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EMPLOYEE TRAINING AND TECHNOLOGY INVESTMENT IN IMPROVING EMPLOYEE PERFORMANCE PRODUCTIVITY WITH INCOME INEQUALITY AS A MODERATING VARIABLE IN THE MANUFACTURING INDUSTRY

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Abstract

This study aims to examine the effect of employee training and technology investment on employee performance productivity, with income inequality as a moderating variable, in the Indonesian manufacturing sector. The research method used is a quantitative approach with secondary data analysis from the Central Statistics Agency (BPS) and the Indonesia Stock Exchange (IDX) during the period 2019–2023. The research sample includes medium and large-scale manufacturing companies, selected through stratified random sampling techniques based on provinces for proportional representation. Data were analyzed using moderated regression. The results of the study indicate that employee training has no significant effect on employee performance productivity. Meanwhile, technology investment has a negative effect if not accompanied by proper management. Income inequality is shown to moderate the relationship between independent and dependent variables in a complex manner, but income inequality weakens the positive effect of employee training but strengthens the relationship between technology investment and productivity. The implication of this study is the importance of synergy between employee training, adoption of technology investment, and management of income inequality distribution to optimally increase employee performance productivity.

Keywords **: *Employee training, technology investment, employee performance productivity, income inequality, manufacturing industry.***

1. INTRODUCTION

Employee performance productivity is one of the main factors that determine the success and competitiveness of manufacturing companies in the era of global competition. In the midst of rapid technological developments, companies are required to continue to improve operational efficiency and employee performance in order to compete in the global market. Two important strategies that can support increased productivity are employee training and technology investment. Effective training improves employee competence, while investment in technology accelerates the production process, reduces costs, and increases output.

The importance of employee training is one of the company's strategic efforts to improve the competence and skills of the workforce. Research by (Ton & Huckman, 2008) shows that effective training can have a direct impact on improving operational performance and work process efficiency. Employees who are equipped with new skills tend to work more productively, innovate better, and present more effective solutions in daily operations.

As industrial technology advances, training becomes increasingly important to ensure employees have the ability to utilize new technologies. (Kanapathipillai & Azam, 2020) emphasizes that every employee must undergo training to improve their skills, knowledge, creativity and employee performance, which in turn contributes to overall employee productivity.

Training not only updates employees' technical skills, but also encourages the development of managerial and soft skills that are essential for organizational success.

Investment in technology also plays an important role in increasing productivity in the manufacturing sector. Technology allows companies to increase production efficiency, reduce operating costs, and increase output per worker. (Novotná et al., 2021) conducted a study investigating the impact of technology investment on production efficiency in manufacturing companies and how different this relationship is for low-tech and high-tech companies. Research conducted by (Tripathi, 2024) shows that the application of digital technologies such as automation and artificial intelligence (AI) can significantly increase productivity in various industrial sectors.

Income inequality occurs when there is a significant difference in the distribution of income between employees at different levels or positions in a company. Research by (Green & Zhou, 2019) found that income inequality can reduce employee motivation to work hard, because employees feel that their hard work is not fairly rewarded. When income inequality is high, employees tend to have low loyalty to the company, which can lead to increased turnover and decreased overall productivity. Research by (Bapuji, 2015) also supports this finding by stating that income inequality within a team can reduce collaboration, which is one of the important elements in increasing productivity in a high-tech work environment.

In the context of the manufacturing industry, where labor and technology are interdependent to achieve efficiency and effectiveness, employee training and technology investment are often considered as two key pillars in driving productivity improvements. However, the effectiveness of these two factors can be reduced if income inequality is not managed properly. (Baduge et al., 2022) show that although industrial training and technology investment are significant in improving operational efficiency, companies must ensure that income inequality among employees is not too high so that productivity can be optimally increased. To effectively improve employee productivity, manufacturing companies need to adopt a comprehensive training strategy and invest in technology that is relevant to current business needs. However, investment in technology and training alone is not enough, management must ensure that employees are rewarded according to their contributions, so that income inequality can be minimized.

Thus, companies can maximize the benefits of the training and technology that has been invested. (Bernhardt et al., 2023) highlight the importance of digital training in accelerating technological transformation in manufacturing-based companies, but they also emphasize that this success can only be achieved if companies pay attention to fairness in employee income distribution. This study brings novelty from previous studies in terms of combining employee training and technology investment, and adding the dimension of income inequality as a moderating variable in the manufacturing sector. This provides a new perspective on how companies can achieve higher productivity, not only through training and technology, but also by ensuring that fair income distribution is maintained within the organization. This is an approach that has not been widely explored in previous literature, especially in the context of developing countries such as Indonesia.

2. IMPLEMENTATION METHOD

2.1 Research Time and Place

This study uses a quantitative approach by analyzing secondary data from official sources, namely the Central Statistics Agency (BPS) and the Indonesia Stock Exchange (BEI).Data from the last five years was selected to reflect current trends in employee training, technology investment, employee performance productivity, and income inequality in the manufacturing sector.

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2.2 Determination of Population and Sample

This population is identified from data where only companies that have complete data on employee training, technology investment, employee productivity, and income inequality are considered as part of the population, while the sample is taken by stratified random sampling based on province to ensure proportional representation from each region. will take 10% of the total population of manufacturing companies in each province in Indonesia that meet the research criteria.

2.3 Data Analysis Technique

The analysis method used in this study is multiple linear regression with moderation analysis. The moderating variable (income inequality) will be tested using the Moderated Regression Analysis (MRA) approach to determine the interaction between income inequality and independent variables. The Research Variables used in this article include:
Independent Variable (X):
X1 : Employee Training
X2 : Technology Investigation,
Dependent Variable (Y): Employee Performance Productivity
Moderating Variable (M): Income inequality
The data analysis steps carried out in this study are:

a) Classical Assumption Test

The Classical Assumption Tests conducted, namely the normality, heteroscedasticity, multicollinearity, autocorrelation, and linearity tests, were conducted to ensure that the regression model used met the required statistical assumptions.

b) Multiple Regression

Multiple regression is used to test the effect of minimum wage policy, economic growth, education level, labor market conditions, and labor regulations on the unemployment rate.
The form of multiple regression analysis in this study is:

$$\mathbf{Y = \alpha + \beta 1\ X1 + \beta 2\ X2 + \varepsilon}$$

c) Moderation Analysis (MRA)

The moderation analysis equation (MRA) is as follows:

$$\mathbf{Y = \alpha + \beta 1\ X1 + \beta 2\ X2 + \beta 3 M + \beta 4 (X1 * M) + \beta 5 (X2 * M) + \varepsilon}$$

Where :
Y = Employee Performance Productivity
β1 = The effect of employee training (X1) on employee performance productivity.
β2 = The effect of technology investigation (X2) on employee performance productivity.
β3= Shows the direct influence of Income Inequality (M) on the dependent variable (Employee Performance Productivity).
β4 to β5 = Measuring the influence of the interaction between the moderating variable (Income Inequality) and each independent variable on Employee Performance Productivity.

d) Significance Test

The significance test in this study was conducted using the t-test or looking at the significant value to test the partial effect of each independent variable on the dependent variable, and the F-test to see the simultaneous effect of all independent variables on the dependent variable with the criteria The hypothesis is accepted if the significance value (p-value) <0.05. In addition, the coefficient of determination (R^2) is used to see how much the independent variable explains the dependent variable.

e) Data Processing

Data processing can be done using statistical software such as SPSS, which allows for efficient regression and moderation analysis.

3. RESULTS AND DISCUSSION

Descriptive Statistical Analysis

Table 1 Descriptive Statistics Results

	N	Minimum	Maximum	Mean	Std.Deviation
Employee Performance Productivity	68	1.04	23.45	2.9413	3.48240
Employee Training	68	.02	30.73	2.9413	6.62496
Technology Investment	68	.11	16.14	2.9416	3.85830
Income Inequality	68	.25	.45	.3428	.04616
Valid N (Listwise)	68				

Data source: BPS (Central Statistics Agency)

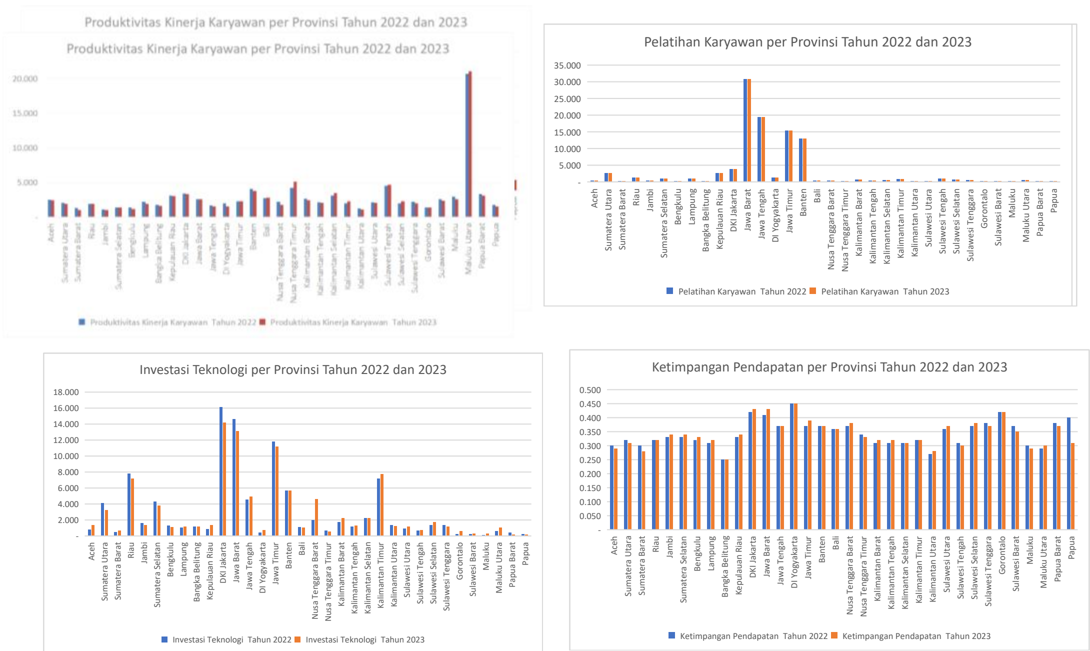

Figure 1 Graph of Employee Productivity Data, Employee Training, Technology Investment and Income Inequality in 2022-2023 Manufacturing Companies

The analysis of 68 samples across 34 provinces in Indonesia (2022–2023) reveals significant variations in employee productivity, training, and technology investment. Productivity ranged from a minimum of 1.04% (likely in North Kalimantan or Gorontalo) to a maximum of 23.45% in North Maluku during 2023, with an average of 2.94% and a standard deviation of 3.48%, indicating notable disparities. Employee training also showed wide variations, from 0.02% in East Nusa Tenggara to 30.73% in West Java (2022–2023), with an average of 2.94% and a high standard deviation of 6.62%. Technology investment ranged from 0.11% (possibly in West Papua or Maluku) to 16.14% in Jakarta during 2022, with an average of 2.94% and a standard deviation of 3.86%, highlighting that only a few provinces had substantial investments.

Classical Assumption Test Results

The following are the results of the Classical Assumption Test produced using data from the BPS (Central Statistics Agency) source.

Table 2 Results of the Classical Assumption Test

Test Type	Method	Statistical Test	Result
Normality Test	Kolmogorov-Smimov Test	Data is normally distributed (sig > 0,05)	P value =0.001<0,05 then normality is not met
Multicollinearity Test	VIF (Variance Inflation Factor)	There is no multicollinearity (VIF < 10)	Obtained VIF value X1&X2 = 1,820 no multikolinearity occurs
Heteroscedasticity Test	Glejser Test	There is no heteroscedasticity (sig > 0,05)	Sig X1=0,808 X2=0,706 > 0,05. heteroscedasticity does not occur
Autocorrelation Test	Durbin-Watson Test	No autocorrelation if between or above DL = 1,54 and DU = 1,66) values	DW value =1,936 DW value calculated above DW table then autocorrelation is not found
Linearity Test	Scatterplot Residual	Linear relationship between independent and dependent variables	Linearity fulfilled

Because one of the tests above is not met, a data transformation of the variables Y, X1 and X2 will be carried out using the Yeo_Johnson transformation using the following formula:

For X=0 (positive value)

$$T(X)=\begin{cases}\frac{(X+1)^{\lambda}-1}{\lambda} & ,jika\ \lambda \neq 0 \\ ln(X+1) & ,jika\ \lambda=0\end{cases}$$

1. If $\lambda \neq 0$

$$T(X)=\frac{(X+1)^{\lambda}-1}{\lambda}$$

This formula raises the value of x+1 to the power of λ, subtracts 1, and divides by λ. This transformation is flexible to reduce the skewness of the data based on the value of λ.

2. If λ=0

$$T(X)=ln(X+1)$$

In this study, the transformation uses natural logarithm. This is effective to overcome skewness if λ=0

After the transformation is carried out, the following are the results of the Classical Assumption Test produced using the Yeo Johnson Transformation Formula.

Table 3 Results of the Classical Transformation Assumption Test

Test Type	Method	Statistical Test	Result
Normality Test	Kolmogorov-Smimov Test	Data is normally distributed (sig >0,05)	P value =0,200>0,05 then normality is met
Multicollinearity Test	VIF (Variance Inflation Factor)	There is no multicollinearity (VIF < 10)	Obtained VIF value X1&X2 = 2,261 no multikolinearity occurs
Heteroscedasticity Test	Glejser Test	There is no heteroscedasticity (sig> 0,05)	Sig X1=0,841 X2=0,083 > 0,05. heteroscedasticity does not occur
Autocorrelation Test	Durbin-Watson Test	No autocorrelation if between or above DL = 1,54 and DU = 1,66) values	DW value =1,563 DW value calculated above DW table then autocorrelation is not found
Linearity Test	Scatterplot Residual	Linear relationship between independent and dependent	Linearity fulfilled

Test Type	Method	Statistical Test	Result
		variables	

Regression Test Results

Multiple Linear Regression Model Testing Results

The multiple linear regression analysis model in this study is stated in the following equation model:

$$Y= \alpha + \beta1\ X1 + \beta2\ X2 + \varepsilon$$

Table 4 Results of Multiple Linear Regression Analysis Test

Coefficients a

	Model	Unstandardized Coefficients B	Std Error	Standardized Beta	Sig
1	(Constant)	3,96E-06	0,12		1
	Employee Training Transformation	0,357	0,181	0,357	0,053
	Technology Investment Transformation	-0,268	0,181	-0,268	0,144

a. Dependent Variable : performance productivity transformation

Based on Table 4, the regression equation can be written as follows:

$$Y = 3.96E\text{-}06 + 0.357\ X1 - 0.268X2$$

The regression equation indicates that if there are no changes in employee training (X1) and technology investment (X2), employee productivity (Y) will remain at 3.96E-06 Employee training has a positive effect, meaning that a 1% increase in training will improve productivity by 0.357%, assuming other factors remain constant. In contrast, technology investment has a negative effect, where a 1% increase in technology investment will reduce productivity by 0.268%, assuming no changes in other variables.

Moderation Regression Analysis Test Results

Results of Moderation Regression Analysis Test Model 1

The regression analysis model with moderation in this study is stated in the following equation model:

$$Y= \alpha + \beta1\ X1 + \beta2M+\beta3(X1*M)+\varepsilon$$

Table 5 Results of Moderation Regression Test Model 1

Coefficients a

	Model	Unstandardized Coefficients B	Std Error	Standardized Beta	Sig
1	(Constant)	0,086	0,985		0,93
	Employee Training Transformation	0,284	1,1	0,284	0,797
	Income Inequality	0,237	2,842	-0,011	0,934
	Training*Inequality	0,339	2,999	-0,124	0,91

a. DDependent Variable : performance productivity transformation

Based on Table 5, the regression equation can be written as follows:

$$Y = 0.086 + 0.284\ X1 - 0.237M - 0.339(X1*M)$$

Employee performance productivity (Y) is influenced by employee training (X1), income inequality (M), and the interaction (X1*M) between the two. In general, employee training has a positive effect on productivity with an increase of 0.284% for every increase in one employee training, if other variables remain constant. However, income inequality has a negative impact, reducing productivity by 0.237% for every increase in one unit of income inequality. In addition, the positive effect of training on productivity weakens significantly when income inequality is high, as indicated by the negative interaction value of -0.339%. This suggests that income inequality can be an obstacle in maximizing the benefits of employee training on productivity.

Results of Moderation Regression Analysis Test Model 2

The regression analysis model with moderation in this study is stated in the following equation model:

$$\mathbf{Y= \alpha + \beta1\ X2 + \beta2M+\beta3(X2*M)+\varepsilon}$$

Table 6 Results of Moderation Regression Test Model 2

Coefficients a

	Model	Unstandardized Coefficients B	Unstandardized Coefficients Std Error	Standardized Beta	Sig
1	(Constant)	0,652	0,937		0,489
	Income Inequality Transformation	2,067	0,961	-2,067	0,035
	Income Inequality	1,77	2,701	0,081	0,515
	Investment*Inequality	5,654	2,618	2,069	0,035
a.	Dependent Variable : performance productivity transformation				

Based on Table 6,The regression equation can be written as follows:

$$\mathbf{Y = -0.652 - 2.067\ X2+1.77M+5.654(X2*M)}$$

Based on Table 6 the constant of -0.652% indicates the baseline value of employee productivity if technology investment and income inequality do not exist (zero value). The coefficient of -2.067% on variable X2 indicates that every one-unit increase in technology investment directly decreases employee productivity by 2.067%, assuming other variables remain constant. Conversely, the coefficient of 1.77% on variable M indicates that every one-unit increase in income inequality increases productivity by 1.77%. However, the interaction between technology investment and income inequality (X2*M) has a strong positive effect with a coefficient of 5.654%, which means that income inequality can strengthen the effect of technology investment on productivity.

It will be seen for model 3 that is if the regression analysis model with moderation looks at the influence on performance productivity involving all variables in this study expressed in the following equation model:

$$\mathbf{Y= \alpha + \beta1\ X1 +\beta2\ X2 + \beta3M+\beta4(X1*M)+\beta5(X2*M)+\varepsilon}$$

Table 7 Results of Moderation Regression Test Model 3

Coefficients a

	Model	Unstandardized Coefficients B	Unstandardized Coefficients Std Error	Standardized Beta	Sig
1	(Constant)	-0,279	0,957		0,771

Coefficients a

Model	Unstandardized Coefficients		Standardized	Sig
	B	Std Error	Beta	
Employee Training Transformation	2,685	1,373	2,685	0,055
Technology Investment Tranformation	-3,464	1,233	-3,464	0,007
Income Inequality	0,887	2,768	0,041	0,75
Training*Inequality	-6,697	3,849	-2,45	0,087
Investment*Inequality	9,054	3,463	3,313	0,011

a.
Dependent Variable : Performance Productivity Transformation

Based on Table 7, the regression equation can be written as follows:

$$\mathbf{Y = -0{,}279 + 2{,}685\ X1 - 3{,}464X2 + 0{,}887M - 6{,}697(X1*M) + 9{,}054(X2*M)}$$

The results of the moderation regression test of model 3 show that constant −0.279% where the initial value of productivity (Y) when all other variables are zero. Employee training (X1) has a positive coefficient of 2.685%, indicating that every 1 unit increase in training increases productivity by 2.685%, while technology investment (X2) has a negative coefficient of −3.464%, indicating that poorly managed technology investment can reduce productivity. Income inequality (M) has a positive direct effect of 0.887%, meaning that small inequality can slightly increase productivity. However, the interaction between employee training and inequality of −6.697% weakens the positive effect of training, while the interaction between technology investment and inequality of 9.054% strengthens the positive effect of technology investment on productivity. This shows that the impact of training and investment is greatly influenced by the conditions of income inequality in the company.

Results of Determination Coefficient Test

Table 8 Results of the Determination Coefficient Test

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.388[a]	0.151	0.082	0.96504

a. Predictors: (Constant), Training*Inequality, Income Inequality

The results shown in Table 8 show that the R-Square value is 0.151%, which means that the model is only able to explain 15.1% of the variation in the dependent variable. In other words, the other 84.9% of the variation is still influenced by factors that are not explained in this model. The Adjusted R-Square value of 0.082% is lower, which measures the complexity of the model (the number of independent variables) and the sample size. A low R-Square value does not always mean a bad model, especially if the data involves complex or non-linear relationships. R-Square may be less accurate in describing the quality of the model in cases like this. (Windmeijer & Cameron, 1995). In fields such as social or economics, low R-Square values are common and acceptable because the data is usually highly variable or influenced by many factors that cannot all be included in the model.

Results of T-test (Partial) and F-test (Simultaneous)

Table 9 Results of T-test (Partial) and F-test (Simultaneous)

Hypothesis	t-calculate	sig	F	Sig
Effect of Employee Training (X1) to employee performance productivity (Y) (H1)	1,972	0,053	1,678	0,200
Effect of Technology Investment (X2) to employee performance productivity (Y) (H2)	-1,477	0,144	2,077	0,134
Moderating Effect of Income Inequality (M) On the relationship between employee training (X1) and employee performance productivity (Y) (H3)	-0,113	0,910	0,549	0,200
Moderating Effect of Income Inequality (M) On the relationship between technology Investment (X2) and employee performance productivity (Y) (H3)	2,038	0,035	1,593	0,200

The analysis shows that employee training has a positive impact on productivity, with a regression coefficient of 0.357, but the effect is not statistically significant ($p = 0.053 > 0.05$). Conversely, technology investment has a negative impact on productivity, with a regression coefficient of -0.268, which is also not significant ($p = 0.144 > 0.05$). Income inequality as a moderating variable shows mixed effects: it weakens the positive impact of training on productivity, with an interaction coefficient of -0.339, but this effect is not significant ($p > 0.05$). However, income inequality strengthens the positive impact of technology investment on productivity, with an interaction coefficient of 5.654, which is statistically significant ($p = 0.035 < 0.05$). In Model 3, when income inequality is included, the effect of technology investment on productivity becomes significant ($p = 0.007 < 0.05$). This highlights the importance of managing income inequality to maximize the positive impact of technology investment on employee productivity

Results of Hypothesis Testing 1 (H1): The Effect of Employee Training on Employee Performance Productivity

The results of the study indicate that employee training has a positive but not significant effect on employee performance productivity in the manufacturing sector. The regression coefficient of 2.685 indicates that every one unit increase in employee training will increase performance productivity by 2.685% (assuming other variables remain constant). This is consistent with the Human Capital theory, which states that training is a form of investment that improves employee skills, competencies, and work efficiency. In the context of manufacturing in Indonesia, where labor is one of the main elements of the production process, increased training can accelerate adaptation to new technologies and increase operational output.

Results of Hypothesis Testing 2 (H2): The Effect of Technology Investment on Employee Performance Productivity

Technology investment has a negative regression coefficient of -3.464, indicating that every one unit increase in technology investment can actually reduce performance productivity by 3.464%. This indicates that poorly managed technology investment without the support of appropriate training or infrastructure can worsen performance. In the context of the manufacturing sector in Indonesia, technology adoption may face obstacles such as a lack of employee readiness to use new devices or a mismatch between the adopted technology and the needs of the production process.The limitations of uncertainty and lack of understanding about technology adoption can be reduced through policies that encourage companies to implement training and use resources to facilitate the transition to the introduction of new technologies for risk management, (Iqbal et al., 2015). This may prompt policymakers to introduce further programs to support companies to continue their digital transformation, aiming to support regional development and create more resilient organizations to cope with disruptions in the digital manufacturing era. When technology and training are strategically combined, companies can create long-term value. Continuous skills training will ensure that the workforce remains relevant and competitive, while investment in technology can accelerate innovation and productivity gains.

Results of Hypothesis Testing 3 (H3): Moderation of Income Inequality on the Relationship between Employee Training and Productivity

Income inequality has a negative moderating effect on the relationship between employee training and productivity, with an interaction coefficient of -6.697%. This means that the positive effect of training on productivity will weaken as income inequality increases. Income inequality can cause employees with lower incomes to feel unmotivated to apply the skills gained from training, because they feel that their hard work is not fairly rewarded. In the manufacturing sector in Indonesia, where there is a large difference in wage levels between factory workers and management, managing this inequality is important to maximize the benefits of training. Based on research conducted by (Satria & Dwi Wulandari, 2018), which focuses on income inequality between workers in the formal and informal sectors in Indonesia in 2017, by reviewing the influence of two main factors, namely discrimination and endowment (such as age, experience and job training). The results indicate that the discrimination factor has a greater influence on income inequality than the endowment factor. This means that there are differences in how workers from the formal and informal sectors are rewarded despite having similar characteristics.

Results of Hypothesis Testing 4 (H4): Moderation of Income Inequality on the Relationship between Technology Investment and Productivity

Income inequality moderates the relationship between technology investment and productivity with a positive effect of 9.054%. This suggests that income inequality can strengthen the relationship between technology investment and productivity. This may be due to the fact that workers with higher incomes (who generally have better skills) are able to utilize new technologies more effectively.In research (Kolade & Owoseni, 2022) with an approach that focuses on technological progress, especially computer-based, more beneficial to high-skilled workers than low-skilled workers, technology increases the productivity of high-skilled jobs and reduces the demand for low-skilled jobs, this means that higher-skilled workers will earn higher wages. Meanwhile, low-skilled workers will be marginalized or only earn low wages. However, this impact can create a bigger gap in the workplace, so companies need to be careful in dealing with the social impact of this inequality. On the other hand New technologies, especially those based on digital and automation, drive productivity increases, but also create inequality between sectors that can adopt high technology and those that cannot.

4. CONCLUSION

This study shows that employee training has a positive effect on employee performance productivity, with a regression coefficient of 0.357, but this effect is not statistically significant ($p = 0.053 > 0.05$). On the contrary, technology investment shows a negative effect on productivity with a regression coefficient of -0.268, which is also not significant ($p = 0.144 > 0.05$). Income inequality as a moderating variable has various effects: on the relationship between employee training and productivity, income inequality weakens the positive effect of training (interaction coefficient -0.339; $p > 0.05$), while on the relationship between technology investment and productivity, income inequality strengthens the positive effect of technology investment (interaction coefficient 5.654; $p = 0.035 < 0.05$). These results indicate that managing income inequality is very important in maximizing the benefits of technology investment on employee productivity in the manufacturing sector.

This study recommends that manufacturing companies prioritize continuous employee training, especially for low-skilled employees, so that the benefits of technology investment can be maximized. Adoption of new technology needs to be accompanied by relevant technical training to ensure that employees are able to utilize it optimally. In addition, it is important to manage income inequality more fairly to create a collaborative and motivated work environment. For the government, providing incentives to companies that actively carry out employee training and technology investment, especially in areas with low productivity, and implementing equitable income distribution policies, can encourage increased labor productivity. For further researchers, it is recommended to consider other variables, such as organizational culture and technology quality, in order to understand more complex relationships, and expand research to other sectors to see their consistency or differences with the manufacturing sector.

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