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Binary Logistic Regression of Student Participation Levels from FMIPA at UNSOED in the 2024 General Elections

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Abstract. Student voter participation is essential for reinforcing democracy, particularly as elections approach. Understanding the factors that drive young people's decisions to participate is critical for fostering political engagement. This study models the voter participation levels of FMIPA students at UNSOED for the 2024 elections using binary logistic regression. This method was selected for its effectiveness in assessing how independent variables influence a dichotomous dependent variable (participation: yes or no). Data were gathered through an online survey targeting FMIPA students, examining factors such as gender, political interest, parental motivation, the impact of social media, and trust in government. Remarkably, 94.7% of respondents reported exercising their voting rights in the 2024 elections. The analysis reveals that political interest, parental motivation, social media influence, and trust in government significantly affect student voter participation.

Keywords: *electoral participation, binary logistic regression, student voters.*

1 Introduction

Elections serve as a means of exercising the sovereignty of the people, conducted in a manner that is direct, general, free, secret, honest, and fair in the Republic of Indonesia, in accordance with Pancasila and the 1945 Constitution [1]. The 2019 elections marked the first occasion in Indonesia where presidential and legislative elections were held simultaneously. In that election, the number of voters under 20 years old totaled 17.5 million, while those aged 21-30 reached 42.8 million out of a total of 192.8 million registered voters. Despite the significant number of first-time and young voters, which totaled 60.3 million, the recorded participation rate in the 2019 elections remained low and passive [2]. As of July 2023, figures from the General Election Commission indicate that approximately 63.9 million voters aged 17-30 will participate in the 2024 elections from a total of 204.8 million voters [3]. The growing number of young voters, particularly among first-time participants, suggests a substantial opportunity to impact electoral outcomes.

This study seeks to identify the factors influencing voter participation among FMIPA students at UNSOED, develop a binary logistic regression model to analyze these relationships, and offer interpretations of the analysis results. The findings are expected to provide valuable insights for academic research on the application of binary logistic regression, serve as a reference for similar studies, and deliver pertinent information to institutions regarding the characteristics of young voters, especially among students.

2 Materials and Methods

2.1 Regression Analysis

Regression analysis is a statistical technique used to assess the relationships between dependent and independent variables. In linear regression analysis, the relationship between the dependent variable (Y) and independent variables $x_1, x_2, \dots, x_p$ is represented by the following model [4]:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip} + \varepsilon_i, i = 1,2, \dots, n \quad (1)$$

In this equation $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ denote the regression parameters. For linear regression, the error term ε_i is assumed to be normally distributed, necessitating that the dependent variable Y_i also be continuous and normally distributed. Consequently, the linear regression model in Equation (2.2) is less suitable for discrete data types, such as binary data.

2.2 Binary Logistic Regression Analysis

Logistic regression is employed to analyze the relationship between independent variables and a categorical dependent variable [5]. The relationship between several independent variables and a binary dependent variable which has only two possible outcomes, typically represented as 0 (failure) and 1 (success)—can be expressed using binary logistic regression. Here, each observation of the dependent variable is assumed to follow a Bernoulli distribution characterized by a success probability $\pi(x_i)$. Denoting x_i and y_i as the pairs of independent and dependent variables for the i-th observation, with the assumption that each pair is independent for $i = 1,2, \dots, n$, the likelihood function for each observation pair is given by:

$$f_i(y_i|x_i,\boldsymbol{\beta}) = \pi_i^{y_i}(1-\pi_i)^{1-y_i} \qquad ; y_i = 0.1$$

where

$$\pi_i = \frac{1}{1+\exp\left(-(\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\dots+\beta_p X_{ip})\right)}. \tag{2}$$

To facilitate parameter estimation, π_i in Equation (2.2) is transformed to produce the logit form of logistic regression:

$$logit(\pi_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip}, -\infty < logit(\pi_i) < \infty. \tag{3}$$

2.3 Parameter Estimation

Maximum Likelihood Estimation (MLE) is a methodology used for estimating parameters in statistical models. MLE estimates logistic regression parameters by maximizing the likelihood function. The likelihood function for the binary logistic regression model can be expressed as:

$$l(\boldsymbol{\beta}) = \prod_{i=1}^{n} f(y_i|x_i,\boldsymbol{\beta}) = \prod_{i=1}^{n} \pi_i^{y_i}(1-\pi_i)^{1-y_i}, \tag{4}$$

where $\beta = (\beta_0, \beta_1, \dots, \beta_p)^T$. The likelihood function is more manageable when expressed in logarithmic form, referred to as the log likelihood, $L(\boldsymbol{\beta})$

$$L(\boldsymbol{\beta}) = \sum_{i=1}^{n} y_i(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip}) + \sum_{i=1}^{n} \ln(1 + \exp(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})). \tag{5}$$

To estimate the logistic regression coefficients, the first derivative of $L(\boldsymbol{\beta})$ with respect to β is set to zero.

2.4 Parameter Significance Testing

A simultaneous test is performed to evaluate the overall significance of the model parameters. This test utilizes likelihood ratio tests, where the test statistic (G) follows a Chi-square distribution and has degrees of freedom (j), representing the total number of parameters in the logistic regression model. The equation for the test statistic (G) [6] is:

$$G = -2\ln\left(\frac{L_0}{L_1}\right) \tag{6}$$

During the simultaneous test, H_0 is rejected if $G > \chi^2_{(\alpha,p)}$ or if $p - value < \alpha$, where $\chi^2_{(\alpha,j)}$ is the critical value from the Chi-square distribution, evaluated at the significance level $\alpha = 0.05$ with j degrees of freedom.

Partial tests are conducted to determine the significance of individual parameters and ascertain which independent variables significantly influence the dependent variable. The Wald test is utilized to assess parameter significance, expressed as (Hosmer et al., 2013: 40):

$$W_j{}^2 = \left(\frac{\hat{\beta}_j}{\widehat{SE}(\hat{\beta}_j)}\right)^2, \tag{7}$$

Here, $\hat{\beta}_j$ represents the estimated value of the *j*-th independent variable, while $\widehat{SE}(\hat{\beta}_j)$ denotes the standard error of the estimate β_j. In partial tests, H_0 is rejected if $W_j{}^2 > \chi^2{}_{(\alpha,1)}$ or if $p - value < \alpha$, where $\chi^2{}_{(\alpha,1)}$ is the critical value from the Chi-square distribution at the significance level $\alpha = 0{,}05$.

2.5 Interpretation of Logistic Regression Parameters

Interpreting logistic regression results involves using odds ratios to evaluate the probability of one category compared to another within an independent variable concerning the dependent variable. The odds comparison between two categories is termed the odds ratio:

$$\begin{aligned} R &= \frac{\frac{\pi_i(1)}{1-\pi_1(1)}}{\frac{\pi_i(0)}{1-\pi_1(0)}} \\ &= \frac{\exp\left(\beta_0 + \beta_1(1) + \beta_2 X_{i2} + \dots + \beta_p X_{ip}\right)}{\exp\left(\beta_0 + \beta_1(0) + \beta_2 X_{i2} + \dots + \beta_p X_{ip}\right)} \\ &= \frac{\exp\left(\beta_0 + \beta_1(1)\right)\exp\left(\beta_2 X_{i2} + \dots + \beta_p X_{ip}\right)}{\exp\left(\beta_0 + \beta_1(0)\right)\exp\left(\beta_2 X_{i2} + \dots + \beta_p X_{ip}\right)} \\ &= \exp(\beta_1). \end{aligned}$$

OThis indicates that the odds of $Y = 1$ for the category $X = 1$ is $\exp(\beta_1)$ times the odds of $Y = 1$ for the category $X = 0$.

When an independent variable is categorical with more than two categories (polytomous), the interpretation follows a similar process as that for binary variables. However, polytomous variables must first be converted into dummy variables. Conversely, for continuous independent variables, a unit increase in the value of X results in a change in the odds of $Y = 1$ by a factor of $\exp(\beta_1)$.

2.6 Research Methodology

This study was conducted at the Mathematics Department of the Faculty of Mathematics and Natural Sciences at Jenderal Soedirman University from May 2024 to January 2025. The subjects of this research included students enrolled in the Faculty of Mathematics and Natural Sciences at the university. A purposive sampling technique was utilized to select participants based on specific criteria that aligned with the study's objectives. The sampling criteria included active students from the faculty as of July 16, 2024, who were also registered voters for the 2024 elections. From a total population of 1,396 students, a sample size of 170 was determined using Slovin's formula, accounting for a margin of error of 10%.

Data were collected through questionnaires distributed to the respondents. The questionnaire served as an instrument consisting of systematically crafted questions designed to gather relevant information that supports the research aims, including both closed and open-ended questions. The research variables encompassed one dependent variable and five independent variables: voter participation (Y) identified by whether students exercised their right to vote (0: no, 1: yes). The independent variables included gender (X_1: 0 for female, 1 for male), political interest (X_2), parental motivation (X_3), the role of social media (X_4), and trust in government (X_5), employing nominal or ordinal scales appropriate to each indicator. For data interpretation, the range of response scores was categorized into three levels: low (1.00–2.33), moderate (2.34–3.67), and high (3.68–5.00), where the "moderate" category signifies a reasonably high level of participation within this study.

The data analysis steps included:

a. Identifying the factors believed to influence student participation as voters in the 2024 election.
b. Developing and distributing the questionnaire to gather data from respondents.
c. Analyzing the qualifying data and processing it using IBM SPSS Statistics 26 software.
d. Describing the collected data to provide an overview of the research variables.
e. Conducting logistic regression analysis.

Interpreting the analysis results and drawing conclusions aligned with the research objectives.

3 Results and Discussion

3.1 Characteristics of Respondents

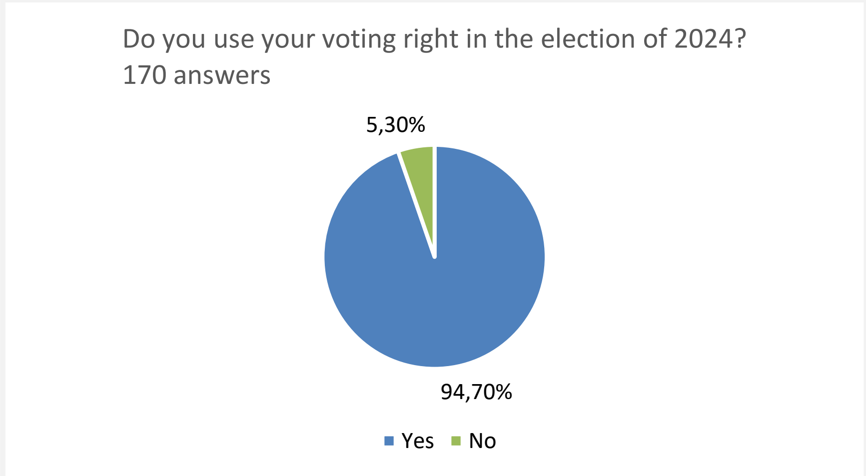

Figure 1 Percentage of FMIPA Students' Participation at UNSOED

The collected data for the dependent variable is illustrated in Figure 1. A total of 161 students exercised their voting rights, while 9 students did not. The details of the characteristics for each independent variable are outlined below:

1) Gender (X_1)

Figure 2 presents the percentage distribution of respondents by gender.

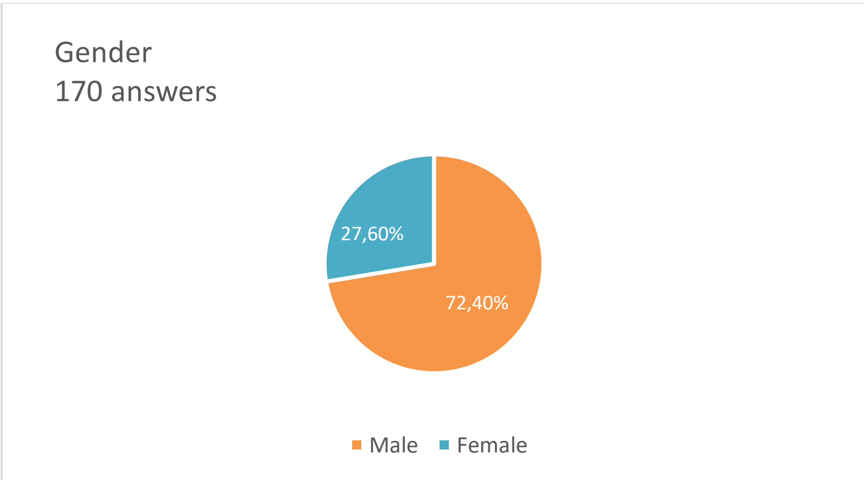

Figure 2 Respondents' Gender Percentage

The data indicates that a significant majority of respondents are female, representing 72.4% (123 students), with 5 of these individuals not utilizing their right to vote. In contrast, male respondents account for 27.6% (47 students), with 4 of them abstaining from participation in the 2024 elections.

2) Political Interest (X_2)

Descriptive statistics related to political interest are shown in Figure 3. These statistics provide an overview of the analyzed data.

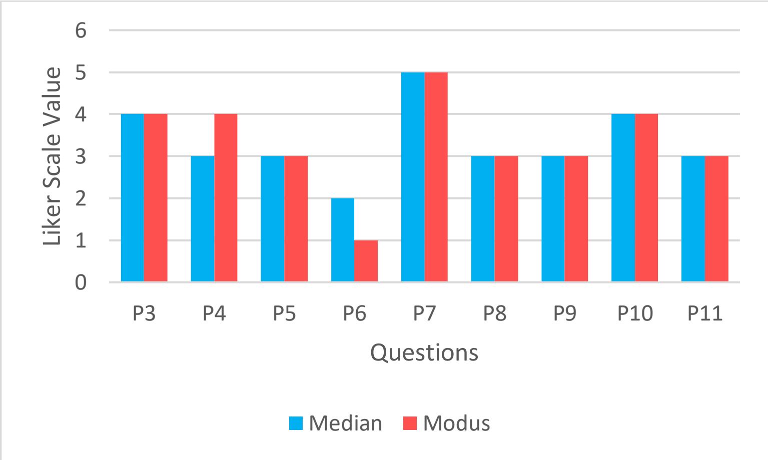

Figure 3 Median and Mode of Political Interest

Figure 3 reveals that the highest median and mode values are recorded at P7 (median = 5, mode = 5), suggesting that most respondents strongly recognize the significance of active student participation in politics and decision-making within society. Overall, respondents display a relatively high interest in political news and policy developments; however, their active engagement in political activities remains low.

3) Parental Motivation (X_3)

Descriptive statistics for the variable of parental motivation are depicted in Figure 4.

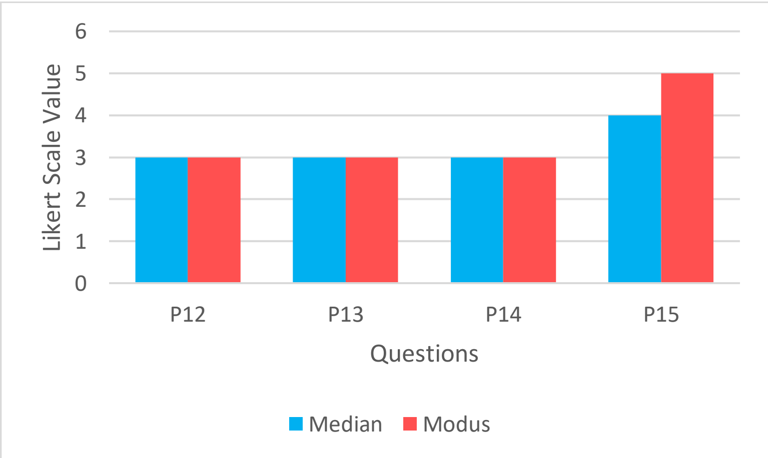

Figure 4 Median and Mode of Parental Motivation

As illustrated in Figure 4, respondents generally exhibit a neutral attitude toward the influence of parental political views on shaping their own political perspectives (P12, P13, P14). Nevertheless, regarding parental encouragement to participate in elections (P15), a trend supporting participation can be observed.

4) Role of Social Media (X_4)

Descriptive statistics for the variable concerning the role of social media are presented in Figure 5.

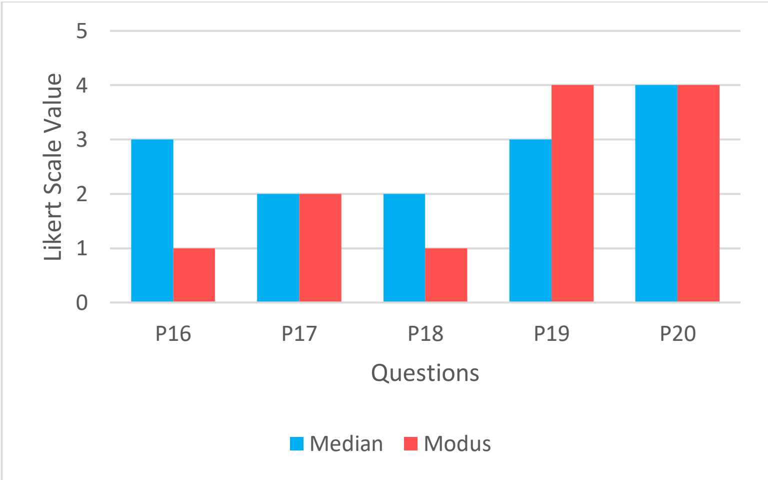

Figure 5 Median and Mode of Role of Social Media

Figure 5 indicates that although direct engagement in political activities on social media (such as discussions and content sharing) is relatively low, social media still significantly shapes respondents' political preferences and choices.

5) Trust in Government (X_5)

Descriptive statistics for the variable of trust in government are shown in Figure 6.

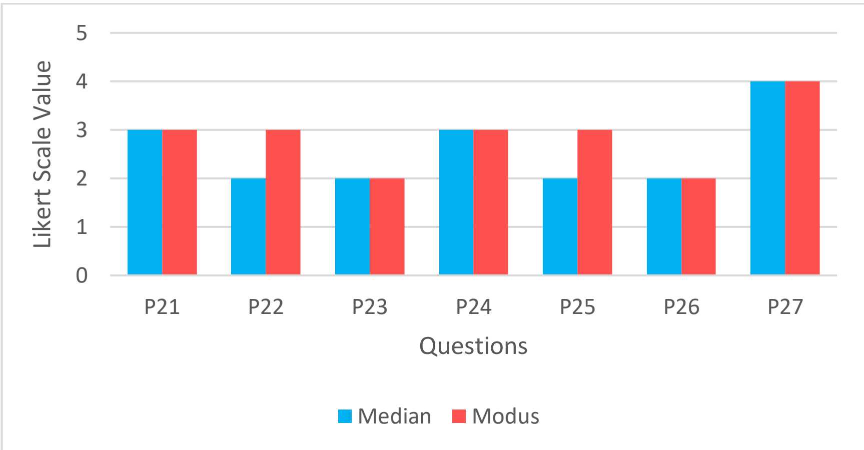

Figure 6 Median and Mode of Trust in Government

Figure 6 suggests that respondents generally maintain a neutral opinion regarding government performance, with median values largely centered around 2 or 3. The predominant modes at values of 3 or 2 reflect a neutral or dissenting attitude toward various aspects of governmental performance and transparency.

3.2 Parameter Estimation for the Model with Complete Independent Variables

Estimation for the logistic regression model was completed using IBM SPSS Statistics 26 software. The resulting data are presented in Table 1.

Table 1 Logistic Regression Model Parameter Values

Variable	β
Gender (1)	2.205
Political Interest	4.633
Parental Motivation	2.529
Role of Social Media	-4.528
Trust in Government	1.800
Constant Value	-8.896

According to Table 4.1, the binary logistic regression model is formulated as follows:

$$logit(\pi_i) = -8.896 + 2.205X_{i1} + 4.633X_{i2} + 2.529X_{i3} - 4.528X_{i4} + 1.8X_{i5}.$$

Based on the logistic regression analysis results, positive coefficients ($\beta > 0$) indicate an increased likelihood of participating in the election associated with these variables. Specifically, the political interest variable ($\beta = 4.633$) and the parental motivation variable ($\beta = 2.529$) demonstrate that higher levels of political interest or parental motivation enhance participation likelihood. In contrast, negative coefficients ($\beta < 0$) suggest a decreased chance of participation, as illustrated by the role of social media variable ($\beta = -4.528$), indicating that a stronger influence from social media correlates with lower participation.

3.3 Model Significance Testing for Complete Independent Variables

Once the parameters were estimated, the adequacy of the logistic regression model was assessed using a likelihood ratio test that compared the model with independent variables against a model without those variables. Using IBM SPSS Statistics 26, results were derived as follows:

Table 2 Values of -2 log likelihood from the model without independent variables

Iteration	-2 log likelihood	constant value
1	84.771	1.788
2	71.641	2.524
3	70.431	2.833
4	70.409	2.883
5	70.409	2.884
6	70.409	2.884

Table 3 Values of -2 log likelihood from the model with independent variables

-2 Log likelihood	Variance
22.621	0.245

According to Tables 2 and 3, the -2 log likelihood value for the model without independent variables is 70.409, while the model with independent variables shows a value of 22.621. The test statistic is computed as $G = 70.409 - 22.621 = 47.788$. Since $G > \chi^2_{(0.05;5)}$, the null hypothesis H_0 is rejected. This outcome implies that at least one independent variable significantly impacts the dependent variable, indicating that the model is appropriate for further analysis.

Once it was established that the model could be analyzed further, the Wald statistical test was applied to identify which independent variables significantly affect the model. The Wald values and p-values are presented in Table 4, yielding the following conclusions:

Table 4 Values of Wald and *p-value*

Independent Variable	Wald Statistical Test	*p-value*	Decision
Gender (X_1)	2.049	0.152	H_0 was accepted
Political Interest (X_2)	6.557	0.010	H_0 was rejected
Parental Motivation (X_3)	6.079	0.014	H_0 was rejected
Role of Social Media (X_4)	7.096	0.008	H_0 was rejected
Trust in Government (X_5)	4.318	0.038	H_0 was rejected

From the calculations carried out using IBM SPSS Statistics 26, as shown in Table 4.4, the variables significantly influencing the model include political interest (X_2), parental motivation (X_3), the role of social media (X_4), and trust in government (X_5). Referring to Table 1, the resulting logistic model $logit(\pi_i)$ can be depicted as follows:

$$logit(\pi_i) = -8{,}896 + 4{,}633X_{i2} + 2{,}529X_{i3} - 4{,}528X_{i4} + 1{,}8X_{i5}.$$

Among the four independent variables, the coefficients for political interest (4.633), parental motivation (2.529), and trust in government (1.8) are positive. This implies that an increase in these variables is likely to enhance student participation in the 2024 elections. In contrast, the negative coefficient for the role of social media (-4.528) suggests that as social media influence increases, student participation is likely to decrease.

3.4 Significance Testing of the Model with Incomplete Independent Variables

In the preceding subsection, the influential variables within the model were identified as X_2, X_3, X_4, and X_5, Therefore, additional testing was conducted to confirm that these variables conform to the logistic regression model. Prior to this testing, the model parameters were re-estimated using the independent variables X_2, X_3, X_4, and X_5. The results of the parameter estimation for these variables, obtained through IBM SPSS Statistics 26 software, are displayed in Table 5.

Table 5 Parameter estimation values for independent variables of $\boldsymbol{X_2}, \boldsymbol{X_3}, \boldsymbol{X_4}$, and $\boldsymbol{X_5}$

Variable	β
Political Interest	3.455
Parental Motivation	2.405
Role of Social Media	-3.525
Trust in Government	1.895
Constant Value	-6.905

Following the estimation of parameters for variables X_2, X_3, X_4, and X_5, a likelihood ratio test was performed. The results from the IBM SPSS Statistics 26 software are as follows:

Table 6 Values of -2 Log likelihood from the model with variables of $\boldsymbol{X_2}, \boldsymbol{X_3}, \boldsymbol{X_4}$, and $\boldsymbol{X_5}$

-2 Log likelihood	Variance
25.041[a]	0.234

According to Table 6, the -2 Log likelihood value for the model containing independent variables X_2, X_3, X_4, and X_5 is 25.041. In contrast, the -2 Log likelihood value for the model without independent variables, as indicated in Table 4.2, is 70.409. Therefore, the value of $G = 70.409 - 25.041 = 45.368$. Given that $G > \chi^2{}_{(0.05;4)}$, we reject the null hypothesis H_0. This outcome confirms that at least one independent variable significantly impacts the dependent variable, suggesting that the model is appropriate for further analysis.

To identify which independent variables have significant effects on the model, the Wald statistical test was utilized. The Wald statistic and p-values for the four variables are presented in Table 4.7.

Table 7 Values of Wald dan *p-value* with four independent variables

Independent Variable	Wald	*p-value*	Decision
Political Interest (X_2)	6.644	0.010	H_0 was rejected
Parental Motivation (X_3)	6.098	0.014	H_0 was rejected
Role of Social Media (X_4)	6.775	0.009	H_0 was rejected
Trust in Government (X_5)	4.813	0.028	H_0 was rejected

From the results produced by IBM SPSS Statistics 26, shown in Table 7, it is evident that political interest (X_2), parental motivation (X_3), the role of social media (X_4), and trust in government (X_5) significantly impact the model. Consequently, the logistic model $logit(\pi_i)$ can be expressed as follows:

$$logit(\pi_i) = -6.905 + 3.455X_{i2} + 2.405X_{i3} - 3.525X_{i4} + 1.895X_{i5}.$$

Among the four independent variables, the coefficient for political interest is 3.455 (positive), indicating that students with a high level of political interest are significantly more likely to participate in the election compared to those with low interest. The parental motivation variable has a coefficient of 2.405 (positive), suggesting that support and encouragement from parents can enhance students' likelihood of participating in the election. In contrast, the coefficient for the role of social media is -3.525 (negative), indicating that a strong influence from social media may decrease students' chances of participating. Lastly, the trust in government variable, with a coefficient of 1.895 (positive), indicates that students with a higher level of trust in the government are more inclined to engage in the election. Therefore, the final logistic regression model can be based on equation (2.2):

$$\pi_i = \frac{\exp(-6.905 + 3.455X_{i2} + 2.405X_{i3} - 3.525X_{i4} + 1.895X_{i5})}{1 + \exp(-6.905 + 3.455X_{i2} + 2.405X_{i3} - 3.525X_{i4} + 1.895X_{i5})}$$

3.5 Assessing the Fit of the Binary Logistic Regression Model

The purpose of the goodness-of-fit test is to determine how well the developed model corresponds to the existing data. In logistic regression, this model fit is evaluated using the Chi-square test through the Hosmer and Lemeshow method. The procedures for the Hosmer and Lemeshow test are outlined as follows:

1. Hypothesis

   H_0: The logistic regression model is suitable for the data (there are no significant differences between the expected and observed values).

   H_1: The logistic regression model is not suitable for the data (there are significant differences between the expected and observed values).
2. Significance level: $\alpha = 0{,}05$.
3. The test statistic derived from the output of IBM SPSS Statistics 26 is shown in Table 4.8 below:

Table 4.8 Hosmer and Lemeshow Tests

Nilai *Chi-square*	*p-value*
0.356	1.000

4. Critical region

   H_0 is rejected if $\hat{C} > \chi^2_{(\alpha, g-2)}$ or $p - value < \alpha$.
5. Kesimpulan

Based on Table 4.9, the p-value is found to be 1, which exceeds 0.05, leading to the acceptance of H_0. This result signifies that the regression model is appropriate for the data since there are no significant discrepancies between the anticipated and observed values.

3.6 Interpretation of the Logistic Regression Model

The purpose of interpreting parameters within the logistic regression model is to assess the impact of significant independent variables on the political participation levels of FMIPA UNSOED students in the 2024 elections. To interpret these model parameters, odds ratios are utilized. The odds ratios are shown in Table 4.9.

Table 4.9 Variable odds ratio Values

Variable	Odds Ratio
Political Interest (X_2)	31.648
Parental Motivation (X_3)	11.074
Role of Social Media (X_4)	0.029
Trust in Government (X_5)	6.650

Based on Table 4.9, the parameters in the final model can be interpreted as follows:

1. The political interest variable (X_2) has an odds ratio of 31.648, indicating that students with a high level of political interest are approximately 31.648 times more likely to participate in the elections compared to their peers with low political interest.
2. The parental motivation variable (X_3) has an odds ratio of 11.074, suggesting that parental support and encouragement can increase the odds of students participating in the elections by up to 11 times compared to those who do not receive such motivation.
3. The role of social media variable (X_4) has an odds ratio of 0.029, indicating that a significant presence on social media reduces students' likelihood of participating in elections. This finding suggests that students who are active on social media tend to participate less than those who are not.
4. The trust in government variable (X_5) has an odds ratio of 6.650, showing that students with a high level of trust in government are approximately 6.6 times more likely to participate in the elections compared to those with low trust.

These interpretations highlight that political interest and parental support are key factors influencing student participation, while the role of social media appears to hinder such engagement.

4 Conclusion

Based on the findings and discussions presented in Chapter 4, we can conclude that the binary logistic regression analysis concerning the voter participation of FMIPA UNSOED students in the 2024 elections, utilizing IBM SPSS Statistics 26, has yielded the following insights:

1. The factors impacting students' political participation in the 2024 elections include political interest, parental motivation, the role of social media, and trust in government.

3. The significant logistic regression model inferred from the data is presented as:

$$\pi = \frac{\exp\left(-6.905 + 3.455X_2 + 2.405X_3 - 3.525X_4 + 1.895X_5\right)}{1 + \exp\left(-6.905 + 3.455X_2 + 2.405X_3 - 3.525X_4 + 1.895X_5\right)};$$

4. The odds ratios are summarized as follows:
   a) Political interest (X_2): Students with high political interest are 31.648 times more likely to participate in elections than those with low political interest.
   b) Parental motivation (X_3): Parental support and encouragement increase the chances of student participation in elections by up to 11 times.
   c) Role of social media (X_4): Social media engagement reduces participation likelihood, with an odds ratio of 0.029.

Trust in government (X_5): Students with high trust in the government are 6.6 times more likely to participate in elections compared to those with low trust.

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