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Exploring The Roots of Human Development: The Role of Poverty, Unemployment, and Education in Indonesia

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ABSTRACT

The Human Development Index (HDI) is a fundamental indicator that describes the level of community welfare through the dimensions of education, health, and income. Understanding the socioeconomic factors that influence the HDI is crucial to ensuring the effectiveness of national development. This study aims to analyze the influence of poverty, unemployment, and education on the HDI in Indonesia over a clear timeframe, namely the period 2014–2023. The study uses a quantitative approach with a panel data regression method, while the data used are official national secondary data processed using EViews 13. The results show that partially, poverty and education have a significant effect on the HDI, while unemployment has no significant effect. Simultaneously, these three variables were proven to have a significant effect on the HDI during the study period. This finding confirms that increasing access to education and reducing poverty are key strategies in efforts to improve people's quality of life. The novelty of this study lies in the use of a data range that covers the phases before, during, and after the pandemic, thus providing a more comprehensive picture of the dynamics of human development and highlighting changes in the influence of socioeconomic variables on the HDI in the post-pandemic context.

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1. Introduction

Development is a multidimensional process encompassing efforts to improve the quality of human life by strengthening social, economic, and environmental aspects. Modern approaches to development emphasize not only economic growth but also the development of people's capabilities to lead productive and valuable lives (Mahadiansar et al., 2020). The United Nations Development Programme (UNDP) emphasizes that human development focuses on three main dimensions: health, education, and a decent standard of living (UNDP, 2022). These three dimensions are then formulated into the Human Development Index (HDI), which is widely used to assess the quality of development in various countries.

In Indonesia, the Human Development Index (HDI) has consistently shown improvement over the past decade. Statistics Indonesia (BPS) (2023) noted that Indonesia's HDI in 2023 reached 74.39, an increase compared to previous years. However, this increase is not always accompanied by equitable development quality

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across all regions. Disparities between provinces remain evident. For example, in 2023, the province with the highest HDI was Jakarta, with 81.65, while Papua had the lowest, with 61.67 (BPS, 2024). This difference indicates substantial disparities in access to education, health care, and a decent standard of living across Indonesia (World Bank, 2023). This situation confirms that despite the increase in the HDI nationally, equitable human development remains a serious challenge.

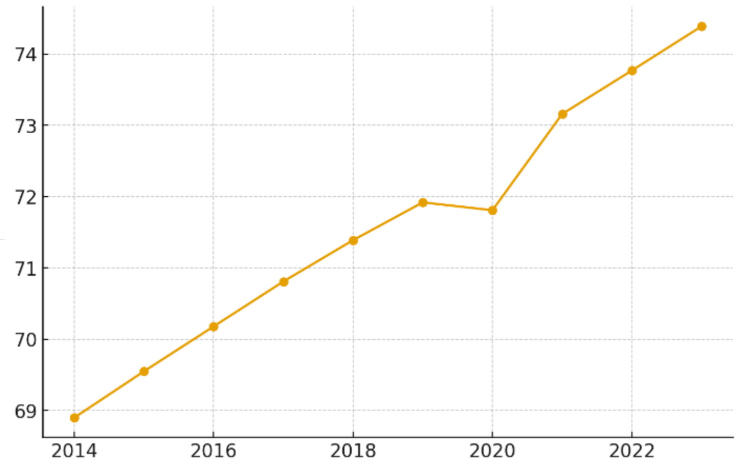

Figure 1. Trend of Indonesia's Human Development Index 2014–2023
Source: BPS 2025

The graph shows that Indonesia's Human Development Index (HDI) has steadily increased from 2014 to 2023, with significant changes post-pandemic. This trend underpins the urgency of analyzing the determinants of the HDI, particularly socioeconomic factors such as poverty, unemployment, and education. One factor considered influential on the HDI is poverty. Poverty reflects the limited ability to meet basic needs, including health services, education, and a decent standard of living, the three main pillars of the HDI (Larasati, 2018). Individuals or households in poverty tend to have limited access to quality education, adequate nutrition, health services, and decent housing. This ultimately negatively impacts HDI achievement. Various studies support these findings, such as those by Fahrika et al. (2020); Kasnelly & Wardiah (2021); and international studies such as Anand & Sen (2000), which show that poverty is closely related to low human development.

Besides poverty, unemployment is also a significant factor influencing the Human Development Index (HDI). High unemployment rates reflect low productivity and limited employment opportunities, which in turn impacts low household income and well-being. Mahroji and Nurkhasanah (2019) emphasized that the quality of human resources is crucial for successful development, particularly in utilizing technology and increasing national productivity. Research by Priambodo (2021) and global studies such as those by UNDP (2021) indicate that high unemployment has the potential to depress the quality of human development by reducing people's economic capacity.

Another factor is education. Education is a key asset in enhancing human capabilities, expanding employment opportunities, and increasing individual productivity in development (Hawari, 2019). Various studies have shown that education has a significant positive impact on the Human Development Index (HDI), both at the national and international levels (Imelda et al., 2021; Barro & Lee, 2015). Increasing educational attainment enables people to acquire the skills and knowledge needed to improve their quality of life.

Although various studies have analyzed the relationship between poverty, unemployment, education, and the Human Development Index (HDI), several research gaps remain. First, most previous studies have used a limited analysis period and have not included socioeconomic dynamics before, during, and after the COVID-19 pandemic. Second, empirical studies at the provincial level in Indonesia have limited use of long-term panel data, which could more comprehensively depict inter-regional variation and changes over time. Third, international references in previous studies are limited, thus not providing a global picture of the determinants of human development.

Therefore, this study aims to fill this gap by analyzing the influence of poverty, unemployment, and education on the Human Development Index in Indonesia using provincial panel data for the period 2014–2023. With a longer data set and encompassing the post-pandemic phase, this study is expected to provide a stronger empirical picture of the determinants of human development and contribute to the formulation of more effective and sustainable development policies.

2. Literature Review

2.1. Poverty

Modern poverty theory is heavily influenced by the Capability Approach introduced by Amartya Sen (1999). According to this theory, poverty is not simply low income, but rather the limited capabilities of a community to access education, health, and welfare. In the context of the Human Development Index (HDI), Sen's approach is fundamental because the HDI measures capability through three indicators: education, health, and income (UNDP, 2023).

Several empirical findings demonstrate a strong link between poverty and low human development. Wodon et al. (2018) showed that countries with high poverty tend to experience stagnant HDI due to limited access to basic social services. This finding supports Sen's theory that a society's basic capabilities are crucial for human development. Chuenyong et al. (2019) added that poverty reduction significantly improves education and health indicators because households are able to increase social spending.

However, there is academic debate regarding the direction of this relationship. Jha & Reza (2020) argue that poverty affects the HDI both directly and indirectly, but in some developing countries, the impact is not always symmetrical. They found that increased access to education can occur even if poverty levels have not drastically decreased. This suggests the need for specific policy interventions in the public service sector, not solely based on increasing income.

In the Indonesian context, this pattern is particularly relevant after the pandemic. Fitrani et al. (2022) stated that post-pandemic recovery requires a multidimensional strategy because poverty in Indonesia impacts the quality of education and health in the long term. This strengthens the argument that human development can only be achieved if poverty alleviation policies target the basic needs of the community.

H_1: Poverty has a negative effect on HDI

2.2. Unemployment

In classical and modern economic theory, unemployment is closely related to productivity and quality of life. According to Becker's (1993) Human Capital Theory, an individual's inability to utilize skills (due to unemployment) reduces long-term productivity and well-being, ultimately lowering the HDI score.

Empirically, Pasini & Sahay (2019) found that unemployment leads to social instability and a decline in the quality of life, leading to a decline in human development. This research serves to emphasize that the impact of unemployment is not only economic but also social.

However, some researchers argue that the relationship is not always linear. Darvas & Nemet (2020) found that in several Eastern European countries, education indicators continued to improve despite high unemployment rates, indicating the resilience of educational institutions.

In contrast to developed countries, research in developing countries shows a stronger impact. Liu & Zhang (2021) confirmed that unemployment in urban Asia significantly lowers health and education indicators due to decreased household spending on basic needs. Liu and Zhang's findings are relevant to the Indonesian context, where the majority of the population relies on household income for access to basic services.

Singh et al. (2022) emphasized that structural unemployment plays a significant role in social inequality and undermines human development. Meanwhile, Liu & Wei (2023) demonstrated that declining income due to unemployment has an indirect impact on the Human Development Index (HDI) through reduced nutritional quality, access to education, and healthcare. These differing research findings demonstrate that the impact of unemployment on the HDI is highly dependent on the economic structure of each country.

H_2: Unemployment has a negative effect on HDI

2.3. Education and Human Development Index

Human capital theory emphasizes that education improves an individual's skills, knowledge, productivity, and income (Becker, 1993). This theory forms the basis of the HDI because its components include average years of schooling and expected years of schooling (UNDP, 2023).

Empirically, Wang et al. (2019) demonstrated that education plays a role in poverty alleviation and improving healthcare. O'Neill et al. (2020) found that improving education quality drives growth in per capita income and life expectancy, thereby simultaneously boosting all components of the HDI.

Recent research supports this view. Sumarno & Yulianti (2021) assert that investment in education has a long-term impact on creating a productive society. Chen & Huang (2022) add that educational quality directly impacts social indicators such as reproductive health and labor force participation. Meanwhile, Lee & Kim (2023) argue that equitable access to education in developing countries can reduce social inequality and improve human development. In Indonesia, this relationship is particularly strong, given that school participation directly influences the HDI in each province. Thus, education is a fundamental variable in accelerating human development.

H_3: Education has a positive effect on HDI

3. Research Method

This study uses a quantitative approach because it aims to empirically test the causal relationship between poverty, unemployment, and education on the Human Development Index (HDI). The selection of panel data is based on the research needs as explained in the background, namely the importance of observing the dynamics of changes in the HDI over a long period, covering the phases before, during, and after the COVID-19 pandemic, as well as the disparities in the HDI between provinces in Indonesia. Panel data is considered most appropriate because it can capture variations between regions and changes over time simultaneously, resulting in more accurate estimates and minimal omitted variable bias, as emphasized by Baltagi (2021) and Hsiao (2014).

The type of data used in this study is secondary data obtained from official publications of the Central Statistics Agency (BPS) for the period 2014–2023. The selection of BPS secondary data aligns with the research focus, which highlights the dynamics of Indonesia's Human Development Index (HDI) over a long period and is relevant for assessing socioeconomic impacts in the pre-pandemic, pandemic, and post-pandemic periods. The data collected includes the Human Development Index (HDI), poverty rate, open unemployment rate, and average years of schooling, where these four indicators are the main determinants of human development based on the theory and empirical findings discussed in the literature review section. Data descriptions are summarized in Table 1.

The population in this study covers all 34 provinces in Indonesia. The sampling technique used purposive sampling, which selects samples based on specific criteria aligned with the research objectives. These criteria include provinces with complete data for all study variables for the 2014–2023 period. This sample selection aligns with the research's need to ensure data consistency and continuity, thereby comprehensively depicting patterns of HDI change in each province over a long period.

Table 1. Operational Definitions of Research Variables

Variables	Symbol	Definition	Unit	Source
Human Development Index	HDI	Measuring human development achievements through the dimensions of health, education, and standard of living	Index (0–100)	BPS

Variables	Symbol	Definition	Unit	Source
Poverty	POV	Percentage of population living below the poverty line	Percentage (%)	BPS
Open Unemployment	UNEMP	Percentage of the workforce that is unemployed and actively seeking work	Percentage (%)	BPS
Education (Average Years of Schooling)	EDU	The average number of years that the population aged ≥ 25 years has undergone formal education	Year	BPS

This study employs a panel data regression model to examine the determinants of the Human Development Index (HDI) across provinces in Indonesia over the period 2014–2023. The empirical model is specified as follows.

$$HDI_{it} = \beta_0 + \beta_1 POV_{it} + \beta_2 UNEMP_{it} + \beta_3 EDU_{it} + \varepsilon_{it},$$

where *HDI* represent Human Development Index of province (*i*) in year (*t*), while *POV*, *UNEMP*, and *EDU* denote poverty level, open unemployment rate, and average years of schooling, respectively. The selection of these variables is grounded in theoretical frameworks and prior empirical literature, and the model is intentionally designed to address the research gap identified in the introduction particularly the need to capture long-term HDI dynamics and interprovincial disparities over a decade-long observation window.

The data analysis follows a systematic multistage procedure to ensure robust and reliable estimation. First, descriptive statistics are computed to summarize the characteristics of all variables across the observation period. Second, a series of specification tests is conducted to determine the most appropriate panel data model, following standard econometric practice (Gujarati, 2013). These include the Chow test to choose between the pooled least squares (PLS) and fixed effects model (FEM), the Hausman test to discriminate between FEM and random effects model (REM), and the Lagrange Multiplier (LM) test to select between PLS and REM. Once the optimal model is identified, panel regression estimation is performed, followed by diagnostic testing for classical assumptions, namely multicollinearity, heteroscedasticity, and autocorrelation, to ensure the validity of the inferred relationships.

To evaluate the statistical significance and explanatory power of the model, both partial (t-test) and simultaneous (F-test) hypothesis tests are administered, along with the coefficient of determination measured by the adjusted R^2. These metrics collectively assess the individual and joint effects of the independent variables on HDI, while also gauging the overall model fit. All data processing and econometric estimations are carried out using EViews 13, a widely recognized software package in empirical economic research, ensuring computational accuracy and replicability of the findings.

4. Result

4.1. Classical Assumption Test

Ghozali (2016) explains that the classical assumption test is a mandatory statistical prerequisite for multiple linear regression analysis using the Ordinary Least Squares (OLS) method. The OLS method involves one dependent variable and more than one independent variable. To determine model accuracy, several classical assumption tests are necessary, namely the normality test, multicollinearity test, heteroscedasticity test, and autocorrelation test.

The first diagnostic check is the normality test, which is used to determine whether the residuals in a regression model follow a normal distribution (Ghozali, 2016). In this study, the normality test is performed using the Jarque–Bera test within the EViews 13 software. According to Winarno (2017), the Jarque–Bera test is a statistical method that evaluates the normality of the residual distribution by measuring the levels of skewness and kurtosis and comparing them with the characteristics of a normal distribution. The decision-making basis for this test is as follows: if the Jarque–Bera (JB) value is less than the χ^2 table value and the probability is greater than 0.05, the residuals are declared to be normally distributed; conversely, if the JB value exceeds the χ^2 table value and the probability is less than 0.05, the residuals are not normally distributed

Table 2 Normality Test Results (Jarque Bera Test)

Statistics	Sign
Observation	175
Maximum	4.312892
Minimum	-11.71405
Jarque-Bera	707.4271
Possibility	0.000000

Source: Eviews 13 Data processed by the author, 2025

Based on Table 2 above on the results of the residual normality test (jarque test), it can be concluded that the probability of the occurrence of the jarque value above has a probability value of 0.000000 < 0.05, if the jarque probability of the value is < a then H1 is accepted or which means the residual is not normally distributed.

The next test is the multicollinearity test. As explained by Ghozali (2016), this test is intended to detect high or perfect correlations between independent variables in a regression model, which is performed by examining the Tolerance and Variance Inflation Factor (VIF) values. The interpretation follows established criteria: a VIF value below 10 indicates the absence of multicollinearity, whereas a VIF value above 10 suggests the presence of multicollinearity among the independent variables.

Table 3 Multicollinearity Test Results

Variables	Coefficient Variance	Uncentered VIF	Centralized VIF
C	1.392635	73.68145	NA
X1	0.000994	7.039246	1.427968

Variables	Coefficient Variance	Uncentered VIF	Centralized VIF
X2	3.08E-05	6.143844	1.076641
X3	0.000248	55.16366	1.479719

Source: Eviews 13 Data processed by the author, 2025

From the table above, it can be seen that the Centered VIF value for X1 is 1.427968, X2 is 1.076641, X3 is 1.479719 where the value is less than 10, so it can be stated that there is no multicollinearity problem in the prediction model.

The heteroscedasticity test aims to determine whether there is inequality in residual variance between observations in a regression model. Ghozali (2016) explains that heteroscedasticity can interfere with the efficiency of regression estimation, thus it needs to be tested before drawing statistical conclusions. To detect heteroscedasticity, this study employs the Breusch–Godfrey test, a hypothesis test conducted by regressing absolute residuals to identify whether a pattern of variance inequality exists. The decision-making basis for this test follows the criteria outlined by Ghozali (2016): if the significance value is ≥ 0.05, the model is considered free from heteroscedasticity; conversely, if the significance value is ≤ 0.05, the model is deemed to experience heteroscedasticity.

Table 4. Heteroscedasticity Test Results

Statistics	Sign	Prob.
F statistic	0.092833	0.9639
Obs *R-squared	0.284549	0.9629
SS explained scale	1.540732	0.6729

Source: Eviews 13 Data processed by the author, 2025

The output showing the p-value is indicated by the Prob. chi square value (3) on Obs * R-Squared is 0.9629. Therefore, the p-value of 0.9629 > 0.05, then H0 is accepted or which means the regression model is homoscedastic or in other words there is no problem with the non-heteroscedasticity assumption.

The fourth assumption test is the autocorrelation test. Ghozali (2016) explains that this test aims to determine whether a linear regression model exhibits a correlation between the error (residual) in period t and the error in period t−1 (the previous period). In this study, the autocorrelation test is performed using the Durbin–Watson statistic to detect whether such residual correlation exists. The decision-making basis follows the criteria outlined by Ghozali (2016): if the Durbin–Watson value falls within the range of DU < DW < 4 − DU, the model is declared to be free from autocorrelation; conversely, if the DW value is less than DL or greater than 4 − DL, the model is considered to experience autocorrelation.

Table 5. Autocorrelation Test Results

Variables	Coefficient	Standard Error	t statistics	Prob.
C	57.80563	1.180099	48.98369	0.0000
X1	-0.210568	0.031525	-6.976419	0.0000
X2	0.004044	0.005549	0.739767	0.4284
X3	0.260008	0.015754	16.50440	0.0000

Source: Eviews 13 Data processed by the author, 2025

Given N = 175 and K (Independent Variable) there are 3 variables, then based on the Durbin Watson reference table with a significance level of 0.05, the results obtained are with a DL value of 1.738, a DU value of 1.799, a 4-DL value of 2.262, a 4-DU value of 2.501, and a Durbin Watson value of 1.033742. DW<DL = 1.033742 < 1.738 It is concluded that the autocorrelation test is not fulfilled or does not pass the autocorrelation test. Therefore, the healing method is carried out using the First Difference Data Transformation. The Durbin-Waston value in the autocorrelation test after healing is carried out can be seen below.

Table 6. First Different Data Transformation Test Results

Variables	Coefficient	Standard Error	t statistics	Prob.
C	0.007112	0.136941	0.051933	0.9586
D(X1)	-0.203434	0.053334	-3.814370	0.0002
D(X2)	0.011497	0.004021	2.845089	0.0050
D(X3)	0.197061	0.022286	8.842195	0.0000

Statistics	Sign
R-squared	0.548043
Adjusted R-squared	0.540067
F statistic	68.71398
Prob(F-statistic)	0.000000
Dependent variable SD	2.663017
Hannan-Quinn Creatures.	4.072301
Durbin-Watson Statistics	2.495036

Source: Eviews 13 Data processed by the author, 2025

After the First Different Data Transformation was carried out, the Durbin Watson value was obtained as 2.495036 with DU < DW < 4-DU = 1.799 < 2.495 < 2.501, so it can be concluded that the autocorrelation test assumption has been fulfilled or passed the autocorrelation test.

Table 7. Best Model Selection Test Results

Test Type	Hypothesis	Prob.	Decision	Selected Model
Chow Test	H0: Pooled OLS is better than FEM	0.0000	Reject H0	FEM
LM Breusch–Pagan test	H0: Pooled OLS is better than REM	0.0000	Reject H0	BRAKE
Hausman test	H0: REM is better than FEM	0.0321	Reject H0	FEM
Mundlak–Wu–Hausman (MWC) test	H0: REM is consistent	0.0185	Reject H0	FEM

Source: Eviews 13 Data processed by the author, 2025

Based on a series of model selection tests, namely the Chow Test, Lagrange Multiplier Test, Hausman Test, and Mundlak–Wu–Hausman (MWC), it was found that the best model to use in this study is the Fixed Effect Model (FEM). The Chow Test shows that FEM is more appropriate than Pooled OLS, while the Hausman Test and MWC indicate that FEM is more robust and consistent than REM (Ghozali, 2016). Therefore, the panel data regression estimation in this study uses the Fixed Effect model.

4.2. Panel Data Regression Analysis Result

For the time series data in this study, the MWC (Model Specification Test) was used. The MWC (Mundlak-Wu-Hausman) test was used to select between FEM and REM, namely using the Fixed Effect Model and the Random Effect Model. Then, the Hausman test was used to determine the best model.
Null Hypothesis (H0): REM is more suitable because its estimates are unbiased.
Alternative Hypothesis (H1): FEM is more appropriate because it is more robust against endogeneity. If the p-value is <0.05, choose FEM; if the p-value is >0.05, choose REM (Ghozali, 2016). The following are the regression results found:

Table 8. Panel Data Regression Analysis Results

Variables	Coefficient	Standard Error	t statistics	Prob.
C	57.73242	1.041727	55.41992	0.0000
X1	-0.210197	0.027774	-7.568048	0.0000
X2	0.005809	0.004948	1.174018	0.2421
X3	0.226002	0.013878	18.57670	0.0000

Source: Eviews 13 Data processed by the author, 2025

Table 9. Panel Regression Statistics Results

Statistics	Sign
R-squared	0.833450
Adjusted R-squared	0.830440
F statistic	273.5521
Prob(F-statistic)	0.000000
Hannan-Quinn Creatures.	3.892655
Durbin-Watson Statistics	0.398881

Source: Eviews 13 Data processed by the author, 2025

To examine the individual effect of each independent variable on the dependent variable, a partial significance test (t-test) is employed, following the criteria established by Sahir (2022) and Satria (2018). In this test, an independent variable is deemed to have a statistically significant influence if the calculated t-value is greater than the corresponding t-table value. Based on the t-test results conducted in this study, the following outcomes are obtained.

a. The t-value for the poverty variable is -7.568048. In addition, the probability value for the poverty variable is 0.0000, which is smaller than the ÿ value (0.05). Thus, it can be statistically concluded that the poverty variable has a significant influence on the HDI variable.
b. The t-value for the unemployment variable is 1.174018. In addition, the probability value for the unemployment variable is 0.2421, which is greater than the ÿ value (0.05). Thus, it can be statistically concluded that the unemployment variable does not have a significant effect on the HDI variable.
c. The t-value for the education variable is 18.78670. In addition, the probability value for the education variable is 0.0000, which is smaller than the ÿ value (0.05). Therefore, it can be statistically concluded that the education variable has a significant influence on the HDI variable.

To assess whether the independent variables jointly influence the dependent variable, a simultaneous test (F-test) is conducted, which also serves to evaluate the overall model suitability and the reliability of the regression results (Satria, 2018). According to Sahir (2022), this test compares the calculated F-value with the F-table value to determine the combined significance of the independent variables on the dependent variable. Based on the regression results, the statistical F-probability value is 0.0000, which is smaller than the significance level of 0.05. Therefore, it can be concluded that poverty level, unemployment rate, and education jointly have a significant effect on the Human Development Index in Indonesia over the 2019–2023 period.

5. Discussion

5.1. The Impact of Poverty on the Human Development Index in Indonesia

The results of the study indicate that poverty has a negative and significant impact on the HDI, indicating that an increase in the number of poor people will reduce human development outcomes in each province. Theoretically, this finding is consistent with the capability approach developed by Sen (1999), which explains that poverty is not simply low income, but rather the limited ability of individuals to access basic services such as education, health, and a decent standard of living. When these capabilities are limited, the HDI dimensions of longevity, knowledge, and standard of living will decline.

Empirically, these findings align with Wodon et al. (2018), who asserted that poor households tend to have lower access to healthcare, higher rates of malnutrition, and lower housing quality, thus lowering life expectancy. Chuenyong et al. (2019) also showed that areas with high poverty rates have low school enrollment rates, leading to long-term educational limitations. Bebbington's (2021) research adds that structural poverty can hinder development because poor households are unable to invest in their children's education, a crucial factor in human development.

In the Indonesian context, these findings are even more relevant. Statistics Indonesia (BPS) data shows that provinces with the highest poverty rates, such as Papua, Highlands Papua, Central Papua, and East Nusa Tenggara, consistently have the lowest Human Development Index (HDI). This phenomenon reinforces Ravallion's (2020) argument that poverty has long-term effects on human development, particularly in areas with limited access to public facilities. Post-COVID-19 pandemic, Fitrani et al. (2022) showed that poorer provinces experienced the slowest recovery due to inadequate education and health infrastructure, resulting in a greater impact on the HDI.

Thus, these results strengthen the research hypothesis that poverty negatively impacts the HDI (H1 is accepted). These findings provide policy implications: poverty alleviation programs should be directed at provinces with a high poverty burden, productivity-based social assistance should be strengthened, and access to health and education for poor families should be improved to prevent widening disparities in human development between provinces.

5.2. The Impact of Unemployment on the Human Development Index in Indonesia

The regression results show that the unemployment rate has no significant effect on the HDI. This insignificance is interesting because it contradicts several classical labor economic theories, which explain that unemployment can reduce welfare and quality of life (Blanchard & Johnson, 2020). However, in the Indonesian context, this phenomenon can be explained by several structural factors.

First, the majority of unemployed in Indonesia are underemployed and informal workers. According to the ILO (2022), approximately 58% of Indonesia's workforce works in the informal sector, so job loss or unemployment often does not reduce access to basic services. This explains why unemployment does not directly reduce education or health, as noted by Liu & Zhang (2021) in their study of developing countries.

Second, regions with high unemployment rates do not necessarily have low HDI. For example, Banten, Jakarta, and West Java have high unemployment rates but still have good educational and health outcomes due to strong regional fiscal support. This finding aligns with Gupta & Verhoeven (2020), who showed that regions with high-quality public services can mitigate the negative impact of unemployment on human development.

Third, previous studies in Indonesia, such as those by Tumbuan & Tumangkeng (2023) and Choirunnisak (2020), also found that unemployment had no significant effect on the HDI in various large cities because education and health indicators increased regardless of labor market fluctuations.

Therefore, this study concludes that unemployment is not the primary factor determining the quality of human development in Indonesia during the 2019–2023 period (H2 is rejected). The policy implication is that the government needs to focus not only on reducing the unemployment rate statistically but also on improving job quality, social protection, and labor productivity to make their impact on the HDI more tangible.

5.3. The Impact of Education on the Human Development Index in Indonesia

Education has been found to have a positive and significant effect on the Human Development Index (HDI). This finding is robust both theoretically and empirically. Becker's (1993) Human Capital Theory states that education improves skills, productivity, employability, and quality of life, thus directly impacting human development. Furthermore, UNESCO (2023) asserts that education is a key determinant of three dimensions of the HDI: life expectancy, knowledge, and standard of living.

The results of this study are consistent with international studies by Barro & Lee (2015), O'Neill et al. (2020), and Chen & Huang (2022), which concluded that increased access to education significantly improves economic growth and public health. In the context of developing countries, Hanushek & Woessmann (2021) showed that quality education boosts cognitive abilities and increases opportunities for better employment.

In the Indonesian context, education is the most dominant indicator influencing the Human Development Index (HDI). Provinces such as DKI Jakarta, Yogyakarta, Bali, and Central Java have the highest average years of schooling nationally, which is directly correlated with increasing per capita income and life expectancy. Conversely, Papua and West Papua have the lowest years of schooling (around 6–7 years), resulting in their HDI rankings at the bottom. This phenomenon is reinforced by research by Imelda et al. (2021) and Hasibuan & Tambunan (2023), which confirm that education is a key determinant of human development in Indonesia.

Thus, the results of this study support Hypothesis 3 (H3 is accepted). The implication is the need to improve educational equity, especially for underdeveloped provinces and 3T (frontier, outermost, and underdeveloped) regions, improve teacher quality, and increase access to secondary education to reduce the disparity in the Human Development Index (HDI) between provinces.

6. Conclusion

This study aims to analyze the influence of poverty, unemployment, and education on the Human Development Index (HDI) in 34 provinces in Indonesia during the period 2019–2023 using a panel data regression model. Based on the results of the best model estimation (Fixed Effect Model), it can be concluded that human development in Indonesia is strongly influenced by socio-economic dynamics between provinces, especially in the dimensions of poverty and education.

First, this study proves that poverty has a negative and significant effect on the HDI, thus Hypothesis 1 (H1) is accepted. This finding confirms that an increase in the number of poor people has a direct impact on decreasing access to education, health, and a decent standard of living, which are the main components of the HDI. Second, the study found that unemployment did not have a significant effect on the HDI, thus Hypothesis 2 (H2) was rejected. This indicates that unemployment fluctuations are not strong enough to affect human development achievements at the provincial level, mainly due to the characteristics of the Indonesian labor market which is dominated by the informal sector. Third, the results of the study show that education has a significant positive effect on the HDI, thus Hypothesis 3 (H3) is accepted. Education has been proven to be a key factor in improving the quality of life of the community through increasing economic, social, and health capabilities.

Simultaneously, these three variables significantly influence the HDI, indicating that human development is the result of a multidimensional interaction of various social and economic factors. Academically, this study contributes to the literature on human development in developing countries by demonstrating that education is the most dominant variable, while unemployment is not always the primary determinant in the Indonesian context. These findings enhance understanding of how domestic economic characteristics and labor force structure influence human development.

Practically, the research findings offer several important policy implications. Central and regional governments need to strengthen poverty alleviation programs by improving access to basic services for poor households. Investment in education, particularly in underdeveloped and remote areas (3T) should be a priority to improve the quality of human resources equitably. Furthermore, although unemployment does not directly impact the HDI, the government needs to focus on improving job quality, labor productivity, and expanding social security to ensure sustainable human development.

This study has several limitations that should be considered. First, the variables used are limited to three indicators, thus not being able to capture all determinants of the HDI, such as health, infrastructure, or government spending. Second, this study does not consider possible mediating and moderating effects between variables. Third, the study's time period is relatively short due to data limitations, so it does not fully reflect the long-term dynamics of human development.

For further research, it is recommended to add other variables such as education spending, health care quality, income inequality, and demographic variables to make the model more comprehensive. Longitudinal research with a longer time span is also important to understand the patterns of change in the HDI more deeply. Furthermore, regional cluster analysis can provide insights into human development disparities across provinces in Indonesia.

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