Analysis of Factors Influencing Household Poverty Status in Banten Province Using Binary Logistic Regression

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ABSTRACT

Household poverty remains a persistent development challenge in Banten Province, where macro-level indicators suggest declining poverty rates, yet micro-level household realities reveal heterogeneous vulnerabilities. Factors such as low education, rural residence, female-headed households, large dependency burdens, and daily tobacco consumption exacerbate the risk of poverty. This study aims to analyze the factors influencing household poverty status in Banten using March 2025 Susenas data and binary logistic regression. The analysis covers 7,310 household heads and includes variables such as gender, age, education level, place of residence, household size, and tobacco consumption. Results indicate that education is the strongest determinant: households with heads holding a university degree (S1/S2/S3) have odds of being non-poor 40.8 times higher than those with no formal schooling, while a Diploma increases the odds 29.4 times. Rural residence, female gender, and daily tobacco use are associated with lower odds of being non-poor. Household size and age positively influence non-poverty, albeit modestly. The logistic regression model demonstrates good fit (Hosmer-Lemeshow p = 0.0659), absence of multicollinearity, and strong discrimination (AUC = 0.8245), with classification accuracy of 75.88%. These findings highlight the importance of education, geographic equity, and household behavioral factors in shaping poverty outcomes and provide evidence for targeted policy interventions to reduce household poverty in Banten.

Introduction

Household poverty remains a complex development issue, as it not only reflects low expenditures but also the limitations households face in accessing education, decent employment, food, housing, sanitation, and social protection. At the micro level, the risk of poverty is often influenced by the characteristics of the household head, household size, job quality, and living conditions. Therefore, poverty analysis should focus on the household as the unit of analysis so that vulnerability sources can be more accurately identified. Findings by Faharuddin & Endrawati (2022) on worker poverty, as well as by Oktalia et al. (2025) on household food security, indicate that work conditions, dependency burdens, and food access are closely related to household welfare.

Specifically, Banten Province is of particular interest because it exhibits contrasting regional characteristics it is located near the national economic center, hosts developing industrial and urban areas, yet still contains vulnerable households in certain regions. Official releases from BPS show that Banten's poverty rate still requires careful monitoring despite recent declines, while the continually changing poverty line indicates that households' ability to meet basic needs remains a critical issue (Jacobus et al., 2018). Micro-level studies across various provinces reveal that differences in residential areas, the education of the household head, employment, and housing conditions can distinguish households' likelihood of being poor or non-poor (Sihombing et al., 2024) (Daud et al., 2023).

The current issue lies in the gap between the macro-level depiction of declining poverty and the heterogeneous micro-level reality of households. In theory, economic development and increased access to

employment should reduce poverty(Hababil et al., 2024). however, in practice, households with low education, high dependency burdens, precarious employment, or inadequate basic facilities may still remain trapped in poverty (Kewa & Ronaldias, 2025)(Daud, 2024). Maulana et al. (2024) demonstrate that education, employment status, and household head characteristics influence extreme poverty among working households, whereas Sihombing et al. (2024) find that sanitation facilities, lighting sources, floor area, family size, and calorie consumption are associated with household poverty status.

The urgency of this research lies in the need to formulate more precise poverty alleviation policies. Policies based on aggregate figures are important but insufficient to identify which households require the most intervention. Analyses using Susenas data can help identify household characteristics associated with poverty, allowing recommendations to target education, employment, social protection, housing improvements, sanitation, and access to basic services. Evidence from Daud et al. (2023) and Sari & Projo (2025) underscores that demographic variables, education, employment, residential area, assets, sanitation, and electricity availability are key indicators for understanding household poverty.

The appropriate method to address these issues is binary logistic regression, as the dependent variable in this study has two categories: poor households and non-poor households. This method allows researchers to estimate the probability of a household being classified as poor based on several explanatory variables while interpreting their effects through odds ratios. In socioeconomic research, binary logistic regression is widely used when the focus is on dichotomous outcomes, including household poverty status. James (2013) explain that logistic regression is suitable for modeling binary categorical responses, while its application to household poverty data is demonstrated by Sihombing et al. (2024) and Maulana et al. (2024).

Several previous studies provide the basis for the selection of variables in this research. Daud et al. (2023) find that residential area, household size, education, and employment sector influence household poverty for female-headed households. Ekaputri et al. (2025) emphasize the importance of gender dimensions and financial inclusion in household poverty in Indonesia. Maulana et al. (2024) highlight the role of education, employment status, and the household head's field of work in extreme poverty among working households. Based on this background, the present study aims to analyze the factors influencing household poverty status in Banten Province using Susenas data and binary logistic regression.

Methods

Data Sources and Unit of Analysis

This study employs a quantitative research design with an explanatory approach. The data used are microdata from the March 2025 National Socioeconomic Survey (Susenas) for Banten Province. Susenas was selected because it provides comprehensive household socioeconomic information, including demographic characteristics, education, place of residence, housing conditions, and consumption/expenditure.

The unit of analysis is the household. Selecting the household as the unit of analysis is based on the concept that poverty in Susenas is calculated from the average per capita monthly household expenditure, which is then compared to the poverty line (BPS, 2025). All household members are assumed to share household consumption jointly. Therefore, the status of poor or non-poor is attributed to the household as a whole and can be used to construct a poverty risk profile based on household head characteristics such as gender, highest education, age, place of residence, household size, and and tobacco consumption.

Operational Definition of Variables

The dependent variable in this study is household poverty status. A household is classified as poor if its average per capita monthly expenditure falls below the national poverty line, and as non-poor if its expenditure equals or exceeds the national poverty line. According to BPS as cited in Darisman (2026), the national poverty line in September 2025 was IDR 641,443 per person per month, equivalent to IDR 3,053,269 per household per month. Based on this classification, poor households are coded as 1, while non-poor households are coded as 0. This coding facilitates model interpretation, as the predicted probability represents the likelihood of a household being poor.

The independent variables include gender, age, education level, place of residence, the number of household members, and number of tobacco comsumption. These variables are available in Susenas and have been supported by previous research findings. The design of the research variables is presented in the following table.

Table 1. Research Variable Design

No.	Variable	Scale	Code	Category
1	Household Poverty Status	Ordinal	$Y^{(0)}$	Poor
			$Y^{(1)}$	Non-poor
2	Gender	Nomial	$X_1^{(0)}$	Male
			$X_1^{(1)}$	Female
3	Age	Numeric	X_2	
4	Education Level	Ordinal	$X_3^{(0)}$	No formal schooling
			$X_3^{(1)}$	Elementary school or equivalent
			$X_3^{(2)}$	Junior high school or equivalent
			$X_3^{(3)}$	Senior high school or equivalent
			$X_3^{(4)}$	Diploma
			$X_3^{(5)}$	Bachelor/Master/Doctoral
5	Place of Residence	Nominal	$X_4^{(0)}$	Urban
			$X_4^{(1)}$	Rural
6	Number of Household Members	Numeric	X_5	
7	Tobacco Consumption	Ordinal	$X_6^{(0)}$	Non-smoker
			$X_6^{(1)}$	Occasionally smokes
			$X_6^{(2)}$	Smokes daily

Population and Sample

The population of this study comprises all household members in Banten Province during the March 2025 Susenas survey, totaling 25,586 individuals. The sample consists of household heads from the Susenas sample in Banten Province who have complete information for both the dependent and independent variables, amounting to 7,310 household heads.

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Binary Logistic Regression Analysis

According to Huda et al. (2025), several steps are required to conduct binary logistic regression analysis, which are described as follows:

a. Parameter Test

The parameter test is conducted to evaluate the effect of each independent variable on the dependent variable. The hypotheses for this test are formulated as follows:

$H_0 : \beta_k = 0$ (The independent variable k has no effect on the dependent variable).

$H_1 : \beta_k \neq 0$ (The independent variable k has a significant effect on the dependent variable)

The statistical analysis for the parameter test is performed using the Wald test (Agresti, 2013).

$$W_k = \frac{\hat{\beta}_k}{S\hat{E}(\hat{\beta}_k)} \quad (1)$$

Where:

$\hat{\beta}_k$ = parameter estimator in k

$\hat{SE}(\hat{\beta}_k)$ = standard error estimator for $\hat{\beta}_k$

At a significance Level = 0,05, the decision rule to reject Ho if $W_k > Z_{\alpha/2}$ or p-value $< \alpha$.

b. Determination of binary logistic regression model

The logistic regression model can be expressed by the following equation:

$$g(x) = c + \sum_{i=1}^{m} \beta_i X_i \quad (2)$$

Where:

m : number of categories that have impact to dependent variable.

c : constant

Equation (4) is subsequently transformed into the logit form of the logistic regression model.

$$\pi(x) = \frac{\exp(g(x))}{1 + \exp(g(x))} \quad (3)$$

c. Interpretation of the model with Odds Ratio

Interpreting the parameter coefficients involves determining the functional relationship between the dependent and independent variables, as well as quantifying the change in the dependent variable associated with a one-unit change in an independent variable. Based on the model specified in Equation (5), the two possible values of $\pi(x)$ and $1 - \pi(x)$ are presented in the following table (Hosmer et al., 2013).

Table 2. Odd Ratio Value of Logistic Regression Model

Dependen Variable (Y)	Independen Variable (X)	
	$x = 1$	$x = 0$
$y = 1$		
$y = 0$		

d. Model Fit Test

The model fit test is conducted to assess whether the logistic regression model adequately represents the observed data. The hypotheses are formulated as follows

H_0 : The model fits the data

H_1 : The model does fits the data

The statistical analysis for the model fit test is carried out using the Goodness-of-Fit test (Hosmer et al., 2013),computed as:

$$\hat{C} = \sum_{i=1}^{k} \frac{(O_i - n_i \hat{\pi}_i)^2}{n_i \hat{\pi}_i (1 - \hat{\pi}_i)} \quad (4)$$

where:

O_i = observed frequency in category i

$\hat{\pi}_i$ = predicted probability for category i

n_i = total number of observations in category i

At a Significance Level =0,05, the decision rule to reject Ho if $\hat{C} > \chi^2_{\alpha,df}$ or p-value $< \alpha$.

e. Classification Accuracy Test

The evaluation of classification accuracy assesses the likelihood of errors produced by a classification function. The Apparent Error Rate (APER) represents the proportion of samples that are incorrectly classified by the function (Johnson & Dean, 2007). In logistic regression, the APER is used to determine the correctness of the classified data. The classification accuracy of the logistic regression model can be evaluated using a classification table, as shown below.

Table 3. Member of Classification Accuracy

Actual Membership	Predicted Membership	
	$y = 1$	$y = 2$
$y = 1$	n_{11}	n_{12}

$y = 2$	n_{21}	n_{22}

where:

n_{11} = Total Y_i of $y = 1$ properly classified as $y = 1$

n_{12} = Total Y_i of $y = 1$ properly classified as $y = 2$

n_{21} = Total Y_i of $y = 2$ properly classified as $y = 1$

n_{22} = Total Y_i of $y = 2$ properly classified as $y = 2$

Based on table 3, APER value is calculated as:

$$APER = \frac{n_{21} + n_{12}}{n} \quad (5)$$

So that the classification accuracy is determined by

$$CA = 1 - APER \quad (6)$$

If the classification accuracy exceeds 50%, the binary logistic regression (logit) model is considered appropriate for representing the dependent variable.

Results and Discussions

Binary Logistic Regression Analysis

Binary logistic regression analysis in this study was conducted using the March 2025 Susenas data, consisting of 7,310 household heads. The first step in the analysis was to perform a parameter test to identify the best predictive model, followed by model interpretation using the odds ratio values. The results of the parameter test, odds ratios, and their interpretations are presented in the following table.

Table 4. Result of Best Estimation Model

Variable	Estimate	p-value	Odd Ratio	Interpretation
Intercept	-2.863	0.000	0.057	Significant, 0.1x Non-poverty
Gender				
Female vs Male	-0.266	0.005	0.767	Significant, 0.8x Non-poverty
Age	0.026	0.000	1.026	Significant, 1x Non-poverty
Education Level				
Elementary school vs No Schooling	0.386	0.071	1.471	Insignificant
Junior high school vs No Schooling	1.362	0.000	3.903	Significant, 3.9x Non-poverty
Senior high school vs No Schooling	2.287	0.000	9.842	Significant, 9.8x Non-poverty
Diploma vs No Schooling	3.380	0.000	29.372	Significant, 29.4x Non-poverty
S1/S2/S3 vs No Schooling	3.709	0.000	40.847	Significant, 40.8x Non-poverty
Place of Residence				
Rural vs Urban	-1.309	0.000	0.270	Significant, 0.3x Non-poverty
Number of Household Members	0.144	0.000	1.154	Significant, 1.2x Non-poverty
Tobacco Consumption				
Occasionally smokes vs Non-smoker	-0.266	0.144	0.766	Insignificant
Smokes daily vs Non-smoker	-0.268	0.000	0.765	Significant, 0.8x Non-poverty

Based on the results, the factors influencing household poverty status are: female gender (compared to male); age; highest education level (SMP, SMA, Diploma, and S1/S2/S3 compared to no schooling); residence in rural areas (compared to urban areas); household size; and daily tobacco consumption (compared to non-smokers). In contrast, the factors that do not significantly affect household poverty are education at the elementary school level (SD) compared to no schooling and occasional tobacco consumption (compared to non-smokers).

Table 4 indicates that the factor with the strongest influence on household poverty is education. Individuals with a highest education level of S1/S2/S3 have odds of being non-poor 40.8 times higher than those with no formal schooling. Similarly, individuals with a Diploma have odds of being non-poor 29.4 times higher than those with no schooling. On the other hand, the factor with the lowest influence is residence in rural areas, with odds of being non-poor 0.3 times that of those living in urban areas. Female gender (compared to male) and daily tobacco consumption (compared to non-smokers) are associated with odds of being non-poor of approximately 0.8 times.

The binary logistic regression model is derived from the estimated coefficients of the factors influencing household poverty. The resulting predictive model for household poverty obtained in this study is as follows:

$$g(x) = -2.863 - 0.266X_1^{(1)} + 0.026X_2 + 1.362X_3^{(2)} + 2.287X_3^{(3)} + 3.38X_3^{(4)} + 3.709X_3^{(5)} - 1.309X_4^{(1)} + 0.144X_5 - 0.268X_6^{(2)}$$

After obtaining the binary logistic regression model above, the next step is to assess the model's goodness-of-fit with the observed data using the Hosmer-Lemeshow test.

Table 5. Hosmer-Lemeshow goodness of fit (GOF) test

df	χ^2 stat	χ^2 tab	p-value	Interpretation
8	12.492	15.507	0.0659	The model fits the data

Table above indicates that binary logistic regression model fits with data observation. Once the model is confirmed to be appropriate, the next step is to test for multicollinearity. Multicollinearity test in binary logistic regression is conducted to detect strong correlations among independent variables, as a good regression model requires that independent variables are not highly correlated.

Based on results presented in the table below, no significant correlations were found among the independent variables. Therefore, the binary logistic regression model is free from multicollinearity. This is evidenced by all Variance Inflation Factor (VIF) values < 10 and all Tolerance values > 0.1, indicating that the multicollinearity assumption is satisfied.

Table 6. Results of Assessment of Multicollinearity

Variable	VIF	Tolerance
Gender	1.46	0.68
Age	1.32	0.75
Education Level	1.31	0.76
Place of Residence	1.08	0.93
Number of Household Members	1.19	0.84
Tobacco Consumption	1.41	0.71

After confirming that the model fits the observed data and that no multicollinearity is present, the next step is to evaluate the model using the Classification Accuracy Test. This test is conducted to assess whether the model provides good predictive performance, including high classification accuracy, sensitivity, and specificity. The model's performance can be evaluated based on the results presented below.

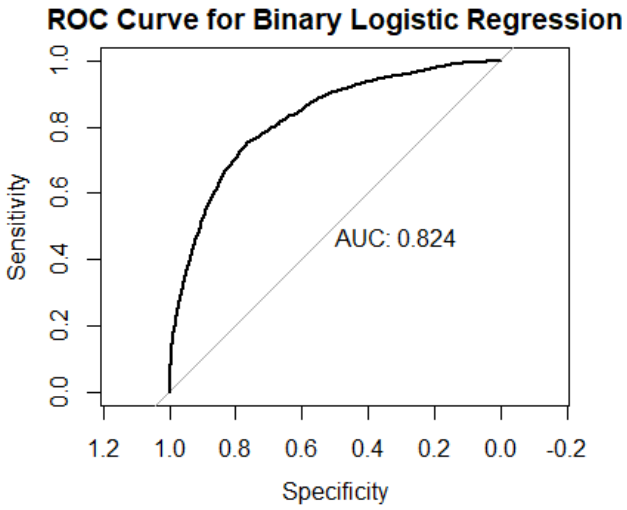


Figure 1. Plots of ROC Curve

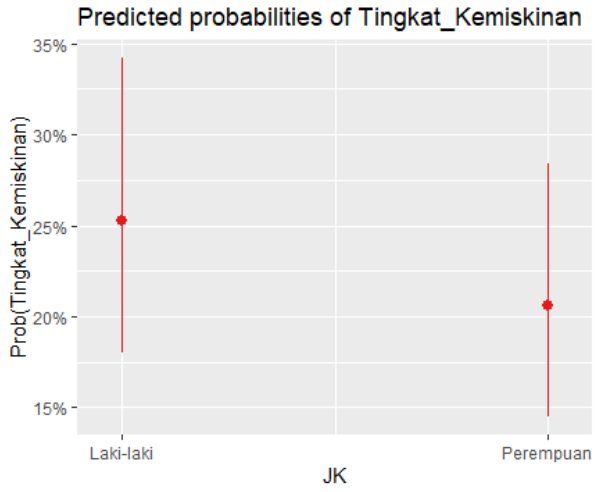
Table 7. Probabilities of Classification

	Probabilities
AUC	0.8245
Accuracy	0.7588

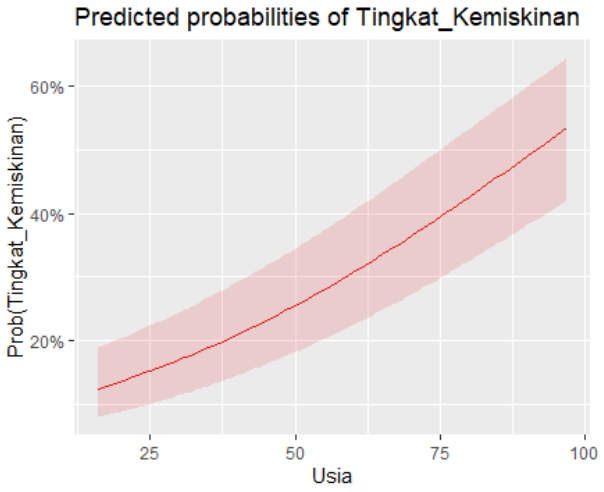
95% CI	0.7488 – 0.7686
Sensitivity	0.7177
Specificity	0.7920

The logistic regression model used has high discrimination with an AUC of 0.8245, which indicates that the model can distinguish residents with poor and non-poor status quite well, but there is still room for improvement. The ROC curve lying above the reference diagonal further supports that the model performs better than random classification. When using a threshold of 0.50, this model has an accuracy of 75.88% and a sensitivity of 71.77%, which is quite good in detecting poverty levels. However, the specificity of 79.20% shows that there are still residents whose poverty status is not correctly detected.

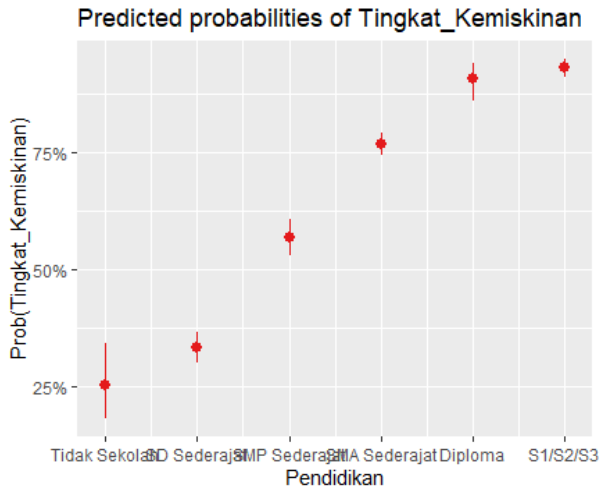
After evaluating the model, next step is to predict household poverty status based on the influencing factors, including gender, age, education level, place of residence, number of household members, and tobacco consumption. Based on the resulting model, the predictions are as follows:



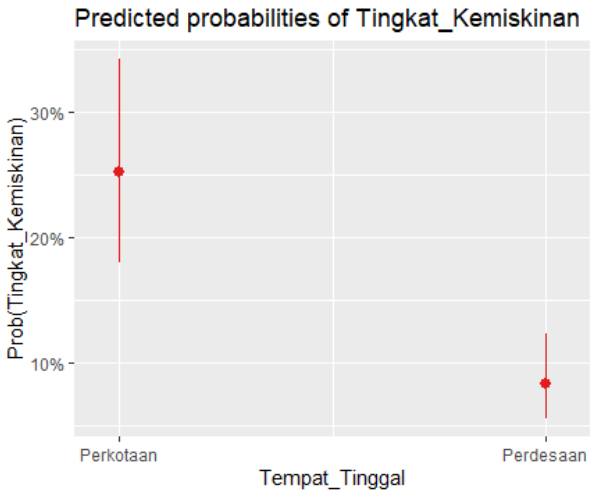
(a)



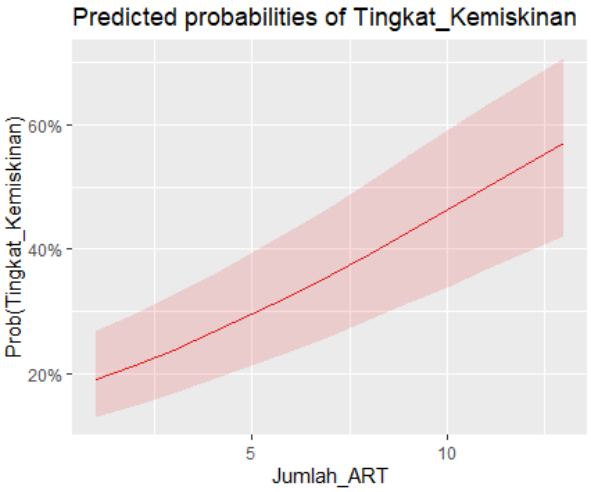
(b)



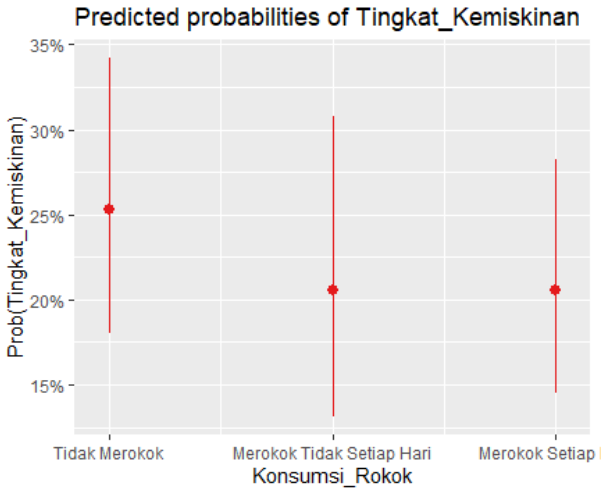
(c)



(d)



(e)



(f)

Figure 2. Prediction of poverty levels based on factors
(a) Poverty Levels vs Gender **(b)** Poverty Levels vs Age
(c) Poverty Levels vs Education Level **(d)** Poverty Levels Place of Residence
(e) Poverty Levels vs Household Members **(f)** Poverty Levels vs Tobacco Consumption

Discussion

The results of the binary logistic regression analysis indicate that household poverty in Banten Province is influenced by several socio-demographic and behavioral factors. Education level emerged as the most significant determinant of poverty status, with individuals having higher education (S1/S2/S3) exhibiting odds of being non-poor approximately 40.8 times greater than those with no formal schooling. Similarly, households headed by individuals with a Diploma have odds 29.4 times higher for non-poverty. These findings are consistent with recent studies highlighting the critical role of education in reducing household poverty, as higher education increases access to formal employment and stable income sources (Suryana & Swarniati, 2022).

The analysis also shows that residence in rural areas significantly reduces the likelihood of being non-poor (odds ratio 0.27). This reflects the persistent urban-rural divide in access to employment, infrastructure, and basic services, aligning with findings by Rambe et al. (2023) who emphasize spatial inequality as a critical factor in poverty persistence. Female-headed households have slightly lower odds of being non-poor (0.77), indicating potential gender-based economic vulnerability, in line with recent evidence on gender disparities in household welfare in Indonesia (Ekaputri et al., 2025).

Other significant factors include age and household size. Older household heads slightly increase the likelihood of being non-poor, which may relate to accumulated experience, assets, and social capital. Larger household size also slightly increases the odds of being non-poor, possibly reflecting the presence of additional working members contributing to household income. Daily tobacco consumption reduces the odds of being non-poor (0.77), suggesting that household expenditures on tobacco may limit resources available for essential needs, corroborating previous research on the economic impact of smoking on low-income households (Efroymson et al., 2001)(Chelwa & Van Walbeek, 2014).

The model's reliability is supported by the Hosmer-Lemeshow goodness-of-fit test ($p = 0.0659$), indicating that the model fits the observed data. Multicollinearity was not detected among independent variables, with all VIF values < 10 and Tolerance > 0.1, confirming that the estimates are stable and reliable. Model performance evaluation via the ROC curve shows an AUC of 0.8245, indicating strong discrimination between poor and non-poor households, while classification accuracy of 75.88%, sensitivity of 71.77%, and specificity of 79.20% further demonstrate the model's predictive adequacy. Although the model performs well, the results suggest that misclassification remains possible, particularly for households with characteristics near the threshold of poverty.

Overall, these findings highlight that poverty alleviation in Banten requires multi-dimensional interventions. Policies should focus on increasing educational attainment, particularly beyond elementary levels, improving access to economic opportunities in rural areas, and promoting targeted financial support for female-headed households. Behavioral factors such as tobacco consumption should also be considered in

designing household-level poverty reduction strategies. These insights are aligned with contemporary approaches to poverty reduction, emphasizing both structural and behavioral determinants.

Conclusions

Based on the analysis, this study demonstrates that several socio-demographic and behavioral factors significantly influence household poverty status in Banten Province. The binary logistic regression results show that education level is the strongest determinant: households headed by individuals with higher education levels (Diploma or S1/S2/S3) have substantially higher odds of being non-poor compared to those with no formal schooling. Other significant factors include residence in rural areas, gender of the household head, age, household size, and daily tobacco consumption. Female-headed households, rural residence, and daily tobacco use are associated with lower odds of being non-poor, while older age and larger household size slightly increase the likelihood of non-poverty. Variables such as elementary education and occasional tobacco consumption were not significant, indicating that the impact of education becomes meaningful only from junior high school level onwards and that minor tobacco use does not strongly affect household welfare.

The binary logistic regression model demonstrates good fit and predictive performance, as indicated by the Hosmer-Lemeshow test, absence of multicollinearity, and a strong AUC value of 0.8245. Classification results further support the model's ability to distinguish poor and non-poor households with reasonable accuracy, sensitivity, and specificity. These findings emphasize the critical role of education, rural-urban disparities, and household behavioral factors in shaping poverty outcomes. Policymakers aiming to reduce household poverty in Banten should prioritize interventions that improve access to education, enhance economic opportunities in rural areas, address gender disparities, and mitigate the economic burden of tobacco consumption, thereby creating more equitable pathways for households to escape poverty

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