Science and Education Journal
Vol 5 No 2 (2026)
E-ISSN : 2962-9713
P-ISSN : 2963-928X

ROBUST REGRESSION MODELING USING GENERALIZED SCALE (GS) AND GENERALIZED M (GM) ESTIMATION ON POVERTY LEVELS IN EAST JAVA PROVINCE

Lutfiya Eka Rahmawati[1], Respatiwulan[2], Sri Sulistijowati Handajani[3]

[1]Program Studi Statistika, Fakultas Matematika dan Ilmu Pengetahuan Alam, Universitas Sebelas Maret, Jawa Tengah, Indonesia lutfiya.eka@student.uns.ac.id

[2]Program Studi Statistika, Fakultas Matematika dan Ilmu Pengetahuan Alam, Universitas Sebelas Maret, Jawa Tengah, Indonesia respatiwulan@staff.uns.ac.id

[3]Program Studi Statistika, Fakultas Matematika dan Ilmu Pengetahuan Alam, Universitas Sebelas Maret, Jawa Tengah, Indonesia rr_ssh@staff.uns.ac.id

Abstract

Poverty is a global social issue that hinders human welfare and socioeconomic development. In Indonesia, poverty remains a serious and complex problem that continues to be a major challenge for national development. One of the main goals of Sustainable Development Goals (SDGs) is the elimination of all forms of poverty. Analysis of factors related to poverty levels in East Java Province was conducted in this study. The data used are sourced from the Central Statistics Agency (BPS), covering 38 districts/cities in East Java Province in 2023. The independent variables used in this study include Life Expectancy (UHH), Expected Years of Schooling (HLS), per capita expenditure, and economic growth. The data are indicated to be non-normally distributed and contain outliers, so modeling is carried out using robust regression. This study was conducted using two methods, Generalized Scaled (GS) and Generalized M (GM) by comparing the two results. The selection of the best model is based on the largest R^2_{adj} value, the lowest AIC value, and the number of outliers. The results of the study showed that the robust regression model of GM estimation was a better model with an R^2_{adj} value of 81.33%, an AIC value of 153. 2172, and one outlier.

Keywords: *Poverty Level, Robust Regression, GS Estimation, GM Estimation*

Abstrak

Kemiskinan merupakan isu sosial berskala global yang menjadi penghambat peningkatan kesejahteraan manusia dan pembangunan sosial ekonomi. Di Indonesia, kemiskinan masih menjadi masalah serius dan kompleks yang terus menjadi tantangan besar bagi pembangunan nasional. Salah satu tujuan utama Pembangunan berkelanjutan (SDGs) adalah penghapusan segala bentuk kemiskinan. Analisis terhadap faktor-faktor yang berkaitan dengan tingkat kemiskinan di Provinsi Jawa Timur dilakukan dalam penelitian ini. Data yang digunakan bersumber dari Badan Pusat Statistik (BPS), mencakup 38 kabupaten/kota di Provinsi Jawa Timur pada tahun 2023. Variabel independen yang digunakan dalam penlitian ini meliputi Umur Harapan Hidup (UHH), Harapan Lama Sekolah (HLS), pengeluaran per kapita, dan pertumbuhan ekonomi. Data terindikasi tidak berdistribusi normal dan memiliki outlier, sehingga pemodelan dilakukan menggunakan regresi robust. Penelitian ini dilakukan dengan menggunakan dua metode *Generalized Scaled* (GS) dan *Generalized M* (GM) dengan membandingkan kedua hasil tersebut. Pemilihan model terbaik didasarkan pada nilai R^2_{adj} terbesar, nilai AIC terendah, dan bayaknya *outlier*. Hasil penelitian menunjukkan bahwa model regresi *robust* estimasi GM adalah model lebih baik dengan nilai R^2_{adj} sebesar 81,33%, nilai AIC sebesar 153,2172, dan terdapat satu *outlier*.

Kata Kunci: *Tingkat Kemiskinan, Regresi Robust, Estimasi GS, Estimasi GM*

SICEDU : Science and Education Journal
Vol X. No X (Bulan, Tahun)
ISSN: XXXX-XXXX EISSN:XXXX-XXXX, DOI:XXXX/sicedu

Corresponding Author:
Lutfiya Eka Rahmawati

Program Studi Statistika, Fakultas Matematika dan Ilmu Pengetahuan Alam, Universitas Sebelas Maret, Jawa Tengah, Indonesia lutfiya.eka@student.uns.ac.id

INTRODUCTION

Poverty is a global social problem that impacts the improvement of human welfare and progress. At the national level, poverty in Indonesia remains a complex issue that has not been fully resolved, although various mitigation programs have been implemented. The first objective of the Sustainable Development Goals (SDGs) emphasizes the importance of eliminating poverty in all its forms as a development priority. The Indonesian government has a moral and constitutional responsibility to address this issue, as stated in Article 34 paragraph (1) of the 1945 Constitution. Poverty is defined as a condition where a person's income is insufficient to meet basic needs for survival (Nisa et al., 2024). Data from the Central Statistics Agency shows that the national poverty rate is still at 9.36%, so this issue still requires serious attention.

East Java Province is one of the regions with a significant poverty population. Although the poverty trend shows a decline, the number of poor people still exceeding four million confirms that this condition remains a development challenge (Prasetyo & Hadi, 2025). The percentage of the poor population has reached 10.29%, or approximately one in ten people living below the poverty line (Fahreza & Pratama, 2024). This situation demonstrates the gap between the hope of achieving equitable development and the reality on the ground, which still shows high poverty rates in several regions.

Poverty is not a standalone cause; it is influenced by health, education, purchasing power, and economic growth. Health indicators, such as life expectancy, indicate the quality of services and public welfare (Dai et al., 2023). The education sector is reflected in the expected years of schooling indicator, which influences the quality of human resources (Hakim, 2024). Per capita expenditure reflects the level of purchasing power and the community's ability to meet their living needs. Economic growth also plays a crucial role in providing employment opportunities and increasing incomes; therefore, when it fails to increase, it can give rise to new social issues related to poverty.

Statistical analysis is necessary to accurately identify variables influencing poverty levels. Problems arise when data contain outliers, which can bias regression estimates. Robust regression is a solution to address this issue because it provides more stable estimates when classical assumptions are violated (Edriani et al, 2021). The Generalized Scale (GS) estimation method is used to suppress the influence of extreme data by minimizing scale deviation, making estimates more robust to deviations (Callisa et al., 2022). Meanwhile, Generalized M (GM) is a development of the M method that is effective in handling outliers in both dependent and independent variables by assigning lower weights to extreme data (Nurfauziyyah, 2025).

Previous research indicates that human development indicators such as education, health, and economic growth have an influence on poverty levels. However, the application of robust regression with the GS and GM estimation approach is still rare, thus providing room for research development in this area. This study aims to analyze the factors that influence the poverty level in East Java Province using robust regression with GS and GM estimation, and determine the best model based on the Adjusted R^2 value, AIC, and the presence of outliers. The results of this study are expected to contribute to the development of more accurate analysis models and can be used as a reference in the formulation of targeted and sustainable poverty alleviation policies in East Java Province.

METHODS

This study uses secondary data obtained from the official website of the East Java Central Statistics Agency (BPS) in 2023 (BPS, 2024). The data used covers 38 districts/cities in East Java. There is one dependent variable and four independent variables as listed in Appendix 1. The dependent variable ($\boldsymbol{Y}$) used is the Poverty Percentage. The independent variables in this analysis are Life Expectancy ($\boldsymbol{X_1}$), Expected Years of Schooling ($\boldsymbol{X_2}$), Per Capita Expenditure ($\boldsymbol{X_3}$), and Economic Growth ($\boldsymbol{X_4}$). Data processing was carried out using RStudio software.

The method used in this study is robust regression modeling with the Generalized Scale (GS) and Generalized M (GM) estimation approaches. Robust regression was chosen because the research data has the potential to contain outliers that can affect the estimation results when using classical linear regression. GS estimation is used to minimize scale deviations and suppress the influence of outliers on the dependent variable through the use of Tukey weighting, thus making the data distribution more stable. Meanwhile, GM estimation is a development of M estimation that is able to handle outliers in the independent variable by utilizing Schweppe weighting to limit the influence of extreme observations. These two approaches are used to obtain a more robust, stable, and accurate model compared to conventional methods. The following are the stages of analysis carried out in this research.

1. Prepare the data used for the dependent and independent variables on the East Java Central Statistics Agency website.
2. Estimate the coefficients of the linear regression model using the Ordinary Least Squares (OLS) Method.
3. Test the classical assumptions of the regression model
   a. Normality test using the Kolmogorov-Smirnov test
   b. Homoscedasticity test using the Breusch-Pagan test
   c. Non-Autocorrelation test between residuals using the Durbin-Watson test
   d. Multicollinearity Detection between variables using VIF
4. Identify outliers if the normality assumption is violated using the DFFITS method.
5. Estimate robust regression parameters using M estimation.

   The main principle of M estimation is to minimize the residual function ρ, the form of M estimation is as follows (Montgomery, 2021).

$$\hat{\beta}_M = \min_{\beta} \rho(e_i) \tag{1}$$

   When ρ is the objective function and e_i is the standardized error. The steps for estimating M are as follows.

   i. Conduct initial estimates with OLS.
   ii. Calculating the residual value using $\boldsymbol{e_i = y_i - \hat{y}_i}$.
   iii. Calculating the residual standard deviation value using $\boldsymbol{\hat{\sigma}_M = \frac{median|e_i - median(e_i)|}{0{,}6745}}$.
   iv. Calculating the value $\boldsymbol{u_i}$ using $\boldsymbol{u_{iM} = \frac{e_i}{\hat{\sigma}_M}}$.
   v. Calculating the weighting value using the Tukey Bisquare weighting using the formula with $\boldsymbol{c_M = 4{,}685}$ **(Stuart, 2011)**.

$$\boldsymbol{w_{iM}(u_{iM}) = \frac{\psi(u_{iM})}{(u_{iM})} = \begin{cases} \dfrac{u_{iM}\left(1-\left(\frac{u_{iM}}{4,685}\right)^2\right)^2}{u_{iM}} & ,|u_{iM}| \le c \\ 0 & ,|u_{iM}| > c \end{cases}} \quad (2)$$

vi. Calculating parameters $\widehat{\boldsymbol{\beta}}_{\boldsymbol{M}}$ using Weighted Least Squares (WLS) with weighting $\boldsymbol{w_i}$.

vii. Steps (ii) to (vi) are repeated repeatedly with subsequent iterations using $\boldsymbol{e_{iM} = y_i - \hat{y}_{iM}}$ to obtained new $\widehat{\boldsymbol{\sigma}}_{\boldsymbol{M}}$ and $\boldsymbol{u_M}$ until a value of $\widehat{\boldsymbol{\beta}}_{\boldsymbol{M}}$ is obtained that reaches the convergence condition.

6. Estimate robust regression parameters using GS estimation.

Generalized Scale (GS) estimation is the result of minimizing the M estimation based on the difference in pairwise residual scales (Croux et al, 1994). The value of $\widehat{\boldsymbol{\beta}}$ is the estimator $\boldsymbol{\beta}$ and $\boldsymbol{e(\widehat{\beta}) = \left(e_1(\widehat{\beta}), \dots, e_n(\widehat{\beta})\right)}$ is the residual vector with the initial residual value in the GS estimation coming from the converged M estimation results. GS estimation can be defined as follows.

$$\hat{\beta}_{GS} = argmin\hat{\sigma}_{GS}\Delta e_{eii'}(\beta) \quad (3)$$

GS Estimation Steps are as follows:

i. Calculating the pairwise residuals based on the residuals from the M estimation results that have converged using $\boldsymbol{\Delta e_{ii}(\beta) = \left(\Delta e_{12}(\beta), \dots, e_{n-1}(\beta)\right)'}$.

ii. Calculating the value $\widehat{\boldsymbol{\sigma}}_{\boldsymbol{GS}}$ using $\widehat{\boldsymbol{\sigma}}_{\boldsymbol{GS}} = \frac{\boldsymbol{median|e_{ii} - median(e_{ii})|}}{\boldsymbol{0,6745}}$.

iii. Calculating the value $\boldsymbol{u_{GS}}$ using $\boldsymbol{u_{GS} = \frac{\Delta e'_{ii}}{\widehat{\sigma_{GS}}}}$.

iv. Calculating the weighting value with the $\boldsymbol{w_{iGS}}$ weighting function using the formula with $\boldsymbol{c_{GS} = 0,9958}$ [12].

$$\boldsymbol{W_{iGS}\begin{cases} \left(1-\left(\frac{u_{iGS}}{c_{GS}}\right)^2\right)^2 & ,|u_{iGS}| \le c_{GS}\,, iterasi = 1 \\ 0 & ,|u_{iGS}| > c_{GS} \\ \frac{\rho(u_{iGS})}{\widehat{\sigma}_{GS}} & ,iterasi > 1 \end{cases}} \quad (4)$$

v. Calculating the estimate $\widehat{\boldsymbol{\beta}}_{\boldsymbol{GS}}$ using the Iteratively Reweighted Least Squares (IRLS) method with $\boldsymbol{w_{iGS}}$ weighting to obtain a new residual.

vi. Steps (i) to (v) are repeated repeatedly until a value of $\widehat{\boldsymbol{\beta}}_{\boldsymbol{GS}}$ is obtained that reaches a convergent condition. For the next iteration, use the formula $\boldsymbol{e_{iGS} = y_i - \hat{y}_{iGS}}$ obtain new $\widehat{\boldsymbol{\sigma}}_{\boldsymbol{GS}}$ and $\boldsymbol{u_{GS}}$.

7. Estimate robust regression parameters using GM estimation.

Generalized M (GM) estimation was developed from M estimation to overcome the limitations of M estimation which is less able to handle outliers in $\boldsymbol{x_i}$ variables (Aristiarto, 2023).

$$\boldsymbol{S(\beta_j) = min \sum_{i=1}^{n} w_i \rho\left(\frac{y_i - \sum_{j=0}^{k} x_{ij}\beta_j}{v(x_i)\widehat{\sigma}}\right)} \quad (4)$$

with the value of $\hat{\sigma} = 1,48M_i$. M_i is the median of the $(n-k)$ largest of e_i and $\psi(x) = \max\{-K, \min(K, x)\}$ is the Huber influence function with $K = 2\sqrt{\frac{k+1}{n}}$ (Wilcox, 2011). GS Estimation Steps are as follows:

i. Conduct initial estimates with OLS.
ii. Calculating the residual value using $e_{iGM} = y_i - \sum_{j=0}^{k} x_{ij}\beta_j$
iii. Calculating the estimated value of $\hat{\sigma} = 1,48M_i$.
iv. Calculating the value u_{iGM} using $u_{iGM} = \frac{e_i}{\hat{\sigma}}$.
v. Calculating Schweppe weighting using the formula

$$w_{iGM} = \frac{\sqrt{1-h_{ij}}}{u_{iGM}}\psi\left(\frac{u_{iGM}}{\sqrt{1-h_{ij}}}\right) \quad i = 1, 2, \ldots, n \tag{5}$$

vi. Calculating the estimator $\hat{\beta}_{GM}$ using Schweppe weighting values.
vii. Repeat steps (ii) to (vi) until a convergent $\hat{\beta}_{GM}$ value is obtained.

8. Compare R^2_{adj} values, AIC values, and outlier detection to determine the best regression model.
9. Draw conclusions and interpret the better model between the robust regression model using GS estimation and GM estimation.

RESULT AND DISCUSSION

Regression Model Using OLS

The regression model of the poverty rate of districts/cities in East Java province in 2023 using OLS as follows.

$$\hat{Y} = 229,5 - 2,68X_1 - 0,7459X_2 - 0,0003354X_3 - 1,15X_4 \tag{6}$$

With an R^2_{adj} value of 64.17% indicating that the independent variables used in this study, namely life expectancy, expected years of schooling, per capita expenditure, and economic growth can explain the dependent variable of poverty level, while the remaining 64.17% is explained by other factors outside the model and produces an AIC value of 185.5735.

Classical Assumption Test

This is followed by a classical assumption test to determine whether the residuals from the model meet the assumptions before entering the robust regression analysis. Classical assumption testing as follows (Martaningtyas, 2024):

a. Normality Test

Normality test using the Kolmogorov-Smirnov test. The results obtained $D = 0.29167 > D_{(38,0,05)} = 0.227$ or $p - value = 0.002335 < a = 0.05$ so that the regression model error is not normally distributed.

b. Homoscedasticity Test

Fulfillment of the homoscedasticity assumption is carried out to determine whether the residuals have a constant variance. The results of the Breush Pagan test obtained a value of $\phi_{hitung} = 6.3976 < X^2_{(0,05,4)} = 9.488$ or $p - value = 0.1714 > a = 0.05$ which means that the residual variance is homogeneous.

c. Non-Autocorrelation Test

The autocorrelation assumption test aims to determine whether the residuals in one observation have a relationship or correlation with the residuals in other observations. The results of the Durbin Watson test obtained a $\boldsymbol{dU = 1.72 < DW = 1,92 < 4 - dU = 2,28}$ or $\boldsymbol{p - value = 0.2973 > \alpha = 0.05}$ which means there is no autocorrelation between the errors.

d. Multicollinearity Detection

Multicollinearity detection aims to assess the correlation between independent variables in a regression model. The results showed that the VIF values for all independent ($\boldsymbol{X_1 = 1,6623}$; $\boldsymbol{X_2 = 2,2633}$; $\boldsymbol{X_3 = 2,8064}$; $\boldsymbol{X_3 = 1,2214}$) $\boldsymbol{< 10}$, thus concluding that there was no multicollinearity between the independent variables.

Outlier Detection

Outlier detection is performed using DFFITS. Data can be considered an outlier if the $\boldsymbol{|DFFITS| > 2\sqrt{\frac{k+1}{38}} = 2\sqrt{\frac{5}{38}} = 0,7255}$. The detection results show that the 27th (1,023) and 29th (1,084) observations are outliers because they have a $\boldsymbol{|DFFITS| > 0,7255}$. The two detected outliers can affect the regression results, particularly the coefficient values and significance.

Robust Regression Modeling Estimation M

The regression coefficients reached convergence at the 14th iteration, resulting in the model in Equation (7).

$$\boldsymbol{\hat{Y}_M = 208,5 - 2,395X_1 - 0,8576X_2 - 0,0002772X_3 - 1,07X_4} \quad (7)$$

The M estimation model shows that when all independent variables are constant, the $\boldsymbol{R^2_{adj}}$ value is 66.75%. This means that the independent variables used in this study, namely life expectancy, expected years of schooling, per capita expenditure, and economic growth, can explain the dependent variable, poverty level, while the remaining 33.25% is explained by other factors outside the model, resulting in an AIC value of 176.0236.

Robust Regression Modeling Estimation GS

The regression coefficients reached convergence at the 14th iteration, resulting in the model in Equation (8).

$$\boldsymbol{\hat{Y}_{GS} = 193,8 - 2,236X_1 - 0,7001X_2 - 0,0002993X_3 - 0,8912X_4} \quad (8)$$

The GS estimation model shows that when all independent variables are constant, the $\boldsymbol{R^2_{adj}}$ value is 76.45%. This means that the independent variables used in this study, namely life expectancy, expected years of schooling, per capita expenditure, and economic growth, can explain the dependent variable, poverty level, while the remaining 23.55% is explained by other factors outside the model, resulting in an AIC value of 159.4058.

Robust Regression Modeling Estimation GM

The regression coefficients reached convergence at the 14th iteration, resulting in the model in Equation (9).

$$\boldsymbol{\hat{Y}_{GM} = 2,406 - 2,378X_1 - 0,6471X_2 - 0,0003467X_3 - 0,9242X_4} \quad (9)$$

The GM estimation model shows that when all independent variables are constant, the $\boldsymbol{R^2_{adj}}$ value is 81.33%. This means that the independent variables used in this study,

namely life expectancy, expected years of schooling, per capita expenditure, and economic growth, can explain the dependent variable, poverty level, while the remaining 18.67% is explained by other factors outside the model, resulting in an AIC value of 153.2172.

Best Model Selection

A model is considered better if it has a higher $\boldsymbol{R^2_{adj}}$, a lower AIC value, and fewer outliers. A summary comparison of these three criteria is presented in the following table.

Tabel 1. Comparison between GS and GM Estimates

Modle	Convergence on Iteration	R^2_{adj}	AIC	*Outlier*
GS Estimation	14	76.45%	159.4058	2
GM Estimation	21	81.33%	153.2172	1

Table 1. shows that the robust regression model using the GS estimation provides superior results in modeling poverty levels in East Java. This superiority is evident in the higher $\boldsymbol{R^2_{adj}}$ value and lower AIC value. Although the GS model produces two outliers and the GM model only one, the presence of these outliers does not reduce the overall quality of the model because the main model selection criteria, namely an increase in $\boldsymbol{R^2_{adj}}$ and a decrease in AIC, still indicate that the GS estimation performs better.

CONCLUSION

The GS estimation method was chosen as the best method in this study because it has a better ability to produce an efficient and stable model compared to GM estimation. This is indicated by the lower AIC value, reflecting a more optimal GS model balance between model complexity and prediction error. A higher value R^2_{adj} indicates that the GS model is able to explain variation in the dependent variable more robustly. The GS method is also theoretically superior in dealing with data containing outliers, as its approach provides more effective handling of error variability than the GM method. GS estimation provides better performance in obtaining a robust regression model that is more accurate and reliable.

ACKNOWLEDGEMENTS

The author would like to thank all those who supported this research. Special thanks go to the Central Statistics Agency (BPS) for providing the data used in the research. The author also gratefully acknowledges the support, guidance, and academic environment provided by Sebelas Maret University. Appreciation is also extended to the supervisors and colleagues who assisted in the preparation of this article.

REFERENCES

Aristiarto, R., Susanti, Y., & Susanto, I. (2023). Analisis regresi robust estimasi gm pada indeks keparahan kemiskinan provinsi-provinsi di indonesia. In *Semnas Ristek (Seminar Nasional Riset dan Inovasi Teknologi)* (Vol. 7, No. 1). https://doi.org/10.30998/semnasristek.v7i1.6273.

Badan Pusat Statistik. (2024). Badan Pusat Statistik. BPS Jawa Timur. https://jatim.bps.go.id.

Callisa, S., Susanti, Y., & Susanto, I. (2022). Robust Regression Generalized Scale (GS) Estimation On Profit Data Of Poultry Farm Companies. The 15th 34 Research Colloqium 2022 Universitas Muhammadiyah Gombong, 88-95.

Croux, C., Rousseeuw, P. J., & Hössjer, O. (1994). Generalized Sestimators. Journal of the American Statistical Association, 89(428), 1271- 1281.

Dai, S. I. S., Canon, S., & Bauty, D. O. (2023). Analisis Pengaruh RLS, Pengeluaran Perkapita, UHH, Dan Tingkat Kemiskinan Terhadap Ketimpangan Distribusi Pendapatan di KBI dan KTI. *Jesya (Jurnal Ekonomi dan Ekonomi Syariah)*, *6*(1), 535-544. https://doi.org/10.36778/jesya.v6i1.950.

Edriani, T. S., Rahmadani, A., & Noor, D. M. M. (2021). Analisis Hubungan Kepadatan Penduduk dengan Pola Penyebaran COVID-19 Provinsi DKI Jakarta Menggunakan Regresi Robust. *Indonesian Journal of Applied Mathematics*, *1*(2), 51. https://doi.org/10.35472/indojam.v1i2.353.

Fahreza, M. B. A., & Pratama, D. P. (2024). Analisis Faktor Sosial Ekonomi terhadap Kesejahteraan Masyarakat di Provinsi Jawa Timur Tahun 2023 Menggunakan Analisis Faktor. *Jurnal Global Ilmiah*, *2*(2), 907-916. https://doi.org/10.55324/jgi.v2i2.136.

M. L. Hakim, "Dinamika Kemiskinan dan Efektivitas Program Pemberdayaan Masyarakat dalam Meningkatkan Indeks Pembangunan Manusia (IPM)," *Pangripta Sembada: Jurnal Perencanaan Pembangunan*, vol. 1, no. 1, pp. 24–39, 2024.

Martaningtyas, N. U., Septiyaningrum, E. A., & Maulana, Z. (2024). Jurnal Ilmiah Multidisiplin Ilmu. *Jurnal Ilmiah Multidisiplin*, *1*(2), 99–105.

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). Introduction to linear regression analysis. John Wiley & Sons.

Nisa, W. K., Simanjuntak, V. I., Kartika, S., & Fadila, A. (2024). Pengaruh Tingkat Kemiskinan Terhadap Tingkat Tindak Kriminalitas di Indonesia Tahun 2022. *Jurnal Akuntansi, Manajemen, dan Perencanaan Kebijakan*, *1*(3), 1-9. https://doi.org/10.47134/jampk.v1i3.220.

Nurfauziyyah, N., Susanti, Y., & Slamet, I. (2025). Pemodelan Regresi. Prosiding Seminar Nasional Teknik Elektro, Sistem Informasi, Dan Teknik Informatika (SNESTIK), 5, 119–126. https://doi.org/10.31284/p.snestik.2025.7645.

Prasetyo, G. T., & Hadi, N. U. (2025). Determinasi Tingkat Pendidikan dan Tingkat Pengangguran terhadap Kemiskinan di Jawa Timur. *Innovative: Journal Of Social Science Research*, *5*(3), 8225-8233. https://doi.org/10.31004/innovative.v5i3.19716.

Stuart, C. (2011). Robust Regression. Department of Mathematical Sciences, Durham University, 169.

Wilcox, R. R. (2011). Isntroduction to robust estimation and hypothesis testing. *Academic press*.