value for the dependent variable using the Stone-Geisser Q-Square Test [44]. The equation model is:

$$N = \beta O + \beta\eta + \eta\varepsilon + \zeta \tag{3}$$

The vector of endogenous variables (α) represents the dependent variables that are being predicted or influenced by other factors in the model, specifically by the exogenous variables (the predictors or independent variables). These dependent latent variables capture the outcome or effect of the relationships hypothesized in the model. On the other hand, the vector of residual variables (δ) represents the unexplained or error terms in the model, which account for the variation in the dependent variables that is not explained by the independent predictors. These residuals are essential for understanding the model's limitations and how well the proposed relationships can predict the outcomes. Together, the endogenous variables and residual variables contribute to refining the model's accuracy by helping to assess the strength of the relationships between the predictors and the outcomes in the research framework. Each dependent latent variable of the latent variable can be specified as follows:

$$pc = \sum_i \beta_{ji}\eta_i + \sum_i \gamma_{jb}\epsilon_b + \zeta_j \tag{4}$$

Where λ_{ji} and λ_{jb} are the path coefficients connecting the endogenous predictor and the exogenous latent variable, and ϵ_j is the inner residual variable. If the results yield an R^2 value greater than 0.2, it can be interpreted that the latent predictor has a significant influence at the structural level. The following is an illustration of the research structural model in Figure 2:

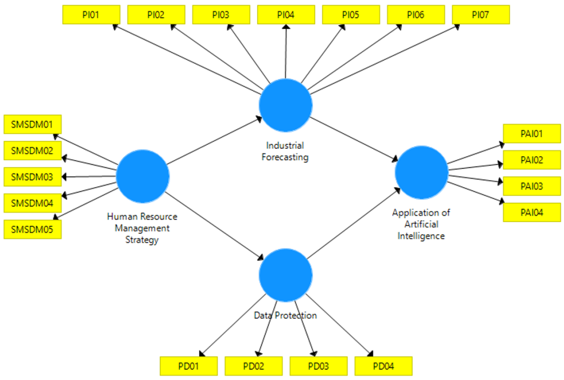

Figure 2. Research Model

Figure 2 shows the structural research model, highlighting the relationships between HRM Strategy, Industrial Forecasting, Data Protection, and the implementation of AI. The model is designed to examine how HRM strategies impact forecasting accuracy, data protection systems, and AI applications in the manufacturing sector [46]. Each component is interconnected, demonstrating the direct and indirect effects of HRM strategies on industrial forecasting and data security. The arrows represent the hypothesized relationships, with the latent variables emphasizing the critical role of HRM in driving technological advancements. This model is tested through hypothesis testing, with the results confirming the strength and significance of each proposed relationship.

3.2.3. Hypothesis Testing

Hypothesis testing (β, γ, and λ) was conducted using the bootstrap resampling method developed [44]. According to [47], the significance of hypothesis support can be measured by comparing the t-table and t-statistic values using the following decision-making criteria:

- If t statistic $> t$ table and p values $<$ sig0.05 means H_a is accepted, H_o is rejected.
- If t statistic $\leq t$ table and p values $\geq$ sig0.05 means H_a is rejected, H_o is accepted.

The results from the hypothesis testing provide valuable insights into the relationship between variables in the study. By comparing the t-statistic values with the t-table values and evaluating the p-values, the significance of each hypothesis can be determined. If the t-statistic exceeds the t-table value and the p-value is less than 0.05, it indicates strong evidence to reject the null hypothesis (Ho) and accept the alternative hypothesis (Ha). Conversely, if the t-statistic is less than or equal to the t-table value, and the p-value is greater than or equal to 0.05, it suggests insufficient evidence to reject the null hypothesis, meaning the null hypothesis is accepted. This statistical approach ensures that only hypotheses with significant relationships are considered valid in the context of the research.

4. RESULT AND DISCUSSION

4.1. Outer Model Analysis

Measurement model testing (outer model) is used to determine the specifications of the relationship between latent variables and their manifest variables. This testing includes convergent validity, discriminant validity and reliability. AI has significant potential in the manufacturing industry, particularly in industrial forecasting and data protection. For instance, AI-based predictive analytics can help manufacturers in Indonesia forecast market demand more accurately, enabling better resource allocation and inventory management [48]. One example is a local automotive manufacturer that uses AI to predict demand trends for spare parts, reducing waste and improving production efficiency.

In terms of data protection, AI-driven cybersecurity solutions, such as machine learning algorithms, can detect and respond to threats in real-time. For example, AI tools are used by Indonesian textile manufacturers to monitor network traffic and identify unusual patterns, helping to prevent cyberattacks before they cause significant damage. These applications of AI not only improve operational efficiency but also provide a higher level of security for sensitive industrial data.

4.1.1. Convergent Validity

According to [45], a correlation can be said to meet convergent validity if it has a loading value of > 0.7. The output shows that the loading factor provides a value above the recommended value of 0.7. However, in the scale development stage of the research, a loading of 0.60 is still acceptable. Therefore, the indicators used in this study have met convergent validity. The structural model in this study is shown in the following Figure 3.

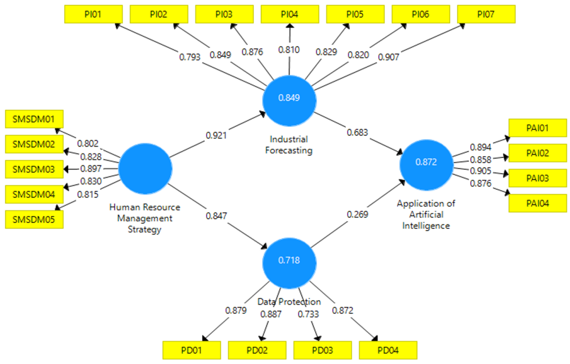

Figure 3. Outer Model, Algorithm Testing

Based on the data in Figure 3, the model illustrates the relationships between the variables and their respective indicators. The outer model algorithm testing shows the path coefficients for HRM Strategy, Industrial Forecasting, and Data Protection in the context of AI application. The arrows connecting the constructs indicate the strength of these relationships, with values closer to 1 indicating a stronger association. Table 1 below presents the outer loading values for the respective indicators, which are used to evaluate the convergent validity of the measurement model.

Table 1. *Outer Loading*

Indicators	HRM Strategy	Application of AI	Industrial Forecasting	Data Protection
SMSDM01	0.802			
SMSDM02	0.828			
SMSDM03	0.897			
SMSDM04	0.830			
SMSDM05	0.815			
PAI01		0.894		
PAI02		0.858		
PAI03		0.905		
PAI04		0.876		
PI01			0.793	
PI02			0.849	
PI03			0.876	
PI04			0.810	
PI05			0.829	
PI06			0.820	
PI07			0.907	
PD01				0.879
PD02				0.887
PD03				0.733
PD04				0.872

Source: SmartPLS Program Output 3.0, 2025

Based on the data in Table 1, the value can be seenouter loadingThe lowest result of the outer test of this research model is 0.733 which is in the PD03 dimension/Data Protection variable statement no. 3.

Referring to the previously determined outer loading limit of 0.7, the results indicate that the model is declared to meet the convergent validity assumption because the lowest outer loading value obtained is 0.733 > 0.7.

4.1.2. Construct Validity and Reliability

Table 2. Construct Validity and Reliability

Variable	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Human Resource Management Strategy	0.891	0.894	0.920	0.698
Application of Artificial Intelligence	0.906	0.907	0.934	0.780
Industrial Forecasting	0.931	0.933	0.944	0.708
Data Protection	0.864	0.874	0.909	0.714

Source: SmartPLS Program Output 3.0, 2025

The data in Table 2 above shows that the lowest AVE value of the four variables is 0.698, which is for the HR strategy variable. This result indicates that all five research variables have met the assumptions.discriminant validityThis is because the lowest AVE value was greater than 0.5. Meanwhile, the Cronbach's alpha and composite reliability results showed that the lowest values were 0.864 and 0.909 for the data protection variable. Therefore, these results also prove that all variables meet the reliability construct assumptions, as the lowest Cronbach's alpha and composite reliability values were > 0.7.

4.2. Inner Model Testing

After conducting the outer model test, the final structural equation model (inner model) needs to be evaluated. The inner model test for this study was conducted by examining the path coefficient and R-square values as follows Table 3.

Table 3. R Square

Variable	R Square	R Square Adjusted
Application of Artificial Intelligence	0.872	0.870
Industrial Forecasting	0.849	0.847
Data Protection	0.718	0.715

Source: Output of Smart PLS 3.0 program, data processed by the author in 2025

Based on Table 3. above, it shows that the valueR Squarefor the AI application variable is 0.872, the acquisition explains that the percentage of the application of AI is 87.2%. This means that the HR strategy variable influences the application of AI by 87.2% and the remaining 12.8% is influenced by other variables, the R Square value for the industrial forecasting variable is 0.849, the acquisition explains that the percentage of the industrial forecasting is 84.9%. This means that the HR strategy variable influences the application of AI through industrial forecasting by 84.9% and the remaining 15.1% is influenced by other variables, while the R Square value for the data protection variable is 0.719, the acquisition explains that the HR strategy variable influences the application of AI through data protection by 71.9% and the remaining 28.1% is influenced by other variables.

Table 4. Results of Inner Model Testing

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Human Resource Management Strategy → Industrial Forecasting	0.921	0.923	0.019	48.639	**0.000**
Human Resource Management Strategy → Data Protection	0.847	0.851	0.030	27.927	**0.000**

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Industrial Forecasting → Application of Artificial Intelligence	0.683	0.702	0.108	6.338	**0.000**
Data Protection → Application of Artificial Intelligence	0.269	0.252	0.110	2.457	**0.014**

Source: Smart PLS 3.0 program output, data processed by the author in 2025

Based on Table 4 above, the results of the evaluation of the structural equation model of the relationship between variables partially explained by the valuepath coefficient(Path Analysis) so that it can be described as follows:

- Path coefficient(Path Analysis) Hypothesis 1 shows that the HR strategy variable has a positive and significant effect on industrial forecasting with a value of 0.921. This result indicates that with a good HR strategy, industrial forecasting will improve.
- The path coefficient (Path Analysis) for hypothesis 2 was 0.847. This value indicates that HR strategy has a significant positive effect on data protection. This result also implies that a good HR strategy will improve data protection.
- The path coefficient (Path Analysis) for Hypothesis 3 was 0.683. This value indicates that industrial forecasting has a positive and significant effect on the implementation of AI. This result also implies that better industrial forecasting will lead to improved AI.
- The path coefficient (Path Analysis) for Hypothesis 4 was 0.269. This value indicates that data protection has a positive and significant effect on the implementation of AI. This result also implies that strong data protection will increase the implementation of AI.

4.3. Hypothesis Testing

This study has six hypotheses, as formulated in the research questions, that need to be tested for their validity. Hypothesis testing in this study uses a t-test, which compares the t-statistic value obtained from the bootstrapping test with the critical limit of the t-table value of 1.984 at a significance level of 5% (0.05). The results of this research hypothesis test are presented as follows Figure 4.

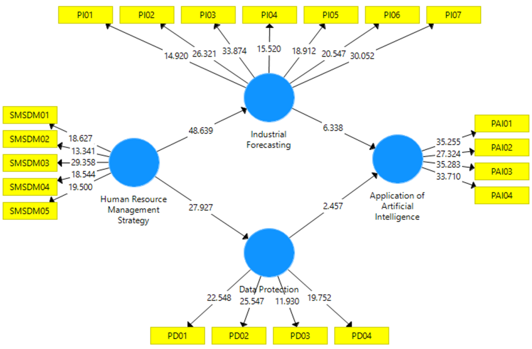

Figure 4. Inner Model, Bootstrapping Testing

Based on the data presented in Figure 4, the inner model testing was conducted using the bootstrap resampling method to evaluate the direct relationships between variables. The model illustrates the connections between HRM Strategy, Industrial Forecasting, Data Protection, and their influence on the implementation of AI. The Table 5, presents the direct test results, showing the original sample values, sample mean, standard deviation, t-statistics, and p-values for each hypothesis. These results help determine the strength and significance of the relationships, with the p-values indicating that all hypotheses are supported by the data, as all have p-values below the 0.05 threshold.

Table 5. Direct Test Results

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Information
Human Resource Management Strategy → Industrial Forecasting	0.921	0.923	0.019	48.639	**0.000**	**Accepted**
Human Resource Management Strategy → Data Protection	0.847	0.851	0.030	27.927	**0.000**	**Accepted**
Industrial Forecasting → Application of Artificial Intelligence	0.683	0.702	0.108	6.338	**0.000**	**Accepted**
Data Protection → Application of Artificial Intelligence	0.269	0.252	0.110	2.457	**0.014**	**Accepted**

Source: Smart PLS 3.0 program output, data processed by the author in 2025

Based on the PLS output (bootstrapping test) of the direct test presented in Table 5, it can be explained that:

- Hypothesis 1: From the original sample value of 0.921, the t-statistic value is 48.639 $>$ 1.984 and the P-value is 0.000. These results prove that the HR strategy has a positive and significant effect on the implementation of AI with a relationship value of 92.1%. The t-statistic value of 48.639 $>$ t-table 1.984 and the P-value of 0.000 $<$ 0.05 prove that hypothesis 1 in this study is accepted.
- Hypothesis 2: From the original sample value of 0.847, the t-statistic value is 27.927 $>$ 1.984 and the P-value is 0.000. These results prove that the HR strategy has a positive and significant effect on data protection with a relationship value of 84.7%. The t-statistic value of 27.927 $>$ t-table 1.984 and the P-value of 0.000 $<$ 0.05 prove that hypothesis 2 in this study is accepted.
- Hypothesis 3: From the original sample value of 0.683, the t-statistic value is 6.338 $>$ 1.984 and the P-value is 0.000. These results prove that industrial forecasting has a positive and significant effect on the application of AI with a relationship value of 68.3%. The t-statistic value of 6.338 $>$ t-table 1.984 and the P-value of 0.000 $<$ 0.05 prove that hypothesis 3 in this study is accepted.
- Hypothesis 4: From the original sample value of 0.269, the t-statistic value is 2.457 $>$ 1.984 and the P-value is 0.014. These results prove that data protection has a positive and significant effect on the application of AI with a relationship value of 26.9%. The t-statistic value of 2.457 $>$ t-table 1.984 and the P-value of 0.014 $<$ 0.05 prove that hypothesis 4 in this study is accepted.

Table 6. Indirect Test Results (Indirect Effect)

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Information
Human Resource Management Strategy → Industrial Forecasting → Application of Artificial Intelligence	0.629	0.649	0.105	6.020	**0.000**	**Accepted**
Human Resource Management Strategy → Data Protection → Application of Artificial Intelligence	0.228	0.214	0.094	2.421	**0.016**	**Accepted**

Source: Smart PLS 3.0 program output, data processed by the author in 2025

Based on the PLS output (bootstrapping test) of the indirect test presented in Table 6, it can be explained that:

- Hypothesis 5: From the original sample value of 0.629, the t-statistic value is 6.020 > 1.984 and the P-value is 0.000. These results prove that the HR strategy has a positive and significant effect on the implementation of AI through industrial forecasting with a relationship value of 62.9%. The t-statistic value of 6.020 > t-table 1.984 and the P-value of 0.000 < 0.05 prove that hypothesis 5 in this study is accepted.

- Hypothesis 6: From the original sample value of 0.228, the t-statistic value is 2.421 > 1.984 and the P-value is 0.016. These results prove that the HR strategy has a positive and significant effect on the implementation of AI through data protection with a relationship value of 22.8%. The t-statistic value of 2.421 > t-table 1.984 and the P-value of 0.016 < 0.05 prove that hypothesis 6 in this study is accepted.

5. MANAGERIAL IMPLICATIONS

HRM in Indonesian manufacturing companies need to prioritize aligning their HR strategies with technological transformation, particularly in AI implementation, industrial forecasting, and data protection. The findings in this study highlight that an adaptive and proactive HR strategy can enhance industrial forecasting capabilities and strengthen data protection, both of which positively impact AI implementation. As cyber threats grow with digitalization, HRM must focus on developing digital competencies and cybersecurity awareness among employees to protect the company's data and AI systems. Additionally, fostering a culture of technological readiness and continuous training will enable HR to effectively support the implementation of AI in manufacturing processes, improving operational efficiency and competitiveness. Therefore, HR leaders must collaborate closely with IT departments to integrate forecasting tools, AI systems, and data protection frameworks, ensuring they work cohesively to drive digital transformation while mitigating cybersecurity risks.

HRM must prioritize the alignment of HR strategies with technological advancements, particularly in AI adoption and cybersecurity. An effective HR strategy should focus on workforce planning, digital competency development, and cultivating a cybersecurity-aware culture. Managers should ensure employees have the necessary skills to handle AI technologies and protect digital systems from increasing cyber threats. Additionally, HR strategies must facilitate a seamless integration of AI with industrial forecasting systems and data protection frameworks, creating a cohesive strategy for digital transformation. Regular employee training programs on AI implementation and cybersecurity measures should be mandatory to foster an environment of continuous learning and resilience against evolving cyber risks.

6. CONCLUSION

The research indicates that HR strategies play a critical role in enhancing industrial forecasting in the cybersecurity era for manufacturing companies in Indonesia. HR strategies have a significant positive impact on both industrial forecasting and data protection, as shown by a t-statistic value of 48.639 and a p-value of 0.000. Manufacturing companies should continue to strengthen HR management strategies, as they significantly influence data protection and AI implementation in the cybersecurity domain. Companies must also prioritize integrating AI technologies into their systems, improving operational efficiency and competitiveness, while maintaining robust data protection frameworks with significant statistical backing (t-statistic of 27.927 and p-value of 0.000).

Furthermore, the study highlights the importance of adopting data protection strategies to successfully implement AI in the cybersecurity era. With t-statistics indicating significant values (27.927 and 6.020), it is evident that manufacturing companies must not only focus on industrial forecasting but also ensure that their AI-driven systems are secure from cyber threats. This underscores the need for a holistic approach that involves HR strategies, data security, and AI forecasting. Companies must align these components to foster a more secure and efficient manufacturing environment.

To ensure the long-term success of these strategies, manufacturing companies should integrate HR strategies into AI implementation and data protection efforts, fostering a culture of cybersecurity awareness. It is recommended that HR strategies move beyond managerial functions to actively contribute to the technological side, particularly in AI forecasting and data security. For future research, it would be valuable to explore the long-term effects of AI in manufacturing, specifically regarding cybersecurity threats and workforce adaptation. Additionally, investigating how AI-driven cybersecurity strategies can evolve alongside global technological changes would provide deeper insights into optimizing security measures in the manufacturing sector.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: AR; Methodology: JJ; Software: SA; Validation: AP and WS; Formal Analysis: DS; Investigation: AR; Resources: AP; Data Curation: JJ; Writing Original Draft Preparation: SA and AR; Writing Review and Editing: WS and DS; Visualization: AR; All authors, AR, JJ, SA, AP, WS, and DS, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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