Jurnal Statistika Dan Komputasi (STATKOM), Vol. 5 No. 1 (June 2026)
ISSN : 2963-038X (print), ISSN : 2963-0398
DOI : https://doi.org/10.32665/statkom.v5i1.6402

STATKOM
JURNAL STATISTIKA DAN KOMPUTASI

Determinants of the Working Poor in the Papua Region of Indonesia: A Multilevel Logistic Regression Analysis

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Submitted: March 19, 2026 ***Revised:*** June 15, 2026 ***Accepted:*** June 18, 2026

Abstract

Background: *The working poor are employed individuals who fail to achieve a minimum standard of living, reflecting that employment does not guarantee economic well-being. The Papua Region of Indonesia exemplifies this paradox.*
Objective: *This study examines the determinants of working poverty at individual and regional levels in 2023.*
Methods: *A multilevel binary logistic regression is applied to hierarchical data of workers nested within regions.*
Results: *Approximately 23.22% of workers are classified as working poor. Male workers are 1.59 times more likely to experience working poverty than females. Rural workers face 1.57 times higher odds compared to urban workers. Informal employment substantially increases vulnerability, with workers 3.21 times more likely to be poor. Those working less than 35 hours per week have 2.06 times higher odds of poverty. Education shows a strong protective effect: workers with primary and secondary education are 2.69 and 2.10 times more likely, respectively, to be poor compared to tertiary graduates. Workers without training are also more vulnerable (OR=1.16). At the regional level, higher GRDP reduces the likelihood of working poverty (OR=0.981).*
Conclusion: *Reducing working poverty requires improving job quality, expanding education and training, and promoting inclusive regional economic growth.*

Keywords : *Working Poor, Multilevel Logistic Regression, Papua Region.*

Abstrak

Latar Belakang: Pekerja miskin adalah individu yang bekerja namun tidak mampu mencapai standar hidup minimum, menunjukkan bahwa bekerja tidak selalu menjamin kesejahteraan ekonomi. Wilayah Papua Indonesia mencerminkan paradoks ini.
Tujuan: Penelitian ini bertujuan menganalisis determinan pekerja miskin pada tingkat individu dan regional tahun 2023.
Metode: Penelitian menggunakan regresi logistik biner multilevel untuk menganalisis data hierarkis pekerja yang terkelompok dalam wilayah.
Hasil: Sebanyak 23,22% pekerja tergolong miskin. Pekerja laki-laki memiliki peluang 1,59 kali lebih besar untuk menjadi pekerja miskin dibandingkan perempuan. Pekerja di perdesaan memiliki peluang 1,57 kali lebih tinggi dibandingkan di perkotaan. Pekerja sektor informal 3,21 kali lebih berisiko menjadi miskin dibandingkan sektor formal. Pekerja dengan jam kerja kurang dari 35 jam per minggu memiliki peluang 2,06 kali lebih besar. Pendidikan berperan protektif: pekerja berpendidikan dasar dan menengah masing-masing 2,69 dan 2,10 kali lebih berisiko dibandingkan lulusan pendidikan tinggi. Pekerja tanpa pelatihan juga lebih rentan (OR=1,16). Pada tingkat regional, peningkatan PDRB menurunkan peluang kemiskinan pekerja (OR=0,981).
Kesimpulan: Penanggulangan pekerja miskin memerlukan peningkatan kualitas pekerjaan, akses pendidikan dan pelatihan, serta pertumbuhan ekonomi daerah yang inklusif.

Kata kunci: Pekerja Miskin, Regresi Logistik Multilevel, Papua.

INTRODUCTION

Poverty alleviation is a fundamental goal for countries worldwide, including Indonesia, as stated in the first goal of the Sustainable Development Goals (SDGs): to end poverty in all its forms everywhere (United Nations Development Programme, 2023). Efforts to address individuals' inability to meet basic needs must be approached through a multidimensional lens, considering aspects such as health, education, and living standards to provide a more comprehensive understanding of poverty (Alkire & Jahan, 2018). One important dimension of poverty is the working poor, individuals who, despite being employed, remain below the poverty line. This condition indicates that a substantial number of individuals or household members are unable to fulfill their basic needs (International Labour Organization, 2023), ultimately exacerbating social inequality and perpetuating the cycle of poverty.

The working poor are defined as individuals who earn wages below a certain threshold of the national median income, rendering them unable to meet basic needs despite being employed (International Labour Organization, 2023). According to data from Statistics Indonesia (Badan Pusat Statistik, 2023a), the regions with the highest percentage of poor populations are Maluku Island and the Papua Region of Indonesia, with a poverty rate of 19.68 percent. The trend of poverty reduction in these regions has been relatively slow, particularly in the Papua Region of Indonesia, which has consistently recorded the highest poverty rate in Indonesia. Therefore, an in-depth and contextual analysis of poverty issues, including the phenomenon of the working poor, is necessary to develop a more comprehensive understanding from multiple perspectives.

Various previous studies have examined the key determinants of the Working Poor . Education level, Human Development Index (HDI), regional own-source revenue (PAD), and the proportion of female workers have been shown to significantly influence the prevalence of Working Poor in Indonesia (Suryana and Swarniati, 2022; Rammohan and Tohari, 2023). Socioeconomic factors, such as educational attainment and residential location, are also highlighted as major determinants of the Working Poor (Le and Chung, 2020). Similarly, marital status, age, education level, gender, working hours, and area of residence have been identified as significant contributors to workers' vulnerability to poverty (Feder and Yu, 2020). A study in South Sumatra Province further demonstrated that regional conditions, particularly HDI, affect the Working Poor at the regional level, in addition to individual characteristics (Kusuma, 2021). Moreover, educational attainment has been recognized as an important factor in reducing poverty rates among workers (Whillans and West, 2022). Both demographic and structural factors play a crucial role in shaping workers' economic vulnerability (Salam et al., 2023). Consistently, other studies have shown that internet access, provincial minimum wages, employment sector and status, asset ownership, access to credit, and geographical location significantly influence the Working Poor (Faharuddin and Endrawati, 2022; Setyanti et al., 2024).

While many studies have extensively examined the issue of the Working Poor in Indonesia, existing literature suffers from critical gaps that this study explicitly aims to bridge. First, research focusing on the regional context of the Papua Region of Indonesia remains severely limited, with most national-level studies treating the country as a homogenous entity or focusing predominantly on the developed Western region (e.g., Java and Sumatra). This spatial blindness overlooks the profound socio-economic dualism, geographical isolation, and structural poverty unique to Papua, thereby failing to capture how localized macro-environments interact with individual vulnerabilities. Second, while conventional analyses heavily rely on standard demographic variables, the role of job training participation, a critical lever for human capital transformation, has been systematically omitted from previous Indonesian Working Poor models. Although global literature highlights that participation in training interventions can significantly improve employment prospects and job quality among vulnerable workers (Grimes et al., 2022), its empirical verification within a highly informal and resource-dependent economy like Papua remains non-existent.

Consequently, the novelty of this study compared to previous research is threefold. First, methodologically, it integrates individual job training with district-level structural factors into a unified multilevel framework, addressing the limitation of past studies that ignore how micro and macro factors simultaneously shape the Working Poor (Cheung and Chou, 2016). Second, in terms of measurement, this research diverges from the conventional use of the official government Poverty Line by utilizing the regional median income, providing a more realistic representation of relative economic strain in Papua. Third, empirically, it shifts from standard consumption surveys to the 2023 National Labor Force Survey (Sakernas) to capture granular, labor-specific dynamics. By addressing these gaps, this study redefines how the Working Poor is measured and modeled in a heterogeneous developing economy.

METHOD

Research Design

This study employed two analytical approaches: descriptive analysis and inferential analysis. Descriptive analysis provided an overview of the status of the working poor in the Papua Region of Indonesia in 2023, presented in tables and maps. Meanwhile, inferential analysis aimed to identify variables that significantly influence the status of the working poor, both at the individual and regional (district/city) levels. The method used in the inferential analysis was multilevel binary logistic regression with a random intercept, with a significance level of five percent.

Population and Sample

The study area encompasses the Indonesian jurisdiction in the Papua Region of Indonesia, covering all its provinces (40 districts and 2 cities). The term "Indonesian Papua region" is subsequently used solely for brevity and refers exclusively to this Indonesian territory, excluding Papua New Guinea. At the individual level, the unit of analysis in this study consists of the working-age population who are part of the labor force and are currently employed within the Indonesian Papua region. The individual-level sample data utilized in this research are secondary data, specifically raw data from the August 2023 National Labor Force Survey (Sakernas), which employs a two-stage stratified sampling design. This yielded a total of 178,284 individuals distributed across all districts and cities, representing the working-age population. Meanwhile, district/city-level data were obtained from official publications of BPS-Statistics Indonesia and gubernatorial decrees regarding the determination of district/city minimum wages.

Sampling Techniques

The individual-level data for poor workers in this paper utilize data from the 2023 National Labor Force Survey (Sakernas). We have also explained in the paper that the sampling technique used is a two-stage stratified sampling design. This yielded a total of 178,284 individuals distributed across all districts and cities, representing the working-age population. Meanwhile, district/city-level data were obtained from official publications of BPS-Statistics Indonesia and gubernatorial decrees regarding the determination of district/city minimum wages.

Research Subjects

Table 1 outlines the variables employed in this study, encompassing both dependent and independent variables at the individual and regional levels, along with their coding schemes and data sources.

Table 1. Research variables.

Variable	Description	Data Source
Dependent Variable		
Working Poor Status	0 = Not working poor* 1 = Working poor	Sakernas
Independent Variable (Individual Level)		
Gender	0 = Female* 1 = Male	Sakernas
Type of Residence Area (Area)	0 = Urban* 1 = Rural	Sakernas
Employment Status (Emp_Status)	0 = Formal* 1 = Informal	Sakernas
Weekly Working Hours (Work_hours)	0 = ≥35 hours* 1 = <35 hours	Sakernas
Education Level (Educ)	0 = Tertiary education* 1 = Secondary education 2 = Primary education	Sakernas
Participation in Training (Training)	0 = Has participated in training* 1 = Has never participated in training	Sakernas
Independent Variable (Regional Level)		
Regency/City Minimum Wage (RWG)	Numeric	Papua Governor's Decree
Gross Regional Domestic Product (GRDP)	Numeric	Statistics Indonesia (BPS)
Labor Force Participation Rate (LFPR)	Numeric	Statistics Indonesia (BPS)
Geographic Characteristics (Elevation)	Numeric	Statistics Indonesia (BPS)

*): Reference category

In this study, the working poor are defined as employed individuals with a per capita income below a specific relative threshold of the regional median income. To maintain consistency throughout the analysis, the threshold is strictly set at 60 percent of the regional median income, which aligns with widely accepted international relative poverty benchmarks (Llosa et al., 2022; Li, 2021).

The study variables consist of a single dependent (response) variable and multiple independent (explanatory) variables. The dependent variable is the working poor status, which is strictly dichotomous and categorical, coded as 1 if the employed individual's household per capita income is below 60 percent of the regional median income (province), and 0 if it is equal to or above this threshold. Although the response variable itself is binary at the individual level, a multilevel analysis framework is utilized because these individuals (Level 1) are hierarchically nested within distinct district/city jurisdictions (Level 2), allowing the model to capture both individual and macro-regional contextual effects simultaneously.

The independent variables are classified into two levels of analysis. At the individual level (Level 1), demographic and employment characteristics are included. Among these, working hours are categorized into underemployment (<35 hours per week) and full employment (≥35 hours per week). This specific cut-off is legally and empirically grounded in Indonesia's National Labor Force framework, which defines 35 hours as the structural boundary distinguishing underemployed workers from full-time workers, where shorter working hours are strongly associated with higher poverty risks due to reduced earning capacity (Badan Pusat Statistik, 2023b; Apella & Zunino, 2018). Meanwhile, the district/city level (Level 2) captures macro-economic indicators of the respective regions.

Data Analysis Techniques

Descriptive and inferential analysis techniques were employed in this study. Binary logistic regression is the most commonly used model for categorical dependent variables with two possible outcomes: 0 and 1 (Agresti, 2019; Card et al., 2017; Nurhikmah and Supandi, 2025). A multilevel approach was applied in this study due to the hierarchical structure of the data, where individual units of analysis are nested within larger regional groups (Hox et al., 2018). In the context of this study, the first level captures individual characteristics, while the second level represents regency/city characteristics in the Papua Region of Indonesia. The multilevel binary logistic regression model with random effects employed in this study is presented in the following equation.

$$ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \gamma_{00} + \gamma_{10}Gender_{ij} + \gamma_{20}Area_{ij} + \gamma_{30}Emp_{status_{ij}} + \gamma_{40}Work_{hours_{ij}} + \gamma_{50}Educ1_{ij} + \gamma_{60}Educ2_{ij} + \gamma_{70}Training_{ij} + \gamma_{01}RWG_j + \gamma_{02}GRDP_j + \gamma_{03}LFPR_j + \gamma_{04}Elevation_j + u_{0j} \quad (1)$$

Description:

π_{ij} : Conditional probability of working poor in i-th individual and j-th group

i : The i-th individu wherer i = 1,2,...,178284

j : The j-th regency/city where j = 1,2,...,42

γ_{00} : Intercept

γ_{10} : The fixed effects coefficient for the independent variable: gender

γ_{20} : The fixed effects coefficient for the independent variable: area

γ_{30} : The fixed effects coefficient for the independent variable employment status

γ_{40} : The fixed effects coefficient for the independent variable: working hours

γ_{50} : The fixed effects coefficient for the independent variable: education (secondary)

γ_{60} : The fixed effects coefficient for the independent variable education (primary)

γ_{70} : The fixed effects coefficient for the independent variable: training

γ_{01} : The fixed effects coefficient for the independent variable: RWG

γ_{02} : The fixed effects coefficient for the independent variable GRDP

γ_{03} : The fixed effects coefficient for the independent variable LFPR

γ_{04} : The fixed effects coefficient for the independent variable: elevation

u_{0j} : Random effect of the j-th area (regency/city)

The development of the multilevel binary logistic regression model began with several preliminary analysis stages. The first stage involved testing for random effects using the likelihood ratio test, aimed at evaluating the suitability of the multilevel model compared to the standard logistic regression model without random effects. Subsequently, the Intraclass Correlation Coefficient (ICC) was calculated to identify the proportion of variance in poor worker status attributable to differences across regencies/cities in the Papua Region of Indonesia. The ICC provides insight into the extent to which regional characteristics contribute to individual-level disparities in poor worker status.

The next stage involved simultaneous parameter testing using the G-test. This test was conducted to assess the joint significance of all independent variables on the dependent variable in the model. The null hypothesis (H_0) states that the independent variables do not have a significant simultaneous effect on the dependent variable. Hypothesis testing was conducted at a significance level (α) of 0.05. The decision rule was defined as follows: H_0 was rejected if the calculated G-test statistic exceeded the critical value or if the p-value was less than 0.05; otherwise, H_0 was not rejected. Rejection of H_0 indicates that at least one independent variable has a significant effect on the dependent variable. Consequently, the analysis proceeded to partial parameter testing to identify which independent variables significantly contributed to the model.

Partial parameter testing aims to identify which independent variables have a significant effect on the dependent variable at each level of the multilevel model (Hox et al., 2018). The Wald test is employed at this stage. The hypothesis tested at the first level is $H_0: \gamma_{p0} = 0$ versus $H_1: \gamma_{p0} \neq 0$, while at the second level, it is $H_0: \gamma_{0q} = 0$ versus $H_1: \gamma_{0q} \neq 0$. The statistical test formula is:

$$\text{Level 1: } W_{p0} = \frac{\hat{\gamma}_{p0}}{se(\hat{\gamma}_{p0})} \sim N(0,1) \quad (2)$$

$$\text{Level 2: } W_{0q} = \frac{\hat{\gamma}_{0q}}{se(\hat{\gamma}_{0q})} \sim N(0,1)$$

Using a significance level of 5% (α = 0.05), the null hypothesis for each parameter is rejected if the p-value is less than 0.05. This indicates that the p-th independent variable at level 1 or the q-th independent variable at level 2 has a statistically significant effect on the dependent variable. Subsequently, interpretation is performed using the odds ratio, as logistic regression is a non-linear model. The odds ratio is used to assess how specific categories of independent variables influence the likelihood of being classified as working poor in the Papua Region of Indonesia, relative to the reference category.

RESULTS AND DISCUSSION

Descriptive Analysis

The study reveals that 23.22 percent of workers in the Papua Region of Indonesia in 2023 were classified as working poor. This figure suggests that nearly one-fourth of the total workforce remains below the poverty line. The distribution of the working poor across regencies/cities in the Papua Region of Indonesia is presented in Figure 1. Darker shades of blue represent higher percentages of working poor, while lighter shades indicate lower percentages. Based on the map, it can be observed that most regencies/cities in the Papua Region of Indonesia have relatively high proportions of working poor. These findings reflect the persistent socioeconomic vulnerability in the region, where a significant portion of the working population still earns insufficient income to meet basic needs. The highest percentage of working poor was recorded in Intan Jaya District, at 77.6 percent.

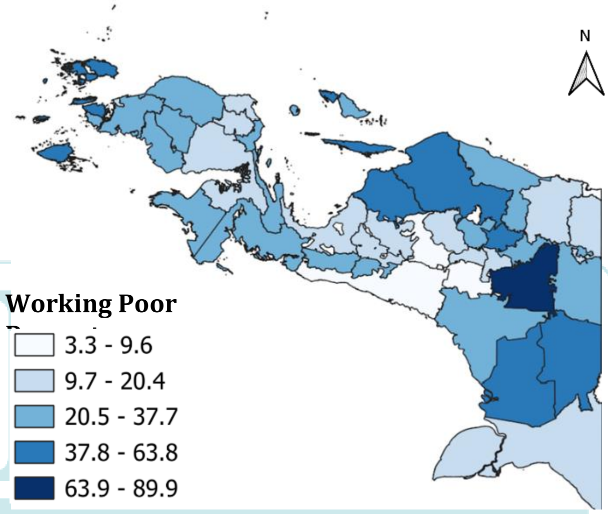

Figure 1. Distribution of the Working Poor Percentage in the Papua Region of Indonesia in 2023.

Information on the general characteristics of workers in the Papua Region of Indonesia by working poor status is presented in Table 2. It shows that 28.68 percent of female workers and 21.44 percent of male workers were classified as working poor. This finding indicates that female workers are more likely to experience poverty compared to their male counterparts. Based on the area of residence, 12.61 percent of workers living in urban areas and 29.29 percent of those in rural areas were identified as working poor. The higher proportion in rural areas suggests limited access to employment opportunities that offer decent wages. In general, rural employment tends to be informal and vulnerable to external disruptions such as extreme weather and natural disasters, which can lead to income instability for workers.

Table 2. Characteristics of Workers by Poverty Status in the Papua Region of Indonesia in 2023.

Variable	Category	Percentage (%)	Poverty Status	
			Poor (%)	Not Poor (%)
Gender	Female	24.64	28.68	71.32
	Male	75.36	21.44	78.56
Type of Residence Area	Urban	36.39	12.61	87.39
	Rural	63.61	29.29	70.71
Employment Status	Formal	29.98	8.23	91.77
	Informal	70.02	29.64	70.36
Weekly Working Hours	≥35 hours	63.52	16.03	83.97
	<35 hours	36.48	35.75	64.25
Education Level	Tertiary	13.50	7.89	92.11
	Secondary	27.20	16.85	83.15
	Primary	59.30	29.64	70.36
Participation in Training	Has participated in training	16.19	13.08	86.92
	Has never participated in training	83.81	25.18	74.82

Based on employment status, 8.23 percent of formal workers and 29.64 percent of informal workers were classified as working poor. The higher percentage among informal workers suggests that employment in the informal sector tends to offer lower wages and unstable working conditions, thereby increasing vulnerability to poverty. Furthermore, in terms of working hours, 16.03 percent of workers who worked more than 35 hours per week and 35.75 percent of those who worked less than 35 hours per week were categorized as working poor. The high proportion of working poor among those with fewer than 35 working hours per week indicates that limited working hours contribute to lower income, which ultimately raises the risk of being unable to meet basic needs.

Based on education level, 7.89 percent of workers with higher education, 16.85 percent with secondary education, and 29.64 percent with lower education were classified as working poor. These findings indicate that education level plays a significant role in determining a worker's poverty status. Workers with lower education levels generally possess limited skills, which restricts their employment options and often leads them to accept low-wage jobs. In terms of participation in training, 13.08 percent of workers who had attended training programs and 25.18 percent of those who had never participated in any training were categorized as working poor. The lack of participation in training may result in workers having only basic skills, which hinders their ability to access better-paying jobs.

Inference Analysis

Individual and regional characteristics presumed to influence working poor status in the Papua Region of Indonesia in 2023 were analyzed using a multilevel binary logistic regression model. The analysis began with a random-effects test using the likelihood ratio (LR) test. The null hypothesis (H_0: $\sigma^2_u = 0$) states that the variance of the random effects is equal to zero, indicating no significant variation between regions and that a single-level logistic regression model is sufficient. The LR test produced a statistic of 24,936.75 with a p-value of 0.000. Using a significance level of 5% ($\alpha = 0.05$), H_0 is rejected if the LR statistic exceeds the critical value of 3.84 or if the p-value is less than 0.05. Since the LR statistic is substantially greater than the critical value and the p-value is below 0.05, H_0 is rejected. Therefore, there is sufficient evidence to conclude that significant regional-level variation exists in working poor status, indicating the presence of random effects and confirming that the multilevel binary logistic regression model is more appropriate than a single-level logistic regression model.

The Intraclass Correlation Coefficient (ICC) was calculated to determine the proportion of variation in working poor status attributable to differences in regional group characteristics. The ICC result of 0.21 indicates that 21 percent of the total variance in working poor in the Papua region of

Indonesia is explained by district-level differences. Practically, this proves that working poor is influenced by macro-regional conditions and not just individual characteristics. One-fifth of workers' vulnerability is determined entirely by contextual factors such as the Regional Minimum Wage, regional economic output (GDP), Labor Force Participation Rate, and Geographic Location. Ignoring these macro-level dynamics will lead to mistargeted and individual-centered policies, fully justifying the need for a multilevel approach.

Simultaneous parameter testing was conducted to evaluate the overall significance of the independent variables in the model. The G-test yielded a statistic of 12,732.03, exceeding the critical value of 16.919. Thus, the null hypothesis (H_0) is rejected at the 5 percent significance level, indicating that at least one independent variable significantly affects the working poor status in the Papua Region of Indonesia in 2023. Given this result, the analysis proceeded with partial parameter testing, as summarized in Table 3.

Table 3. Parameter estimates, p-value, and odds ratio

Variable		$\hat{\gamma}$	*p-value* (one-tailed)	*Odds ratio*
Constant		-2.067	0.000*	0.1266
Gender	Female			
	Male	0.462	0.000*	1.588
Type of Residence Area	Urban			
	Rural	0.450	0.000*	1.568
Employment Status	Formal			
	Informal	1.166	0.000*	3.209
Weekly Working Hours	≥35 hours			
	<35 hours	0.723	0.000*	2.060
Education Level	Tertiary education			
	Secondary education	0.741	0.000*	2.099
	Primary education	0.990	0.000*	2.691
Participation in Training	Has participated in training			
	Has never participated in training	0.145	0.010*	1.156
Regency/City Minimum Wage (RWG)		0.062	0.877	1.064
Gross Regional Domestic Product (GRDP)		-0.019	0.000*	0.981
Labor Force Participation Rate (LFPR)		-0.017	0.131	0.983
Geographic Characteristics (Elevation)		-0.001	0.999	0.999

The results of the partial parameter testing presented in Table 3 show that individual-level characteristics significantly associated with working-poor status in the Papua Region of Indonesia in 2023 include gender, area of residence, employment status, working hours, education level, and participation in training. At the regional level, only Gross Regional Domestic Product (GRDP) was found to have a significant effect on working poor status. Other regional-level variables, namely District/City Minimum Wage (RWG), Labor Force Participation Rate (LFPR), and geographic location, did not show a statistically significant effect at the 5 percent level. Based on these results, the multilevel binary logistic regression equation with random effects can be formulated as follows:

$$\begin{aligned} ln\left(\frac{\hat{\pi}_{ij}}{1-\hat{\pi}_{ij}}\right) = & -2{,}067 + 0{,}462Gender^{*}_{ij} \\ & + 0{,}450Area^{*}_{ij} + 1{,}166Emp_{Status}{}^{*}_{ij} \\ & + 0{,}723Work_{Hours}{}^{*}_{ij} + 0{,}741Educ1^{*}_{ij} \\ & + 0{,}990Educ2^{*}_{ij} + 0{,}145Training^{*}_{ij} \\ & + 0{,}062RWG_j - 0{,}019GRDP^{*}_j \\ & - 0{,}017LFPR_j - 0{,}001Elevation_j \\ & + \hat{u}_{0j} \end{aligned}$$

Based on the results of the multilevel logistic regression, the gender variable showed a different pattern than the initial descriptive statistics. While the descriptive analysis revealed a higher percentage of Working Poor among female workers (28.68%) compared to male workers

(21.44%), the inferential model yielded a significant odds ratio of 1.588 for male workers ($p < 0.05$), with female workers as the reference category. This indicates that when all other individual and regional characteristics are held constant (ceteris paribus), male workers in the Papua region of Indonesia are actually 1.588 times more likely to be classified as working poor than female workers.

This discrepancy between descriptive and inferential findings represents a classic statistical phenomenon driven by variables in a hierarchical structure, commonly referred to as "Simpson's Paradox" (Wang et al., 2018). From a descriptive perspective, women are more likely to be working poor due to their high concentration in low-income areas. However, in models that account for variables like employment, hours worked, and district/city-level economic variation (such as GDP, minimum wage, TPAK, and geographic location), there is a shift in the results for the gender variable. This risk for men can be scientifically explained by labor market behavior in Papua; men are culturally expected to be the primary breadwinners, leading them to accept informal or typically high-risk daily contract work in sectors like construction or manual labor. While these jobs sometimes yield higher temporary wages, their extreme instability and lack of worker protection, under the same demographic and regional conditions, make male workers more likely to fall below the threshold of working poor. The impact of working poor has been shown to have a stronger impact on men's mental health due to the demands of the role as primary breadwinner (Pförtner & Demirer, 2022).

The area of residence variable was found to have a significant effect on working-poor status in the Papua Region of Indonesia in 2023. An odds ratio of 1.568 indicates that workers residing in rural areas are 1.568 times more likely to be classified as working poor compared to those living in urban areas, assuming other variables remain constant. Workers in rural areas, particularly in mountainous and highland regions, often face limited access to information about job opportunities, training programs, and new technologies. These limitations hinder their ability to enhance skills and increase income. Disparities in access to resources and employment opportunities are among the key factors contributing to the high poverty rates in rural areas (Ningsih, 2018).

Employment status has a significant effect on the working poor status in the Papua Region of Indonesia in 2023. An odds ratio of 3.209 indicates that workers in the informal sector are 3.209 times more likely to be classified as working poor compared to those in the formal sector, assuming other variables remain constant. This can be explained by the characteristics of the informal sector, which generally do not require high skill levels, resulting in relatively low income. This sector is often dominated by workers with limited expertise, leading to low productivity and limited ability to earn a decent wage (Satriawan, 2022). In contrast, formal workers such as permanent employees have better access to labor protection and stable income, making them less likely to face the risk of poverty (Faharuddin & Endrawati, 2022).

The test results indicate that working hours have a significant effect on the working poor status in the Papua Region of Indonesia in 2023. Workers who worked fewer than 35 hours per week were 2.060 times more likely to be classified as working poor compared to those who worked more than 35 hours per week, assuming other variables remain constant. Shorter working hours reflect limited time allocated for income-generating activities, which results in lower total earnings and increases the risk of being unable to meet basic living needs. Workers with fewer working hours often have weak job attachment, both structurally and contractually, contributing to higher levels of poverty.

Education level also significantly influences the working poor status in the Papua Region of Indonesia in 2023. The odds ratios were 2.691 for workers with primary education and 2.099 for those with secondary education. This indicates that individuals with only primary education are 2.691 times more likely to be classified as working poor compared to those with higher education, while those with secondary education are 2.099 times more likely, assuming other variables remain constant. Education is a key factor in accessing decent employment. Workers with higher education levels tend to possess better knowledge, technical skills, and adaptive capacity, which enhance their opportunities to secure well-paying and stable jobs. In contrast, individuals with lower education often face limited job options and are more likely to accept low-productivity, low-income jobs.

Training participation also shows a significant effect on working-poor status. An odds ratio of 1.156 suggests that workers who never participated in training programs are 1.156 times more likely to be classified as working poor compared to those who did, assuming other variables remain constant. Training plays a critical role in improving workers' knowledge and technical skills, increasing their chances of obtaining productive and better-paying jobs. Trained workers are generally more prepared to adapt to labor market dynamics and possess greater competitiveness, which ultimately reduces their risk of poverty (Permana et al., 2024).

The Gross Regional Domestic Product (GRDP) variable also has a significant effect on working poor status, with a coefficient of –0.019. This implies that for every one billion rupiah increase in GRDP, the likelihood of being classified as working poor decreases by a factor of 0.019, assuming other variables remain constant. GRDP reflects the level of economic activity in a region. Higher GRDP is expected to stimulate regional economic growth, thereby generating more employment opportunities and improving access to decent income. As such, economic growth has the potential to reduce the number of working poor through job creation and increased productivity. Additionally, policies such as minimum wage increases can further enhance worker welfare and reduce income inequality, particularly for low-income worker groups (Munarni et al., 2024).

CONCLUSION

Conclusion

In 2023, 23.22 percent of the workforce in Indonesia's Papua region was classified as working poor, a condition driven by a complex interaction of individual and regional factors. At the individual level, the study concluded that workers living in rural areas, engaging in informal employment, working less than 35 hours per week, and having limited education or vocational training were significantly predisposed to being Working Poor. Furthermore, while descriptive statistics indicate a higher proportion of Working Poor among women, multivariate models revealed that under identical demographic and structural conditions (ceteris paribus), male workers face a significantly higher likelihood of becoming working poor, primarily driven by their concentration in highly unstable and temporary informal employment. At the regional level, Regional Gross Domestic Product (GDP) is a statistically significant variable, indicating the profound influence of macroeconomic output on the economic resilience of the region's workforce.

Suggestions

To effectively reduce the working poor in the region, policymakers must shift from general assistance to targeted interventions that are structurally aligned with the statistically significant determinants identified in this study. First, given that Regional Gross Domestic Product (GDP) emerges as the only significant macro-level determinant, the government should implement a pro-poor economic growth strategy that deliberately diversifies the Papuan economy from capital-intensive extraction sectors to labor-intensive ones. This structural shift is crucial to ensuring that regional economic output directly translates into sustainable wage growth for the local workforce. Second, to address the high vulnerability found among rural and low-educated workers, the local government should implement decentralized vocational training programs tailored to local needs, directly bridging the skills gap within rural groups. Third, to address the high poverty risk associated with underemployment (<35 hours per week) and informal employment, policies should prioritize the formalization of informal small businesses through simplified licensing and subsidized access to social security (BPJS Ketenagakerjaan). This formal safety net is crucial for mitigating income fluctuations for male workers, who face a higher risk of in-work poverty in this model due to their concentration in unstable and temporary manual jobs. Finally, future research should incorporate a qualitative framework to unravel the specific socio-cultural dynamics and labor market mechanisms that drive the pronounced vulnerability among male workers in the Papuan context.

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