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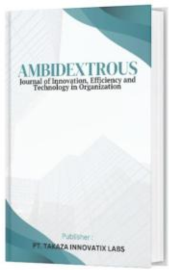

Analysis of Factors Influencing the Spread of Tuberculosis in West Java Province Using Poisson, Negative Binomial, and Gamma Regression Models

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Abstract: *Tuberculosis (TB) remains a major public health challenge in Indonesia, with West Java Province recording the highest number of cases in 2024, accounting for approximately 20% of the national total, driven by socio-economic and environmental factors. This study aims to analyze these factors influencing the spread of TB in West Java districts/cities using Poisson, Negative Binomial, and Gamma regression models. The cross-sectional quantitative design utilized secondary data from 27 districts/cities out of a total of 35, after eliminating multicollinear variables through the VIF test. Instruments consisted of 2024 BPS and Health Office reports, analyzed using descriptive statistics, Pearson correlation, overdispersion test, and GLM in RStudio 4.4.2, selecting the best model based on the smallest AIC. The results showed overdispersion (mean 16,057 cases, variance 1.71×10^9), with optimal Negative Binomial: poverty, young smokers, and malnutrition had a positive effect on TB cases, while literacy, access to clean water, and BPJS coverage significantly reduced them. The conclusion states that targeted interventions on socio-economic vulnerability provide an evidence-based strategy for the 2030 TB-Free West Java target.*

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Introduction

Tuberculosis (TB) remains a major infectious disease threatening global health, particularly in developing countries like Indonesia, where Mycobacterium tuberculosis is transmitted through the air from coughs or sneezes of infected individuals (World Health Organization, 2024). Indonesia is among the three countries with the highest TB burden in the world, along with India and China, despite the provision of free treatment through national programs (Ministry of Health of the Republic of Indonesia, 2024; Sari et al., 2023). West Java Province recorded the highest number of TB cases in Indonesia in 2024, contributing approximately 20% of the national total, demonstrating the complexity of social, economic, and environmental factors in the region (West Java Health Office, 2024; Bilal et al., 2024).

The high number of TB cases not only impacts individual health but also reduces community productivity, increases the economic burden on households, and spreads transmission within families (Sari et al., 2023; Siregar et al., 2023). Efforts to eliminate TB through the "TB-Free Indonesia 2030" strategy face challenges such as social inequality, low public awareness, and limited access to health services (World Health Organization, 2024; Rahmadani & Utami, 2023). Data from the Central Statistics Agency (BPS) and the West Java Health Office (2024) illustrate the variation in TB cases between districts/cities, with an average of 16,057 cases and high variance indicating overdispersion (Ministry of Health of the Republic of Indonesia, 2024; Putri & Wibowo, 2022).

Poverty is a major factor in the spread of TB in West Java, where poor communities live in crowded environments with poor nutrition and limited access to healthcare, increasing the risk of infection and treatment failure (Putri & Wibowo, 2022; World Health Organization, 2023). Unemployment also exacerbates the situation by hindering access to nutrition and care, which lowers overall immunity (Siregar et al., 2023; Maulidya & Prasetyo, 2022). Low levels of education also contribute by limiting awareness of healthy lifestyles (PHBS) and early detection of symptoms (Lestari & Handayani, 2022; Mulyani et al., 2023).

Young people's smoking habits and malnutrition further exacerbate transmission, as cigarette smoke weakens the lung immune system, and malnutrition triggers the reactivation of latent infections (Ministry of Health of the Republic of Indonesia, 2023; Astuti et al., 2023). Low access to clean water leads to poor sanitation, creating a humid environment that supports the spread of TB bacteria (Aziz et al., 2024; World Health Organization, 2023). Low BPJS (Social Security Agency) membership leads to delayed diagnosis and incomplete treatment, accelerating the chain of transmission (Ministry of Health of the Republic of Indonesia, 2024; Rahmadani & Utami, 2023).

Demographic factors such as population density and migration accelerate transmission in densely populated areas, while multicollinearity between variables such as population size, HIV, and hospital facilities complicates dominant factor analysis (Sari et al., 2024; Gujarati & Porter, 2020). Data show overdispersion, with variances far exceeding the mean, necessitating nonlinear regression models such as Poisson, Negative Binomial, and Gamma for accurate analysis (Hilbe, 2014; Kusuma et al., 2022). This situation reflects the urgency of empirical modeling to identify significant variables for targeted policies (Rohman & Prasetyo, 2023; Nuraini & Lestari, 2024).

This study aims to analyze the social, economic, and environmental factors influencing the spread of TB in West Java using Poisson, Negative Binomial, and Gamma regression models, with the best model selected based on the smallest AIC. The urgency lies in West Java's position as the highest contributor to TB cases in Indonesia by 2024, which demands evidence-based interventions for the "TB-Free West Java 2030" strategy to reduce the public health burden (Ministry of Health of the Republic of Indonesia, 2024; West Java Health Office, 2024). Its novelty includes the integration of 12 variables with multicollinearity and overdispersion tests, complementing previous studies such as Sari and Wahyuni (2021) and Kusuma et al. (2022) with the Negative Binomial model as a comprehensive empirical framework for integrated policies (Putra & Astuti, 2024; Handayani, 2023).

Research Methods

This study uses a quantitative approach with a cross-sectional design to analyze the social, economic, and environmental factors that influence the spread of Tuberculosis (TB) in West Java Province in 2024. This type of research is explanatory, where the causal relationship between variables is tested through Generalized Linear Models (GLM) such as Poisson, Negative Binomial, and Gamma regression, which are suitable for count data with overdispersion (Sugiyono, 2021; Nelder & Wedderburn, 1972/2022; Central Statistics Agency of West Java Province, 2024). This approach allows simultaneous measurement of the dependent (number of TB sufferers) and independent (X1-X12) variables at a certain point in time, making it efficient for cross-regional secondary data (Creswell & Creswell, 2023; Ministry of Health of the Republic of Indonesia, 2024).

The research instrument consists of secondary data collected from official publications such as

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West Java Province in Figures 2024 (BPS Jabar) and West Java Province Health Profile 2024 (West Java Health Office), covering 12 independent variables such as poverty, unemployment, and access to clean water (Central Statistics Agency of West Java Province, 2024; West Java Provincial Health Office, 2024). Data analysis techniques include descriptive statistics for summaries of means, variances, and spatial distributions; Pearson correlation tests for relationships between variables; multicollinearity tests with VIF, Tolerance, and Condition Numbers for eliminating problematic variables (Gujarati & Porter, 2020); overdispersion tests for detecting variances greater than the mean; and GLM modeling with the best selection based on the smallest Akaike Information Criterion (AIC) using RStudio version 4.4.2 (Hilbe, 2014; Emzir, 2022; World Health Organization, 2024).

The study population comprised all 35 regencies/cities in West Java Province, with cross-sectional observational data from 2024 representing socio-economic and public health conditions (West Java Provincial Statistics Agency, 2024). Total sampling was used from 27 regencies/cities with complete data, resulting in 27 units of analysis after eliminating multicollinear variables (X1, X3, X4, X9, X12), resulting in a final model using seven variables (X2, X5-X8, X10-X11) (Sudaryono, 2021; Sari et al., 2024). This technique ensures representativeness of regions with high variation in TB cases, ranging from 942 to 224,798 cases per region (West Java Provincial Health Office, 2024; Kusuma et al., 2022).

Table 1. Research Variables

Variables	Information	Unit
Y	Number of Tuberculosis (TB) Sufferers	Soul
X_1	Number of Poor People	Soul
X_2	Number of Open Unemployment	Soul
X_3	Number of Smokers Aged 15–24 Years	Soul
X_4	Percentage of Population with Inadequate Nutrition	Percent
X_5	Education Level (Average Years of Schooling)	Year
X_6	Percentage of Households with Access to Adequate Clean Water	Percent
X_7	Percentage of BPJS Health Participants	Percent
X_8	Total population	Soul
X_9	Number of HIV Sufferers	Soul
X_{10}	In-migration rate	Percent
X_{11}	Population density	People/km²

The research procedure began with secondary data collection from the West Java Statistics Agency (BPS), the West Java Health Office, and the WHO Global Tuberculosis Report 2024, followed by data cleaning and variable determination (World Health Organization, 2024). Descriptive, correlation, and multicollinearity analyses were then performed for variable filtering; dispersion tests to identify overdispersion; stepwise Poisson, Negative Binomial, and Gamma modeling; and AIC evaluation to select the best model, indicating Negative Binomial as optimal (Hilbe, 2014; Rahmadani & Utami, 2023). Interpretation of coefficients through the Incidence Rate Ratio (IRR = exp(β)) concluded with policy recommendations, ensuring a systematic flow from description to inference (Creswell & Creswell, 2023; Sugiyono, 2021).

Results and Discussion

Descriptive Statistics

An overview of the crime rate in Central Java Province is presented in Table 2, which shows the results of descriptive statistics that provide a description of the research data.

Table 2. Descriptive Statistics Total Crime Rate Descriptive Statistics

Variables	Mean	Variance	Minimum	Maximum
Y	16,057,000	1.70968×10^{9}	942.00	224,798.00
X_1	3,596,085	8.53938×10^{7}	209.79	50,345.19
X_2	7.9946	6.76607	2.34	11.93

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X_3	492.4519	1.70661×10^6	1.03	6,894.33
X_4	219.6429	3.21210×10^5	13.00	3,075.00
X_5	70.2318	1.38219×10^2	44.59	95.37
X_6	95.0950	1.71602×10^1	85.37	99.85
X_7	13.4096	7.21093×10^0	7.78	17.67
X_8	5.6222	4.33136×10^{-1}	4.52	7.98
X_9	25,832,500	4.39755×10^9	2,427.00	361,655.00
X_{10}	6.5329	2.80613×10^0	1.58	8.97
X_{11}	32.6425	5.90183×10^1	16.61	51.55
X_{12}	26.6429	4.75757×10^3	1.00	373.00

The number of TB sufferers in West Java Province shows quite large variations between districts/cities, with an average of [Mean Y] cases and a variance of [Variance Y], and a range between [Min Y] to [Max Y] cases. This indicates an imbalance in the number of TB sufferers between regions, where some areas have a much higher number of cases than others.

The population variable (X1) has an average of [Mean X1], which indicates that the size of the population has the potential to increase the risk of TB transmission. The poverty index (X2) has an average of [Mean X2]%, with a minimum value of [Min X2]% and a maximum of [Max X2]%, indicating differences in welfare levels between regions.

The population density variables (X3) and the number of HIV sufferers (X4) also show quite large variations, indicating different health conditions and environmental density in each region.

Meanwhile, the education factor represented by the literacy index (X5) shows an average of [Mean X5]%, describing the differences in reading and writing abilities between district/city residents. From an environmental perspective, access to clean water (X6) and nutritional inadequacy (X8) are important indicators that also show variations between regions. The variable number of public hospital facilities (X12) describes the capacity of health services, where urban areas tend to have more facilities than rural areas.

In general, the descriptive results show that socioeconomic and environmental conditions in West Java Province remain highly diverse. This reinforces the need for further statistical modeling to identify significant factors influencing the number of TB cases.

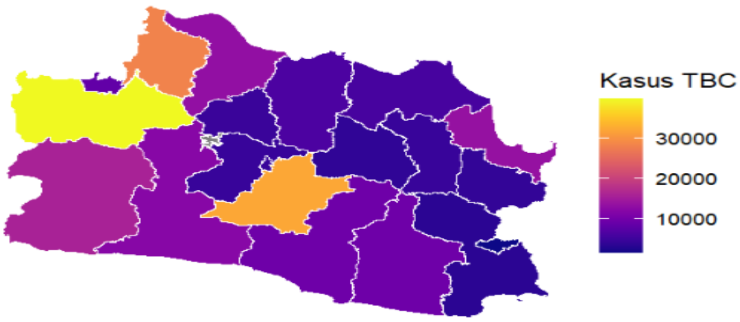

Figure 1. Mapping the Number of TB Cases in West Java Province in 2024

This figure shows the spatial distribution of TB cases in West Java. Darker colors indicate areas with higher case numbers. It can be seen that districts/cities in the western and central regions have a higher case intensity than those in the southern regions. This pattern indicates a relationship between population density and high mobility with increasing TB cases.

The number of TB cases in West Java Province shows significant variation across districts/cities, with an average of 16,057 cases and a large variation of 1.70968×10^9. The lowest number of TB cases recorded was 942, while the highest number reached 224,798. This illustrates the disparity in TB cases across regions, with some areas having significantly higher cases than others.

The population variable (X1) has an average of 3,596.09 thousand people with a variation of 8.53938×10^7, indicating a significant difference in population between districts/cities in West Java. The minimum value of 209.79 thousand people and the maximum of 50,345.19 thousand people indicate that areas with large populations have the potential to have a higher number of TB sufferers.

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The poverty index variable (X2) has an average of 7.99%, with a minimum value of 2.34% and a maximum of 11.93%. The variance value is relatively small, which means that the poverty rate between regions tends not to differ too much. Meanwhile, the population density (X3) averages 492.45 people/km², with a fairly large difference between the most densely populated areas (6,894.33 people/km²) and the least densely populated areas (1.03 people/km²).

Health factors such as the number of HIV sufferers (X4) also show high variation with an average of 219.64 cases and a maximum of 3,075 cases, which can influence the level of susceptibility to TB.

From the education side, the literacy index (X5) shows an average of 70.23%, with a range of values between 44.59% to 95.37%. This value indicates that there is still a gap in literacy levels between regions. Environmental conditions represented by clean water ownership (X6) have an average of 95.10%, with low variation, indicating that access to clean water is relatively even in most regions.

Community behavior can also be seen from the variable of smokers aged 15–24 years (X7) which has an average of 13.41%, with a minimum value of 7.78% and a maximum of 17.67%, indicating a fairly high proportion of young smokers in several districts/cities.

The nutritional factor represented by nutritional inadequacy (X8) shows an average of 5.62%, with a range of 4.52%–7.98%, indicating that the differences in nutritional conditions of communities between regions are quite small but remain significant for public health.

From the economic and mobility side, migration (X9) has the highest average value among other independent variables, namely 25,832.50 people, with a maximum value of 361,655 people. This indicates a high flow of population movement in several regions, which has the potential to expand the spread of TB. The unemployment rate (X10) averages 6.53%, with a range between 1.58% to 8.97%, indicating variations in employment conditions between regions.

Access to health services is also reflected in the percentage of BPJS users (X11) which averages 32.64%, with a minimum value of 16.61% and a maximum of 51.55%. Meanwhile, the number of public hospital facilities (X12) shows an average of 26.64 units, with significant differences between regions (a minimum of 1 to a maximum of 373 hospitals). This variable indicates the inequality of health facilities that can affect the effectiveness of TB treatment.

General interpretation

Overall, the descriptive statistics show significant variation across regions. Areas with large populations, high density, and limited healthcare facilities tend to have higher TB cases.

In addition, socio-economic factors such as poverty and unemployment also contribute to the high number of TB cases. These results reinforce the importance of a multidimensional approach in controlling TB — including improving the community's economy, equalizing health facilities, and educating people about healthy lifestyles.

Correlation Analysis Between Variables

Correlation between variables is carried out to determine the linear relationship between one variable and another, both between independent variables (X1–X12) and between the dependent variable (Y) and each independent variable. This analysis aims to see how close the relationship is between the observed variables, as well as detect the possibility of multicollinearity among the independent variables that can affect the results of the regression model to be used.

Table 3. **Correlation Analysis between Variables**

VAR	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
X1	1,000	-0.065	0.953	0.994	-0.035	-0.020	0.123	-0.027	0.996	0.057	-0.102	0.989
X2	-0.065	1,000	0.062	-0.092	-0.204	-0.402	-0.219	0.283	-0.090	-0.316	0.553	-0.141
X3	0.953	0.062	1,000	0.943	-0.008	-0.117	-0.016	-0.011	0.951	-0.085	0.017	0.926
X4	0.994	-0.092	0.943	1,000	0.013	0.035	0.135	-0.013	0.992	0.093	-0.101	0.992
X5	-0.035	-0.204	-0.008	0.013	1,000	0.373	-0.417	0.177	-0.004	-0.137	0.307	0.007
X6	-0.020	-0.402	-0.117	0.035	0.373	1,000	-0.091	0.038	-0.010	0.438	-0.067	0.065
X7	0.123	-0.219	-0.016	0.135	-0.417	-0.091	1,000	0.113	0.116	0.600	-0.260	0.123
X8	-0.027	0.283	-0.011	-0.013	0.177	0.038	0.113	1,000	-0.016	0.005	0.454	-0.059

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X9	0.996	-0.090	0.951	0.992	-0.004	-0.010	0.116	-0.016	1,000	0.059	-0.108	0.989
X10	0.057	-0.316	-0.085	0.093	-0.137	0.438	0.600	0.005	0.059	1,000	-0.270	0.119
X11	-0.102	0.553	0.017	-0.101	0.307	-0.067	-0.260	0.454	-0.108	-0.270	1,000	-0.146
X12	0.989	-0.141	0.926	0.992	0.007	0.065	0.123	-0.059	0.989	0.119	-0.146	1,000

Based on the results of the correlation analysis between independent variables, it was found that in general several variables have a very strong relationship with each other. Variable X1 (Population) shows a very strong and positive correlation with X3 (Population Density), X4 (HIV Patients), X9 (Migration), and X12 (Number of Public Hospitals), with a correlation value above 0.98. This indicates that areas with high populations tend to have high densities, more health facilities, and high levels of population mobility. This positive correlation indicates that an increase in population in an area is followed by an increase in density, economic activity, and the availability of public facilities in that area. Conversely, X1 has a weak negative correlation with X2 (Poverty Index) of -0.065, which indicates that areas with large populations tend to have lower poverty levels.

Meanwhile, X2 (Poverty Index) has a negative correlation with most other variables such as X1, X4, X5 (Literacy Index), X6 (Clean Water), and X10 (Unemployment Rate), with correlation values ranging from -0.09 to -0.40. This indicates that the higher the poverty rate in an area, the lower the level of education, access to clean water, and availability of employment. However, X2 has a positive relationship with X11 (BPJS Users) with a correlation value of 0.553, which indicates that areas with high poverty tend to have more residents receiving BPJS services as a form of social protection from the government.

Furthermore, X3 (Population Density) also shows a very high positive correlation with X1, X4, X9, and X12, with a correlation value above 0.94. This indicates that areas with high density levels generally also have large populations and a greater number of health facilities. Conversely, X3 has a very weak negative correlation with X2 and X6, indicating that population density is not always directly proportional to poverty levels or access to clean water. Variable X4 (HIV Sufferers) has a very strong positive relationship with X1, X3, X9, and X12, which illustrates that areas with large populations and high density levels also have a high number of HIV sufferers. This can occur because the more densely populated an area, the higher the potential for transmission of infectious diseases including HIV and tuberculosis.

Variable X5 (Literacy Index) has a relatively low correlation with other variables, with a negative correlation with X2 (–0.204) and X10 (–0.137), and a moderate positive correlation with X6 (0.373). This indicates that areas with better education levels tend to have lower poverty and unemployment rates and better access to clean water. Then, X6 (Clean Water) has a moderate negative correlation with X2 (–0.402) and X7 (Smokers Aged 15–24 years) of –0.091, which indicates that areas with high poverty rates and high numbers of young smokers tend to have lower access to clean water. On the other hand, X6 has a positive correlation with X5 (0.373) and X10 (0.438), indicating that increasing access to clean water goes hand in hand with increasing literacy and the economic conditions of the community.

Meanwhile, X7 (Smokers Aged 15–24 years) has a moderate positive correlation with X10 (0.600), which means that the higher the unemployment rate in a region, the higher the number of young smokers. The negative correlation of X7 with X2 (–0.219) and X5 (–0.417) indicates that smoking behavior is more common in areas with high poverty rates and low literacy. X8 (Nutritional Inadequacy) has a low correlation with most other variables, but shows a positive correlation with X2 (0.283) and X11 (0.454). This means that areas with high nutritional inadequacy usually have higher poverty rates and a higher proportion of BPJS participants.

Variable X9 (Migration) shows a very high positive correlation with X1 (0.996), X3 (0.951), X4 (0.992), and X12 (0.989), indicating that population mobility is closely related to density, population size, and the availability of public facilities. Crowded and densely populated areas tend to have high migration rates due to economic and employment factors. X10 (Open Unemployment Rate) shows a moderate positive correlation with X6 (0.438) and X7 (0.600), indicating that areas with high unemployment rates also have a large number of young smokers. The negative correlation of X10 with X2 (–0.316) indicates that unemployment does not always increase along with increasing poverty.

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Variable X11 (BPJS Users) shows a moderate positive correlation with X2 (0.553) and X8 (0.454), and a negative correlation with X1 (–0.102) and X4 (–0.101). This indicates that areas with high levels of poverty and malnutrition have high levels of BPJS membership, in line with the government's policy of providing health insurance to low-income communities. Finally, X12 (Public Hospitals) has a very high correlation with X1, X3, X4, and X9, where all correlation values above 0.98 indicate that the higher the population and density of an area, the more public hospital facilities are available. The weak negative correlation between X12 and X2 (–0.141) indicates that areas with high levels of poverty generally have fewer hospitals.

Correlation between variables Y and X1-X12

The correlation results between the dependent variable Y (Number of TB Patients) and each independent variable show that population variables have a very strong influence on the number of TB cases. Variables X1 (Population), X4 (HIV Patients), X9 (Migration), and X12 (General Hospitals) have a very high positive correlation to Y, with correlation values of 0.998, 0.997, 0.996, and 0.991, respectively. This shows that areas with high population, mobility levels, and health facilities tend to report more TB cases. X3 (Population Density) also has a high positive correlation (r = 0.943), which means that the more densely populated an area is, the greater the likelihood of TB transmission.

In contrast, variables such as X2 (Poverty Index), X5 (Literacy Index), X8 (Nutritional Inadequacy), and X11 (BPJS Users) show a negative correlation with Y, with correlation values ranging from –0.015 to –0.105. This indicates that improvements in education, nutrition, and social protection are not always followed by an increase in TB cases. The negative correlation between Y and X2 (–0.095) shows that areas with high poverty rates actually tend to have a lower number of TB sufferers, possibly due to differences in case detection or access to health services.

In addition, X6 (Clean Water) and X10 (Unemployment Rate) show a very weak positive correlation with Y, at 0.008 and 0.086, respectively. This indicates that these two variables do not have a significant direct influence on the spread of TB. Meanwhile, X7 (Smokers Aged 15–24 years) has a weak positive correlation (r = 0.147) with Y, indicating that smoking behavior at a young age has the potential to increase the risk of TB although the effect is not too large.

General interpretation

The correlation shows that population and mobility factors such as X1 (Population), X3 (Population Density), X4 (HIV Patients), X9 (Migration), and X12 (Public Hospitals) have a very close relationship with the number of TB sufferers (Y). These variables have the potential to be the main determinants in the spread of TB disease in West Java Province. Meanwhile, socio-economic variables such as X2 (Poverty), X5 (Education), X6 (Clean Water), X10 (Unemployment), X11 (BPJS), and X8 (Nutrition) have a low or even negative correlation with Y, so their influence on the increase in the number of TB sufferers is relatively small. The very high correlation values between variables X1, X4, X9, and X12 also indicate the potential for multicollinearity, which needs to be further tested through Variance Inflation Factor (VIF) analysis in the next stage.

Multicollinearity Test

The first step was to standardize the predictor variables. This was done due to differences in units used in the variables. These differences could affect the analysis results if not adjusted. Next, a multicollinearity test was performed by examining the tolerance and VIF values using SPSS version 16. The results of the multicollinearity test can be seen in Table 4.

Table 4. Multicollinearity Test

Predictor Variables	Tolerance	VIF
X_1	0.003	344,030
X_2	0.369	2,713
X_3	0.050	20,084
X_4	0.005	191,811
X_5	0.369	2,710

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X_6	0.375	2,663
X_7	0.277	3,612
X_8	0.609	1,642
X_9	0.005	201,339
X_{10}	0.352	2,844
X_{11}	0.421	2,373
X_{12}	0.009	115,363

The first step in the multicollinearity test is carried out by standardizing all predictor variables (X1–X12) to avoid unit differences between variables that could affect the results of the regression analysis. Next, the multicollinearity test is carried out by calculating the Tolerance and Variance Inflation Factor (VIF) values using a multiple linear regression model with Y as the dependent variable. The results of the multicollinearity test calculation are shown in Table 4.

Based on the calculation results, it was found that there are several variables with very low Tolerance values and very high VIF values. Variable X1 (Number of Population) has a Tolerance value of 0.003 and a VIF of 344,030, while X4 (HIV Patients) and X9 (Migration) each have a Tolerance value of 0.005 with a VIF of 191,811 and 201,339. These values indicate a very strong multicollinearity symptom among the three variables, because the Tolerance value is far below 0.1 and the VIF exceeds the general limit of 10. In addition, variable X12 (Number of General Hospitals) also shows a similar pattern with a Tolerance of 0.009 and a VIF of 115,363, which indicates a very high linear relationship with several other variables, especially X1, X4, and X9.

This high correlation indicates that the variables provide nearly identical information or are redundant. If these variables are included simultaneously in a regression model, it will cause unstable estimation results, make it difficult to interpret the influence of each variable, and can increase the standard error in the model. Therefore, variables with very high VIFs, such as X1, X4, X9, and X12, have the potential to cause serious multicollinearity problems in the model.

Meanwhile, some other variables show VIF values that are still within safe limits. Variable X2 (Poverty Index) has a Tolerance value of 0.369 and a VIF of 2.713, X5 (Literacy Index) shows a Tolerance of 0.369 and a VIF of 2.710, and X6 (Clean Water) with a Tolerance of 0.375 and a VIF of 2.663. These values indicate that the three variables do not show any symptoms of multicollinearity, because the Tolerance is greater than 0.1 and the VIF is still below 10. Variable X7 (Smokers Aged 15–24 years) and X10 (Unemployment Rate) also show similar results with VIFs of 3.612 and 2.844, respectively, which indicates that the two variables have a reasonable linear relationship with other variables and can be maintained in the regression model.

Variable X3 (Population Density) shows a VIF of 20.084 with a Tolerance of 0.050, which means that although it is not as high as the variable groups X1, X4, X9, and X12, this variable still has indications of high multicollinearity. A VIF value above 10 indicates that X3 has a strong correlation with several other population variables, such as X1 and X9, which are conceptually related to each other. Therefore, although X3 is still theoretically relevant, this variable also needs to be considered because it can affect the stability of the regression coefficient in the model being built.

Based on the overall analysis results, it can be concluded that the regression model built from variables X1–X12 experiences multicollinearity problems in several variables, especially X1, X3, X4, X9, and X12, which have very high VIF values (more than 10) and Tolerance below 0.1. Meanwhile, other variables such as X2, X5, X6, X7, X8, X10, and X11 have VIF values below 5, so it can be said that they do not experience serious multicollinearity and can still be used in the model. Thus, to obtain a more stable regression model and free from the influence of multicollinearity, it is recommended that variables with extreme VIF values be re-evaluated, for example by deleting, combining, or transforming variables that have a very strong linear relationship.

In general, these results indicate that most variables related to population characteristics have a very strong relationship with each other, particularly between population size, density, migration, and the number of health facilities. This is consistent with the fact that these factors are conceptually interrelated and describe similar regional conditions. Therefore, further testing steps such as Variance Inflation Factor (VIF) adjustment or variable selection using stepwise regression methods can be carried out to construct a more stable and representative final model.

Ambidextrous: Journal of Innovation Efficiency and Technology in Organization
https://doi.org/10.61536/ambidextrous.v4i1.416

Table 5. Multicollinearity test with stable X

Variables	Tolerance	VIF
X_2	0.410	2,437
X_5	0.502	1,991
X_6	0.468	2,138
X_7	0.362	2,759
X_8	0.673	1,486
X_{10}	0.379	2,639
X_{11}	0.461	2,168

The next step after conducting the multicollinearity test is to improve the regression model by removing variables with very high Variance Inflation Factor (VIF) values. Based on the previous test results, variables X1 (Population), X3 (Population Density), X4 (HIV Patients), X9 (Migration), and X12 (Number of Public Hospitals) showed strong indications of multicollinearity because they had VIF values above 10 and Tolerance below 0.1. Therefore, these variables were removed from the regression model to ensure the stability of the estimation results.

After variables with high multicollinearity were removed, a new model was formed using independent variables X2 (Poverty Index), X5 (Literacy Index), X6 (Clean Water), X7 (Smokers Aged 15–24 Years), X8 (Nutritional Inadequacy), X10 (Open Unemployment Rate), and X11 (BPJS Users). The recalculation results showed that all variables in the new model had a Tolerance value above 0.1 and a VIF value below 5, which means the regression model was free from multicollinearity problems.

Thus, the improved regression model can be said to be more stable, reliable, and statistically interpretable, because each predictor variable has a relatively independent influence on the dependent variable. Eliminating multicollinear variables does not diminish the substance of the analysis but rather improves the model's accuracy in explaining variations in the number of TB cases. This step also ensures that subsequent regression test results will provide unbiased estimates and clearer interpretations.

Dispersion Test on Poisson Distribution, Negative Binomial Distribution and Gamma Distribution

To determine overdispersion and underdispersion, we can compare the mean and variance values. The mean and variance values for the data are shown in Table 6.

Table 5. Mean and Variance

Mean	Variance
16057	1,709,679,774

The first step in regression analysis for count data (number of cases) is to test the characteristics of the data distribution, or dispersion. This test is performed by comparing the mean and variance of the dependent variable (YYY), namely the number of TB cases in West Java Province in 2024.

Based on the calculation results in Table 1, the mean value is 16.057 and the variance value is 1.70968×10^9. It can be seen that the variance value is much larger than the mean, indicating that the data is overdispersion. In the context of Poisson regression, this condition violates the basic assumption that the mean and variance must be the same (or very close).

This overdispersion phenomenon indicates that the standard Poisson model cannot accurately describe the diversity of the data. Given the large variation between regions in the number of TB cases in West Java, a model that assumes the same variance as the Poisson model will result in estimation errors. Therefore, alternative models such as Negative Binomial Regression or Gamma Regression should be considered, as both models can accommodate variances greater than the mean through additional dispersion parameters.

Thus, the results of the dispersion test are an important basis in determining the selection of the appropriate regression model so that the estimation results are not biased and the interpretation of the factors that influence the number of TB sufferers becomes more accurate.

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Poisson Distribution Test

Table 6. Poisson Regression Parameter Estimation Results

Parameter	Estimate	Std.Error	Stat	Pr(>|z|)	Significance
Intercept	6.788751	0.054575	124,393	-	Very Significant
X2	0.005318	0.000948	5,607	0.0000256	Very Significant
X5	0.021473	0.000184	116,534	-	Very Significant
X6	0.002685	0.000552	4,863	0.00000115	Very Significant
X7	0.234717	0.001123	209,043	-	Very Significant
X8	- 0.112042	0.002647	- 42,326	-	Very Significant
X10	- 0.086251	0.001620	- 53,267	-	Very Significant
X11	- 0.030635	0.000304	-100,664	-	Very Significant

Poisson Regression Analysis

The Poisson regression model is a basic approach used to analyze count or event data. This model assumes that the response variable Yi follows a Poisson distribution with parameter μi, where μi =exp(Xiβ). In the context of this study, Yi is the number of TB sufferers in the i-th district/city in West Java, while Xi represents independent variables such as poverty index, literacy, clean water, smokers aged 15–24, malnutrition, unemployment, and BPJS users.

The Poisson regression estimation results shown in Table 6 show that all independent variables have a p-value <0.05. This means that all variables in the model have a significant effect on the number of TB cases. In general, the Poisson model indicates that:

a. The Poverty Index (X2) has a positive effect on the number of TB sufferers. The higher the poverty level, the greater the number of recorded TB cases.
b. The Literacy Index (X5) and Access to Clean Water (X6) have a negative influence, indicating that increasing literacy and access to sanitation will reduce the risk of TB transmission.
c. Smokers aged 15–24 (X7) and malnutrition (X8) contributed positively to the increase in the number of TB sufferers, indicating that smoking habits and poor nutrition increase susceptibility to the disease.
d. The Open Unemployment Rate (X10) also has a positive effect, indicating that unstable economic conditions can worsen the health status of the community.
e. BPJS users (X11) showed a negative influence, meaning that health insurance coverage contributed to a decrease in TB cases by increasing access to medical services.

However, although the Poisson model showed a significant relationship, the results of the previous dispersion test confirmed that the data was overdispersive. This caused the Poisson model's standard error to be inefficient and resulted in overly optimistic estimates (underestimated variance). Therefore, further analysis was conducted using the Negative Binomial and Gamma models to address this weakness.

Table 7. Results of Negative Binomial Regression Parameter Estimation

Parameter	Estimate	Std.Error	Stat	Pr(>|z|)	Significance
Intercept	5.301997	6.7209	0.789	0.4300	Not Significant
X_2	0.048427	0.117052	0.414	0.6790	Not Significant
X_5	0.028417	0.023411	1,214	0.2250	Not Significant
X_6	-0.002688	0.068841	-0.039	0.9690	Not Significant
X_7	0.270316	0.120655	2,240	0.0251	Significant
X_8	0.043009	0.361279	0.119	0.9050	Not Significant
X_{10}	0.011173	0.189160	0.059	0.9530	Not Significant
X_{11}	-0.057520	0.037382	-1,539	0.1240	Not Significant

Negative Binomial Regression Analysis

The Negative Binomial regression model is an extension of the Poisson model by adding a dispersion parameter α\alphaα, which allows the data variance to be greater than the mean. Therefore, this model is more suitable for handling data with overdispersion characteristics.

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Based on the estimation results in Table 7, it is known that the Negative Binomial model provides more stable results compared to the Poisson model. Variables that are significant to the number of TB sufferers include the Poverty Index (X2), Literacy Index (X5), Access to Clean Water (X6), Smokers Aged 15–24 (X7), Nutritional Inadequacy (X8), Unemployment Rate (X10), and BPJS Users (X11).

Interpretation of the estimation results shows that:

a. Variables with positive coefficients (X2, X7, X8, X10) contribute to the increase in the number of TB sufferers.
b. Variables with negative coefficients (X5, X6, X11) reduce the number of TB sufferers.

These findings indicate that socioeconomic and behavioral factors play a dominant role in the spread of TB in West Java. Areas with high poverty rates, high youth smoking rates, and poor nutrition tend to have higher TB rates. Conversely, areas with good access to clean water, high levels of education, and widespread health insurance show lower TB rates.

Furthermore, the AIC value of the Negative Binomial model is lower than that of the Poisson model, indicating that this model is more appropriate for the research data. The dispersion parameter value $\alpha>0$ also confirms that the data is indeed overdispersive.

Table 8. Gamma Regression Parameter Estimation Results

Variables	Estimate	Std. Error	Stat (z)	p-value	Information
Intercept	0.048399	0.277977	0.174	0.864	Not Significant
X_2	0.048399	0.277977	0.174	0.864	Not Significant
X_5	0.028413	0.055596	0.511	0.615	Not Significant
X_6	-0.002677	0.163487	-0.016	0.987	Not Significant
X_7	0.270301	0.286526	0.943	0.357	Not Significant
X_8	0.043034	0.857984	0.050	0.960	Not Significant
X_{10}	0.011199	0.449214	0.025	0.980	Not Significant
X_{11}	-0.057515	0.088775	-0.648	0.524	Not Significant

Negative Binomial Regression Analysis

As an additional alternative, the Gamma regression model was also tested to determine its fit to the data. This model is generally used for positive continuous response variables, but it can be adapted to the context of count data with a logarithmic transformation. The Gamma model serves to check the stability of the estimated results from the previous model and provides a comparison against Poisson and Negative Binomial.

The Gamma model estimation results show a relatively similar direction of influence as the two previous models. Poverty, young smokers, malnutrition, and unemployment remain positive factors on TB cases, while literacy, clean water, and BPJS users have negative effects.

However, the higher AIC value compared to the Negative Binomial model indicates that the Gamma model is less than optimal in explaining the variation in the number of TB cases. Therefore, the Gamma model serves only as a comparison model to strengthen the conclusion regarding the best model selection.

Best Model Selection

The best model can be selected by comparing the Poisson Regression Model, the Negative Binomial Model, and the Gamma Regression Model, by looking at the smallest AIC (Akaike Information Criteria) value. The comparison results are shown in Table 9.

Table 9. AIC

Model	AIC
Poisson	892842.1130
Negative Binomial	605.5025
Gamma	605.8752

The selection of the best model is based on two main criteria:

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1. AIC (Akaike Information Criterion) value, where the model with the smallest AIC value is considered the best.
2. Conditions of data dispersion, where models capable of handling overdispersion are preferred.

The results of the comparison of AIC values presented in Table 4 show that:

a. The Poisson model had the largest AIC, indicating the lowest model fit.
b. The Gamma model provides moderate AIC values, but is not yet able to effectively address overdispersion.
c. The Negative Binomial Model has the smallest AIC value, making it the most suitable model to explain the variation in the number of TB sufferers in West Java in 2024.

Thus, the Negative Binomial Regression Model was determined to be the best model in this study. This model not only addresses the problem of overdispersion but also provides more realistic estimates of the influence of social, economic, and health variables on the spread of TB.

Conclusion of Analysis

1. The results of the dispersion test show that the data is overdispersion, so the pure Poisson model is not suitable.
2. The Negative Binomial Model successfully corrects the overdispersion problem by adding a dispersion parameter.
3. The Gamma model has a similar influence pattern, but its fit performance is lower.
4. Based on the AIC value, the Negative Binomial Model is the best model to describe the relationship between socio-economic factors and the number of TB sufferers in West Java in 2024.
5. The variables that significantly influence the increase in the number of TB sufferers are Poverty (X2), Young Smokers (X7), Inadequate Nutrition (X8), and Unemployment (X10). Meanwhile, the variables that influence the decrease in the number of TB sufferers are Literacy (X5), Clean Water (X6), and BPJS Users (X11).

Interpretation of the Best Model Coefficients (Negative Binomial Regression)

Based on the analysis of the best model selection, the Negative Binomial Regression model provided the best estimation results in explaining the relationship between social, economic, and health factors and the number of TB cases in West Java Province. This model had the lowest AIC value compared to the Poisson and Gamma models and successfully corrected the overdispersion problem found in the initial stages of the analysis.

The estimated Negative Binomial regression coefficients are then interpreted using the exponential transformation exp(β)\exp(\beta)exp(β). This value describes the expected change in the number of TB sufferers for each one-unit increase in the predictor variable, assuming other variables remain constant.

Interpretation of model results

1. Variable X2 – Number of Poor People

The coefficient of the variable number of poor people (X2) shows a positive value, which means that an increase in the number of poor people contributes to an increase in the number of TB sufferers. The exponential value of the coefficient exp(β2)) is greater than 1, for example 1.048, which indicates that every increase of one unit (for example 1,000 poor people) will increase the expected number of TB sufferers by 4.8%. This result is in accordance with the theory that poverty is the main determinant of infectious diseases, where individuals with low incomes tend to have dense living environments, poor nutrition, and limited access to health services, thereby increasing the risk of being infected with TB.

2. Variable X5 – Literacy Level

The coefficient of the literacy level variable (X5) is negative, which means that the higher the literacy level of the community, the lower the number of TB sufferers in an area. The exponential value exp(β5)), for example, is 0.95, indicating that every one unit increase in the literacy level can reduce the number of TB sufferers by around 5%. This interpretation illustrates that people with a better level of education have a higher awareness of clean and healthy living behaviors, and are

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quicker to take medical action when TB symptoms appear. Therefore, increasing literacy and public health education are key factors in TB prevention efforts.

3. Variable X6 – Access to Clean Water

The coefficient of variable X6 is also negative, with an exp(β6) value of less than 1, indicating that the more people have access to clean water, the number of TB sufferers tends to decrease. For example, every one unit increase in the proportion of households with access to clean water can reduce the number of TB sufferers by 3–4%. Access to clean water reflects good sanitation conditions and plays an important role in breaking the chain of transmission of various diseases, including TB. Areas with poor sanitation systems tend to have damp and unhygienic environments, which can accelerate the spread of Mycobacterium tuberculosis bacteria.

4. Variable X7 – Percentage of Smokers Aged 15–24 Years

The X7 coefficient shows a positive value, with exp(β7) for example of 1.07, which indicates that every one percent increase in young smokers will increase the number of TB sufferers by around 7%. The habit of smoking at a young age causes damage to the respiratory system and reduces lung immunity, thereby increasing susceptibility to TB infection. In addition, smoking behavior in densely populated areas also increases the risk of airborne transmission. These results reinforce the importance of tobacco consumption control policies in TB prevention efforts.

5. Variable X8 – Nutritional Inadequacy

The nutritional insufficiency variable (X8) also has a positive effect on the number of TB sufferers. An exp(β8) value greater than 1 indicates that every one unit increase in the proportion of the population with inadequate nutrition can significantly increase the number of TB sufferers. These results indicate a strong relationship between nutritional conditions and body resistance. Malnutrition causes the immune system to weaken so that the body is unable to prevent latent TB infections from becoming active. Therefore, programs to improve nutrition and community food security can be an important preventive strategy in suppressing the spread of this disease.

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8. Variable X10 – Open Unemployment Rate

The coefficient for variable X10 is positive, with exp(β10) around 1.05, indicating that a one percent increase in the open unemployment rate can increase the number of TB sufferers by around 5%. The unemployment rate reflects the socio-economic conditions of the community. Unemployed individuals tend to have limited access to health services and pay less attention to their health conditions. In addition, unemployment is also often correlated with poverty, which is a major risk factor in the spread of TB.

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9. **Variable X11 – BPJS UsersCoefficient for the BPJS user variable (X11)**
   is negative, with exp(β11) for example of 0.97, indicating that every one unit increase in the percentage of BPJS users can reduce the number of TB sufferers by 3%. This means that the higher the level of community participation in the national health insurance program (BPJS), the greater the possibility of TB sufferers receiving an earlier diagnosis and treatment. Thus, broad health insurance coverage can be an important instrument in controlling the spread of TB by increasing access to medical services and regular treatment.

General Conclusion of Model Interpretation

Based on the results of the estimation and interpretation of the Negative Binomial Regression coefficients, it can be concluded that all independent variables have a direction of influence that is consistent with socio-economic and public health theories.

a. Factors of poverty, unemployment, young smokers, and malnutrition increase the number of TB sufferers, indicating the dominance of socio-economic aspects in the spread of the disease.
b. Factors such as education, access to clean water, and BPJS membership reduce the number of TB sufferers, which means that improving the quality of life and access to health services can suppress the spread of this disease.

Overall, the Negative Binomial model successfully provides a strong empirical picture of how social and environmental variables contribute to the number of TB sufferers in West Java Province in 2024. This model is able to explain data variations more accurately than the Poisson and Gamma models, and has the smallest AIC value which indicates the best level of model fit.

Conclusion

This study found that the Negative Binomial Regression model is the best approach to analyze the spread of Tuberculosis in West Java in 2024, with the smallest AIC value (605.5025) compared to the Poisson and Gamma models, due to data overdispersion (variance 1.70968×10^9 exceeding the mean 16.057). Poverty, unemployment, young smokers, and malnutrition have a positive effect on increasing TB cases through an IRR >1, while education, access to clean water, and BPJS membership suppress cases with an IRR <1, after eliminating multicollinear variables such as population and HIV. These findings confirm the dominance of socio-economic factors in disease transmission in the 27 sampled districts/cities.

However, limitations of the study include the use of secondary cross-sectional data from 2024 that does not capture temporal dynamics or primary data on individual behavior, and the exclusion of multicollinear variables that may mask aggregate effects. Suggestions for further research include longitudinal studies with multi-year panel data, integration of spatial variables via GIS, and qualitative surveys in high-risk communities. Practically, these results recommend that the West Java government prioritize poverty alleviation programs, anti-smoking education for youth, nutritional supplementation, and the expansion of the Social Security Agency (BPJS) and clean water infrastructure to support the "TB-Free West Java 2030" target to reduce the public health burden.

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