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Association and Predictive Ability of LDL and HDL Cholesterol for Coronary Heart Disease Using Binary Logistic Regression

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Abstract: *Coronary heart disease (CHD) is a major cause of mortality worldwide and is closely related to lipid profile abnormalities. This study aimed to examine the effects of Low-Density Lipoprotein (LDL) and High-Density Lipoprotein (HDL) cholesterol levels on CHD incidence using binary logistic regression. Primary data were collected from medical records and interviews at RSUA, involving 38 patients. CHD status was treated as a binary response variable, while LDL and HDL served as predictors. Descriptive results showed that 65.8% of patients were diagnosed with CHD, with noticeable variation in lipid profiles. Logistic regression analysis indicated that HDL had a significant negative association with CHD ($p < 0.05$), whereas LDL was not statistically significant. Model evaluation demonstrated acceptable performance, with an accuracy of 73.7%, sensitivity of 84%, specificity of 53.8%, and an AUC value of 0.840, indicating good discriminative ability. Overall, HDL showed a stronger contribution to CHD prediction than LDL.*

Keywords— coronary heart disease; binary logistic regression; LDL; HDL; AUC; odds ratio

1. Introduction

Coronary Heart Disease (CHD) is the leading cardiovascular disease and the highest cause of death globally. CHD occurs due to narrowing or blockage of the coronary arteries, primarily caused by atherosclerosis, which is the accumulation of fatty plaque on the walls of blood vessels, thereby disrupting the supply of blood and oxygen to the myocardium [1]. The World Health Organization (WHO) reported that cardiovascular disease accounted for about 19 million global deaths in 2021, with CHD being the largest contributor in the group of diseases [2, 3].

Lipid metabolism disorders are an important risk factor in the development of CHD. Low-Density Lipoprotein (LDL) is atherogenic because it is easily oxidized and accumulates on the walls of blood vessels, thus triggering the formation of atherosclerotic plaques and narrowing of coronary arteries [4, 5]. In contrast, High-Density Lipoprotein (HDL) plays a protective role by transporting cholesterol from peripheral tissue back to the liver. Low HDL levels or HDL dysfunction can decrease protection against atherosclerosis and increase the risk of CHD [6].

Previous studies have shown a significant relationship between LDL and HDL levels and the incidence of CHD. Di Angelantonio et al. (2009) in a large cohort study reported that an increase in atherogenic lipid fractions, including LDL, as well as a decrease in HDL levels were significantly associated with an increased risk of coronary heart disease [7]. These results are reinforced by Ference et al. (2017), who show that decreased LDL levels are consistently associated with a reduced risk of cardiovascular events, thus confirming the important role of LDL as a major predictor of CHD [8].

Binary logistic regression is a commonly used statistical method to analyze the relationship between risk factors and CHD incidence as a binary variable. This method allows estimation of the chance of CHD incidence and produces association measures in the form of odds ratios that are interpretive and clinically relevant. In this study, binary logistic regression was applied to assess the predictive effects of LDL and HDL on CHD incidence as a basis for supporting evidence-based prevention strategies and clinical decision-making.

2. Literature Review

2.1 Coronary Heart Disease (CHD)

Coronary heart disease (CHD) is one of the leading causes of morbidity and mortality worldwide and shows an increase in cases in Indonesia, with a prevalence of heart disease based on doctors' diagnosis of around 1.5% with the number of cases continuing to increase in recent years [9, 10]. CHD is a cardiovascular disease that occurs due to impaired blood flow in the coronary arteries, which supply oxygen to the heart muscle. This disruption is generally triggered by atherosclerosis, which is the process of plaque buildup on the walls of blood vessels that causes narrowing of the artery lumen, thereby reducing blood flow to the myocardium and potentially leading to ischemia and myocardial infarction [11, 12]. The process of atherosclerosis is closely related to the body's metabolic condition, especially the balance of LDL and HDL blood lipid profiles, which are widely used as indicators in assessing the risk of coronary heart disease.

2.2 Low-Density Lipoprotein (LDL)

Low-Density Lipoprotein (LDL) is a type of lipoprotein that functions to transport cholesterol from the liver to various tissues in the body [13]. LDL provides cholesterol required by cells to maintain the structure and function of cell membranes under physiological conditions. Elevated LDL levels in the bloodstream can cause LDL particles to undergo oxidation within blood vessel walls, triggering endothelial dysfunction and an inflammatory response [14]. This process contributes to the formation of atherosclerotic plaques that narrow the coronary arteries and disrupt blood supply to the myocardium. If this process progresses over a prolonged period, it may result in reduced myocardial perfusion and increase the likelihood of coronary heart disease.

2.3 High-Density Lipoprotein (HDL)

High-Density Lipoprotein (HDL) is a lipoprotein fraction that plays a protective role in the cardiovascular system through the mechanism of reverse cholesterol transport, which is the transport of excess cholesterol from peripheral tissues and blood vessel walls back to the liver [13]. This mechanism helps reduce lipid accumulation in the arteries and maintain cholesterol balance in the body. In addition, HDL has antioxidant and anti-inflammatory properties that can inhibit LDL oxidation and maintain blood vessel endothelial function [15]. Low HDL levels or dysfunctional HDL can reduce these protective effects, thereby accelerate the process of atherosclerosis and increasing the risk of coronary heart disease.

2.4 Binary Logistic Regression

Binary logistic regression is a statistical method used to model the relationship between a dichotomous response variable and predictor variables [16]. The response variable Y_i takes a value of 1 if the event occurs and 0 if it does not occur, with the probability of the event $\pi(x_i) = P(Y_i = 1 \mid \mathbf{x}_i)$ modeled using a logistic function [17]. The logistic regression model is expressed as:

$$\pi(x_i) = \frac{e^{\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}}}{1+e^{\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}}} \quad (1)$$

or in logit function form:

$$logit(\pi_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} \quad (2)$$

The parameter β represents the effect of the predictor variable on the change in the log odds of the event. A positive coefficient value indicates an increase in the probability of the event, while a negative value indicates a decrease in the probability of the event.

2.5 Evaluation Metric

Evaluation metrics are used to evaluate the classification performance of the binary logistic regression model in predicting CHD events. Evaluation metrics are based on a classification matrix consisting of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative). The classification matrix, also known as a confusion matrix, describes the comparison between actual observations and predicted classification results, as presented in **Table 1**.

Table 1. Confusion Matrix for Binary Classification

Actual	Predicted	
	Positive	**Negative**
Positive	TP	FN
Negative	FP	TN

In this matrix, TP represents correctly predicted positive cases, TN represents correctly predicted negative cases, FP indicates negative cases incorrectly classified as positive, and FN indicates positive cases incorrectly classified as negative. Based on this classification matrix, several evaluation measures can be calculated to assess model performance, including accuracy, sensitivity, and specificity. The formulas for each evaluation measure are as follows [18]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (4)$$

$$Specificity = \frac{TN}{TN+FP} \quad (5)$$

2.6 Area Under the Curve (AUC)

The AUC value indicates the model's ability to discriminate between event and non-event classes. The AUC is obtained from the Receiver Operating Characteristic (ROC) curve and represents the probability that the model correctly distinguishes between individuals with and without the event. The interpretation of the AUC value is shown in **Table 2** [19].

Table 2. AUC Value Interpretation Category

AUC Value	Interpretation
0.90-1.00	Excellent Classification
0.80-0.90	Good Classification
0.70-0.80	Fair Classification
0.60-0.70	Poor Classification
<0.60	Failure

AUC is considered a robust performance measure because it evaluates model discrimination independently of classification thresholds.

2.7 Odds Ratio

Odds are defined as the ratio between the probability of an event occurring and the probability of the event not occurring. If the probability of an event is expressed as $\pi(x)$, then the odds are formulated as:

$$Odds = \frac{\pi(x)}{1-\pi(x)} \quad (6)$$

The Odds Ratio (OR) is the ratio of odds between two observation groups, for example, the group with $x = 1$ and $x = 0$, which is expressed as:

$$OR = \frac{\frac{\pi_1}{1-\pi_1}}{\frac{\pi_0}{1-\pi_0}} \quad (7)$$

with π_1 is the probability of an event in a group $x = 1$ and π_0 is the probability of an event in a group $x = 0$ [20].

In the logistic regression model, OR is obtained from the exponentiation of the regression parameter coefficient.

$$OR = e^{\beta} \quad (8)$$

An $OR > 1$ indicates increased odds of the event, $OR < 1$ indicates a protective effect, and $OR = 1$ indicates no association between the predictor and the event [21].

3. Data and Procedure

3.1 Research Variable

This study used primary data obtained from medical record observations and interviews conducted at RSUA. The dataset consists of patients' lipid profile measurements, including Low-Density Lipoprotein (LDL) and High-Density Lipoprotein (HDL) cholesterol levels, along with coronary heart disease (CHD) status as the response variable. A total of 38 observations were included in the analysis.

The definitions and roles of the research variables used in this study are presented in **Table 3**.

Table 3. Research Variables

Variabel	Variabel Name	Scale	Description
Y	CHD	Nominal	CHD status (1 = Yes, 0 = No)
X_1	LDL	Rasio	LDL cholesterol level (mg/dL)
X_2	HDL	Rasio	HDL cholesterol level (mg/dL)

3.2 Research Procedure

The research procedures in this study were carried out systematically using SPSS 2022 software in the following order:

1. Conduct descriptive statistical analysis to provide an overview of the sample characteristics.
2. Develop a binary logistic regression model by assigning CHD as the dependent variable and LDL and HDL as the independent variables to examine the relationships between variables.
3. Execute goodness-of-fit tests using the Hosmer and Lemeshow Test and -2 Log Likelihood to evaluate whether the model fits the observed data.
4. Evaluate the model classification accuracy through the "Classification Table" to obtain accuracy, sensitivity, and specificity values in predicting coronary heart disease events.
5. Measure the predictive ability by analyzing the ROC curve to obtain the AUC value.
6. Interpret the OR to determine the magnitude of risk or association between LDL and HDL levels and coronary heart disease.

4. Result And Discussion

4.1 Descriptive Statistics of Research Variables

Table 4. Distribution of CHD Status

CHD Status	Frequency	Percentage
No (0)	13	34.2%
Yes (1)	25	65.8%
Total	**38**	**100%**

Descriptive statistical analysis was performed to summarize the characteristics of the research variables. As presented in **Table 4**, the analysis included 38 observations with no missing data. The distribution of CHD indicates that 25 patients (65.8%) were identified as having CHD, whereas 13 patients (34.2%) were categorized as non-CHD.

Table 5. Descriptive Statistics of LDL and HDL Cholesterol Levels

Variable	Min.	Max.	Mean	Std. Deviation
LDL	31	272	116.32	47.10
HDL	19	92	47.87	16.01

Based on **Table 5**, lipid profile measurements indicate that LDL cholesterol levels ranged from 31.00 mg/dL to 272.00 mg/dL, with a mean value of 116.32 mg/dL and a standard deviation of 47.10, suggesting considerable variability among individuals. In contrast, HDL cholesterol levels ranged from 19.00 mg/dL to 92.00 mg/dL, with an average value of 47.87 mg/dL and a standard deviation of 16.01.

Overall, the results indicate notable variation in patients' lipid profiles, which may contribute to differences in coronary heart disease risk. The wide dispersion of LDL values suggests heterogeneous cardiovascular risk exposure, while the variability in HDL levels reflects differences in protective lipid characteristics within the study population.

4.2 Binary Logistic Regression Model Results

Binary logistic regression analysis was conducted to examine the relationship between LDL and HDL cholesterol levels and the occurrence of CHD.

Table 6. Binary Logistic Regression Estimation Results

Variable	β	Std. Error	Wald	Sig.	e^{β}
LDL	0.014	0.012	1.326	0.250	1.014
HDL	-0.124	0.046	7.386	0.007	0.883
Constant	5.215	1.968	7.022	0.008	184.091

Based on **Table 6**, the binary logistic regression model can be expressed as:

$$logit(\pi_i) = 5.215 + 0.014(LDL_i) - 0.124(HDL_i)$$

where π_i represents the probability of a patient experiencing CHD. The LDL shows a positive regression coefficient (β = 0.014), indicating that higher LDL levels tend to increase the probability of CHD occurrence. However, the significance value obtained (0.250) > 0.05, implying that LDL does not significantly influence CHD incidence in this study. In

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contrast, HDL exhibits a negative coefficient ($\beta = -0.124$) and is statistically significant (0.007) < 0.05. These results indicate that higher HDL levels reduce the probability of CHD occurrence. The negative relationship is consistent with the biological role of HDL as a protective lipid that facilitates reverse cholesterol transport and reduces atherosclerotic risk. Overall, the results indicate that HDL cholesterol shows a stronger association than LDL cholesterol in explaining the variation of CHD occurrence among the observed patients.

4.3 Model Goodness-of-Fit Evaluation

The adequacy of the logistic regression model was evaluated using the Omnibus Test, −2 Log Likelihood, and the Hosmer and Lemeshow goodness-of-fit test.

Table 7. Model Fit Evaluation

Test	Value	df	Sig.
Omnibus Test (Chi-square)	13.907	2	0.001
-2 Log Likelihood	34.917	-	-
Hosmer-Lemeshow Test	10.154	8	0.254

Based on **Table 7,** the Omnibus Test result is statistically significant (0.001) < 0.05, indicating that the model including LDL and HDL predictors provides a significantly better fit compared to the intercept-only model. This implies that the independent variables collectively contribute to explaining CHD occurrence. The Hosmer and Lemeshow Test yields a significance value of 0.254 (> 0.05), indicating no significant difference between observed and predicted values. Therefore, the model can be considered adequately fitted to the data. Additionally, the −2 Log Likelihood value of 34.917 reflects an improvement in model fit compared to the baseline model. Overall, these results demonstrate that the logistic regression model is statistically acceptable and suitable for further interpretation.

4.4 Classification Matrix and Classification Performance

Table 8. Confusion Matrix and Classification Results

Observed	Predicted	
	CHD	Non-CHD
CHD	21	4
Non-CHD	6	7

The classification performance measures were calculated based on equations 3, 4, and 5:

$$Accuracy = \frac{21+7}{21+7+4+6} = 0.737 = 73.7\%$$

$$Sensitivity = \frac{21}{21+4} = 0.840 = 84\%$$

$$Specificity = \frac{7}{7+6} = 0.538 = 53.8\%$$

Based on **Table 8** and the calculated results, the logistic regression model achieved an overall classification accuracy of 73.7%, indicating that the model correctly classified 28 out of 38 observations. The sensitivity value reached 84%, demonstrating that the model has a strong ability to correctly identify patients with CHD. This result suggests that most CHD cases were successfully detected by the model. In contrast, the specificity value was lower at 53.8%, indicating moderate performance in correctly identifying non-CHD patients. The relatively lower specificity shows that several healthy individuals were misclassified as CHD cases. This pattern suggests that the model tends to predict CHD more frequently than non-CHD.

4.5 ROC Curve and AUC Analysis

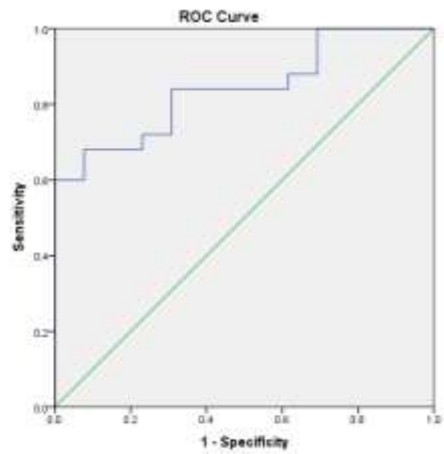

Figure 1. ROC Curve

Table 9. AUC Value

Value	Indicate
0.840	Good Classification

Based on **Table** 9, the ROC analysis produced an Area AUC value of 0.840, indicating good classification performance. An AUC of 0.840 implies that the model has an approximately 84% probability of correctly distinguishing between patients with CHD and non-CHD individuals when randomly selecting one observation from each group. The ROC curve lies well above the diagonal reference line, demonstrating that the model performs substantially better than random classification.

LDL variable was not statistically significant individually, but the combined logistic regression model still exhibits strong discriminatory power, suggesting that the predictors collectively contribute to effective classification performance.

4.6 Odds Ratio Interpretation

Table10. Odds Ratio and 95% Confidence Interval

Variable	OR (e^{β})	95% CL for OR
LDL	1.014	0.990-1.039
HDL	0.883	0.808-0.965

Based on Table 10, the OR values describe the magnitude and direction of the association between each predictor and CHD. The OR for LDL cholesterol is 1.014, indicating that an increase of 1 mg/dL in LDL level tends to increase the odds of CHD by about 1.4%. However, the 95% confidence interval (0.990–1.039) includes the value 1, suggesting that this effect is not statistically significant and therefore should be interpreted with caution.

Meanwhile, HDL cholesterol has an OR value of 0.883 with a 95% confidence interval ranging from 0.808 to 0.965. Since the interval does not include 1, HDL can be considered significantly associated with CHD occurrence. This result indicates that higher HDL levels are associated with lower odds of CHD, where each 1 mg/dL increase in HDL corresponds to an approximate 11.7% reduction in CHD odds.

Overall, these results indicate that HDL cholesterol shows a more meaningful contribution to CHD prediction than LDL cholesterol within the analyzed sample, highlighting its protective role in cardiovascular health.

5. Conclusion

This study applied binary logistic regression to examine the relationship between lipid profile indicators and CHD incidence. The estimated logistic regression model is expressed as:

$$logit(\pi_i) = 5.215 + 0.014(LDL_i) - 0.124(HDL_i)$$

where π_i represents the probability of a patient experiencing CHD.

The results show that HDL cholesterol is significantly associated with CHD and acts as a protective factor, while LDL cholesterol does not exhibit a statistically significant individual effect, although its coefficient direction remains consistent with cardiovascular risk theory. Higher HDL levels reduce CHD probability, whereas higher LDL levels tend to increase CHD risk without statistical significance.

Model evaluation indicates that the fitted model adequately explains the data. The model achieved an accuracy of 73.7%, with high sensitivity in detecting CHD cases but moderate specificity in identifying non-CHD patients. The AUC value of 0.840 suggests that the model has good classification ability to distinguish between patients with and without CHD.

Overall, HDL appears to provide a more meaningful contribution to CHD prediction than LDL in this study. Future research with larger samples and additional risk factors is recommended to improve model performance and generalizability.

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7. References

[1] R. Prajapati, P. Patel, and U. Upadhyay, "A Review on Coronary Artery Disease," *World J. Pharm. Res.*, vol. 10, no. 13, pp. 775–790, 2021, doi: 10.20959/wjpr202113-22133.

[2] World Health Organization, "Noncommunicable Diseases," World Health Organization. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases

[3] World Health Organization, "Noncommunicable Diseases: Mortality," Global Health Observatory. [Online]. Available: https://www.who.int/data/gho/data/themes/topics/topic-details/GHO/ncd-mortality

[4] P. Das and N. Ingole, "Lipoproteins and Their Effects on the Cardiovascular System," *Cureus*, vol. 15, no. 11, 2023, doi: 10.7759/cureus.48865.

[5] J. Vekic, A. Zeljkovic, A. F. G. Cicero, A. Janez, A. P. Stoian, A. Sonmez, and M. Rizzo, "Atherosclerosis Development and Progression: The Role of Atherogenic Small, Dense LDL," *Medicina (B. Aires).*, vol. 58, no. 2, 2022, doi: 10.3390/medicina58020299 Academic.

[6] C. Madaudo, G. Bono, A. Ortello, G. Astuti, G. Mingoia, A. R. Galassi, and V. Sucato, "Dysfunctional High-Density Lipoprotein Cholesterol and Coronary Artery Disease : A Narrative Review," *J. Pers. Med.*, vol. 14, no. 9, 2024, doi: 10.3390/ jpm14090996 Academic.

[7] E. D. Angelantonio, N. Sarwar, P. Perry, S. Kaptoge, K. K. Ray, A. Thompson, A. M. Wood, S. Lewington, N. Sattar, C. J. Packard, R. Collins, S. G. Thompson, and J. Danesh, "Major Lipids, Apolipoproteins, and Risk of Vascular Disease," *Jama*, vol. 302, no. 18, pp. 1993–2000, 2009, doi: 10.1001/jama.2009.1619.

[8] B. A. Ference, H. N. Ginsberg, I. Graham, K. K. Ray, C. J. Packard, E. Bruckert, R. A. Hegele, R. M. Krauss, F. J. Raal, H. Schunkert, G. F. Watts, J. Borén, S. Fazio, J. D. Horton, L. Masana, S. J. Nicholls, B. G. Nordestgaard, B. van de Sluis, M. Taskinen, L. Tokgözoğlu, U. Landmesser, U. Laufs, O. Wiklund, J. K. Stock, M. J. Chapman, and A. L. Catapano, "Low-Density Lipoproteins Cause Atherosclerotic Cardiovascular Disease. 1. Evidence from Genetic, Epidemiologic, and Clinical Studies. A Consensus Statement from the European Atherosclerosis Society Consensus Panel," *Eur. Heart J.*, vol. 38, pp. 2459–2472, 2017, doi: 10.1093/eurheartj/ehx144.

[9] Kementerian Kesehatan RI, *Laporan Nasional*

Riskesdas 2018. Jakarta, 2019.

[10] Kementerian Kesehatan RI, *Profil Kesehatan Indonesia 2022*. Jakarta: Kementerian Kesehatan Republik Indonesia, 2023.

[11] World Health Organization, "Cardiovascular Diseases (CVDs)," World Health Organization. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

[12] L. M. Buja, "Pathobiology of Myocardial Ischemia and Reperfusion Injury: Models, Modes, Molecular Mechanisms, Modulation, and Clinical Applications," *Cardiol. Rev.*, vol. 31, no. 5, pp. 252–264, 2023, doi: 10.1097/CRD.0000000000000440.

[13] C. J. Fielding, "Lipoprotein Receptors, Plasma Cholesterol Metabolism, and the Regulation of Cellular Free Cholesterol Concentration," *FASEB J.*, vol. 6, no. 13, pp. 3162–3168, 1992, doi: 10.1096/fasebj.6.13.1327930.

[14] H. Jiang, Y. Zhou, S. M. Nabavi, A. Sahebkar, P. J. Little, S. Xu, J. Weng, and J. Ge, "Mechanisms of Oxidized LDL-Mediated Endothelial Dysfunction and Its Consequences for the Development of Atherosclerosis," *Front. Cardiovasc. Med.*, vol. 9, pp. 1–11, 2022, doi: 10.3389/fcvm.2022.925923.

[15] P. J. Barter, S. Nicholls, K. A. Rye, G. M. Anantharamaiah, M. Navab, and A. M. Fogelman, "Antiinflammatory Properties of HDL," *Circ. Res.*, vol. 95, no. 8, pp. 764–772, 2004, doi: 10.1161/01.RES.0000146094.59640.13.

[16] F. E. Harrell, "Binary Logistic Regression," in *Regression Modeling Strategies*, Cham: Springer, 2015. doi: 10.1007/978-3-319-19425-7_10.

[17] D. W. Hosmer, S. Lemeshow, and R. X. Sturdivant, *Applied Logistic Regression*, 3rd ed. Hoboken: John Wiley & Sons, Inc., 2013.

[18] M. Wanyonyi, Z. N. Morris, F. M. Musyoka, and D. M. Kitavi, "Predicting Coronary Heart Disease Using Classical Statistical Models: A Comparative Evaluation of Logistic Regression and Cox Proportional Hazards," *IAENG Int. J. Appl. Math.*, vol. 55, no. 12, pp. 4173–4190, 2025.

[19] R. S. Wahono, N. S. Herman, and S. Ahmad, "A Comparison Framework of Classification Models for Software Defect Prediction," *Adv. Sci. Lett.*, vol. 20, pp. 1945–1950, 2014, doi: 10.1166/asl.2014.5640.

[20] R. H. Situngkir and P. Sembiring, "Analisis Regresi Logistik untuk Menentukan Faktor-Faktor yang Mempengaruhi Kesejahteraan Masyarakat Kabupaten/Kota di Pulau Nias," *FARABI J. Mat. dan Pendidik. Mat.*, vol. 6, no. 1, pp. 25–31, 2023, doi: 10.47662/farabi.v6i1.432.

[21] M. Szumilas, "Explaining Odds Ratios," *J. Can. Acad. Child Adolesc. Psychiatry*, vol. 19, no. 3, pp. 227–229, 2010, doi: 10.1136/bmj.c4414.