CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 11 (2) (2026), Pages 2429–2455
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Partial Least Squares Structural Equation Modeling with Prediction-Oriented Segmentation for Analyzing Community Welfare in East Java Province

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Abstract

This study examines the relationships between infrastructure development, community empowerment, government governance, and community welfare across 38 regencies and cities in East Java, Indonesia, using secondary data from 2022–2024. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze these relationships, while Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS) explored regional heterogeneity. Infrastructure development was positively and significantly associated with community welfare and government governance, but negatively associated with community empowerment. Community empowerment and government governance were not significantly related to community welfare, and none of the tested indirect effects was significant. PLS-POS identified two exploratory segments: Segment 1 (14 regions; 36.84%) had relatively higher welfare and infrastructure development scores but lower empowerment and governance scores, whereas Segment 2 (24 regions; 63.16%) showed the opposite pattern relative to the overall mean. Most structural relationships showed similar patterns across segments, although the community empowerment–welfare relationship differed in sign. Run 12 achieved the highest objective criterion value among 20 runs, but variation in segment membership across random starts and the absence of formal between-segment significance tests limit the conclusions. These findings should therefore be interpreted as exploratory. Future research should use larger datasets and formal tests, such as Multi-Group Analysis (MGA) or permutation tests, to assess whether segment differences are statistically significant.

Keywords: Community Welfare; PLS-POS; PLS-SEM; Segmentation

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1. Introduction

Community welfare is commonly conceptualized in terms of quality of life, as reflected in adequate access to public services, respect for social rights, and economic security [1]. In East Java Province, community welfare still faces persistent challenges: the poverty rate was 10.38%, and the unemployment rate was 4.81% as of March 2022 [2, 3]. Although 95.05% of households have access to safe drinking water, high poverty levels, limited budgets for poverty alleviation,

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Received: August 07, 2026 Revised: October 13, 2026 Accepted: October 22, 2026
DOI: https://doi.org/10.18860/cauchy.v11i2.45524

and uneven infrastructure development remain concerns [4, 5]. These conditions are consistent with disparities in community welfare indicators across regencies and cities in East Java Province and warrant further investigation.

Community welfare has been linked to social, economic, and institutional factors, with community empowerment, infrastructure development, and government governance frequently discussed as key correlates [6–8]. Community empowerment strengthens local capabilities, infrastructure development facilitates access to and the distribution of goods and services, and good governance supports effective, transparent, and accountable policies [9–11].

This study combines Partial Least Squares–Structural Equation Modeling (PLS-SEM) with Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS). PLS-SEM was chosen for its ability to analyze complex relationships between latent variables that are not directly measurable but are represented by several measurable indicators [12]. Furthermore, the PLS-POS approach is used to detect unobserved heterogeneity by grouping observations into multiple segments to improve the model's predictive power [13].

Numerous studies on community welfare have been conducted using various analytical methods. Nurhidayati (2023) applied PLS-SEM to examine the associations between latent variables and community welfare in rural areas of East Java Province [14]. However, this study assumed data uniformity and therefore did not account for differences between regions. Eliani (2023) used PLS-POS to detect heterogeneity, but the study was limited to the health sector [15]. Furthermore, Utaminingsih and Suwendra (2022) applied linear regression, which only models direct relationships between variables and does not fully account for complex relationships between latent variables [16]. Finally, Standsyah's (2021) work showed that the MASEM approach with generalized method of moments (GMM) estimation allows for the estimation of structural relationships based on a synthesis of previous research results [17]. However, this study focused on developing a meta-analytical estimation method and did not explore community welfare at the district/city level or identify regional heterogeneity. Thus, a research gap exists because PLS-SEM and PLS-POS have not yet been used together to study community welfare at the district or city level.

This study examines associations among community empowerment, infrastructure development, government governance, and community welfare across the regencies and cities of East Java Province and explores whether these associations differ across unobserved segments. The contribution of this research lies in combining PLS-SEM and PLS-POS to evaluate community welfare at the regency and city level. The findings are intended to provide an empirical basis for further discussion of regional development priorities [18].

2. Methods

This section describes the methods used to assess the associations among community empowerment, infrastructure development, government governance, and community welfare across the regencies and cities of East Java Province. The research framework combines Partial Least Squares Structural Equation Modeling (PLS-SEM) with Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS). The analysis proceeded in the following stages: data collection and preparation; specification of the measurement and structural models; evaluation of the measurement and structural models, including predictive assessment using PLSpredict; hypothesis testing, including the assessment of specific indirect effects; segmentation using PLS-POS; and interpretation of the results. The settings used for each analytical procedure are reported to facilitate replication.

2.1. Research Procedure

This study used secondary observational data from the Central Statistics Agency (BPS) of East Java Province, the East Java One data portal, and performance reports published by relevant government agencies, covering 38 regencies and cities in East Java Province for 2022–2024. To

summarize the data for each region over this period, the values of each indicator for 2022, 2023, and 2024 were averaged, yielding a single value per indicator for each regency or city. These averaged values were then used as input for the PLS-SEM analysis. Thus, although the source data covered three years, the resulting dataset was cross-sectional, with 38 regional observations.

This study includes four constructs: community welfare, infrastructure development, community empowerment, and government governance. Community welfare, community empowerment, and government governance are endogenous constructs, whereas infrastructure development is an exogenous construct. Each construct is measured by several indicators, as presented in Table 1.

Table 1: Constructs and Measurement Indicators

No.	Constructs	Indicators	Reference
1	Endogenous Constructs		
	Community Welfare	CW_1: Income (GRDP) CW_2: Average years of schooling CW_3: Life expectancy	[19]
	Community Empowerment	CE_1: Village-owned enterprise (BUMDesa) ratio CE_2: Women's business empowerment (PUSPA) ratio CE_3: Posyandu ratio	[20–22]
	Government Governance	GG_1: Criminal case resolution rate GG_2: Government agency performance accountability (SAKIP) evaluation score GG_3: Electronic-based government system (SPBE) index	[23]
2	Exogenous Construct		
	Infrastructure Development	ID_1: Percentage of households with access to improved drinking water ID_2: Hospital ratio ID_3: Percentage of households with access to adequate sanitation	[24, 25]

Population sizes vary across regencies and cities, so relying solely on absolute counts can lead to misleading conclusions. To facilitate comparisons across regions, selected indicators originally expressed as absolute counts were converted into relative measures using appropriate denominators. For instance, the number of hospitals, village-owned enterprises (BUMDesa), women's business empowerment programs (PUSPA), and integrated health posts (Posyandu) were expressed as ratios using the population or another appropriate denominator, as listed in Table 1. These ratios represent the relative availability of facilities or programs rather than their absolute numbers [26].

Specifically, the hospital ratio (RSU) was calculated by dividing the number of general hospitals by the total population and multiplying the result by 100000. The BUMDesa ratio was calculated by dividing the number of BUMDesa by the number of villages and multiplying the result by 100. The PUSPA ratio was calculated by dividing the number of PUSPA units by the female population and multiplying the result by 1000. Similarly, the Posyandu ratio was calculated by dividing the number of Posyandu units by the total population and multiplying the result by 1000. The same calculation procedures were applied consistently across all 38 regencies and cities in East Java.

Following the conversion of the relevant indicators into ratios, the average value of each indicator for each regency or city over the 2022–2024 period was calculated. The resulting average values were then standardized using the Z-score method. This procedure placed indicators measured in different units or with different value ranges on a comparable scale, reducing the influence of differences in measurement scales on the analysis. The standardized values were subsequently used as inputs for the PLS-SEM analysis.

After data preparation and standardization, the measurement and structural models were specified based on the research framework. The measurement model shows how the constructs

are linked to their specific indicators, while the structural model specifies the hypothesized associations among the constructs studied. The model used in this study is shown in Fig. 1.

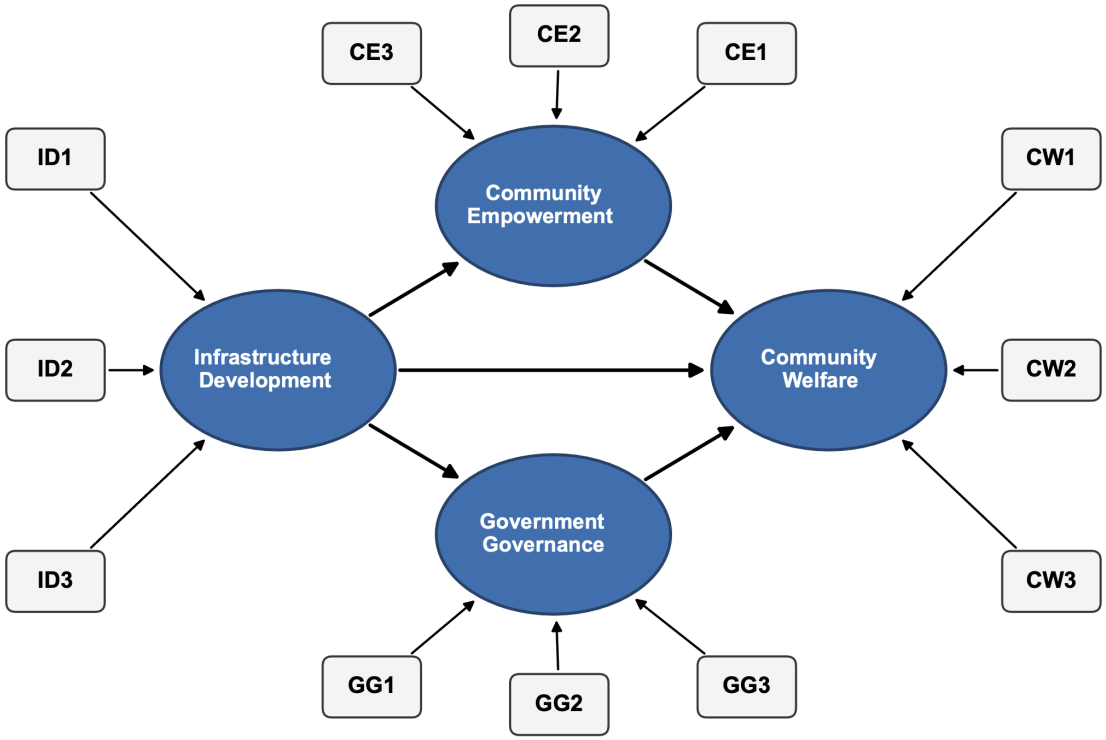


Fig. 1: Measurement and Structural Models of Community Welfare

In this study, community welfare, community empowerment, infrastructure development, and government governance were specified using formative measurement models. This specification reflects the premise that the indicators represent distinct dimensions and collectively constitute the construct; consequently, they are neither interchangeable manifestations nor necessarily strongly intercorrelated [27].

Community welfare is measured by income (GRDP), life expectancy, and average years of schooling, which represent the economic, health, and educational dimensions, respectively. Community empowerment is measured by village-owned enterprises (BUMDesa), women's business empowerment programs (PUSPA), and integrated health posts (Posyandu), which represent women's economic empowerment, the village's economic and institutional capacity, and community health services, respectively [20–22]. Infrastructure development is measured by access to clean water, access to sanitation, and the ratio of healthcare facilities; the first two represent basic infrastructure and the third represents health infrastructure, and the presence of one does not guarantee the presence of the others [24, 25]. Government governance is measured by the resolution of criminal cases, the Government Agency Performance Accountability System (SAKIP), and the Electronic-Based Government System (SPBE), which represent case processing, performance accountability, and administrative digitalization, respectively [23]. The indicators thus provide distinct, non-interchangeable information that collectively represents each construct's conceptual scope.

The model was evaluated using a formative measurement approach, which involved assessing indicator collinearity and evaluating the importance and relevance of each indicator. Redundancy analysis is commonly used to assess the convergent validity of formative constructs by comparing the formative construct with an independent global or reflective measure of the same concept. However, redundancy analysis was not performed in this study because an appropriate independent global or alternative measure of the corresponding constructs was unavailable in the dataset. The collinearity of the indicators was checked by means of variance inflation factor (VIF) values

to identify potential multicollinearity that could affect the estimation of outer weights. The significance and relevance of each indicator were assessed using its outer weight. For non-significant weights, the corresponding outer loading was examined to assess the indicator's contribution to the construct.

Once the measurement model's validity was confirmed, the analysis proceeded to evaluate the structural model (inner model). This evaluation followed several sequential steps. The first step involved checking for structural collinearity using Variance Inflation Factor (VIF) values for the predictor constructs to ensure the absence of multicollinearity, which could bias path coefficient estimates among the constructs. The second step used the coefficient of determination (R^2) to assess the variance explained in each endogenous construct. In the third step, effect size (f^2) was calculated to examine the contribution of each predictor construct to the target endogenous construct. The final step involved assessing the model's out-of-sample predictive ability with respect to the endogenous constructs using the PLSpredict procedure (10-fold cross-validation, 10 repetitions), by means of Q^2_{predict} and RMSE compared against a linear model (LM) benchmark.

In the next stage, the hypotheses were tested using bootstrap resampling with 5000 subsamples. This nonparametric method makes no assumptions about the distribution of the data. T-statistics and p-values were employed to determine the significance of the path coefficients. Since the research framework includes mediation pathways, the significance of the particular indirect paths was assessed by means of 95% percentile confidence intervals. A direct path was regarded as significant when its p-value was less than 0.05, and an indirect path was considered significant if its confidence interval did not include zero.

The analysis phase then involved segmentation using the Partial Least Squares-Prediction-Oriented Segmentation (PLS-POS) technique to detect hidden heterogeneity. This process divides districts or cities into more uniform groups based on how latent variables relate to each other. The findings from this segmentation were then used to draw conclusions about the associations of community empowerment, infrastructure development, and government governance with community welfare, as well as to explain the characteristics of the relationships between variables within each identified group. The analysis and segmentation were performed using SmartPLS.

2.2. Data Standardization

The indicators of all constructs were standardized using the Z-score transformation to account for differences in measurement scales [28]. This standardization assigns each indicator a mean of zero and a standard deviation of one [29]. The Z-score for each observation was calculated using Eq. (1):

$$Z_{ij} = \frac{X_{ij} - \bar{X}_j}{s_j} \tag{1}$$

where X_{ij} represents the value of construct j for observation i, $\bar{X}_j$ is the mean of construct j, and s_j is the standard deviation of construct j.

2.3. Partial Least Squares–Structural Equation Modeling (PLS-SEM)

2.3.1. Measurement Model

The measurement model in Partial Least Squares–Structural Equation Modeling (PLS-SEM) explains how constructs relate to the indicators used to evaluate them. Measurement models are either reflective or formative [30]. This study uses formative measurement models, in which the indicators collectively constitute the constructs [31]. The relationship between the formative indicators and their corresponding construct is expressed in Eq. (2).

$$\eta = \gamma_1 x_1 + \gamma_2 x_2 + \cdots + \gamma_n x_n + \zeta \tag{2}$$

where η represents the formative construct, x_i is the i-th formative indicator, γ_i is the weight or contribution parameter of the i-th indicator, and ζ is the disturbance term representing the portion of the construct not explained by the indicators used [32].

Researchers evaluate formative measurement models by examining convergent validity, collinearity among indicators, and the significance and relevance of indicator weights (outer weights). Convergent validity can be assessed using redundancy analysis, which involves correlating the formative construct with an alternative reflective measure or a single-item measure of the same concept. A formative construct is considered to exhibit adequate convergent validity if the correlation value is greater than or equal to 0.708 [31]. However, redundancy analysis was not performed in this study because an appropriate independent global or alternative measure of the corresponding constructs was unavailable in the dataset. Therefore, convergent validity through redundancy analysis could not be assessed.

Collinearity among indicators is evaluated using Variance Inflation Factor (VIF) values to confirm that multicollinearity does not distort indicator weighting estimates. A VIF of 5 or higher shows a serious collinearity problem. Values from 3 to 5 are usually acceptable, while a VIF below 3 indicates no major collinearity issues [31].

The significance of the indicator weights (outer weights) is tested using a bootstrapping procedure, with significance established if the t-statistic exceeds 1.645 ($\alpha = 0.10$), 1.960 ($\alpha = 0.05$), or 2.576 ($\alpha = 0.01$) in a two-tailed test [31].

The importance of indicators that have significant weights is determined by the size of those weights: the larger the significant weight of an indicator, the more substantial its relative contribution to the construct. Indicators with non-significant weights can be retained if their outer loadings are at least 0.50 and statistically significant [31].

2.3.2. Structural Model

The structural model used in PLS-SEM describes the relationships between constructs. The assumptions of this model are tested using a bootstrap resampling procedure.

The bootstrap method is a non-parametric statistical technique used to test significance in PLS-SEM models; it achieves this by resampling with replacement to calculate the standard error values involved in hypothesis testing. Bootstrapping helps reduce unreliability by generating surrogate data with characteristics similar to those of the original data. The structural model is expressed in Eq. (3):

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3}$$

where B is the matrix of path coefficients describing the relationships among endogenous constructs, Γ is the matrix of path coefficients representing the associations between the exogenous construct and endogenous constructs, and ζ is the vector of structural error terms.

A structural collinearity test used Variance Inflation Factor (VIF) values for the predictor constructs to ensure multicollinearity was absent, as it could bias path coefficient estimates. A VIF value ≥ 5 indicates a critical collinearity issue; values between 3 and 5 are generally considered tolerable, whereas VIF values < 3 indicate the absence of significant structural collinearity issues [31].

The R^2 value indicates the proportion of variance in an endogenous construct explained by its predictors. In PLS structural equation modeling (PLS-SEM), R^2 measures in-sample predictive power because it uses the entire sample dataset. An R^2 of 0.75 is seen as substantial, 0.50 as moderate, and 0.25 as weak. Still, it is important to consider the model's context and complexity, so these numbers should not be used as strict cutoffs. Very high R^2 values can mean the model is overfitting, so it is best to interpret them carefully and compare them with the adjusted R^2 value [31].

The effect size (f^2) assesses how much an exogenous construct contributes to the R^2 of an endogenous construct if that construct were removed from the model. An f^2 value of 0.02 is a small effect, 0.15 a medium effect, and 0.35 a large effect [33].

Predictive ability was assessed using PLSpredict with k-fold cross-validation (10 folds, 10 repetitions). Q^2_{predict} and RMSE were reported for each indicator of the endogenous constructs, and then the PLS model RMSE was compared with that of a linear model (LM) benchmark. A

Q^2_{predict} value greater than zero indicates that the PLS model predicts better than a simple mean prediction. Predictive ability was evaluated across all indicators of the endogenous constructs: it was considered high if the PLS RMSE was lower than the LM RMSE for all indicators, medium for most indicators, low for a minority of indicators, and absent if none of the indicators met this condition [34].

2.3.3. Hypothesis Testing

The significance of the hypothesized direct relationships between constructs is assessed by bootstrapping the path coefficients. This significance is evaluated using the t-statistic and p-values; the significance criterion is met when the t-statistic exceeds 1.96 (at a 0.05 significance level) in a two-tailed test or when the p-value is below 0.05. The direction of the relationship between the constructs is shown by the positive or negative sign of the path coefficient (β), and the magnitude of β shows the strength of the association between an exogenous construct and an endogenous construct [35].

The research model includes mediation pathways from the exogenous construct to the endogenous construct. The significance of the specific indirect paths was assessed using bootstrapping with 5000 subsamples [36], based on t-statistics, p-values, and 95% percentile confidence intervals (2.5% and 97.5% bounds) obtained from bootstrapping. A specific indirect path was regarded as significant if its p-value was below 0.05 and its confidence interval did not contain zero [31].

2.4. Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS)

Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS) is a segmentation approach integrated with PLS path modeling to identify unobserved heterogeneity in structural relationships. The method partitions observations into groups with potentially different structural model relationships. It iteratively assigns observations to segments based on a distance measure designed to improve the predictive performance of the model, evaluated using the coefficient of determination R^2 of the endogenous target construct [37]. The distance measure used in the PLS-POS procedure is defined in Eq. (4).

$$D_i(k \to g) = \sqrt{\sum_b \frac{e^2_{i,b,g}}{\sum_{j \in I_k} e^2_{j,b,k}}} \tag{4}$$

In this equation, $e^2_{i,b,g}$ represents the squared residual of observation i when assigned to the alternative segment g where $k \neq g$ and $k, g \in G$. The term $\sum_{j \in I_k} e^2_{j,b,k}$ denotes the sum of squared residuals for all observations in the initial segment k. The symbol b represents the endogenous latent variable, while I_k denotes the sample size of the initial segment k.

Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS) was conducted to explore potential unobserved heterogeneity across 38 regencies and cities in East Java Province, Indonesia. The number of segments was set to two to investigate potential differences in structural relationships between groups of observations.

The PLS-POS algorithm uses a hill-climbing approach to optimize the Sum of Target Construct R-square criterion, taking community welfare as the target construct. While optimizing, the observations are reallocated among the segments until either no additional improvement can be made in the objective criterion or the maximum of 1000 iterations is reached. The search depth was set to 38, corresponding to the number of observations. To assess sensitivity to the initial partition and possible convergence to a local optimum, PLS-POS was run 20 times using different initial partitions but with the same model specifications. The solution that obtained the highest value for the objective criterion was selected as the best-performing solution among the 20 runs, and segment membership was compared across runs to assess segmentation consistency [37].

3. Results and Discussion

The results are organized into five sections: measurement model evaluation, structural model evaluation, hypothesis testing, PLS-POS segmentation results, and analysis of the findings. Each section focuses on the methods relevant to the research objectives.

3.1. Measurement Model Evaluation

In formative measurement models, convergent validity can be assessed using redundancy analysis, which involves comparing a formative construct with an independent global or alternative measure of the same concept. However, redundancy analysis was not performed in this study because appropriate independent global or alternative measures were unavailable for the four constructs examined: community welfare, community empowerment, infrastructure development, and government governance. The indicators used to form these constructs, as well as indices derived from the same indicators, were not considered suitable independent measures for this purpose. Therefore, convergent validity through redundancy analysis could not be assessed. Instead, the formative measurement models were evaluated by examining indicator collinearity using the variance inflation factor (VIF), the significance and relevance of outer weights and outer loadings, and the theoretical relevance of each indicator to its respective construct.

Indicator collinearity was assessed using the variance inflation factor (VIF) to identify potential multicollinearity among the formative indicators. High multicollinearity may affect the estimation and interpretation of outer weights. The results of this assessment are presented in Table 2.

Table 2: Collinearity Assessment of Formative Indicators Using VIF

Constructs	Indicators	VIF
Community Welfare	1. Income (GRDP)	1.296
	2. Average years of schooling	2.412
	3. Life expectancy	2.337
Community Empowerment	1. Village-owned enterprise (BUMDesa) ratio	1.660
	2. Women's business empowerment (PUSPA) ratio	1.714
	3. Posyandu ratio	1.043
Government Governance	1. Criminal case resolution rate	1.037
	2. Government agency performance accountability (SAKIP) evaluation score	1.588
	3. Electronic-based government system (SPBE) index	1.587
Infrastructure Development	1. Percentage of households with access to improved drinking water	1.097
	2. Hospital ratio	1.469
	3. Percentage of households with access to adequate sanitation	1.426

The collinearity assessment shows that indicator VIF values range from 1.037 to 2.412; the highest value corresponds to "Average years of schooling" (2.412), and the lowest to "Criminal case resolution rate" (1.037). Because all VIF values were below the threshold of 3, multicollinearity was not considered a major concern among the formative indicators. The outer weights were then examined to assess the relative contribution of each indicator to its respective construct.

The outer weight results in Table 3 show that for the community welfare construct, only average years of schooling has a statistically significant outer weight, whereas per capita income and life expectancy are not statistically significant. This indicates that education makes a statistically significant relative contribution to the construct. For the community empowerment construct, the women's economic empowerment ratio is the only indicator with a statistically significant outer weight. The village-owned enterprise (BUMDesa) ratio has a p-value of 0.096; therefore, it does not reach the 5% significance level, while the integrated health post (Posyandu) ratio is not statistically significant. For the government governance construct, the electronic government system index (SPBE) has a statistically significant outer weight, whereas the criminal case resolution rate and the government agency performance accountability system (SAKIP) are

Table 3: Initial Outer Weights of Formative Indicators

Indicator → Construct	Outer Weights	T-statistic	P-Value	Information
Income (GRDP) → Community Welfare	0.111	0.579	0.563	Not Significant
Average years of schooling → Community Welfare	0.937	4.988	< 0.001	Significant
Life expectancy → Community Welfare	0.009	0.045	0.964	Not Significant
Village-owned enterprise (BUMDesa) ratio → Community Empowerment	0.487	1.663	0.096	Not Significant
Women's business empowerment (PUSPA) ratio → Community Empowerment	0.591	1.997	0.046	Significant
Posyandu ratio → Community Empowerment	0.118	0.476	0.634	Not Significant
Criminal case resolution rate → Government Governance	0.224	0.721	0.471	Not Significant
Government agency performance accountability (SAKIP) evaluation score → Government Governance	0.125	0.368	0.713	Not Significant
Electronic-based government system (SPBE) index → Government Governance	0.855	3.035	0.002	Significant
Percentage of households with access to improved drinking water → Infrastructure Development	0.100	1.025	0.305	Not Significant
Hospital ratio → Infrastructure Development	0.584	3.395	0.001	Significant
Percentage of households with access to adequate sanitation → Infrastructure Development	0.516	2.894	0.004	Significant

not statistically significant. This finding highlights the relative contribution of the SPBE index to the construct. Finally, for the infrastructure development construct, both the ratio of healthcare facilities and access to adequate sanitation have statistically significant outer weights, whereas access to adequate drinking water does not. These results indicate that healthcare facilities and adequate sanitation make statistically significant relative contributions to the infrastructure development construct.

In accordance with the evaluation criteria for formative models, we examined indicators with non-significant weights in greater detail based on their outer loading values (threshold ≥ 0.50) to determine whether to retain them in the model, as shown in Table 4.

The results in Table 4 show that four indicators with non-significant outer weights—income (GRDP), life expectancy, the BUMDesa ratio, and the SAKIP evaluation score—had statistically significant outer loadings above 0.50 and were therefore retained in the model. In contrast, the Posyandu ratio, the criminal case resolution rate, and access to safe drinking water had outer loadings below 0.50 and were excluded from the model.

After removing the three indicators from the model, the variance inflation factor (VIF) values were reassessed to evaluate collinearity in the revised model. Table 5 presents the results of this assessment.

The results in Table 5 show that all VIF values in the revised model were below the threshold of 3, ranging from 1.296 to 2.412. These findings indicate that multicollinearity was not a major concern in the revised formative measurement model. Therefore, the model proceeded to the next stage of evaluation.

The next step is to re-examine the importance and relevance of the outer weights in the revised model. Table 6 presents the results of this assessment.

Table 6 presents the outer weight test results for the revised model, showing a pattern generally consistent with the initial model. Average years of schooling, the women's economic empowerment ratio, the SPBE index, the hospital ratio, and access to sanitation infrastructure remained significant. In contrast, GRDP, life expectancy, the BUMDesa ratio, and SAKIP were non-significant. For indicators with non-significant outer weights, their outer loadings were

Table 4: Initial Outer Loadings of All Formative Indicators

Indicator → Construct	Outer Loading	T-statistic	P-Value	Information
Income (GRDP) → Community Welfare	0.546	4.020	< 0.001	Significant
Average years of schooling → Community Welfare	0.995	19.831	< 0.001	Significant
Life expectancy → Community Welfare	0.760	6.870	< 0.001	Significant
Village-owned enterprise (BUMDesa) ratio → Community Empowerment	0.869	6.054	< 0.001	Significant
Women's business empowerment (PUSPA) ratio → Community Empowerment	0.921	7.254	< 0.001	Significant
Posyandu ratio → Community Empowerment	0.273	1.148	0.251	Not Significant
Criminal case resolution rate → Government Governance	0.389	1.162	0.245	Not Significant
Government agency performance accountability (SAKIP) evaluation score → Government Governance	0.680	2.862	0.004	Significant
Electronic-based government system (SPBE) index → Government Governance	0.968	6.354	< 0.001	Significant
Percentage of households with access to improved drinking water → Infrastructure Development	0.384	2.334	0.020	Significant
Hospital ratio → Infrastructure Development	0.891	10.882	< 0.001	Significant
Percentage of households with access to adequate sanitation → Infrastructure Development	0.855	10.054	< 0.001	Significant

Table 5: VIF Values of Formative Indicators After Indicator Removal

Constructs	Indicators	VIF
Community Welfare	1. Income (GRDP)	1.296
	2. Average years of schooling	2.412
	3. Life expectancy	2.337
Community Empowerment	1. Village-owned enterprise (BUMDesa) ratio	1.655
	2. Women's business empowerment (PUSPA) ratio	1.655
Government Governance	1. Government agency performance accountability (SAKIP) evaluation score	1.576
	2. Electronic-based government system (SPBE) index	1.576
Infrastructure Development	1. Hospital ratio	1.413
	2. Percentage of households with access to adequate sanitation	1.413

examined further to assess their relevance and determine whether they should be retained in the model, as shown in Table 7.

The outer loading values in Table 7 show that all indicators with previously non-significant outer weights–GRDP, life expectancy, the BUMDesa ratio, and SAKIP–have statistically significant outer loadings above 0.50. These four indicators were retained in the model based on their absolute contributions to their constructs, despite their non-significant outer weights, which reflect their relative contributions compared to other indicators in the same construct. Considering the overall assessment of the measurement model and the theoretical relevance of the indicators, retaining them was appropriate for further analysis. The analysis then proceeded to structural model evaluation (inner model).

Table 6: Outer Weights of Formative Indicators in the Revised Model

Indicator → construct	Outer Weights	T-statistic	P-Value	Information
Income (GRDP) → Community Welfare	0.098	0.621	0.534	Not Significant
Average years of schooling → Community Welfare	0.942	6.687	< 0.001	Significant
Life expectancy → Community Welfare	0.012	0.068	0.946	Not Significant
Village-owned enterprise (BUMDesa) ratio → Community Empowerment	0.488	1.668	0.095	Not Significant
Women's business empowerment (PUSPA) ratio → Community Empowerment	0.618	2.170	0.030	Significant
Government agency performance accountability (SAKIP) evaluation score → Government Governance	0.162	0.434	0.664	Not Significant
Electronic-based government system (SPBE) index → Government Governance	0.894	3.293	0.001	Significant
Hospital ratio → Infrastructure Development	0.620	4.077	< 0.001	Significant
Percentage of households with access to adequate sanitation → Infrastructure Development	0.518	3.410	0.001	Significant

Table 7: Outer Loadings of Formative Indicators in the Revised Model

Indicator → construct	Outer Loading	T-statistic	P-Value	Information
Income (GRDP) → Community Welfare	0.536	4.602	< 0.001	Significant
Average years of schooling → Community Welfare	0.996	24.711	< 0.001	Significant
Life expectancy → Community Welfare	0.761	7.271	< 0.001	Significant
Village-owned enterprise (BUMDesa) ratio → Community Empowerment	0.877	6.498	< 0.001	Significant
Women's business empowerment (PUSPA) ratio → Community Empowerment	0.925	8.081	< 0.001	Significant
Government agency performance accountability (SAKIP) evaluation score → Government Governance	0.702	2.951	0.003	Significant
Electronic-based government system (SPBE) index → Government Governance	0.992	11.412	< 0.001	Significant
Hospital ratio → Infrastructure Development	0.900	12.029	< 0.001	Significant
Percentage of households with access to adequate sanitation → Infrastructure Development	0.853	10.913	< 0.001	Significant

3.2. Structural Model Evaluation

Structural model assessment begins with a test for structural collinearity (inner VIF) to ensure there is no multicollinearity among predictor constructs, which could bias path coefficient estimates. Table 8 presents the results of this test.

Table 8: Inner VIF Values for Assessing Structural Model Collinearity

Constructs	VIF
Community Empowerment → Community Welfare	1.724
Government Governance → Community Welfare	1.349
Infrastructure Development → Community Welfare	2.126
Infrastructure Development → Community Empowerment	1.000
Infrastructure Development → Government Governance	1.000

The structural collinearity assessment based on the inner VIF values, as given in Table 8, reveals that all the VIF values are under the 3.0 threshold, varying between 1.000 and 2.126. The highest VIF value relates to the association between infrastructure development and community

welfare (2.126), while the lowest values correspond to the relationships between infrastructure development and community empowerment and between infrastructure development and government governance (1.000 in each case). These findings suggest that structural collinearity is not a problem among the predictor constructs and therefore support the interpretation of the path coefficient estimates. The coefficient of determination (R^2) was then examined to assess the proportion of variance in each endogenous construct explained by its predictors, as shown in Table 9.

Table 9: Coefficient of Determination (R^2) for Endogenous Constructs

Constructs	R-square	R-square adjusted
Community Empowerment	0.418	0.401
Community Welfare	0.797	0.779
Government Governance	0.256	0.235

The coefficient of determination results in Table 9 show that community welfare has the highest explanatory power, with an R^2 value of 0.797 and an adjusted R^2 of 0.779. This indicates that the predictor constructs jointly account for 79.7% of the variance in community welfare. Community empowerment has an R^2 value of 0.418 and an adjusted R^2 of 0.401, while government governance has the lowest R^2 value, at 0.256, with an adjusted R^2 of 0.235. Based on the criteria adopted in this study, the explanatory power is substantial for community welfare and moderate for both community empowerment and government governance. The relatively small differences between the R^2 and adjusted R^2 values indicate that the estimates remain similar after adjustment for the number of predictors and sample size. However, these results alone do not establish that the model is free from overfitting or has strong predictive performance. Finally, the effect size (f^2) was assessed to examine the relative contribution of each exogenous construct to the endogenous constructs, as presented in Table 10.

Table 10: Effect Size (f^2) of Exogenous Constructs on Endogenous Constructs

Constructs	f-square
Community Empowerment → Community Welfare	0.175
Government Governance → Community Welfare	0.003
Infrastructure Development → Community Welfare	1.126
Infrastructure Development → Community Empowerment	0.717
Infrastructure Development → Government Governance	0.344

Table 10 shows that effect sizes (f^2) vary across structural relationships. Infrastructure development exhibits a large effect size for community welfare ($f^2 = 1.126$) and community empowerment ($f^2 = 0.717$) and a medium effect size for government governance ($f^2 = 0.344$). Community empowerment also exhibits a medium effect size for community welfare ($f^2 = 0.175$), whereas government governance exhibits a negligible effect size for community welfare ($f^2 = 0.003$). Overall, infrastructure development exhibits the largest effect sizes among the exogenous constructs. The model's out-of-sample predictive performance was subsequently assessed using PLSpredict, as presented in Table 11.

Table 11 shows that each of the indicators of the endogenous constructs had a Q^2_{predict} value above zero (ranging from 0.019 to 0.696), which shows that the model performs better than a simple mean prediction. However, the PLS model had a lower RMSE than the LM benchmark for only three of the seven indicators: the women's business empowerment (PUSPA) ratio, the electronic-based government system (SPBE) index, and income (GRDP). These differences were generally small. Therefore, the model's out-of-sample predictive ability is considered to be low.

The structural model assessment, including the collinearity test (VIF), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2 and PLSpredict), provides a basis for proceeding to the hypothesis-testing stage.

Table 11: Out-of-Sample Predictive Performance Assessment Using PLSpredict

Constructs	Indicators	Q^2 Predict	RMSE PLS	RMSE LM
Community Empowerment	Village-owned enterprise (BUMDesa) ratio	0.300	0.861	0.802
	Women's business empowerment (PUSPA) ratio	0.252	0.888	0.943
Government Governance	Government agency performance accountability (SAKIP) evaluation score	0.019	1.015	0.996
	Electronic-based government system (SPBE) index	0.237	0.898	0.909
Community Welfare	Income (GRDP)	0.046	1.003	1.042
	Average years of schooling	0.696	0.564	0.559
	Life expectancy	0.469	0.746	0.735

3.3. Hypothesis Testing

The initial hypothesis test assesses the significance of each indicator's contribution to its corresponding construct in the formative measurement model. In this model, the indicators form the construct rather than reflect it; therefore, the significance of their outer weights (denoted as γ) is examined. The statistical hypotheses are formulated in Eq. (5):

$$\begin{aligned} H_0 &: \gamma_k = 0 \quad \text{(weight of indicator } k \text{ is not statistically significant)} \\ H_1 &: \gamma_k \neq 0 \quad \text{(weight of indicator } k \text{ is statistically significant)} \end{aligned} \tag{5}$$

If an indicator's outer weight is not statistically significant, a supplementary assessment of its outer loading (λ) is conducted to evaluate its relevance to the construct. The corresponding hypotheses are formulated in Eq. (6):

$$\begin{aligned} H_0 &: \lambda_k = 0 \quad \text{(loading of indicator } k \text{ is not statistically significant)} \\ H_1 &: \lambda_k \neq 0 \quad \text{(loading of indicator } k \text{ is statistically significant)} \end{aligned} \tag{6}$$

The outer weight test results presented in Table 6 indicate that five of the nine indicators have statistically significant weights: average years of schooling, women's business empowerment (PUSPA) ratio, electronic-based government system (SPBE) index, hospital ratio, and percentage of households with access to adequate sanitation. For these five indicators, H_0 was rejected in favor of H_1. In contrast, the remaining four indicators–income (GRDP), life expectancy, village-owned enterprise (BUMDesa) ratio, and government agency performance accountability (SAKIP) evaluation score–had non-significant outer weights; therefore, H_0 was not rejected for these indicators. A supplementary assessment of their outer loadings was then conducted, as presented in Table 7. The results show that all four indicators have statistically significant outer loadings exceeding the 0.50 threshold. Accordingly, H_0 was rejected in favor of H_1 in the supplementary outer loading tests. Thus, all nine indicators satisfied at least one of the statistical significance criteria and were retained in the final formative measurement model.

Following the evaluation of the formative measurement model, hypothesis testing was conducted to assess the statistical significance of the structural relationships among the constructs. These relationships include those between exogenous and endogenous constructs, as well as those among endogenous constructs.

The statistical hypotheses for the relationships between exogenous and endogenous latent constructs are formulated in Eq. (7):

$$\begin{aligned} H_0 &: \gamma = 0 \quad \text{(there is no statistically significant direct relationship between constructs)} \\ H_1 &: \gamma \neq 0 \quad \text{(there is a statistically significant direct relationship between constructs)} \end{aligned} \tag{7}$$

Similarly, the statistical hypotheses for the relationships among endogenous latent constructs are formulated in Eq. (8):

$$\begin{aligned} H_0 &: \beta = 0 \quad \text{(there is no statistically significant direct relationship between constructs)} \\ H_1 &: \beta \neq 0 \quad \text{(there is a statistically significant direct relationship between constructs)} \end{aligned} \tag{8}$$

The results of the structural path coefficient tests are presented in Table 12. The path coefficient results presented in Table 12 indicate that the structural model can be expressed through three equations, each corresponding to an endogenous construct: community empowerment, government governance, and community welfare.

Table 12: Structural Path Coefficients and Significance Tests

Inner Model	Path Coefficient Estimation	T-statistic	P-Value	Information
Government Governance → Community Welfare	0.031	0.299	0.765	Not Significant
Infrastructure Development → Community Welfare	0.697	4.017	< 0.001	Significant
Infrastructure Development → Government Governance	0.506	4.003	< 0.001	Significant
Infrastructure Development → Community Empowerment	-0.646	6.034	< 0.001	Significant
Community Empowerment → Community Welfare	-0.247	1.647	0.100	Not Significant

The structural relationship between infrastructure development and community empowerment is expressed in Eq. (9):

$$\eta_1 = -0.646\xi_1 + \zeta_1 \tag{9}$$

The structural relationship between infrastructure development and government governance is expressed in Eq. (10):

$$\eta_2 = 0.506\xi_1 + \zeta_2 \tag{10}$$

The structural relationships of infrastructure development, government governance, and community empowerment with community welfare are expressed in Eq. (11):

$$\eta_3 = 0.697\xi_1 + 0.031\eta_2 - 0.247\eta_1 + \zeta_3 \tag{11}$$

The variables in these equations are defined as follows:

$$\begin{aligned} \xi_1 &= \text{Infrastructure Development (ID)} \\ \eta_1 &= \text{Community Empowerment (CE)} \\ \eta_2 &= \text{Government Governance (GG)} \\ \eta_3 &= \text{Community Welfare (CW)} \\ \zeta_1, \zeta_2, \zeta_3 &= \text{disturbance terms in the respective equations} \end{aligned}$$

The estimated structural relationships can be interpreted as follows.

1. Infrastructure development has a statistically significant negative association with community empowerment. Across the regencies and cities examined, higher levels of infrastructure development are associated with lower levels of community empowerment. In the final measurement model, infrastructure development is represented by the hospital ratio and access to adequate sanitation, whereas community empowerment is represented by the BUMDesa and PUSPA ratios. These findings suggest that regions with more advanced infrastructure development do not necessarily exhibit higher levels of community empowerment. One possible explanation is that infrastructure development and community empowerment initiatives follow different patterns across regions. However, this explanation requires further empirical investigation.

2. Infrastructure development has a statistically significant positive association with government governance, indicating that regions with more developed infrastructure tend to exhibit higher levels of government governance. One possible interpretation is that this association reflects differences in regional budgetary and administrative capacities, which may be relevant to public accountability and the implementation of digital government, as represented by the SAKIP and SPBE indicators. Nevertheless, this explanation requires further empirical investigation.
3. Infrastructure development has a statistically significant positive association with community welfare. In contrast, neither government governance nor community empowerment shows a statistically significant association with community welfare in the estimated model. However, these non-significant findings should not be interpreted as evidence that government governance and community empowerment have no relationship with community welfare.

In addition to the direct relationships, this study examines the indirect associations between infrastructure development and community welfare through community empowerment and government governance. These indirect effects are evaluated to assess the proposed mediation hypotheses. The results are presented in Table 13.

Table 13: Specific Indirect Effects of Infrastructure Development on Community Welfare

Mediation Pathway	Indirect Effect	T-statistic	P-Value	97.5%	2.5%	Information
Infrastructure Development → Government Governance → Community Welfare	0.016	0.265	0.791	0.162	-0.084	Not Significant
Infrastructure Development → Community Empowerment → Community Welfare	0.160	1.350	0.177	0.448	-0.008	Not Significant

The bootstrapping results for the specific indirect effects presented in Table 13 indicate that neither of the mediation pathways is statistically significant because the 95% confidence intervals for both indirect effects contain zero. In contrast, the direct path coefficient from infrastructure development to community welfare is statistically significant, as stated in Table 12. There is therefore insufficient statistical evidence that either government governance or community empowerment mediates the relationship between infrastructure development and community welfare. These findings are consistent with the non-significant path coefficients from both government governance and community empowerment to community welfare.

The direct and indirect hypothesis tests yield the following findings on the relationships among infrastructure development, government governance, community empowerment, and community welfare in East Java Province:

First, infrastructure development was negatively associated with community empowerment. This finding indicates that, in the estimated model, regions with higher infrastructure development scores tended to have lower community empowerment scores. Community empowerment was represented by indicators including the BUMDesa ratio and the PUSPA ratio. One possible explanation is that regional differences in resource allocation or development priorities may contribute to this observed relationship. However, the proposed explanation involving budgetary trade-offs and differing regional priorities remains speculative and requires further empirical investigation [38].

Second, infrastructure development was positively associated with government governance. This finding suggests that regions with higher infrastructure development scores also tended to have higher government governance scores. One possible interpretation is that infrastructure provision and governance capacity may develop alongside one another. This interpretation is consistent with previous studies reporting associations among local government capacity, public service delivery, and governance performance. Nevertheless, the mechanisms underlying this

relationship require further investigation [39].

Third, infrastructure development had a positive and statistically significant association with community welfare. This finding is consistent with development perspectives that emphasize the role of infrastructure in supporting quality of life. However, because this study used observational data, the observed association should not be interpreted as evidence that infrastructure development directly causes improvements in community welfare [40].

Fourth, community empowerment was not significantly associated with community welfare. In this study, community empowerment was represented by indicators including the BUMDesa ratio, the PUSPA ratio, and the Posyandu ratio. The non-significant relationship indicates that the analysis did not provide sufficient statistical evidence of a direct association between the community empowerment construct and community welfare. Differences in regional contexts or in the implementation of community empowerment programs may be relevant to understanding this finding, but these explanations require further empirical investigation [41].

Fifth, government governance was not significantly associated with community welfare. Government governance was measured using indicators including the criminal case resolution rate, the SAKIP evaluation score, and the SPBE Index. The results did not provide sufficient statistical evidence of a direct association between government governance and community welfare in the regions examined. Other factors, such as budgetary efficiency and the quality of public services, may also be relevant to this relationship, although they were not directly examined in this study. Further research is therefore needed to investigate these possibilities [42].

Regarding the mediation analysis, neither community empowerment nor government governance had a statistically significant indirect effect on the relationship between infrastructure development and community welfare. Thus, the findings did not support the proposed mediation pathways. However, the non-significant indirect effects do not establish that mediation effects are absent; they indicate that the present analysis did not provide sufficient statistical evidence to support them [43].

A single global model may not fully capture regional differences in structural relationships. PLS-POS was therefore used to explore unobserved heterogeneity by identifying regional segments with relatively homogeneous structural relationships.

3.4. Clustering Using PLS-POS

The consistency of the segmentation results and the selection of the best-performing solution were evaluated through 20 PLS-POS runs with different initializations and the number of segments fixed at two. Each run produced a segment assignment for the observations and an objective criterion value, which was used to compare the optimization performance across solutions. Table 14 presents the objective criterion values and the corresponding rankings for all 20 runs.

The objective criterion values ranged from 1.791 to 1.957. Run 12 achieved the highest value of 1.957, with 14 observations assigned to Segment 1 and 24 assigned to Segment 2, and was therefore selected as the best-performing solution among the 20 runs. Runs 8, 9, 14, and 16 ranked second to fifth, with objective criterion values of 1.956, 1.954, 1.949, and 1.941, respectively. The proximity of the objective criterion values among several top-ranked solutions indicates that their optimization performance was relatively similar. Differences in segment composition across runs with different initializations were subsequently examined to assess variations in the assignment of regencies and cities to segments.

The subsequent evaluation compared the segment membership of the 38 regencies and cities in each repeated run with Run 12 as the reference solution. Before the comparison, the labels of Segment 1 and Segment 2 were aligned to account for possible label switching across runs. The agreement rate was calculated as the proportion of regencies and cities assigned to the same segment as in the reference solution after label alignment. The results of the membership agreement evaluation are presented in Table 15.

The results in Table 15 show that membership agreement with the reference solution ranged

Table 14: Segment Sizes, Objective Criterion Values, and Rankings Across 20 PLS-POS Runs

Runs	Segment 1	Segment 2	Objective Criterion	Rankings
1	18	20	1.888	7
2	9	29	1.865	11
3	22	16	1.857	13
4	13	25	1.829	17
5	13	25	1.861	12
6	12	26	1.866	10
7	11	27	1.879	8
8	25	13	1.956	2
9	15	23	1.954	3
10	17	21	1.812	19
11	20	18	1.868	9
12	14	24	1.957	1
13	11	27	1.842	15
14	26	12	1.949	4
15	13	25	1.890	6
16	14	24	1.941	5
17	9	29	1.833	16
18	11	27	1.828	18
19	18	20	1.844	14
20	22	16	1.791	20

Table 15: Segment Membership Agreement Rates Across 20 PLS-POS Runs Relative to Run 12

Rankings	Repeated Runs	Membership Agreement (%)
1	Run 12	100.00
2	Run 8	97.37
3	Run 9	81.58
4	Run 14	78.95
5	Run 16	68.42
6	Run 20	68.42
7	Run 18	65.79
8	Run 2	65.79
9	Run 15	60.53
10	Run 13	60.53
11	Run 17	60.53
12	Run 5	60.53
13	Run 1	57.89
14	Run 3	57.89
15	Run 11	57.89
16	Run 4	55.26
17	Run 7	55.26
18	Run 10	55.26
19	Run 6	52.63
20	Run 19	52.63

from 52.63% to 100.00%. The 100.00% agreement for Run 12 was not used as an indicator of agreement across runs because it was compared with itself. Among the other solutions, Run 8 showed the highest agreement rate at 97.37%, followed by Run 9 at 81.58% and Run 14 at 78.95%. In contrast, Run 6 and Run 19 had the lowest agreement rates, at 52.63%. These results indicate that segment membership agreement varied across the repeated runs. Accordingly, differences in segment membership were observed for some regencies and cities across solutions obtained from different initializations.

These variations indicate that the segmentation results were not identical across all random starts. Yet, several solutions with high optimization performance produced membership structures that were fairly similar to those of Run 12. For example, Run 8 had an objective criterion value

of 1.956, close to Run 12's value of 1.957, and membership agreement of 97.37%. However, lower agreement in other runs indicates sensitivity to initialization.

Run 12 was selected as the best-performing two-segment solution because it achieved the highest objective criterion value among the 20 repeated runs. This solution divided the 38 regencies and cities into Segment 1, comprising 14 regions (36.84%), and Segment 2, comprising 24 regions (63.16%). Run 12 was subsequently used as the basis for conducting PLS-SEM analyses separately for each segment. This selection should not be interpreted as evidence that the segmentation structure was fully stable, but rather as the selection of the solution with the best optimization performance among the runs evaluated. The membership agreement results were used as supporting information to assess variations in segment membership in relation to differences in initializations. Based on the solution from Run 12, the 38 regencies and cities in East Java were divided into two segments. Segment 1 comprises 14 administrative units, while Segment 2 has 24. Table 16 lists which regencies and cities belong to each segment.

Table 16: Segment Membership of Regencies and Cities in East Java Based on Run 12

Segment 1 ($n = 14$)	**Segment 2** ($n = 24$)	
Pacitan	Ponorogo	Ngawi
Trenggalek	Tulungagung	Tuban
Blitar	Lumajang	Lamongan
Kediri	Jember	Gresik
Malang	Banyuwangi	Pamekasan
Sidoarjo	Bondowoso	Kota Blitar
Nganjuk	Situbondo	Kota Probolinggo
Magetan	Probolinggo	Kota Pasuruan
Bojonegoro	Pasuruan	Kota Mojokerto
Bangkalan	Mojokerto	Kota Madiun
Sampang	Jombang	Kota Surabaya
Sumenep	Madiun	Kota Batu
Kota Kediri		
Kota Malang		

The distribution of the 38 regencies and cities based on the Run 12 segmentation results was visualized using a thematic map. The map is presented in Fig. 2 to provide an overview of the spatial distribution of Segment 1 and Segment 2 across East Java. The characteristics of each segment were described using the construct scores for community empowerment, infrastructure development, government governance, and community welfare. A comparison of the construct scores between the two segments is presented in Table 17.

Table 17: Comparison of Construct Scores Between PLS-POS Segments

Constructs	Segment 1	Segment 2
Community Welfare	0.0724	-0.0422
Community Empowerment	-0.2192	0.1280
Government Governance	-0.0805	0.0470
Infrastructure Development	0.0230	-0.0136

The results of the segmentation shown in Table 17 indicate two segments with different patterns of construct scores based on their positions relative to the overall mean. For Segment 1, the scores for community welfare and infrastructure development are slightly above the overall mean, while those for community empowerment and government governance are below the overall mean. In contrast, Segment 2 has scores above the overall mean for community empowerment and government governance, while its scores for community welfare and infrastructure development are slightly below the overall mean. Overall, the construct scores in both segments are relatively

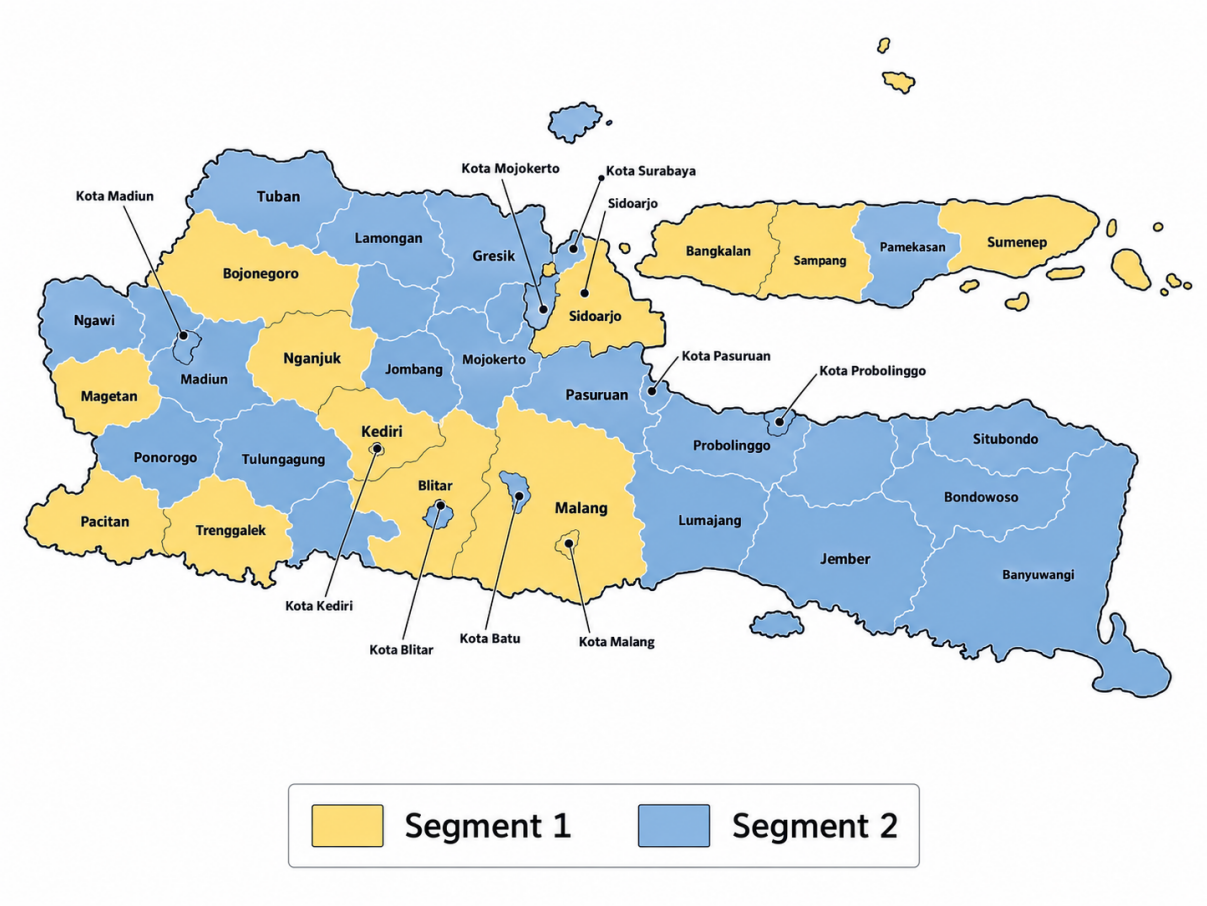


Fig. 2: Spatial Distribution of PLS-POS Segments Across Regencies and Cities in East Java

close to the overall mean. These profiles should therefore be interpreted as descriptive tendencies, rather than evidence that one segment is clearly superior to the other.

The subsequent PLS-SEM analysis was conducted separately for each segment to describe the patterns of relationships among the constructs. Segment 1 comprised 14 regencies and cities, while Segment 2 comprised 24 regencies and cities. The estimation results included path coefficients, t-statistics, and p-values. Table 18 presents these estimates. Given the small sample sizes, the results were interpreted cautiously as exploratory descriptions of relationship patterns.

Table 18: Structural Path Coefficients and Significance Tests for Each PLS-POS Segment

Structural Relationship	**Segment 1**			**Segment 2**		
	Path	t	p	**Path**	t	p
Government Governance → Community Welfare	-0.349	0.841	0.400	-0.028	0.297	0.767
Infrastructure Development → Community Welfare	1.479	2.309	0.021	0.945	6.692	< 0.001
Infrastructure Development → Government Governance	0.563	2.994	0.003	0.502	2.314	0.021
Infrastructure Development → Community Empowerment	-0.790	4.240	< 0.001	-0.677	4.637	< 0.001
Community Empowerment → Community Welfare	0.431	0.947	0.344	-0.072	0.448	0.654

The structural model estimates in Table 18 show that the relationships between government governance and community welfare, as well as between community empowerment and community welfare, are not statistically significant in either segment. In contrast, the relationships between infrastructure development and each of the following constructs–community welfare, government governance, and community empowerment–are statistically significant in both Segment 1 and Segment 2. The path coefficients for the relationships between infrastructure development and community welfare and between infrastructure development and government governance

are positive, while the path coefficient for the relationship between infrastructure development and community empowerment is negative in both segments. Although the magnitude of the path coefficients varies between Segment 1 and Segment 2, these differences are interpreted descriptively and cannot be regarded as statistically significant without further statistical testing between segments. Moreover, the estimation results should be interpreted with caution because the sample sizes in both segments are relatively small.

The path coefficient for the relationship between infrastructure development and community welfare in Segment 1 warrants careful interpretation since its value is 1.479, which is above one. A sensitivity analysis was therefore conducted by comparing the estimation results from various PLS-POS solutions with high objective criterion values. This analysis assessed whether the direction and magnitude of the path coefficients were consistent across segmentation solutions. The results are presented in Table 19.

Table 19: Sensitivity Analysis of the Infrastructure Development → Community Welfare Path Coefficient Across PLS-POS Solutions

Run	Objective Criterion	Infrastructure Development → Community Welfare Path Coefficient
14	1.949	0.997
9	1.954	1.468
8	1.956	0.945
12	1.957	1.479

A sensitivity analysis was carried out on the four PLS-POS solutions with the highest objective criterion values in order to examine the consistency of the path coefficient estimates for the relationship between infrastructure development and community welfare as the segment membership changed. As indicated in Table 19, the path coefficient lies between 0.945 and 1.479. Even though the objective criterion values are fairly similar among the solutions, the path coefficients exhibit considerable variation. This indicates that the estimated relationship between infrastructure development and community welfare is sensitive to changes in the segmentation solution. Since Run 12 was chosen as the best-performing exploratory solution because it obtained the highest objective criterion value, not because it had the largest path coefficient, the estimated relationship between infrastructure development and community welfare should be treated with caution and should not be regarded as definitive evidence of differences in the structural relationships between segments.

The coefficient of determination (R^2) was analyzed to assess the model's capacity to explain variance in the endogenous constructs within each segment. Table 20 presents the R^2 values for Segment 1 and Segment 2.

Table 20: Coefficient of Determination R^2 for Endogenous Constructs Across PLS-POS Segments

Endogenous Constructs	R^2 (Segment 1)	R^2 (Segment 2)
Community Welfare	0.994	0.963
Government Governance	0.317	0.252
Community Empowerment	0.623	0.459

The R^2 values given in Table 20 show the amount of variance in the endogenous constructs that is accounted for by the predictors in the model. With regard to community welfare, the model accounts for 99.4% of the variance in Segment 1 and 96.3% in Segment 2. For government governance, the corresponding figures are 31.7% and 25.2%, and for community empowerment, they are 62.3% and 45.9%. Descriptively, the R^2 values for Segment 1 are higher than those for Segment 2 for all of the endogenous constructs. However, the differences cannot be regarded as statistically significant based solely on differences in R^2 values. Since the sample sizes are relatively small, with 14 observations in Segment 1 and 24 observations in Segment 2, these results should be interpreted with caution as exploratory findings.

The Variance Inflation Factor (VIF) was used to assess multicollinearity among predictor

constructs within each segment. Table 21 presents the VIF values for Segment 1 and Segment 2.

Table 21: Inner VIF Values for Assessing Structural Collinearity Across PLS-POS Segments

Structural Relationship	VIF (Segment 1)	VIF (Segment 2)
Government Governance → Community Welfare	1.610	1.341
Infrastructure Development → Community Welfare	3.913	2.240
Infrastructure Development → Government Governance	1.000	1.000
Infrastructure Development → Community Empowerment	1.000	1.000
Community Empowerment → Community Welfare	2.922	1.852

The VIF values presented in Table 21 indicate that all VIF values in both segments are below the threshold of 5, which means there are no serious concerns regarding multicollinearity. The highest VIF values are found in the relationship between infrastructure development and community welfare, at 3.913 in Segment 1 and 2.240 in Segment 2. Descriptively, the VIF values in Segment 2 are equal to or less than those in Segment 1 for all the structural paths, implying that Segment 2 has comparatively lower levels of collinearity. Overall, the VIF values in both segments remain within the acceptable range.

The results of the PLS-SEM analysis show that the relationships between infrastructure development and community welfare, between infrastructure development and government governance, and between infrastructure development and community empowerment are statistically significant in both segments. In contrast, the relationships between government governance and community welfare and between community empowerment and community welfare are not statistically significant in either segment. Descriptively, the main structural relationships are similar in the two segments: the path coefficients for the relationships between infrastructure development and community welfare and between infrastructure development and government governance are positive, while that for the relationship between infrastructure development and community empowerment is negative. However, the path coefficient for the relationship between community empowerment and community welfare differs in direction between Segment 1 and Segment 2, even though this relationship is not statistically significant in either segment. The differences in the magnitude and direction of the path coefficients cannot be interpreted as evidence of statistically significant differences in the structural relationships between the segments, since formal statistical tests are needed to confirm such differences.

The analysis of the PLS-POS results identified two segments with different construct characteristics. Segment 1 had relatively higher scores for community welfare and infrastructure development, whereas Segment 2 had relatively higher scores for community empowerment and government governance. Conversely, Segment 1 had below-average scores for community empowerment and government governance, while Segment 2 had below-average scores for community welfare and infrastructure development. These patterns indicate that the two segments differ in their relative construct profiles, rather than demonstrating that one segment is clearly superior to the other. The differences in construct characteristics, along with the variations in the pattern of the path coefficients, provide preliminary indications of unobserved heterogeneity in the relationships across regions. However, these findings remain exploratory and cannot at this stage be considered definitive evidence of structural heterogeneity.

The interpretation of the results should take into account the small number of regions in the two segments, 14 in Segment 1 and 24 in Segment 2, and the variation in membership that was seen across different random starts. Even though Run 12 yielded the highest objective criterion value and several solutions with similar objective criterion values showed relatively high membership agreement, not all of the repeated runs resulted in the same partitions. For this reason, Run 12 was chosen as the best-performing exploratory solution, based on its highest objective criterion value, rather than on evidence of full segmentation stability.

Formal tests of between-segment differences in path coefficients were not conducted because the Multi-Group Analysis (MGA) option was unavailable in the SmartPLS version used. As

a result, the differences in the path coefficients between the segments were interpreted in a descriptive and exploratory manner rather than being regarded as statistically significant differences. Future research should compare segments using MGA, permutation tests, or another suitable method to assess differences in structural relationships.

4. Conclusion

This study investigates the relationships among infrastructure development, community empowerment, government governance, and community welfare across 38 regencies and cities in East Java Province using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that infrastructure development is positively and statistically significantly associated with both community welfare and government governance but negatively and statistically significantly associated with community empowerment. However, the relationships between community empowerment and community welfare, as well as between government governance and community welfare, are not statistically significant. Tests of indirect effects further reveal that none of the pathways involving mediation through community empowerment or government governance are statistically significant. Consequently, the findings do not provide sufficient statistical evidence to support the mediating roles of these two constructs in the relationship between infrastructure development and community welfare.

An analysis using Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS) identified two regional segments with different construct characteristics. Segment 1 had relatively higher scores for community welfare and infrastructure development, whereas Segment 2 had relatively higher scores for community empowerment and government governance. Conversely, community empowerment and government governance scores were below the overall mean in Segment 1, while community welfare and infrastructure development scores were below the overall mean in Segment 2. These results indicate differences in the relative construct profiles of the two segments, rather than demonstrating that one segment is generally superior to the other. Most structural relationships exhibited similar patterns across the two segments. Infrastructure development was positively and significantly associated with community welfare and government governance but negatively and significantly associated with community empowerment in both segments. However, the relationships between community empowerment and community welfare and between government governance and community welfare were not statistically significant in either segment. While the path coefficient for the relationship between community empowerment and community welfare varied in direction across the two segments, formal statistical testing is necessary to assess whether this difference is statistically significant. Hence, the results provide only preliminary indications of possible structural heterogeneity and do not establish definitive evidence of such heterogeneity.

The interpretation of the PLS-POS results should take into account the relatively small number of regions in each of the two segments, namely 14 regions in Segment 1 and 24 regions in Segment 2, as well as the fact that there was variation in segment membership depending on the different random starts. Although Run 12 was regarded as the best-performing exploratory solution since it obtained the highest value for the objective criterion among the 20 repeated runs, this does not establish full segmentation stability. Moreover, as the Multi-Group Analysis (MGA) function was not available in the version of SmartPLS used, formal tests were not carried out on the differences in path coefficients between the segments. Hence, any differences in the path coefficients and construct characteristics between the segments must be interpreted descriptively and exploratorily.

The study stresses the need to take account of regional characteristics when looking at the connections between infrastructure development, community empowerment, government governance, and community welfare. However, the findings do not support causal conclusions, and the statistical significance of differences in relationship patterns between segments has not been established. Future research should use a larger dataset by including additional regions or

extending the observation period. It should also carry out formal comparisons of the segments using techniques such as Multi-Group Analysis (MGA), permutation tests, or other appropriate methods. Researchers could also examine regional socioeconomic conditions, public service quality, and budget allocation to better understand variations in regional characteristics and relationship patterns in East Java Province.

CRediT Authorship Contribution Statement

Siti Fadilatul Khasanah: Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing–Original Draft. **Rahmawati Erma Standsyah:** Conceptualization, Methodology, Validation, Writing–Review and Editing, Supervision, Project Administration.

Declaration of Generative AI and AI-assisted technologies

Generative AI (ChatGPT) was utilized exclusively for language editing, sentence flow enhancement, grammar refinement, and vocabulary suggestions. All authors have reviewed and approved the AI-assisted outputs and accept responsibility for the final manuscript.

Declaration of Competing Interest

The authors declare no competing interests.

Ethics Approval and Consent to Participate

This study did not require ethics approval.

Funding and Acknowledgments

This research received no external funding.

The authors thank Statistics Indonesia (BPS) of East Java Province, the public agencies that published the performance reports, and the East Java Province Open Data Portal for providing the official data used in this study. These secondary data cover regencies and cities in East Java Province from 2022 to 2024.

Data and Code Availability

The dataset for this study is available from the corresponding author upon reasonable request. The data were obtained from official Indonesian government agencies and are subject to their respective data sharing policies.

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