

Modeling Human Development Index Determinants in Central Java: A Comparison of Gamma GLM and Linear Regression

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ABSTRACT

The Human Development Index (HDI) and the Gender Development Index (GDI) are important indicators to describe the development conditions in a region. This study aims to analyze the influence of socio-economic indicators on the HDI and GDI in regencies/cities in East Java Province. The data used comes from the official publication of the Central Statistics Agency (BPS) of East Java Province in 2024. The socio-economic variables studied include population density, Open Unemployment Rate (OUR), percentage of poor people (PPM), mean years of schooling (MYS), and Gross Regional Domestic Product (GRDP). The analysis was carried out using multivariate regression to estimate the influence of independent variables on two response variables, namely the HDI and GDI simultaneously. The results showed that in the HDI model, the MYS and GRDP variables had a significant positive effect on the HDI at a significance level of 5%, while population density, OUR, and PPM did not have a significant effect. In the GDI model, the OUR variable had a significant positive effect on the GDI at a significance level of 5%, while the other variables did not show a significant effect. In general, these results indicate that education and economic conditions play a role in increasing the HDI, while variations in the GPI are more influenced by the open unemployment rate. The multivariate regression model used provides a snapshot of the influence of socioeconomic variables on the HDI and GPI simultaneously.

KEYWORDS

entral Java, Gamma GLM, Human Development Index, Multiple Linear Regression.

1. INTRODUCTION

The Human Development Index (HDI) is a composite indicator that has been widely used to assess the success of human development through three main dimensions: health, education, and a decent standard of living [1, 2, 3]. This indicator not only reflects the economic achievements of a region but also captures the quality of human resources as a fundamental pillar of sustainable development. In Indonesia, HDI serves as a strategic indicator in evaluating regional development performance and monitoring progress toward the Sustainable Development Goals (SDGs) [4]. Persistent disparities in HDI achievement across regions indicate that human development has not progressed evenly [5]. Therefore, empirical investigations into the determinants of HDI are essential to support the formulation of more effective and equitable development policies.

According to data from the Central Bureau of Statistics 2024, the HDI of Central Java Province reached 72.67, ranking 14th among 34 provinces in Indonesia. Although this figure shows an upward trend, substantial disparities remain across districts and municipalities. For instance, the City of Semarang recorded an HDI of 77.91, whereas Brebes Regency achieved only 66.90 [6]. These disparities reflect unequal access to education, healthcare services, and socioeconomic opportunities across

regions. Persistent inequalities in HDI may widen welfare gaps and reduce the effectiveness of regional development strategies [7]. Consequently, analyzing the determinants of HDI at the district and municipal levels is particularly crucial, especially in provinces with heterogeneous regional characteristics such as Central Java.

Education, health, and economic conditions constitute the core components shaping human resource quality. Educational indicators, including Expected Years of Schooling (EYS) and Mean Years of Schooling (MYS), represent access to and continuity of education, which directly influence labor productivity [8]. Meanwhile, the health dimension, measured through Life Expectancy at Birth (LEB), reflects overall quality of life and the availability of healthcare services [9]. Economic factors, such as poverty and unemployment rates, also affect HDI by constraining purchasing power and limiting access to basic services [10]. The interaction among education, health, and economic conditions positions HDI as a multidimensional indicator that requires a comprehensive analytical approach.

Numerous empirical studies have examined the factors influencing HDI in Indonesia. Syafira, Khoiruddin, and A'yun found that per capita expenditure, life expectancy, and mean years of schooling significantly affect HDI in Papua Province [11]. Further, Istiqomah et al. reported that poverty has a negative impact on HDI in West Java Province, while education and health contribute positively [12]. Similar findings were also documented by Kiha, Seran, and Lau in Belu Regency [13]. However, most of these studies rely on conventional linear regression models that assume normality of the dependent variable. According to [10], HDI is a positive continuous variable that tends to exhibit right-skewed distributional characteristics, which may violate the normality assumption inherent in linear regression models.

The Generalized Linear Model (GLM) with a Gamma distribution offers an alternative approach that is more suitable for modeling positive continuous data with non-constant variance [14]. This approach has been shown to be more flexible and robust than multiple linear regression in the context of HDI analysis, as demonstrated by [10]. In addition, sectoral economic factors also play an important role in shaping community welfare, which ultimately affects HDI outcomes [15]. Nevertheless, studies that explicitly compare the performance of multiple linear regression and Gamma-based GLM in modeling HDI at the district and municipal levels in Central Java Province remain limited. Therefore, this study aims to model the determinants of HDI in Central Java Province in 2024 by comparing Multiple Linear Regression and the Gamma Generalized Linear Model (GLM) to identify the most appropriate model as an empirical basis for evidence-based human development policy formulation.

2. METHODOLOGY

2.1 Data and Research Variables

This study employs secondary data obtained from the Central Bureau of Statistics (Badan Pusat Statistik, BPS) of Central Java Province for the year 2024. The unit of analysis consists of 35 districts and municipalities in Central Java Province. The response variable used in this study is the Human Development Index (HDI), a composite indicator designed to measure the level of human development achievement within a given region. This study employs secondary cross-sectional data obtained from the official statistical database of the Central Bureau of Statistics (Badan Pusat Statistik/BPS) of Central Java Province for the year 2024. The dataset was collected from multiple statistical tables published on the official BPS Central Java website (<https://jateng.bps.go.id>), covering 35 regencies and municipalities in Central Java Province.

The response variable used in this study is the Human Development Index (HDI), which represents a composite indicator of human development achievement at the regional level. The explanatory variables analyzed include educational, health, and socioeconomic indicators, namely Life Expectancy at Birth (LEB), Expected Years of Schooling (EYS), Mean Years of Schooling (MYS), Open Unemployment Rate, Poverty Rate, Health Insurance Participation (BPJS), Health Complaints, and Labor Force Participation Rate (LFPR). All variables were measured using their original scales, including ratio and percentage units, depending on the characteristics of each indicator. Prior to model estimation, diagnostic tests were conducted to evaluate the assumptions of Multiple Linear Regression. The normality of the HDI variable was assessed using the Shapiro–Wilk and Anderson–Darling tests, while multicollinearity among explanatory variables was examined using the Variance Inflation Factor (VIF).

In addition, descriptive statistical analysis was performed to summarize the characteristics of the data and to identify regional variations across regencies and municipalities. Data processing, statistical modeling, and spatial visualization of HDI distribution were conducted using R software.

2.2 Multicollinearity Assessment

Before constructing the regression models, multicollinearity among the explanatory variables is examined using the Variance Inflation Factor (VIF). High multicollinearity may lead to unstable parameter estimates and reduce the accuracy of statistical inference [16]. In this study, explanatory variables with VIF values exceeding the acceptable tolerance threshold are considered to exhibit strong linear relationships with other predictors.

To address multicollinearity, variables with excessively high VIF values are excluded from the regression model to ensure more stable and reliable parameter estimation. After the variable selection process, the regression models are estimated using only the explanatory variables that satisfy the multicollinearity assumption, allowing the analysis to proceed to parameter estimation and model evaluation.

2.3 Multiple Linear Regression Model

As a baseline model, this study applies Multiple Linear Regression to examine the relationship between the Human Development Index (HDI) and the selected explanatory variables. The Multiple Linear Regression model is specified as equation (1):

$$Y_i = \beta_0 + \sum_{k=1}^5 \beta_k X_{ki} + \varepsilon_i \quad (1)$$

where Y_i denotes the HDI value for the i -th region, X_{ki} represents the k -th explanatory variable, β_k denotes the regression coefficients to be estimated, and ε_i is the error term.

The model assumes that the error terms are normally distributed with a mean of zero and constant variance, as expressed in equation (2):

$$\varepsilon_i \sim N(0, \sigma^2) \text{ and } \text{Var}(Y_i) = \sigma^2 \quad (2)$$

The regression parameters are estimated using the Ordinary Least Squares (OLS) method. Multiple linear regression assumes a linear relationship between the dependent variable (HDI) and the explanatory variables, which in this study include indicators of education, health, and socioeconomic conditions. Although this approach is widely applied in HDI-related studies, its validity may be compromised when the assumptions of normality and homoskedasticity are violated [17].

2.4 Generalized Linear Model (GLM) with Gamma Distribution

As an alternative to multiple linear regression, this study employs a Generalized Linear Model (GLM) with a Gamma distribution. The selection of this model is motivated by the characteristics of HDI data, which are continuous, strictly positive, and tend to exhibit right-skewed distributions. The Gamma GLM is specified as equation (3):

$$Y_i \sim \text{Gamma}(\mu_i, \phi), \quad \log(\mu_i) = \beta_0 + \sum_{k=1}^5 \beta_k X_{ki} \quad (3)$$

where $\mu_i = E(Y_i)$ denotes the expected value of HDI for the i -th region, and ϕ represents the dispersion parameter. The variance function of the Gamma model is given by equation (4):

$$\text{Var}(Y_i) = \phi \mu_i^2 \quad (4)$$

The regression parameters are estimated using Maximum Likelihood Estimation (MLE). The use of a log link function allows for a nonlinear relationship between the explanatory variables and the mean HDI while ensuring that predicted HDI values remain positive. Compared to multiple linear regression, the Gamma GLM offers greater flexibility in handling non-normal data and heteroskedastic variance structures [18].

2.5 Model Selection Criteria

The selection of the best model between Multiple Linear Regression and the Gamma GLM is based on the Akaike Information Criterion (AIC), as formulated in equation (5).

$$AIC = -2 \ln(L_{\max}) + 2p \quad (5)$$

where $L_{\max}$ denotes the maximum likelihood value and p represents the number of estimated parameters in the model. The model with the lower AIC value is considered to provide the optimal balance between goodness of fit and model complexity. In addition to the AIC, the statistical significance of regression parameters is evaluated at a 5% significance level ($p < 0.05$). The best-performing model is determined based on the lowest AIC value and its ability to identify statistically significant and substantively relevant variables in explaining regional variations in HDI.

3. RESULT & DISCUSSION

This study aims to analyze the factors influencing variations in the Human Development Index (HDI) across districts and municipalities in Central Java Province in 2024, as well as to compare the performance of Multiple Linear Regression and the Gamma Generalized Linear Model (GLM) in modeling HDI. The analysis utilizes secondary data from the Central Bureau of Statistics, encompassing indicators of education, health, and socioeconomic conditions. Overall, the findings reveal substantial disparities in HDI across regions, with education and health emerging as the dominant drivers of HDI improvement, while poverty and adverse health conditions act as major constraints. Furthermore, the model comparison indicates that the Gamma GLM provides a better fit than multiple linear regression, consistent with the positive and non-symmetric distributional characteristics of HDI.

3.1 Descriptive Analysis

Descriptive analysis was conducted to summarize the characteristics of HDI and the explanatory variables across 35 districts and municipalities in Central Java Province in 2024. As illustrated in Figure 1, the average HDI of Central Java is 75.54 with a variance of 14.05, indicating substantial disparities in human development achievement across regions. The Salatiga City records the highest HDI at 84.16, whereas Banjarnegara Regency exhibits the lowest HDI at 69.60. This variation suggests that human development in Central Java has not progressed evenly. The spatial pattern displayed in **Figure 1** further highlights pronounced regional heterogeneity. Urban areas and economic centers, such as Semarang and Surakarta, tend to exhibit higher HDI values compared to predominantly rural areas, particularly in the southern and western parts of the province. This pattern indicates that the concentration of educational facilities, healthcare services, and economic opportunities in urban areas contributes to higher HDI achievements. Conversely, regions with limited infrastructure and restricted access to basic services generally exhibit lower HDI levels. These findings reinforce evidence of spatially uneven human development [19]. **Figure 2** presents interregional comparisons of the explanatory variables, illustrating variations in educational, health, and socioeconomic indicators across districts and municipalities. Educational indicators such as Life Expectancy at Birth (LEB), Expected Years of Schooling (EYS), and Mean Years of Schooling (MYS) are relatively high in most regions, although noticeable disparities persist. Banjarnegara, Brebes, and Pemalang exhibit higher poverty and unemployment rates compared to major cities such as Semarang and Surakarta. Health insurance participation (BPJS) and labor force participation rates display moderate variation, while reported health complaints are relatively low in most regions, despite several areas exhibiting higher complaint levels.

Substantively, these descriptive findings indicate that regional disparities in HDI are closely associated with differences in education, health, and socioeconomic conditions. Regions with lower HDI levels tend to experience higher poverty and unemployment rates, along with more limited access to education and healthcare services. This pattern is consistent with previous studies emphasizing education and health as key determinants of human development [20,21]. Thus, the descriptive analysis provides preliminary evidence that HDI disparities in Central Java reflect not merely numerical differences but also deeper structural inequalities across regions.

3.2 Multicollinearity and Correlation Analysis

Prior to regression modeling, multicollinearity diagnostics are performed to ensure the absence of strong linear relationships among explanatory variables that could compromise parameter stability. The Variance Inflation Factor (VIF) is used for this purpose. Initial diagnostics indicate that VIF values range from 1.616 to 16.010, with Mean Years of Schooling (MYS) exhibiting the highest VIF. The elevated VIF value for MYS suggests the presence of serious multicollinearity, particularly with other education-related variables.

To address this issue, the MYS variable is excluded from the regression models. Following its removal, all remaining explanatory variables display VIF values between 1.507 and 3.943, as shown in **Table 1**, indicating that multicollinearity is

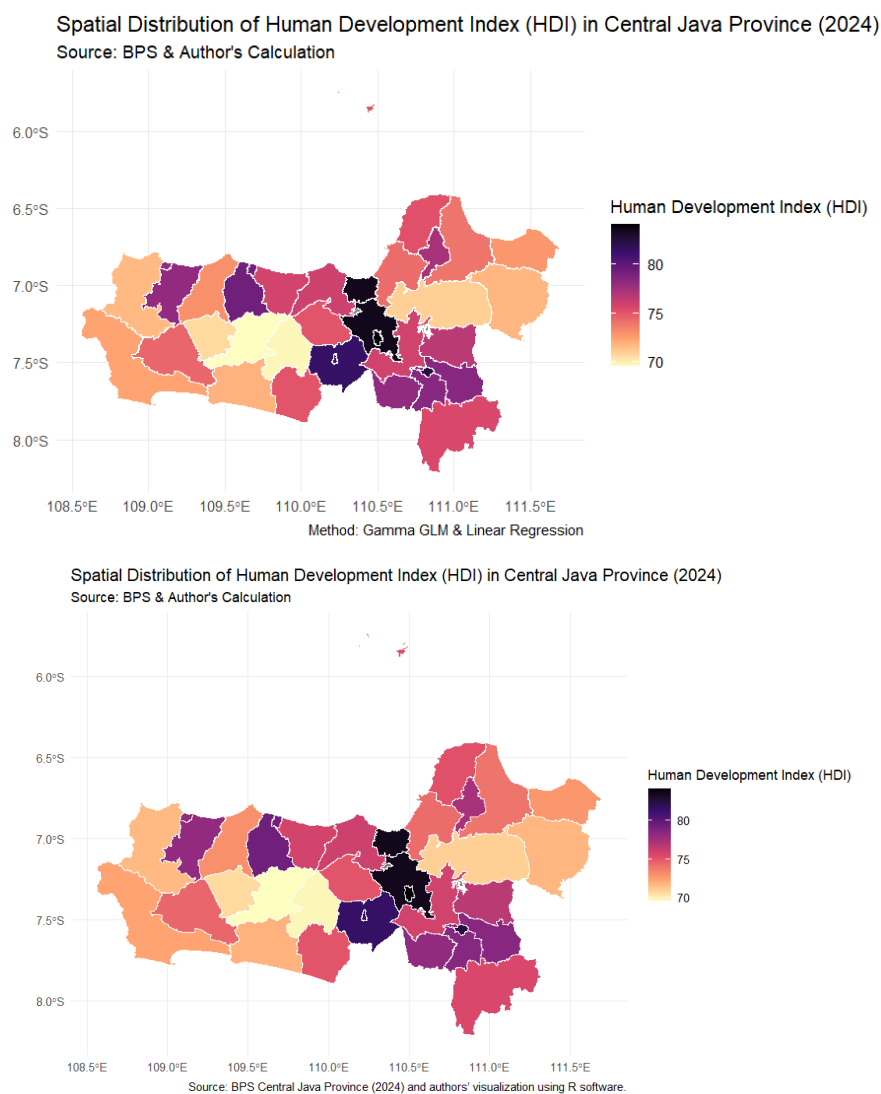


Figure 1. Spatial Distribution of HDI in Central Java Province, 2024

no longer a concern. From a substantive perspective, excluding MYS also allows the analysis to focus on Expected Years of Schooling (EYS) as a more forward-looking indicator of educational continuity. In addition to multicollinearity diagnostics,

Table 1. Variance Inflation Factor (VIF) for Explanatory Variables

Variable	VIF
X_1 – Life Expectancy at Birth (LEB)	3.088
X_2 – Expected Years of Schooling (EYS)	3.959
X_4 – Open Unemployment Rate	1.523
X_5 – Poverty Rate	2.394
X_6 – BPJS Health Insurance Participation	1.840
X_7 – Health Complaints	1.889
X_8 – Labor Force Participation Rate (LFPR)	1.749

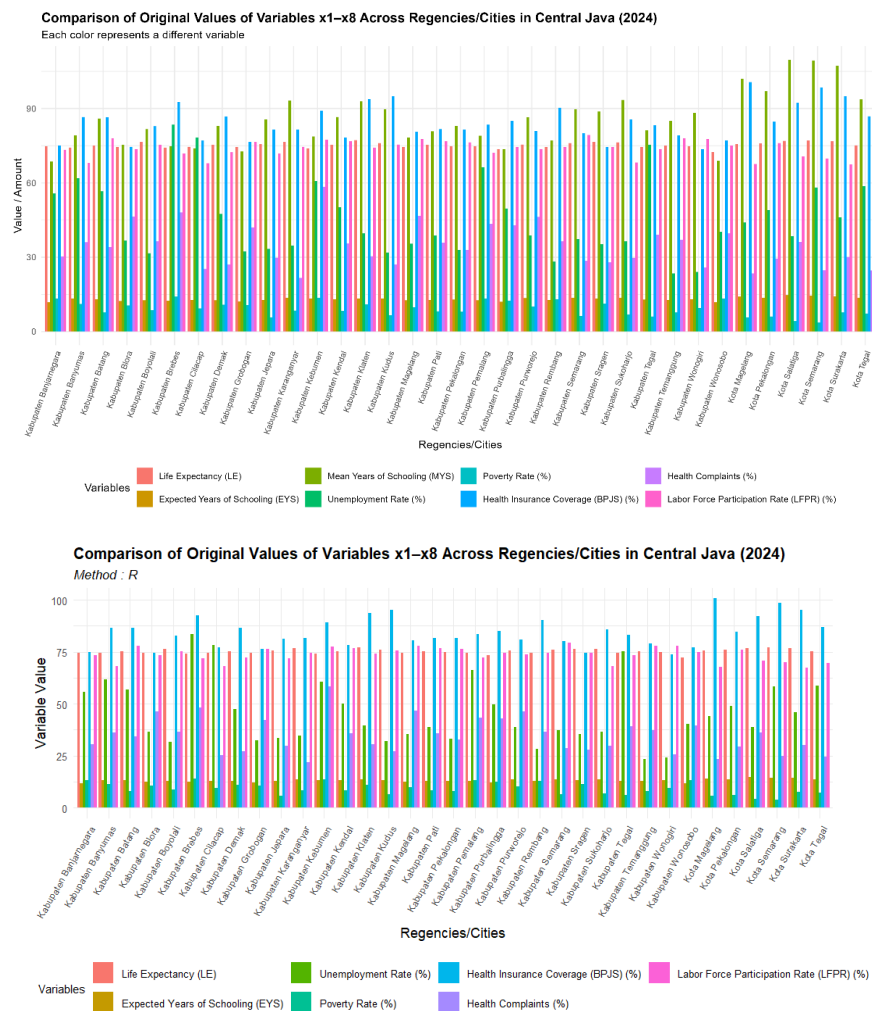


Figure 2. Comparison of Explanatory Variables ($X_1 \sim X_8$) across Districts/Municipalities in Central Java, 2024

correlation analysis is conducted to examine the direction and strength of relationships between HDI and each predictor. The results show that Expected Years of Schooling exhibits the strongest positive correlation with HDI ($r = 0.9334$), followed by Life Expectancy at Birth ($r = 0.8392$). In contrast, Poverty Rate and Health Complaints demonstrate relatively strong negative correlations with HDI ($r = -0.7775$ and $r = -0.5677$, respectively).

These correlation patterns carry important statistical and substantive implications. Statistically, they confirm that education and health variables are strongly associated with HDI and thus appropriate for inclusion in regression models. Substantively, the strong correlation between EYS and HDI underscores the central role of educational continuity in enhancing human development, consistent with findings by [20]. Conversely, the negative correlations associated with poverty and health complaints indicate that socioeconomic pressures and poor health conditions remain key obstacles to improving HDI [21]. Overall, education and health emerge as primary drivers, while poverty constitutes a structural constraint on human development.

3.3 Multiple Linear Regression Model

Multiple Linear Regression is employed to identify linear relationships between HDI and the explanatory variables after addressing multicollinearity. The estimation results are presented in **Table 2**. Overall, the model demonstrates strong explanatory power, with an R^2 of 0.9584 and an adjusted R^2 of 0.9476, indicating that approximately 95.8% of the variation in HDI across districts and municipalities in Central Java can be explained by the included variables. The results indicate that

Table 2. Estimation Results of the Multiple Linear Regression Model

Variable	Coefficient	Std. Error	t-value	p-value	Significance
Intercept	-10.6210	16.5010	-0.644	0.525	Not significant
X_1 – Life Expectancy at Birth (LEB)	0.6829	0.2351	2.904	0.007	Significant
X_2 – Expected Years of Schooling (EYS)	2.8596	0.4192	6.821	< 0.001	Highly significant
X_4 – Open Unemployment Rate	-0.0173	0.0120	-1.445	0.160	Not significant
X_5 – Poverty Rate	-0.2273	0.0807	-2.818	0.009	Significant
X_6 – BPJS Health Insurance Participation	0.0650	0.0282	2.303	0.029	Significant
X_7 – Health Complaints	-0.0485	0.0240	-2.025	0.053	Marginally significant
X_8 – Labor Force Participation Rate (LFPR)	-0.0490	0.0577	-0.849	0.403	Not significant
$R^2 = 0.9584$					
Adjusted $R^2 = 0.9476$					
Uji F: $p < 0.001$					

Expected Years of Schooling has a positive and statistically significant coefficient of 2.8596. This implies that a one-year increase in expected years of schooling is associated with an increase of approximately 2.86 points in HDI, holding other factors constant. The magnitude of this coefficient highlights education—particularly educational continuity—as the most dominant factor explaining regional HDI variation. This finding suggests that investments in educational access and sustainability have a direct and substantial impact on human development outcomes [22].

Life Expectancy at Birth also exhibits a positive and significant effect on HDI, with a coefficient of 0.6829. Improvements in life expectancy reflect better health conditions and overall quality of life, which in turn contribute to higher HDI values. Although its effect is smaller than that of education, health remains a crucial pillar of human development, consistent with the conceptual framework of HDI [23]. In contrast, Poverty Rate exerts a negative and significant influence on HDI, with a coefficient of -0.2273. This indicates that a one-percentage-point increase in poverty is associated with a 0.23-point reduction in HDI. This finding aligns with Yanti, Ilham, and Khasan [24], who argue that economic deprivation and limited purchasing power directly hinder improvements in human development by restricting access to education and healthcare services.

Health insurance participation (BPJS) shows a positive and significant effect on HDI, suggesting that broader coverage of health insurance contributes to higher human development outcomes. Access to health insurance enhances quality of life by mitigating health risks and supporting productivity [25]. Meanwhile, the Open Unemployment Rate, Health Complaints, and Labor Force Participation Rate do not exhibit statistically significant effects at the 5% significance level, although their coefficient signs align with theoretical expectations. As depicted in **Figure 3**, the HDI distribution exhibits slight asymmetry. However, formal evaluations using the Shapiro–Wilk ($p = 0.2026$) and Anderson–Darling ($p = 0.3496$) tests indicate no significant deviation from normality ($p > 0.05$). Thus, Multiple Linear Regression remains a statistically appropriate baseline model. Nevertheless, given the theoretical nature of HDI as a strictly positive continuous variable and its visual asymmetric tendency, the Gamma Generalized Linear Model (GLM) is retained as a robust comparative approach. Both models are subsequently compared using the Akaike Information Criterion (AIC).

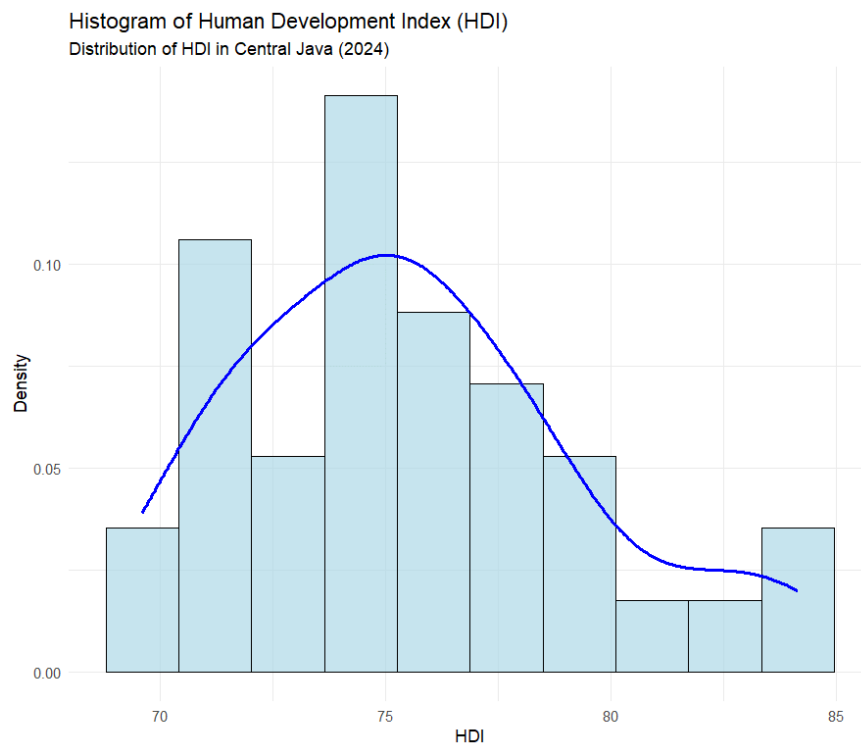


Figure 3. Histogram of Human Development Index (HDI) Distribution in Central Java, 2024

3.4 Gamma Generalized Linear Model (GLM)

To accommodate the positive and right-skewed nature of HDI, this study applies a Gamma Generalized Linear Model with a log link function. The estimation results are presented in Table 3. The model yields an Akaike Information Criterion (AIC) value of 93.82, which is lower than that of the linear regression model, indicating superior model fit. The Gamma GLM results confirm that Expected Years of Schooling remains the most influential and statistically significant determinant of HDI. The coefficient of 0.0376 indicates that an increase in expected years of schooling is associated with a proportional increase in mean HDI, after controlling for other variables. The persistence of EYS as the dominant predictor reinforces the central role of education in human development across both linear and distributionally appropriate modelling approaches [22].

Life Expectancy at Birth (LEB) shows a positive and statistically significant effect in the Gamma GLM, with a coefficient of 0.0092. Because the Gamma GLM utilizes a log-link function, this indicates that a one-year increase in life expectancy is associated with an approximate 0.92% increase in HDI, holding other variables constant. Although the magnitude is smaller than that of education, this finding confirms that improvements in public health contribute to higher HDI levels [21].

Health insurance participation (BPJS) also demonstrates a positive and significant effect, with a coefficient of 0.0008, implying that a one-percentage-point increase in BPJS coverage contributes to an approximate 0.08% increase in HDI. This suggests that expanded access to formal healthcare services plays a measurable, although relatively modest, role in enhancing human development.

Conversely, the Poverty Rate exhibits a negative and statistically significant effect, with a coefficient of -0.0029. This implies that a one-percentage-point increase in poverty is associated with an approximate 0.29% decrease in HDI. The negative impact of poverty underscores persistent economic constraints on human development in Central Java [26]. Similarly, Health Complaints show a negative and significant effect, with a coefficient of -0.0007, indicating that a one-percentage-point increase in reported health complaints leads to an approximate 0.07% decrease in HDI.

Notably, Health Complaints become statistically significant in the Gamma GLM, whereas they are only marginally significant in the linear model. This indicates that the Gamma approach is more sensitive in capturing health-related effects on HDI, particularly when accommodating the structural properties of the dependent variable. Overall, both models yield substantively consistent conclusions. Expected Years of Schooling and Life Expectancy at Birth exert positive effects, while Poverty Rate

Table 3. Estimation Results of the Gamma GLM

Variable	Coefficient	Std. Error	t-value	p-value	Significance
Intercept	3.1675	0.2075	15.268	< 0.001	Significant
X_1 – Life Expectancy at Birth (LEB)	0.0092	0.0030	3.104	0.004	Significant
X_2 – Expected Years of Schooling (EYS)	0.0376	0.0053	7.134	< 0.001	Highly significant
X_4 – Open Unemployment Rate	-0.0002	0.0002	-1.441	0.161	Not significant
X_5 – Poverty Rate	-0.0029	0.0010	-2.901	0.007	Significant
X_6 – BPJS Health Insurance Participation	0.0008	0.0004	2.284	0.030	Significant
X_7 – Health Complaints	-0.0007	0.0003	-2.232	0.034	Significant
X_8 – Labor Force Participation Rate (LFPR)	-0.0005	0.0007	-0.660	0.515	Not significant
AIC = 93.82					
Residual Deviance = 0.0031					

negatively affects HDI. Among all variables, Expected Years of Schooling exhibits the largest effect size, confirming education as the most dominant driver of HDI improvement.

Nevertheless, the key distinction between the two models lies in their statistical assumptions and goodness of fit. While multiple linear regression assumes normality and constant variance, the Gamma GLM is specifically designed for positive continuous data with asymmetric distributions. This difference is reflected in the lower AIC value of the Gamma GLM, indicating a better balance between model fit and complexity [27]. Moreover, the Gamma GLM demonstrates greater sensitivity in detecting the influence of health-related variables, such as health complaints, which are less evident in the linear framework [10, 28]. Therefore, although multiple linear regression remains informative as a baseline model, the Gamma GLM provides a more appropriate and methodologically robust framework for modeling HDI and informing evidence-based human development policies.

Nevertheless, the key distinction between the two models lies in their statistical assumptions and overall model performance. While Multiple Linear Regression assumes normality and constant variance, the Gamma GLM is specifically designed for positive continuous data with asymmetric distributions. To ensure a consistent comparison between modeling approaches, both models were evaluated using the Akaike Information Criterion (AIC). The Multiple Linear Regression model produced an AIC value of 102.46, whereas the Gamma GLM yielded a lower AIC value of 93.86, indicating a better balance between goodness of fit and model complexity [27].

Although the Multiple Linear Regression model demonstrated high explanatory power, with an R^2 of 0.9521 and an adjusted R^2 of 0.9397, these statistics primarily describe the proportion of variance explained rather than comparative model performance across different frameworks. Moreover, the Gamma GLM demonstrated greater sensitivity in detecting the influence of health-related variables, such as health complaints, which were less evident in the linear framework [10, 28]. Therefore, although Multiple Linear Regression remains informative as a baseline model, the Gamma GLM provides a more appropriate and methodologically robust framework for modeling HDI and informing evidence-based human development policies.

4. CONCLUSION

This study concludes that Expected Years of Schooling, Life Expectancy at Birth, and BPJS Health Insurance participation have a positive effect on the Human Development Index (HDI), while poverty and health complaints exert a negative influence. Education emerges as the most dominant determinant of HDI, followed by health and social protection dimensions. Model comparison indicates that the Gamma Generalized Linear Model with a log link provides a better fit than multiple linear regression, making it more appropriate for modeling HDI as a positive continuous variable. Nevertheless, this study is limited to cross-sectional aggregated data for a single year, which restricts its ability to capture temporal dynamics in human development. Future research is therefore encouraged to employ panel data and incorporate institutional or spatial variables to achieve a more comprehensive understanding of regional human development determinants.

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