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# Bivariate Binary Logistic Regression Analysis for Modeling Educational Level and Employment Status in Central Java

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## Abstract

Education and employment are two essential components of human development, yet studies that simultaneously examine both outcomes in the context of Central Java remain limited. This research makes a novel contribution by applying bivariate binary logistic regression to jointly model educational attainment and employment status, an approach that has not been previously used for the Central Java population. Using 3,874 observations from the 2024 National Labor Force Survey (Sakernas), the study incorporates two binary response variables and ten predictors to capture the interdependence between education and labor market outcomes. The independence test confirms a significant association between the two responses, supporting the need for a joint modeling framework. Parameter estimation using the Maximum Likelihood method, followed by partial and simultaneous likelihood ratio testing, reveals that marital status and type of institution significantly and simultaneously affect both educational attainment and employment status. The final model achieves classification accuracies of 85.932% and 80.356%, demonstrating strong predictive performance. This study contributes to the literature by presenting an integrated statistical approach that enhances our understanding of how sociodemographic and institutional factors jointly influence human capital and labour participation in Central Java.
**Keywords:** Educational level; Employment status; Bivariate binary logistic regression; Maximum Likelihood method.

## Abstrak

*Pendidikan dan pekerjaan adalah dua komponen penting dari pembangunan manusia, namun studi yang secara bersamaan memeriksa kedua hasil dalam konteks Jawa Tengah masih terbatas. Penelitian ini memberikan kontribusi baru dengan menerapkan regresi logistik biner bivariat untuk memodelkan bersama pencapaian pendidikan dan status pekerjaan, suatu pendekatan yang belum pernah digunakan sebelumnya untuk populasi Jawa Tengah. Dengan menggunakan 3.874 observasi dari Survei Angkatan Kerja Nasional (Sakernas) 2024, studi ini menggabungkan dua variabel respons biner dan sepuluh prediktor untuk menangkap saling ketergantungan antara pendidikan dan hasil pasar tenaga kerja. Uji independensi mengonfirmasi hubungan yang signifikan antara kedua respons, yang mendukung perlunya kerangka kerja pemodelan bersama. Estimasi parameter menggunakan metode Kemungkinan Maksimum, diikuti oleh pengujian rasio kemungkinan parsial dan simultan, mengungkapkan bahwa status perkawinan dan jenis lembaga secara signifikan dan simultan memengaruhi pencapaian pendidikan dan status pekerjaan. Model akhir mencapai akurasi klasifikasi sebesar 85,932% dan 80,356%, yang menunjukkan kinerja prediktif yang kuat. Penelitian ini memberikan kontribusi terhadap literatur dengan menyajikan pendekatan statistik terpadu yang meningkatkan pemahaman kita tentang bagaimana faktor sosiodemografi dan kelembagaan bersama-sama memengaruhi modal manusia dan partisipasi tenaga kerja di Jawa Tengah.*
***Kata Kunci:*** *Tingkat pendidikan; Status pekerjaan; Regresi logistik biner bivariat; Metode Kemungkinan Maksimum.*

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## 1. INTRODUCTION

Education and decent work are two key pillars of the Sustainable Development Goals (SDGs), namely Goal 4 on quality education and Goal 8 on decent work and economic growth [1]. Unfortunately, challenges remain evident from the results of the Programme for International Student Assessment (PISA) survey, where Indonesia's reading scores reached only 359, far below the average of the Organisation for Economic Co-operation and Development (OECD) [2]. On the other hand, Indonesia's labor productivity in 2023, according to the International Labour Organization (ILO), ranks fifth in ASEAN with a GDP value of $14 per hour of work, still lagging behind neighboring countries. This gap highlights the need for an integrated strategy to improve access to quality education and enhance labor competitiveness.

To better understand the national challenges in education, it is essential to examine educational level as a measurable indicator of individual educational attainment. Educational level is a key indicator in human resource development. Quality and equitable education play a role in expanding employment opportunities and promoting community welfare [3]. One measure that can be used to assess the quality of education is the average length of schooling (ALS). According to the United Nations, Indonesia ranked sixth among ASEAN countries in terms of ALS in 2019, with an average life expectancy of 8.2 years. Previous research has shown that various factors such as place of residence and gender, age and reading interest, as well as educational level, marital status, and employment status significantly influence an individual's educational achievement [4], [5], [6].

In addition to educational level, employment status is also an important indicator in efforts to escape poverty. Better employment status, especially in the formal sector, can improve access to economic resources [7]. One indicator of employment status is the minimum wage, where Indonesia still lags behind its regional peers, despite having the largest economy in Southeast Asia. In 2024, according to the Ministry of Manpower, the average minimum wage in Indonesia was IDR 3,311,359, with Central Java recording the lowest minimum wage of IDR 2,036,947. This discrepancy is worth further investigation, given its proximity to Jakarta, which has the highest minimum wage. Previous studies have shown that employment status is influenced by various factors, including household size, gender, education, disability status, sector of employment, and psychological conditions, as demonstrated in studies [8], [9], [10].

Appropriate statistical methods are necessary to analyze the complex interactions between education and employment status, especially those capable of handling categorical data [11]. Regression analysis is widely used to identify factors influencing social outcomes, with logistic regression being particularly effective when the response variables are binary, such as distinguishing between bachelor and non-graduate bachelor educational levels or formal and informal employment [12], [13]. This method enables researchers to investigate how various predictor variables, including gender, household size, and marital status, influence the likelihood of specific outcomes.

A more advanced approach is required when two response variables, such as education and employment status, are present and potentially correlated. Bivariate binary logistic regression is a suitable method for simultaneously analyzing two binary outcome variables while accounting for their interdependence [14], [17]. This technique enables the simultaneous identification of both shared and distinct influencing factors. It estimates parameters using the Maximum Likelihood Estimation (MLE) method, which cannot be achieved by univariate logistic regression. The bivariate model provides a more comprehensive understanding of the socioeconomic dynamics affecting individuals by capturing the joint variability in educational attainment and employment status.

## 2. METHODS

### 2.1. Data and Research Variables

The data used in this study were sourced from the Central Statistics Agency or *Badan Pusat Statistik* (BPS), namely data from the Central Java National Labor Force Survey or *Survei Angkatan Kerja Nasional* (Sakernas) in February 2024. There were 3,874 observations in this study. This study involved two response variables and ten predictor variables. Details of the variables shows in Table 1.

**Table 1.** Response and Predictor Variables

| Variable | Notation | Description |
|---|---|---|
| Educational Level | $Y_1$ | 0: Non-graduate bachelor or diploma I/II/III<br>1: Minimum Bachelor's degree |
| Employment Status | $Y_2$ | 0: Informal job<br>1: Formal job |
| Regional Classification | $X_1$ | 0: Urban<br>1: Rural |
| Gender | $X_2$ | 0: Female, 1: Male |
| Age | $X_3$ | 0:Productive age<br>1: Non-productive age |
| Marital Status | $X_4$ | 0: Never married, 1: Married,<br>2: Divorced, 3: Widowed |
| Number of Household Members | $X_5$ | 0: < 4 people<br>1: 4 people<br>2: > 4 person |
| Training Experience | $X_6$ | 0: No training experience<br>1: Has training experience |
| Household Size | $X_7$ | 0: ≤ 35 hours<br>1: > 35 hours |
| Internet Use at Work | $X_8$ | 0: Does not use internet<br>1: Uses internet |
| Type of Institution | $X_9$ | 0: Government<br>1: International/non-profit org.<br>2: For-profit (e.g., LLC, LP)<br>3: Self-employed/home-based<br>4: Household<br>5: Not in categories 0 – 4<br>6: Unknown |
| Mode of Transportation | $X_{10}$ | 0: Private vehicle<br>1: Public vehicle |

Education is the process of developing an individual's potential through learning to build knowledge, skills, and character [23]. Education has a major influence on improving the quality of human resources, which ultimately contributes to increasing individual income and national economic growth [24]. Additionally, a good educational level opens up greater opportunities for obtaining decent employment, thereby reducing unemployment rates, according to the Central Statistics Agency or *Badan Pusat Statistik* (BPS). Pursuing education to the highest possible level is crucial because education provides the opportunity to adapt to changes in the times, leverage technology, and improve the standard of living for society [25], [26].

According to BPS, employment status refers to a person's position in their work activities. Employment status has a significant impact on individual income; for example, workers with permanent status tend to have higher incomes than those with non-permanent status [27]. Having a decent employment status is important because it can improve employee performance, which in turn contributes to achieving company goals [28], [29].

### 2.2. Research Procedures

Data analysis using the bivariate binary logistic regression method was carried out to identify factors associated with education level and employment status in Central Java through the following steps.

1. Conduct data exploration to obtain a descriptive overview of the response variables.
2. Perform an independence test using Pearson's chi-square statistic to determine whether a relationship exists between variables $Y_1$ and $Y_2$. The hypotheses for the chi-square test [16] are formulated as follows:
   $H_0$ : There is no association between variables.
   $H_1$ : There is an association between variables.
   The chi-square test statistic is obtained by comparing the computed value $\chi^2_{calculated}$ with the critical value $\chi^2_{\alpha,v}$ where $\alpha = 0{,}05$ and $v$ dentes the degree of freedom. The formula for calculating the chi-square statistics:

$$\chi^2_{calculated} = \sum_{m=1}^{r} \sum_{n=1}^{c} \frac{(O_{mn} - E_{mn})^2}{E_{mn}}, \tag{1}$$

   where $O_{mn}$ is the observed frequency in row $m$ (variable 1) and column $n$ (variable 2), $E_{mn}$ is the exprected frequency in row $m$ and column $n$, $r$ is the number of row, and $c$ is the number of columns. The decision rule for the test is: Reject $H_0$ if $\chi^2_{calculated} > \chi^2_{table}$. Rejecting $H_0$ indicates that the two response variables are related.
3. Construct the simultaneous bivariate binary logistic regression model by specifying the joint distribution of the two binary response variables $Y_1$ and $Y_2$.
   Let $Y_1, Y_2 \in \{0,1\}$. The joint outcomes (1,1), (1,0), (0,1), and (0,0) are associated with probabilities:

$$\pi_{11} = P(Y_1 = 1, Y_2 = 1);\ \pi_{10} = P(Y_1 = 1, Y_2 = 0),$$
$$\pi_{01} = P(Y_1 = 0, Y_2 = 1);\ \pi_{00} = P(Y_1 = 0, Y_2 = 0).$$

   The marginal probabilities for two responses are defines as

$$\pi_1(x) = P(Y_1 = 1),\ \pi_2(x) = P(Y_2 = 1).$$

   For $k$ independent variables $x_1, x_2, \dots, x_k$, the marginal probabilities follow the logistic form [18], [19], [20]:

$$\pi_1(x) = \frac{exp(\beta_{0,1} + \beta_{1,1}x_1 + \dots + \beta_{k,1}x_k)}{1 + exp(\beta_{0,1} + \beta_{1,1}x_1 + \dots + \beta_{k,1}x_k)}, \tag{2}$$

$$\pi_2(x) = \frac{exp(\beta_{0,2} + \beta_{1,2}x_1 + \dots + \beta_{k,2}x_k)}{1 + exp(\beta_{0,2} + \beta_{1,2}x_1 + \dots + \beta_{k,2}x_k)}. \tag{3}$$

   Applying the logit transformation yields the linear predictors [14], [15], [21], [22].

$$g_1(x) = logit\, \pi_1(x) = \ln\left[\frac{\pi_1(x)}{1 - \pi_1(x)}\right] = \beta_{0,1} + \beta_{1,1}x_1 + \dots + \beta_{k,1}x_k = \boldsymbol{\beta}_1^T\boldsymbol{X},$$
$$g_2(x) = logit\, \pi_2(x) = ln\left[\frac{\pi_2(x)}{1 - \pi_2(x)}\right] = \beta_{0,2} + \beta_{1,2}x_1 + \dots + \beta_{k,2}x_k = \boldsymbol{\beta}_2^T\boldsymbol{X}.$$

   To model the dependence between $Y_1$ and $Y_2$, the odds ratio is parameterized as

$$g_3(x) = \ln\psi = \gamma_0 + \gamma_1 x_1 + \dots + \gamma_k x_k = \theta = \boldsymbol{\gamma}^T\boldsymbol{X} \text{ where } \psi = \frac{\pi_{11}\pi_{00}}{\pi_{10}\pi_{01}}. \tag{4}$$

The parameter $\psi$ quantifies the association between the two responses. If $\psi = 1$, then $Y_1$ and $Y_2$ are independent; otherwise, the responses are dependent.

4. Partially model the relationship between $Y_1$ and $Y_2$ and each predictor variable, and identify which variables are statistically significant.
5. Develop the final model based on significant parameters through simultaneous testing of variables identified in the partial analyses, and subsequently compute the marginal probabilities for $Y_1$ and $Y_2$.
6. Interpret the analytical results: including logit coefficients, odds ratios, and marginal probabilities, to understand the influence of each predictor on the response variables.

## 3. RESULTS

### 3.1. Data Exploration

In general, the data in this study was sourced from BPS, namely data from the Central Java Sakernas in February 2024, which consisted of 3,874 observations. Figure 1 showed the percentage of the population of Central Java in the February 2024 Sakernas, grouped by education level (a) and employment status (b).

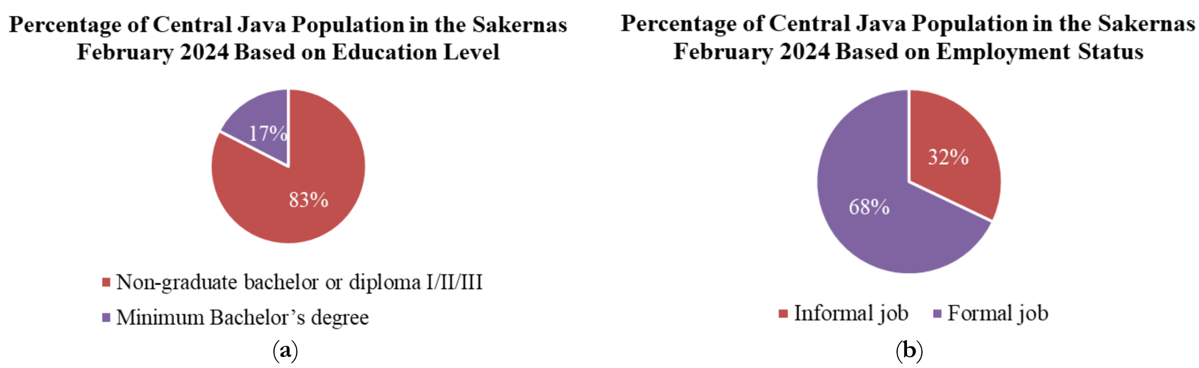


**Figure 1.** Percentage of Central Java residents in the Sakernas February 2024 based on education level (**a**) and employment status (b)

Based on Figure 1(a) and (b), from a total of 3,874 observations in the Sakernas February 2024 in Central Java, 83% (3,198) of individuals had a non-bachelor education level, while 17% (676) were bachelor graduates. In terms of employment status, 68% (2,630) had formal jobs, and 32% (1,244) were engaged in informal work. These results indicate that most Central Java residents in the dataset had a non-college education and a formal employment status.

### 3.2. Independence of Educational Level and Employment Status

The chi-square independence test was conducted to examine whether a significant association exists between Educational Level and Employment Status. The analysis, performed using R software, produced a chi-square calculated value of 219.94, which is substantially greater than the chi-square critical value of 3.841 at the 5% significance level. The corresponding p-value < 0.05 further confirms the statistical significance of the result. Based on these findings, the null hypothesis of independence is rejected, indicating a significant association between Educational Level and Employment Status.

## 3.3. Bivariate Binary Logistic Regression Analysis

### 3.3.1. Simultaneous Test

The simultaneous test evaluates whether the set of predictor variables listed in Table 1 collectively exerts a significant effect on each response variable - Educational Level ($Y_1$) and Employment Status ($Y_2$). The Likelihood Ratio Test (LRT) is employed to assess the joint significance of all predictors. The hypotheses are formulated as follows:

$$H_0: \beta_{j,1} = \beta_{j,2} = 0, j = 1,2, \dots ,10,$$
$$H_1: \text{At least one } \beta_{j,s} \neq 0, j = 1,2, \dots ,10;\ s = 1,2,$$

where $j$ indexes the predictor variables $X_1 - X_{10}$ (e.g., Regional Classification, Gender, Age, Marital Status, Household Size, Training Experience, Household Working Hours, Internet Use at Work, Type of Institution, and Mode of Transportation), and $s$indexes the response variables.

The test statistic was computed using the Likelihood Ratio Test based on the model results generated by R software. The simultaneous test produced a likelihood ratio value of G = 50.530, which exceeds the chi-square critical value of 43.773 at the 5% significance level with 30 degrees of freedom. The corresponding p-value < 0.05 indicates a statistically significant overall effect. Thus, the null hypothesis $H_0$ is rejected. This result confirms that at least one predictor variable from Table 1 significantly influences the response variables, implying that the predictors collectively contribute to explaining variations in both Educational Level ($Y_1$) and Employment Status ($Y_2$).

### 3.3.2. Partial Test

Partial significance testing was conducted to identify which predictor variables from Table 1 exert a significant influence on the response variables $Y_1$ and $Y_2$ in the bivariate binary logistic regression models. The Wald test was applied for individual parameter assessment using the following hypotheses:

$$H_0: \beta_{j,s} = 0, j = 1,2, \dots ,10;\ s = 1,2,$$
$$H_1: \beta_{j,s} \neq 0, j = 1,2, \dots ,10;\ s = 1,2,$$

Table 3 presents the results of the partial significance testing, including the Wald statistics (G) for each predictor. Based on the likelihood ratio test values shown in Table 3, two predictor variables exhibit statistically significant effects on the response variable Marital Status ($X_4$) shows a likelihood ratio value of 57.961, which exceeds the chi-square critical value $\chi^2_{(0.05;15)} = 24.996$. This indicates that marital status significantly influences at least one of the response variables. Variable Type of Institution ($X_9$) yields a likelihood ratio value of 541.555, which is greater than the chi-square critical value $\chi^2_{(0.05;6)} = 12.591$. Thus, type of institution also significantly affects the response variables. In contrast variable Household Size ($X_5$) does not show a significant effect, as its test statistic of 4.301 is less than the critical value $\chi^2_{(0.05;4)} = 7.815$. Based on these results, Marital Status ($X_4$) and Type of Institution

($X_9$) meet the criteria for inclusion in the subsequent modeling stages, as both variables significantly influence the response variables $Y_1$ and $Y_2$.

**Table 2.** Partial Significance Testing of Bivariate Binary Logistic Regression Parameters

| Predictor Variable | Parameter | | | | | | $G$ |
|---|---|---|---|---|---|---|---|
| | $\beta_{0,1}$ | $\beta_{0,2}$ | $\gamma_0$ | $\beta_{j,1}$ | $\beta_{j,2}$ | $\gamma_j$ | |
| $X_1$ | 1.439 | -0.935 | 1.669 | 0.763 | 0.905 | 2.062 | 0.000 |
| $X_2$ | 1.124 | -0.997 | 2.267 | 0.789 | 0.389 | -0.648 | 0.000 |
| $X_3$ | 1.539 | -0.778 | 1.973 | 1.279 | 1.450 | -2.423 | 0.000 |
| $X_4$ | 1.514 | -1.199 | 1.777 | 0.049 | 0.504 | 0.178 | 57.961 |
| $X_5$ | 1.383 | -0.688 | 1.952 | 0.218 | -0.074 | 0.015 | 4.301 |
| $X_6$ | 2.175 | -0.429 | 1.982 | -1.466 | -1.166 | -0.655 | 0.000 |
| $X_7$ | 1.410 | -0.170 | 2.367 | 0.214 | -0.881 | -0.582 | 0.000 |
| $X_8$ | 2.054 | -0.507 | 1.473 | -0.593 | -0.299 | 0.547 | 0.000 |
| $X_9$ | -0.385 | -5.791 | -0.502 | 1.019 | 1.915 | 0.396 | 541.555 |
| $X_{10}$ | 1.491 | -0.823 | 1.977 | 0.847 | 0.712 | -0.676 | 0.000 |

### 3.3.3. Simultaneous Test of Significant Variables

After conducting partial parameter significance testing, a simultaneous significance test was performed for the variables marital status ($X_4$) and type of institution ($X_9$) to determine whether these two variables jointly influence the educational level ($Y_1$) and employment status ($Y_2$) response variables [14]. For the overall test, the Likelihood Ratio Test method was used with the following hypothesis:

$$H_0: \beta_{4,1} = \beta_{4,2} = \beta_{9,1} = \beta_{9,2} = 0; j = 4,9 \text{ versus } H_1\text{: at least one } \beta_{js} \neq 0;\ j = 4,9;\ s = 1,2,$$

where $j$ denotes the $j$-th predictor variable and $s$ denotes the index of the response variable.

Table 3. Simultaneous Significance Testing of Bivariate Binary Logistic Regression Parameters

| Predictor Variable | Parameter | | | | | | $G$ |
|---|---|---|---|---|---|---|---|
| | $\beta_{01}$ | $\beta_{02}$ | $\gamma_0$ | $\beta_{j,1}$ | $\beta_{j,2}$ | $\gamma_j$ | |
| $X_4$ | 0.806 | -3.727 | 0.595 | 0.139 | 0.860 | 0.650 | 2015.074 |
| $X_9$ | | | | 0.330 | 0.790 | -0.030 | |

Based on the likelihood ratio test shown in Table 4, it was found that the predictor variables marital status ($X_4$) and type of institution ($X_9$) jointly influence the educational level ($Y_1$) and employment status ($Y_2$). This conclusion is supported by the likelihood ratio test statistic ($G$) for the predictor variables, which is equal to 2015.074 and exceeds the critical value $\chi^2_{(0.05;75)} = 96.217$. The logit model for educational level is given by:

$$g_1(x) = \beta_{0,1} + \beta_{4,1}x_4 + \beta_{9,1}x_9 = 0{,}806 + 0{,}139x_4 + 0{,}330x_9. \quad (5)$$

The logit model for employment status is as follows.

$$g_2(x) = \beta_{0,2} + \beta_{4,2}x_4 + \beta_{9,2}x_9 = -3{,}727 + 0{,}860x_4 + 0{,}790x_9. \quad (6)$$

The resulting odds ratio transformation model is

$$g_3(x) = \gamma_0 + \gamma_4 x_4 + \gamma_9 x_9 = 0,595 + 0,650x_4 - 0,030x_9. \tag{7}$$

Another way to express models (5) and (6) is through the marginal probability models for $Y_1$and $Y_2$, formulated as

$$\pi_1(x) = \frac{\exp\,(\beta_{0,1}+\beta_{4,1}x_4+\beta_{9,1}x_9)}{1+\exp\,(\beta_{0,1}+\beta_{4,1}x_4+\beta_{9,1}x_9)} = \frac{\exp\,(0,806+0,139x_4+0,330x_9)}{1+\exp\,(0,806+0,139x_4+0,330x_9)}, \tag{8}$$

$$\pi_2(x) = \frac{\exp\,(\beta_{0,2}+\beta_{4,2}x_4+\beta_{9,2}x_9)}{1+\exp\,(\beta_{0,2}+\beta_{4,2}x_4+\beta_{9,2}x_9)} = \frac{\exp\,(-3,727+0,860x_4+0,790x_9)}{1+\exp\,(-3,727+0,860x_4+0,790x_9)}. \tag{9}$$

### 3.4 Classification Accuracy of the Model

Based on the calculations for the education level variable $(Y_1)$, the model achieved a classification accuracy of 85.932% and a classification error rate (APER) of 14.068%. For the employment status variable $(Y_2)$, the model achieved a classification accuracy of 80.356% and an APER of 19.644%. These results indicate that the model is capable of accurately classifying the data on education level and employment status in Central Java, as of February 2024.

### 3.5 Interpretation of Significant Variables

#### 3.5.1 Marital Status $(X_4)$

Based on Table 4, it can be seen that the marital status variable $(X_4)$ has a significant effect on educational level $(Y_1)$ and employment status $(Y_2)$ in Central Java Province when other variables are constant. From equations (5), (6), and (7), the odds ratio values are obtained in Table 5.

**Table 4.** Model Interpretation for Marital Status

| Model | Odds Ratio | Description |
|---|---|---|
| Logit 1 | 1.149 | The odds ratio of individuals in marital status married, divorced, or widowed is 1.149 times greater chance of obtaining a bachelor's degree compared to individuals with unmarried status. |
| Logit 2 | 2.363 | The odds ratio of individuals in marital status married, divorced or widowed is 2.363 times greater chance of obtaining formal employment status compared to individuals with unmarried status. |
| Logit 3 | 1.915 | The odds ratio of individuals in marital status married, divorced, or widowed in comparison to the odds of a bachelor's degree, if known to have formal employment, is 1.915 times greater odds than individuals with unmarried status. |

#### 3.5.2 Type of Institution $(X_9)$

Based on Table 4, it can be seen that the type of institution variable $(X_9)$ has a significant effect on educational level $(Y_1)$ and employment status $(Y_2)$ in Central Java Province when other variables are constant. The odds ratio values are obtained as presented in Table 6.

**Table 5**. Model Interpretation for Type of Institution

| Model | Odds Ratio | Description |
|---|---|---|
| Logit 1 | 1.390 | The odds ratio of individuals working in non-profit organizations, for-profit organizations, home-based businesses, households, other organizations, or unknown organizations is 1.390 times more likely to obtain a bachelor's degree than individuals working in government organizations. |
| Logit 2 | 2.203 | The odds ratio of individuals working in non-profit organizations, for-profit organizations, home-based businesses, households, other organizations, or unknown organizations is 2.203 times more likely to obtain formal employment status than individuals working in government organizations. |
| Logit 3 | 0.970 | The odds ratio of individuals in non-profit organizations, for-profit organizations, home-based businesses, households, other organizations, or unknown organizations in comparison to the odds of a bachelor's degree, if known to have formal employment, is 0.970 times lower than that of individuals in government organizations, assuming they have formal employment. |

## 4. DISCUSSION

The results obtained for marital status $(X_4)$ in Table 5 shows consistency with the study by Jafrin et al. [30], which found that marital status significantly affects an individual's employment probability, with effects that may vary depending on educational level and type of job. Similarly, Øien-Ødegaard et al. [31] reported that married individuals tend to have higher levels of education. In addition, the results obtained for employment status $(X_9)$ in Table 6 shows consistency with the study by Amalia [32] demonstrated that the type of institution, such as government agencies, state-owned enterprises, or private companies, plays a role in shaping the combination between education and employment. This is further supported by Suh [33], who found that individuals working in both profit and non-profit sectors generally possess higher levels of education.

Based on the partial significance test of parameters using the likelihood ratio test, it was found that the predictor variables marital status $(X_4)$ and type of institution $(X_9)$ had a significant simultaneous effect on the response variables education level $(Y_1)$ and employment status $(Y_2)$. This is indicated by the likelihood ratio (G) value for marital status $(X_4)$ of 57.961, which is greater than $\chi^2_{(0,05;6)} = 12{,}591$, and the G value for type of institution $(X_9)$ of 541.555, which is greater than $\chi^2_{(0,05;15)} = 24{,}996$. Meanwhile, the variable number of household members $(X_5)$ did not have a significant effect, as the G value of 4.307 was smaller than $\chi^2_{(0,05;4)} = 7{,}815$. Thus, it can be concluded that marital status $(X_4)$ and type of institution $(X_9)$ significantly influence both education level $(Y_1)$ and employment status $(Y_2)$.

## 5. CONCLUSIONS

This study applied the bivariate binary logistic regression method to simultaneously analyze the determinants of educational level and employment status in Central Java using data from the 2024 Sakernas. The chi-square independence test confirmed a significant association between the two response variables, indicating the necessity of a joint modeling approach. The simultaneous likelihood ratio test demonstrated that the set of predictor variables collectively influenced both educational outcomes and employment conditions.

Partial parameter testing identified two predictors, marital status and type of institution, as significant factors affecting the probability of attaining a bachelor's degree and securing formal employment. The subsequent simultaneous significance test further validated that these two variables jointly affect both response variables at the 5% significance level. The estimated logit models and odds ratio interpretations revealed that individuals who are married, divorced, or widowed are more likely to achieve higher educational attainment and formal employment compared to unmarried individuals. Likewise, individuals working outside government institutions tend to have higher probabilities of holding a bachelor's degree and obtaining formal employment.

The classification accuracy of 85.932% for educational level and 80.356% for employment status indicates that the resulting bivariate logistic regression model performs well in classifying individual outcomes within the observed population. Overall, the findings emphasize the importance of marital status and institutional type in shaping educational and employment trajectories in Central Java, offering valuable insights for policymakers seeking to improve human capital development and labor market outcomes.

## REFERENCES


[1] United Nations Secretariat, "Sustainable Developmental Goals Briefing Book 2023 (UN Office for Partnerships)," 2023.

[2] OECD, "PISA 2022 Results (Volume I)," OECD, Dec. 2023. doi: 10.1787/53f23881-en.

[3] A. Nurmutiazifah and A. F. Yuniasih, "Penerapan Model Regresi Data Panel : Determinan Ketimpangan Capaian Pendidikan di Kawasan Timur Indonesia (KTI) 2015-2019," 2019.

[4] K. Hulu, Y. Zega, R. N. Mendrofa, N. K. Mendrofa, P. Studi, and P. Matematika, "Identifikasi Faktor-Faktor yang Mempengaruhi Prestasi Akademik Mahasiswa Pendidikan Matematika Menggunakan Metode CHAID," vol. 5, no. 3, 2024, doi: 10.46306/lb.v5i3.752.

[5] S. Wulandari *et al.*, "Pemodelan Literasi Membaca Siswa di Daerah Terpencil Menggunakan Regresi Logistik Biner," May 2021.

[6] O. Ozturk, "A Logistic Regression Analysis of Factors Affecting Enrollment Decisions of Prospective Students of Distance Education Programs in Anadolu University," *Turkish Online Journal of Distance Education*, 2019, [Online]. Available: https://orcid.org/0000-0002-9739-2025

[7] K. Umam and I. Furqon, "Pengaruh Pendidikan, Tenaga Kerja, dan Ketimpangan Distribusi Pendapatan terhadap Kemiskinan di Indonesia pada Tahun 2021," 2024.

[8] R. Sihombing, K. Notodiputro, and B. Sartono, "Klasifikasi Status Bekerja Individu di Provinsi Banten Tahun 2020 dengan Menggunakan Metode LASSO dan Adaptive LASSO," vol. 21, no. 1, May 2021.

[9] V. S. Permatasari and L. Yuliana, "Penerapan Regresi Logistik Biner pada Status Kesejahteraan Rumah Tangga di Provinsi Bali Tahun 2020," 2020.

[10] T. K. Daradkeh and L. Karim, "Predictors of Employment Status of Treated Patients with DSM-III-R Diagnosis. Can Logistic Regression Model Find A Solution?," 1994.

[11] A. Agresti, *An Introduction to Categorical Data Analysis*. 2019. [Online]. Available: http://www.wiley.com/go/wsps

[12] V. M. Santi, "Pengembangan Model Regresi Logistik Multinomial untuk Klasifikasi Politik pada Pemilihan Umum," *Jurnal Statistika dan Aplikasinya (JSA)*, vol. 1, no. 1, 2018.

[13] G. E. Kusumawardhani, Suyono, and V. M. Santi, "Analisis Survival dengan Model Regresi pada Data Tersensor Berdistribusi Log-logistik," *Jurnal Statistika dan Aplikasinya (JSA)*, vol. 2, no. 2, 2018.

[14] S. Rani Yelfera, H. Yozza, and P. S. Studi, “Faktor-Faktor yang Mempengaruhi Masa Studi dan Indeks Prestasi Kumulatif Mahasiswa dengan Model Regresi Logistik Biner Bivariat,” *Jurnal Matematika UNAND*, vol. 11, no. 1, pp. 82–94, 2022.
[15] N. G. Arsyi, “Pemodelan Penderita Tuberkulosis Paru dan Diabetes Melitus di Kota Surabaya Menggunakan Regresi Logistk Biner Bivariat,” (Doctoral dissertation, Institut Teknologi Sepuluh November), 2017.
[16] G. Upton, *Categorical Data Analysis by Example*. 2017. [Online]. Available: www.allitebooks.com
[17] D. A. Viestari and Purhadi, “Pemodelan Log Linier dan Regresi Logistik Biner Bivariat Pada Hasil Medical Check-Up Pegawai Negeri Sipil (PNS) Institut Teknologi Sepuluh Nopember (ITS),” 2015.
[18] D. W. Hosmer and S. Lemeshow, *Applied Logistic Regression*. 2000.
[19] B. Sumargo, “Comparing Better Environmental Knowledge Based on Education and Income Using the Odds Ratio,” *Procedia Comput Sci*, vol. 135, pp. 105–112, 2018, doi: 10.1016/j.procs.2018.08.155.
[20] Y. Rahmawati and P. C. Taylor, Eds., *Empowering Science and Mathematics for Global Competitiveness*. Jakarta: CRC Press, 2019. doi: 10.1201/9780429461903.
[21] V. M. Santi, S. A. Angela, and Y. Mahatma, “Perception Analysis of Students of FMIPA UNJ in Using Distance Learning Application with Multinomial Logistic Regression,” *Jurnal Sains dan Matematika Unpam*, vol. 4, no. 2, p. 13220, 2022.
[22] R. M. Akhsanti, W. Rahayu, and V. M. Santi, “Klasifikasi Diagnosis Penyakit Kanker Payudara dengan Pendekatan Regresi Logistik Biner dan Metode Classification and Regression Trees (CART),” 2017.
[23] Ahdar, *Ilmu Pendidikan*. 2021.
[24] E. S. B. Siburian, M. D. Syafitri, R. S. Muliana, I. Maipita, and M. Rinaldy, “Pengaruh Tingkat Pendidikan, Pertumbuhan Ekonomi terhadap Pengangguran di Indonesia,” *JALAKOTEK: Journal of Accounting Law Communication and Technology*, vol. 1, no. 2, 2024.
[25] N. Yarrow *et al.*, “Janji Pendidikan di Indonesia,” 2019.
[26] F. Agustina Sairmaly, P. Studi Ekonomi Pembangunan, F. Ilmu Sosial dan Humaniora, and U. Lelemuku Saumlaki, “Human Capital Development and Economic Growth: A Literature Review on Information Technology Investment, Education, Skills, and Productive Labour,” *Jurnal Minfo Polgan*, vol. 12, no. 2, 2023, doi: 10.33395/jmp.v12i2.12491.
[27] M. R. A. Yonanda, N. I. Azzaahiroh, and A. Kurniya, “Analisis Pengaruh Tingkat Pendidikan dan Status Pekerjaan terhadap Pendapatan di Indonesia,” 2022.
[28] I. D. Apriliyani, M. Mochklas, and R. Maretasari, “Pengaruh Status Pekerja dan Disiplin Kerja terhadap Kinerja Karyawan pada PT Dana Purna Investama Kota Surabaya,” 2022.
[29] J. Duan, A. M. Peluso, L. Yu, and M. Pilati, “How employment relationship types influence employee work outcomes: The role of need for status and vigor,” *J Bus Res*, vol. 128, pp. 211–221, May 2021, doi: 10.1016/j.jbusres.2021.01.051.
[30] N. Jafrin, D. Ghosh, and A. N. M. Saif, “Do socio-demographic characteristics affect graduates’ employment status?,” *Discover Sustainability*, vol. 6, no. 1, Dec. 2025, doi: 10.1007/s43621-025-00850-5.
[31] C. Øien-Ødegaard, L. J. Hauge, and A. Reneflot, “Marital status, educational attainment, and suicide risk: a Norwegian register-based population study,” *Popul Health Metr*, vol. 19, no. 1, Dec. 2021, doi: 10.1186/s12963-021-00263-2.

[32] H. S. Amalia, "The Effect of Government Spending in The Education Sector and Employement Opportunities on The Human Development Index in Indonesia, 2015-2019," *Jurnal Pendidikan Ekonomi, Perkantoran dan Akuntansi*, pp. 2015–2019, Nov. 2022, doi: 10.21009/JPEPA.007.x.x.
[33] J. Suh, "Human capital inflow in nonprofits: Entry-level employees' sector shift," *Nonprofit Manag Leadersh*, vol. 28, no. 4, pp. 471–489, Jun. 2018, doi: 10.1002/nml.21303.