Gender Empowerment and Women's Socioeconomic Conditions as Predictors of Poverty: Evidence from Indonesia's Panel Data (2020–2024)

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Abstrak

This study examines whether gender empowerment and women's socioeconomic conditions help explain poverty variation in Indonesia during 2020–2024, a period when persistent poverty reduction efforts coincided with continuing gender gaps in education, work, and economic decision-making. The study aims to estimate the effects of the Gender Empowerment Index (GEI), women's average years of schooling (AYSW), the female labour force participation rate (FLFPR), and women's revenue contribution (RCW) on the percentage of poor population (P0). Using balanced provincial panel data, panel regression was applied and model selection tests (Chow, Hausman, and Lagrange Multiplier) indicated that the Random Effects Model is the most appropriate specification. The results show that GEI and AYSW have significant negative associations with poverty, implying that stronger empowerment and higher female educational attainment are linked to lower poverty rates across provinces. In contrast, RCW has a positive and significant association with poverty, suggesting that a higher female

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income ratio may reflect structural vulnerability (such as declining male earnings or low-quality, distress-driven work) rather than improved household welfare. FLFPR is negative but not statistically significant, indicating that participation alone does not necessarily reduce poverty without adequate job quality and earnings. Overall, the study concludes that gender empowerment and women's education are key levers for poverty reduction, while labour-market indicators require more nuanced interpretation. This research contributes recent provincial evidence on gender–poverty linkages and underscores policy implications for expanding women's education, strengthening empowerment, and promoting decent work conditions rather than focusing solely on participation rates.

Keywords
Gender empowerment, panel data regression, poverty, women's education

Introduction

Poverty remains a persistent global challenge. High poverty rates signal unequal development and reduced quality of life. In Indonesia, poverty has generally declined over recent decades, yet disparities across social groups, including between men and women, continue to be a significant concern (Badan Pusat Statistik 2025).

From a sustainable development perspective, strengthening women's empowerment is a strategic pathway for reducing poverty. Women often face structural barriers in accessing education, decent employment, and income-generating opportunities, despite their central role in supporting household and community well-being. As a result, gender-sensitive policy design is essential to ensure that poverty alleviation efforts address these constraints.

Women's empowerment in economic and political spheres is commonly captured by the Gender Empowerment Index (GEI), which reflects women's participation in decision-making, engagement in economic activity, and access to resources (Wisnujati 2020). Improvements in the GEI are expected to contribute to poverty reduction by enhancing women's ability to control resources and influence decisions that shape household welfare. Education is another critical dimension. Women's mean years of schooling (MYS) indicates access to learning opportunities that build skills and improve employability. Yacoub et al. (2023) emphasize that efforts to reduce poverty among women require strengthening both the quantity and quality of women's resources. Higher MYS can expand women's opportunities to secure decent work and stable income, with downstream effects on household welfare.

Labor market engagement is also central to the poverty–gender relationship. The Female Labor Force Participation Rate (FLFPR) captures the extent to which working-age women are economically active. Greater participation can raise household income and strengthen economic resilience, which may reduce poverty (Zahra & Usman, 2024). Beyond participation, women's income directly affects household purchasing power and living standards; larger earnings contributions by women have been associated with lower poverty levels (Ikhsan and Zulkifli 2022). Together, these indicators suggest that empowerment, education, and labor-market outcomes can jointly shape poverty dynamics.

Despite this growing scholarship, important gaps remain in Indonesia's evidence base. Much subnational quantitative research emphasizes pre-pandemic periods or limited time frames, while 2020–2024 captures COVID-19 disruptions and recovery dynamics that may have reshaped labour markets, schooling trajectories, and household coping strategies. In addition, many studies examine women-related factors separately rather than jointly modelling empowerment (GEI/IDG), education (women's MYS), labour participation (FLFPR), and women's income contribution in a single framework.

Against this backdrop, this study therefore aims to estimate the effects of (1) the GEI/IDG empowerment measure, (2) women's mean years of schooling, (3) the female labour force participation rate, and (4) women's income contribution on provincial poverty levels in Indonesia from 2020 to 2024 using panel data regression.

This study contributes in three ways. Empirically, it updates and strengthens evidence on gender–poverty linkages in Indonesia by focusing on the policy-relevant 2020–2024 period and leveraging provincial panel variation. Methodologically, it uses panel regression to account for unobserved regional heterogeneity and to better capture temporal and spatial dynamics than single-year cross-sectional approaches. Practically, it provides an evidence base for gender-responsive poverty reduction strategies, supporting the design of interventions that improve women's bargaining power and public participation (through empowerment), expand human capital (through schooling), widen access to decent work (through labour participation), and strengthen household resilience (through women's earnings).

Based on theoretical and empirical expectations, the study tests the following hypotheses: H1: Higher Gender Empowerment Index (GEI/IDG) is associated with lower regional poverty levels (P0); H2: Higher women's mean years of schooling is associated with lower regional poverty levels (P0); H3: Female labour force participation rate (FLFPR) has no statistically significant association with regional poverty levels (P0); and H4: Higher women's income contribution is associated with higher regional poverty levels (P0).

The findings are expected to inform gender-responsive poverty reduction policies by identifying which dimensions of women's empowerment and economic inclusion are most strongly associated with poverty outcomes across provinces. Academically, the study contributes updated empirical evidence on gender and poverty linkages in Indonesia during a period of major economic and social disruption, strengthening the broader literature on empowerment and welfare in developing-country contexts.

Method

Data Collection

This study uses secondary data obtained from Badan Pusat Statistik (BPS) covering 34 provinces in Indonesia over the period 2020 to 2024. The data sourced from BPS is selected due to its credibility as an official provider of socio-economic information across various regions in Indonesia.

The variables used in this study include the Percentage of Poor Population as P0, Gender Empowerment Index as GEI, Average Years of Schooling for Women as AYSW, Female Labor Force Participation Rate as FLFPR, and Revenue Contribution of Women as RCW. Each variable plays an important role in illustrating the quality of life and poverty levels in the regions analysed:

1) Percentage of Poor Population measures the level of poverty in a region (Y);

2) GEI assesses gender equality in access to and participation in economic, political, and decision-making domains in a region (X_1);
3) AYSW represents the average number of years of education completed by females aged 15 and above reflecting the level of education in a region (X_2);
4) FLFPR indicates the proportion of working-age women who are economically active in a region (X_3); and
5) RCW measures the proportion of income earned by women from the total income in a particular region (X_4).

The data collected from BPS is used to analyze the relationship between gender empowerment and the socio-economic factors of women with poverty, which is the primary focus of this research. Using this dataset, the study aims to explore the factors influencing poverty in Indonesia.

Panel Regression

Panel data regression is a statistical method used to examine the influence of multiple predictor variables on a response variable using data structured in panel form. The general form of a panel regression model is as follows (Alamsyah et al. 2022):

$$Y_{it} = \beta_{0it} + \sum_{k=1}^{n} \beta_{kit} X_{kit} + e_{it}$$

Where:

Y_{it} = Value of the dependent variable for cross-section unit *i* and time period *t*.

β = Intercept for cross-section unit *i* and time period *t*.

X_{kit} = Value of the k-th independent variable for cross-section unit *i* and time period *t*.

e_{it} = Error term for cross-section unit *i* and time period *t*.

i = Cross-section unit (1, 2, 3, ..., *N*).

t = Time period (1, 2, 3, ..., *T*).

k = Number of predictor variables (1, 2, 3, ..., *n*)

Panel Regression Models

a. Common Effect Model (CEM)

The common effect model combines cross-sectional and time-series data into a single model without accounting for individual or temporal differences. This is the simplest model among the three. The general equation is (Alamsyah et al., 2022):

$$Y_{it} = \beta_0 + \sum_{k=1}^{n} \beta_k X_{kit} + e_{it}$$

Where:

Y_{it} = Value of the dependent variable for cross-section unit *i* and time period *t*.

β_0 = Intercept.

X_{kit} = Value of the k-th independent variable for cross-section unit *i* and time period *t*.

e_{it} = Error term for cross-section unit *i* and time period *t*.

i = Cross-section unit (1, 2, 3, ..., *N*).

t = Time period (1, 2, 3, ..., *T*).

k = Number of predictor variables (1, 2, 3, ..., *n*)

b. Fixed Effect Model (FEM)

The fixed effect model estimates panel data by incorporating dummy variables as additional elements. This model assumes that there are significant individual-specific effects that can be explained through variations in each individual's intercept. Therefore, in FEM, each individual is treated as an unknown parameter estimated using dummy variable techniques, often referred to as the Least Square Dummy Variable (LSDV) method. The general equation is:

$$Y_{it} = \beta_{it} + \sum_{k=1}^{n} \beta_k X_{kit} + e_{it}$$

Where:

Y_{it} = Value of the dependent variable for cross-section unit *i* and time period *t*.

β_{it} = Intercept for cross-section unit *i* and time period *t*.

X_{kit} = Value of the k-th independent variable for cross-section unit *i* and time period *t*.

e_{it} = Error term for cross-section unit *i* and time period *t*.

i = Cross-section unit (1, 2, 3, ..., *N*).

t = Time period (1, 2, 3, ..., *T*).

k = Number of predictor variables (1, 2, 3, ..., *n*)

c. Random Effect Model (REM)

The random effect model estimates panel regression by considering individual and temporal differences through the error structure. The error term in this model consists of two components: one for the individual and one for time. Thus, the model error must be decomposed accordingly (Septianingsih, 2022). The general equation is:

$$Y_{it} = \beta_0 + \sum_{k=1}^{n} \beta_k X_{kit} + \varepsilon_i + e_{it}$$

Where:

Y_{it} = Value of the dependent variable for cross-section unit *i* and time period *t*.

β_0 = Intercept.

X_{kit} = Value of the k-th independent variable for cross-section unit *i* and time period *t*.

ε_i = Error term for cross-section unit *i*.

e_{it} = Error term for cross-section unit *i* and time period *t*.

i = Cross-section unit (1, 2, 3, ..., *N*).

t = Time period (1, 2, 3, ..., *T*).

k = Number of predictor variables (1, 2, 3, ..., *n*)

Panel Model Selection Tests

The selection of the panel regression model aims to identify the most appropriate and accurate model among the three types: common effect model, the fixed effect model, and the random effect model. To determine the most suitable panel regression model, the following tests are conducted (Alamsyah et al. 2022):

a. Chow Test

The Chow test is used to compare the common effect model and the fixed effect model. The hypotheses for the Chow test are as follows (Alamsyah et al. 2022):

H_0 : The model used is the common effect model

H_1 : The model used is the fixed effect model

The test statistics for the Chow test is as follows:

$$Chow = \frac{\frac{RRS-URRS}{N-1}}{\frac{URRS}{NT-N-K}}$$

Where:

RSS = $\sum e_i^2$

$URSS$ = $\sum e_j^2$

N = Number of individuals.

T = Number of time periods.

K = Number of independent variables.

e_i^2 = Sum of squared errors from the common effect panel data estimation.

e_j^2 = Sum of squared errors from the fixed effect panel data estimation.

If the Chow value $> F_{(n-1),(nT-n-K)}$ or p-value <α, then H_0 is rejected, indicating that the fixed effect model is the better fit. If the fixed effect model is selected, the next step is to conduct the Hausman test.

b. Hausman Test

The Hausman test is used to determine the better model between the fixed effect model and the random effect model. The hypotheses for the Hausman test are (Alamsyah et al. 2022):

H_0 : The model used is the random effect model

H_1 : The model used is the fixed effect model

The test statistics for the Hausman test is as follows:

$$\chi^2(K) = (b-\beta)'[var(b-\beta)]^{-1}(b-\beta)$$

Where:

b = Random efffect coefficient

β = Fixed Effect coefficient

The Hausman statistic follows a chi-square distribution. If the computed χ^2 value is greater than $\chi^2_{(K,\alpha)}$, where K is number of independent variables, or p-value $< \alpha$, then there is sufficient evidence to reject H_0 , and vice versa.

c. Lagrange Multiplier (LM) Test

The LM test is used to select the better model between the common effect model and the random effect model. The hypotheses for the LM test are (Fitrianasari, 2021):

H_0 : The model used is the common effect model

H_1 : The model used is the random effect model

The test statistics for the LM test is as follows:

$$LM = \frac{NT}{2(T-1)}\left[\frac{\sum_{i=1}^{N}\left(\sum_{t=1}^{T} e_{it}\right)^2}{\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}^2} - 1\right]^2$$

Where:

N = Number of individuals.

T = Number of time periods.

e_{it} = Error term from the random effect panel data estimation.

The LM statistic follows a chi-square distribution. If the computed χ^2 value is greater than $\chi^2_{(1,\alpha)}$ or p-value $< \alpha$, then there is sufficient evidence to reject H_0, and vice versa.

Residual Assumption Tests

a. Normality Test

The normality of residuals can be formally tested using the Jarque-Bera method (Nur et al. 2022), based on the following hypotheses:

H_0 : The residuals are normally distributed.

H_1 : The residuals are not normally distributed.

Test statistic:

$$JB = NT\left[\frac{S_k^2}{6} + \frac{(K-3)^2}{24}\right]$$

Where:

S_k = Skewness

K = Kurtosis

Rejection region: Reject H_0 if $JB > \chi^2_{2,\alpha}$

b. Multicollinearity Test

Multicollinearity occurs when there is a linear relationship between independent variables in the regression model (Nur et al., 2022). One method for detecting multicollinearity is by calculating the Variance Inflation Factor (VIF), with the following hypotheses:

H_0 : No multicollinearity in the data.

H_1 : Multicollinearity exists in the data.

Test statistic:

$$VIF_j = \frac{1}{1-R_j^2}; j = 1, 2, \ldots, k$$

Where R_j^2 is the coefficient of determination from the auxiliary regression between the j-th independent variable and the remaining $(k-1)$ independent variables.

Rejection region: Reject H_0 if $VIF > 10$.

c. Heteroscedasticity Test

Heteroscedasticity in panel regression can be tested using the LM test (Nur et al. 2022). The hypotheses are:

H_0 : No heteroscedasticity in the data.

H_1 : Heteroscedasticity exists in the data.

Test statistics:

$$LM = \frac{T}{2}\sum_{i=2}^{N}\left[\frac{\widehat{\sigma_i}^2}{\hat{\sigma}^2} - 1\right]^2$$

Where:

N = Number of individuals.

T = Number of time periods.

$\widehat{\sigma_i}^2$ = Residual variance of the equation for the i-th cross-section unit.

$\widehat{\sigma_i}^2$ = Residual variance of the system equation

Rejection region: Reject H_0 if $LM \geq \chi^2_{(N,-1;\alpha)}$

d. Autocorrelation Test

The assumption of independence relates to the absence of autocorrelation over time in the residuals (Nur et al. 2022). Autocorrelation refers to the correlation between one residual component and another. One commonly used method is the Durbin-Watson test, with the following hypotheses:

H_0 : No autocorrelation in the data.

H_1 : Autocorrelation exists in the data.

Test statistics:

$$d = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\left(\hat{u}_{it} - \hat{u}_{it} - 1\right)^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{u}_{it}}$$

Where $\hat{u}_{it}$ = residual of cross-section unit i at time t

Decision rule: As seen in Table 1.

Table 1. Decision Criteria for the Durbin-Watson Test

Durbin-Watson d Value	Conclusion
$0 < d < d_L$	Reject H_0 (positive autocorrelation)
$d_L \leq d \leq d_U$	No decision
$d_U \leq d \leq 4 - d_U$	Fail to reject H_0
$4 - d_U \leq d \leq 4 - d_L$	No decision
$4 - d_L \leq d \leq 4$	Reject H_0 (negative autocorrelation)

Parameter Significance Tests

a. Simultaneous Test

The simultaneous test is used to determine the influence of all independent variables on the dependent variable (Kusumaningrum et al. 2022), with the following hypotheses:

H_0 : $\beta_1 = \beta_2 = \ldots = \beta_k = 0.$

H_1 : At least one $\beta_j \neq 0$ for $j = 1, 2, \ldots, k.$

Test statistic:

$$F = \frac{\frac{R^2}{N+k-1}}{\frac{1-R^2}{NT-N-k}}$$

Rejection region: Reject H_0 if $F > F_{N+k-1;NT-N-k;\alpha}$

b. Partial Test

The partial test is used to identify individual independent variables that significantly affect the dependent variable (Kusumaningrum et al. 2022), with the following hypotheses:

$H_0 \quad : \beta_j = 0$
$H_1 \quad : \beta_j \neq 0$ for $j = 1, 2, \ldots, k$

Test statistic:

$$t = \frac{\widehat{\beta_j}}{se\left(\widehat{\beta_j}\right)}$$

Rejection region: Reject H_0 if $|t| > t_{\left(NT-k; \frac{\alpha}{2}\right)}$

Results

Descriptive Statistics

Based on Table 2, the Percentage of Poor Population (P0), which was used as the poverty indicator (Y), has a mean of 10.43 and a standard deviation of 5.39. Values range from 3.47 to 27.74, indicating substantial regional variation in poverty levels.

Table 2. Descriptive Statistics

Statistics	**P0**	**GEI**	**RCW**	**FLFPR**	**AYSW**
Minimum	3.47	79.59	23.64	42.25	5.7
Median	8.71	90.69	34.58	53.05	8.345
Mean	10.43	90.43	33.39	53.41	8.361
Maximum	27.74	95.56	44.58	70.63	11.19
Standard Deviation	5.387	3.142	4.274	6.116	0.995

The Gender Empowerment Index (GEI) (X_1), which captures women's access to economic resources, political participation, and decision-making, has an average of 90.43 with a standard deviation of 3.14. The index ranges from 79.59 to 95.56, suggesting that most regions demonstrate relatively strong gender empowerment, although some still record comparatively lower scores.

Women's average years of schooling (AYSW) (X_2), reflecting educational attainment among women aged 15 and above, shows a mean of 8.36 years and a standard deviation of 0.99. The values span from 5.70 to 11.19 years, implying that women in many regions have completed around junior high school on average, while a number of regions remain below that level.

The Female Labor Force Participation Rate (FLFPR) (X_3) averages 53.41% with a standard deviation of 6.12%, ranging from 42.25% to 70.63%. This points to generally moderate-to-high female labour market participation, alongside notable differences across regions.

Finally, PP (X_4), used as an indicator of average female income, has a mean of 33.39 and a standard deviation of 4.27, with values between 23.64 and 44.58. This wide range indicates pronounced disparities in women's average income across regions.

Panel Data Regression Model Estimation Results

As seen in Table 3, the Chow test result shows a p-value < 0.001, which is lower than the significance level of 0.05. This indicates that the null hypothesis is rejected, meaning the fixed effect model is preferable to the common effect model.

Furthermore, to determine whether the fixed effect or random effect model is more appropriate, the Hausman test was conducted and yielded a p-value of 0.829. Since this value is greater than 0.05, the null hypothesis fails to be rejected, indicating that the random effect model is more efficient and appropriate than the fixed effect model.

In addition, the Lagrange Multiplier (LM) test comparing the common effect and random effect models also resulted in a p-value < 0.001, indicating that the null hypothesis is rejected and that the random effect model outperforms the common effect model.

Table 3. Model Selection Results

Model Selection Test	***p-value***
Chow Test	$p < 0.001$
Hausman Test	0.829
LM Test	$p < 0.001$

Based on the model selection results above, it can be concluded that the most appropriate model for this study is the random effect model (REM). Hence, the research model is formulated as follows:

$$\hat{Y}_{it} = 48.5513^{*} - 0.4715X_1^{*} - 1.0116X_2^{*} + 0.0246X_3 + 0.3494X_4^{*}$$

Where:

Y_{it} = P0, or percentage of poor population

X_1 = GEI, or gender empowerment index

X_2 = AYSW, or mean years of schooling for women

X_3 = FLFPR, or female labor force participation rate

X_4 = PP, or revenue contribution of women

Assumption Tests

The multicollinearity test indicates that all independent variables have VIF values below 10. Therefore, the assumption of no multicollinearity is satisfied. The normality test using the Jarque-Bera statistic yields a p-value of 0.7408, which is greater than the 5 percent significance level. This implies that the residuals are normally distributed, fulfilling the normality assumption.

However, the Durbin-Watson test results indicate the presence of autocorrelation, as the p-value < 0.001, which is below the 5 percent threshold. Similarly, the heteroskedasticity test yields a p-value < 0.000, indicating that the residual variance is not constant.

Parameter Significance Test

The results of the multiple linear regression analysis show that the model is statistically significant, as indicated by the chi-square test statistic of 1600.52 with 4 degrees of freedom and a p-value < 0.000. The R-squared value is 0.615, and the adjusted R-squared is 0.608, indicating that approximately 60.797% of the variation in the Percentage of Poor Population (P0) can be explained by the independent variables used in the model, namely GEI, PP, FLFPR, and AYSW.

Partially, the GEI variable has a regression coefficient of -0.4715 with a p-value of 0.0001, indicating a negative and significant effect on poverty. This means that a one-unit increase in GEI will reduce poverty by 0.472

points, assuming other variables remain constant. This finding reinforces that gender equality contributes to poverty reduction.

The PP variable has a positive coefficient of 0.3494 and is significant with a p-value of 0.0016. This finding suggests that when the ratio of women's income to men's income increases, poverty also tends to increase. This may occur because an increase in the ratio does not necessarily imply a rise in women's income, but could instead result from a decline in men's income or other structural economic inequalities.

Meanwhile, the FLFPR variable shows a negative coefficient of 0.0246 but is not statistically significant ($p = 0.1729$), thus there is insufficient evidence to conclude a direct effect of female labour force participation on poverty levels. This may be due to the male labour force participation rate reaching 84.66%, which is significantly higher than the female rate of 56.42%, reflecting a gender gap in labour market participation. This discrepancy suggests that many working-age women are either unemployed or not actively seeking employment, which may be due to various factors such as household responsibilities, limited access to job opportunities, prevailing social and cultural norms that place women in domestic roles, and the lack of women-friendly workplace facilities such as childcare services.

The AYSW variable (average years of schooling for women) has a significant negative effect on the percentage of poor population, with a coefficient of -1.0116 and a p-value < 0.002. This suggests that an increase in the average years of schooling for women is associated with a reduction in poverty. This finding indicates the potential of education to alleviate poverty in regions across Indonesia.

Discussion

This study highlights that gender-related capabilities are strongly associated with regional poverty variation in Indonesia. Two results are consistent and theoretically coherent: higher Gender Empowerment Index (GEI) and higher women's average years of schooling (AYSW) are both linked to lower poverty incidence (P0). Together, these findings suggest that poverty reduction is not only a matter of aggregate growth, but also of how opportunities and resources are distributed across gendered social and economic structures.

The negative association between GEI and poverty aligns with empowerment theory that frames empowerment as a process through which resources translate into agency and, ultimately, improved well-being (Kabeer 1999). It is also consistent with broader evidence that gender equality is “smart economics,” where women’s expanded decision-making and access to opportunities improve household allocation and productivity (Duflo 2012; World Bank 2011). Indonesian evidence is generally supportive: Rohmatilah (2023), using district-level panel data, reports that improvements in gender equality indicators are associated with poverty reduction, reinforcing the idea that empowerment can operate as a structural lever rather than merely a social outcome.

Women’s schooling shows the largest poverty-reducing coefficient, which is in line with human-capital and capability perspectives: education enhances productivity, expands access to higher-quality employment, and strengthens bargaining power within households (World Bank 2011). Cross-country panel research similarly shows that gender gaps in education and employment are economically consequential and can suppress development outcomes (Klasen & Lamanna, 2009). In the present results, AYSW likely captures both direct lab or-market returns and indirect intergenerational effects (such as improved child health and schooling), which are repeatedly documented in development research (Duflo 2012).

Two findings require more cautious interpretation. First, FLFPR is negative but not statistically significant, echoing arguments that participation rates alone do not guarantee poverty reduction when women are concentrated in informal, low-paid, or unpaid family work (Verick 2014). For Indonesia, long-run analysis shows that trends in female participation depend heavily on urban–rural differences, job availability, and movement from unpaid/informal work into wage employment (Schaner and Das 2016). This helps explain why FLFPR may not map neatly onto poverty outcomes: what matters is the *quality and remuneration* of jobs, not simply entry into the labour force.

Second, the positive association between PP (women’s income contribution ratio) and poverty contrasts with some Indonesian studies that find women’s income is poverty-reducing (e.g., Adnan and Amri 2021). This difference may be measurement-driven: a rising income ratio can occur because men’s earnings fall (such as sectoral shocks), not because women’s earnings rise. It may also reflect “coping” dynamics where women increase labour supply in low-wage work when households face distress (Verick 2014). In this sense, a higher PP could signal vulnerability rather than empowerment.

Practically, the results imply that poverty policy should prioritize (a) investments that raise women's educational attainment and skills and (b) empowerment-enhancing reforms (access to resources, voice, and decision-making). At the same time, labour policy should move beyond participation targets toward "decent work" pathways (formalization, childcare support, safe transport, and enforcement of fair pay) to convert women's labour into poverty-reducing income.

Several limitations should be noted. The presence of heteroskedasticity and autocorrelation suggests that inference should rely on robust/clustered standard errors. Endogeneity is plausible (poverty can influence schooling and empowerment), and the random-effects assumption may be violated if unobserved regional traits correlate with regressors. Finally, P0 captures incidence rather than depth of poverty; future work could incorporate poverty gaps, explore nonlinearities, and test mechanisms (such as job quality mediating FLFPR and PP effects).

Conclusion

This study set out to estimate how four gender-related factors (the Gender Empowerment Index (GEI/IDG), women's mean years of schooling, the female labour force participation rate (FLFPR), and (4) women's income contribution) affect regional poverty levels in Indonesia over 2020–2024 using panel data regression. It indicates that (1) GEI shows a negative and statistically significant association with poverty, indicating that higher women's empowerment is linked to lower provincial poverty rates; (2) women's mean years of schooling also has a negative and significant effect, suggesting that improved female educational attainment is a strong predictor of poverty reduction; (3) FLFPR does not exhibit a statistically significant effect on poverty within the model, implying that participation alone may be insufficient to reduce poverty without considering job quality, informality, or wage conditions; (4) women's income contribution is positively and significantly associated with poverty, suggesting that increases in women's relative income contribution may reflect structural vulnerabilities such as declining male earnings or unequal labour-market conditions rather than a straightforward improvement in women's welfare. Methodologically, model selection tests indicate that the random effects model is the most appropriate specification for the provincial panel dataset.

Several limitations should be acknowledged. The diagnostic tests indicate heteroskedasticity and autocorrelation, which may affect statistical efficiency and inference if not fully addressed with robust approaches. In addition, the study relies on available provincial indicators and a poverty headcount measure (P0), which may not capture poverty depth or severity. Finally, potential endogeneity and reverse causality cannot be fully ruled out, as poverty may also shape women's education, empowerment, and labour outcomes.

Future research should extend this work in three directions. First, studies should incorporate additional contextual controls, such as health access, sectoral employment structure, informality rates, social protection coverage, and regional price levels, to better isolate mechanisms linking gender variables to poverty. Second, researchers should test alternative poverty outcomes, such as poverty gap, severity, and explore non-linearities and interaction effects, such as education and employment structure, to capture heterogeneous impacts across provinces. Third, applying stronger causal strategies, such as instrumental variables, dynamic panel models, or quasi-experimental designs, would help clarify whether improvements in empowerment and schooling *cause* poverty reduction and why women's income contribution shows a positive association in this period.

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