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CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 11 (2) (2026), Pages 1–11
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Structural Equation Modeling Partial Least Squares-Prediction Oriented Segmentation on Community Welfare in East Java Province Using

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Abstract

The standard of community welfare is indicated by quality of life, which can be defined as adequate access to public services, recognition of social rights, and economic security. In East Java Province, community welfare still faces a number of problems, leading to differences in welfare levels among districts and municipalities. Because of these new issues, a study has been carried out to examine the factors that contribute to community welfare and identify differences between regions using the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method and the Partial Least Squares-Prediction-Oriented Segmentation(PLS-POS) approach. The results from the PLS-SEM analysis show that infrastructure development has a positive impact on improving government governance and on enhancing community empowerment, but it has no direct effect on community welfare. Moreover, governance does not have a significant effect on community welfare, whereas community empowerment has a significant negative effect. The structural model explains 41.3% of the variation in community welfare. Lastly, the PLS-POS analysis divided the 38 districts and cities in East Java Province into two segments: Segment 1, which includes 17 districts and cities, and Segment 2, which includes 21 districts and cities, showing that there are differences in social welfare features among the regions. This fact shows that social welfare policies should not only pay attention to infrastructure development but also work to improve governance and the quality of community empowerment initiatives, as this form og segmentation allows policymakers to draw up more specific regional development policies which are suited to the particular features of each group of regions.

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

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1. Introduction

The standard of community welfare is determined by quality of life, as shown by adequate access to public services, respect for social rights, and economic security [1]. In East Java Province, there are still many difficulties to be overcome if improvements are to be made in community welfare.

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Submitted: mm dd, yyyy Reviewed: mm dd, yyyy Accepted: mm dd, yyyy
DOI: https://doi.org/10.18860/cauchy.v11i2.xxxxx

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The poverty rate was 10.38%, and the unemployment rate was 4.81% as of March 2022 [2], [3]. Although 95.02% of households can access safe drinking water, community welfare is still held back by high levels of poverty, limited budgets for poverty alleviation, and uneven infrastructure development [4], [5]. These conditions account for disparities in various welfare indicators across districts and cities in East Java province and call for further investigation.

Community welfare is affected by social, economic, and institutional factors, and the main influences in this regard are Community empowerment, infrastructure development, and governance [6], [7], [8]. When communities are empowered, they develop their abilities. Better infrastructure development helps make it easier to access and share goods and services. Effective, transparent, and accountable policies are produced as a result of good governance [9], [10], [11].

This study uses the following analytical methods: Partial Least Squares–Structural Equation Modeling (PLS-SEM) and the Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS) approach. 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) demonstrated that PLS-SEM can describe the interactions between latent variables that influence 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. Conversely, Eliani (2023) used PLS-POS to detect heterogeneity, but its application remains limited to the health sector [15]. Furthermore, Utaminingsih and Suwendra (2022) applied a linear regression method that 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.

The shortcomings in earlier studies inspired this research, which examines how community empowerment, infrastructure progress, and governance affect community welfare in both districts and cities within East Java Province, while highlighting differences across regions. The uniqueness of this research stems from its combination of PLS-SEM and PLS-POS in evaluating well-being at the district and city scales. Therefore, this study aims to enhance analytical techniques in research concerning population well-being and offer support for creating more efficient and focused regional development strategies.[18]

2. Methods

The approach utilized to assess how community empowerment, infrastructure advancement, and governance affect the well-being of people at both district and city levels in East Java province is detailed. The suggested research framework combines Partial Least Squares-Structural Equation Modeling (PLS-SEM) with Partial Least Squares-Prediction Oriented Segmentation (PLS-POS). The research is carried out in a systematic way by going through a number of stages: collecting and preparing data, constructing the measurement and structural models, evaluating the measurement and structural models, verifying the hypotheses, carrying out segmentation by means of the Partial Least Squares-Prediction Oriented Segmentation (PLS-POS), and then interpreting the results. Each of these stages is intended to ensure that the analytical approach is systematic, clear, and repeatable.

2.1. Research Procedure

The research followed a clear process with several steps. It started by describing and preparing the dataset used for the analysis.

The data for this study were collected from the Central Statistics Agency (BPS) of East Java Province, the Directorate General of Budgetary Balance (DJPK) of the Ministry of Finance of

Structural Equation Modeling

Indonesia, and the East Java Province Single Data Portal. The data covers the years 2022 to 2024. The data collection focuses on an analytical unit that encompasses 38 districts and cities within East Java Province. To ensure consistency in the data and reduce the impact of annual variations, the average value for each variable over the period 2022 to 2024 was calculated. The resulting figure thus gives the correct value for each variable for each district or city and is then used in the analysis. The study incorporates four latent variables: community welfare, infrastructure development, community empowerment, and governance. The variable identified as community welfare is categorized as an endogenous variable, whereas infrastructure development, community empowerment, and governance are considered exogenous variables. Each latent variable is measured using several indicators, also known as manifest variables. These are shown in Table 1.

Table 1 : Variable Measurement

No	Latent Variable		Indicator	Reference
1	**Endogenous Variable** Community Welfare	CW_1 CW_2 CW_3	1. Income (PDRB) 2. Average Years of Schooling 3. Life Expectancy (Age)	
2	**Exogenous Variable** Infrastructure Development	ID_1 ID_2 ID_3	1. Number of General Hospitals 2. Percentage of Households with Access to an Improved Drinking Water Source 3. Number of Schools	
	Community Empowerment	CE_1 CE_2 CE_3	1. Number of Beneficiary Families 2. Labor Force Participation Rate 3. Number of Integrated Health Posts (Posyandu)	
	Government Governance	GG_1 GG_2 GG_3	1. Realization of regency government revenue 2. Capital Expenditure 3. Number of PUSPA Program Beneficiaries	

The average results were then standardized using the Z-score method. This made sure all indicators were measured on the same scale and had comparable characteristics, ensuring that indicators with a wider range of values would not affect the analysis results. These standardized values were then used as representative values for each indicator in each district/city and as input data for subsequent analysis steps.

The first step in the analysis was to create both a measurement model and a structural model based on the connections between the latent variables described in the research framework. The measurement model shows how the latent variables are linked to their specific indicators, while the structural model explains the cause-and-effect relationships among the latent variables studied. The model used in this study is shown in Fig. 1.

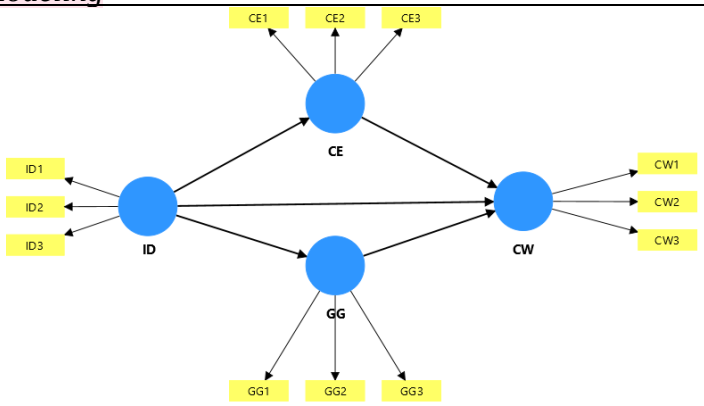


Fig. 1 : Model

The created model was evaluated using a measurement model consisting of convergent validity, discriminant validity, and reliability. If any indicator did not meet the validity or reliability standards, it was removed from the model. The evaluation process was repeated until each required indicator met the predetermined validity and reliability standards.

The next stage is to evaluate the structural model. The evaluation uses the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) to measure the quality of the resulting structural model.

The next stage after model evaluation is to examine the hypothesis by using bootstrap resampling. Bootstrap resampling is a statistical technique that makes no assumptions about the distribution; it is used to assess a model's performance by calculating path coefficients, t-statistics, and p-values, thereby determining the relevance of the relationships between the latent variables.

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 impact of community empowerment, infrastructure improvement, and government effectiveness on population well-being, as well as to explain the characteristics of the relationships between variables within each identified group. The analysis and grouping process for this study was carried out using SmartPLS software.

2.2. Data Standardization

All latent variable indicators are standardized using the *Z-score* transformation to account for differences in measurement scales [19]. This standardization assigns each indicator a mean of zero and a standard deviation of one [20]. The *Z-score* for each observation is computed as follows:

$$Z_{ij} = \frac{X_{ij} - \overline{X_j}}{S_j}$$

where X_{ii} represents the value of variable j for observation i, is $\overline{X_j}$ is the mean of variable j , and S_j is the standard deviation of variable j.

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

1. Measurement Model

The measurement model in Partial Least Squares–Structural Equation Modeling (PLS-SEM) explains how latent variables relate to the indicators used to evaluate them. Measurement models are either reflective or formative. [21]. In this study, a reflective measurement model is used, meaning that latent variables are shown through their indicators. The following sections describe the measurement models for both exogenous and endogenous latent variables.

$$x = \Lambda_x \xi + + \varepsilon_x$$

$$y = \Lambda_y \eta + + \varepsilon_y$$

Where x and y denote the indicators of the exogenous and endogenous latent variables, Λ_x and Λ_y represent the loading matrices describing the relationships between the indicators and the exogenous and endogenous latent variables, ξ and η denote the vectors of the exogenous and endogenous latent variables, $\varepsilon_x$and ε_y represent the vectors of measurement errors associated with the indicators of the exogenous and endogenous latent variables.

The measurement model is evaluated by looking at convergent validity, discriminant validity, and composite reliability. Convergent validity shows how well a latent variable matches its indicators. A model has convergent validity if the outer loading value is above 0.6 [22]. Discriminant validity focuses on the relationship between indicators and latent variables. A model is said to have discriminant validity if the correlation of a latent variable with its indicators is stronger than the correlation with other latent variables [23]. Furthermore, reliability assessment is conducted to clarify internal construct consistency by utilizing composite reliability and Cronbach's alpha coefficient. A construct is reliable if its composite reliability score is above 0.70. Cronbach's alpha coefficient is also used as an indicator of internal construct consistency, in line with recent recommendations in the literature regarding PLS-SEM models[24].

2. Structural Model

The structural model used in PLS-SEM describes the relationships between latent variables. 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 values obtained are path coefficients and R^2 values [25].

Based on the obtained path coefficient values, the structural model is illustrated as follows[26]:

$$\eta = B\eta + \Gamma\xi + \zeta$$

Where B is the matrix of path coefficients describing the relationships among endogenous latent variables, Γ is the matrix of path coefficients representing the effects of exogenous latent variables on endogenous latent variables, and ζ is the vector of structural error terms.

The coefficient of determination (R^2) is used to evaluate structural models since it measures the model's predictive power; it also shows how much the exogenous latent variables account for the variance in the endogenous latent variables. The R^2 values lie between 0 and 1, and the higher they are, the greater the predictive ability in the model [27]. Henseler et al. (2009) state that there are theoretically three types of R^2 thresholds: an R^2 greater than 0.67 is considered substantial and means that the contribution of the exogenous variables to the endogenous variables is strong; an R^2 between 0.33 and 0.67 is classified as moderate and shows that the contribution of the exogenous variables to the endogenous variables is sefficient or medium; meanwhile, an R^2 between 0.19 and 0.33 is regarded as weak [28].

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

The PLS approach includes a path modeling technique based on latent responses, known as Prediction-Oriented Segmentation (POS). It eliminates inference bias by examining the PLS paths and thus identifies unobserved heterogeneity. POS uses a clustering procedure that divides observations into more pertinent groups to enhance the model's predictive ability. More precisely, the method clusters observations and then uses a distance measure to reassign them to groups that are likely to increase the model's predictive power, as assessed by the coefficient of determination R^2 of the endogenous latent variable [29]. The distance measures employed are as follows :

$$D_{kig} = \sum_{b=1}^{B} \sqrt{\frac{e_{big}^2}{\sum_{i=k}^{I_k} e_{big}^2}}$$

In this equation, e_{big}^2 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 $\sum_{i=k}^{I_k} e_{big}^2$ 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.

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

The evaluation of a measurement model begins with an assessment of convergent validity. Convergent validity indicates the strength of the relationship between a latent variable and its indicators. An outer loading value exceeding 0.60 demonstrates adequate convergent validity. The results of this evaluation for the proposed model are shown in Fig. 2.

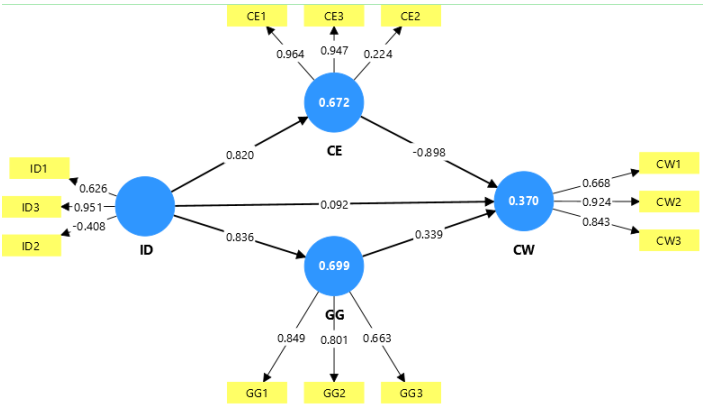


Fig. 2 : Evaluation of Convergent Validity

Fig. 2 indicates that the outer loading values for indicators CE2 and ID2 are below 0.60; as a result, these indicators fail to meet the requirements for convergent validity and are removed from the model.

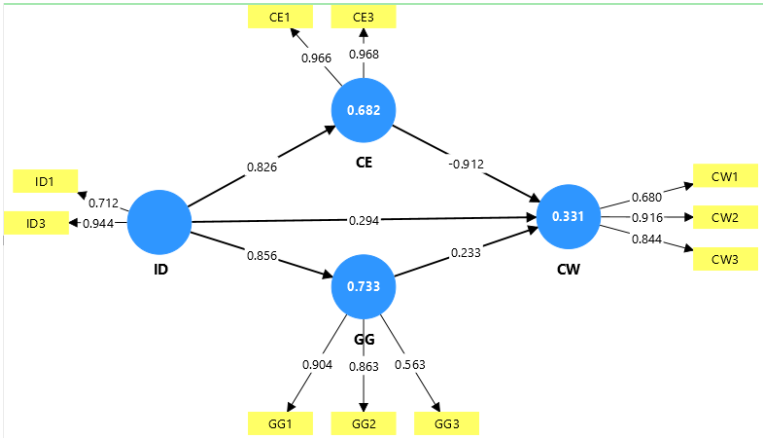


Fig. 3 : Measurement model after the removal of indicators ID2 and CE2.

The model evaluation results shown in Fig. 3 indicate that the GG3 indicator consistently had an outer loading value below 0.60. Consequently, the GG3 indicator was removed from the measurement model to meet convergent validity requirements.

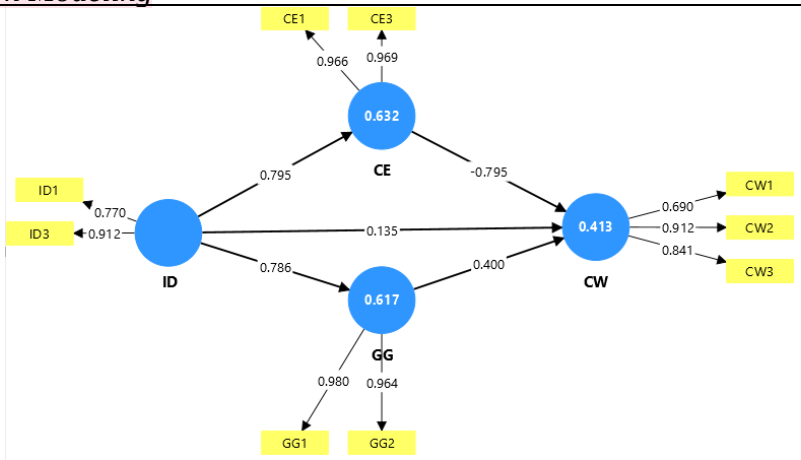


Fig. 4 : Measurement model after the removal of indicator GG3

All indicators exhibit outer loading values greater than 0.60, as seen in Fig. 4 As a result, the measurement model satisfies convergent validity requirements.

The subsequent step involves conducting a discriminant validity test by comparing the Fornell-Larcker criteria for each latent variable. This approach aims to confirm that each latent variable demonstrates a stronger correlation with its own measurement indicators than with those of other latent variables.

Table 2 : Evaluation of Discriminant Validity

Indicator	Community Empowerment	Community Welfare	Government Governance	Infrastructure Development
Community Empowerment	0.967			
Community Welfare	-0.491	0.820		
Government Governance	0.490	0.117	0.972	
Infrastructure Development	0.795	-0.182	0.786	0.844

Table 2 demonstrates that each construct satisfies the Fornell–Larcker criteria for discriminant validity. This is indicated by the square root of the Average Variance Extracted from each construct, which is higher than its correlation with other constructs. Consequently, each construct is distinct from other latent constructs and has sufficient discriminant validity.

The next stage is to examine the reliability of the measurement model using Composite Reliability (CR) and Cronbach's Alpha. Composite Reliability looks at the internal consistency of the indicators that measure a latent construct, whereas Cronbach's Alpha looks at the consistency of the indicators. A construct is deemed reliable if both the Composite Reliability and Cronbach's Alpha are greater than 0.7.

Table 3 : Evaluation of Reliability

Variable	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)	Information
Community Welfare	0.753	0.859	0.672	Reliable
Government Governance	0.942	0.971	0.944	Reliable
Community Empowerment	0.931	0.967	0.935	Reliable
Infrastructure Development	0.612	0.831	0.713	Reliable

Table 3 shows that all the Composite Reliability figures for the latent variables are greater than 0.70, indicating that they satisfy all recommended reliability standards. The Cronbach's alpha values for

the variables Community Welfare, Government Governance, and Community Empowerment are also above 0.70. Although the variable Infrastructure Development construct has a Cronbach's Alpha value of 0.612, its Composite Reliability value of 0.831 exceeds the recommended minimum threshold of 0.70. Therefore, the variable is considered to have adequate internal reliability, as Composite Reliability is perceived as a more appropriate measure of internal consistency than Cronbach's Alpha in PLS-SEM [24], [30].

3.2 Structural Model Evaluation

The structural model evaluation in PLS-SEM is performed by assessing the model's quality using the coefficient of determination (R^2) of each endogenous latent variable, which indicates the predictive capacity of the structural model. The R^2 values obtained are as follows:

Table 4 : Coefficient of Determination (R^2) Value of Endogenous Latent Variables

Endogenus latent variable	R^2
Community Welfare	0.413
Government Governance	0.617
Community Empowerment	0.632

Table 4 indicates that the model has a moderate ability to explain the endogenous latent variables. The R^2 values of 0.413, 0.617, and 0.632 indicate that the model accounts for 41.3% of the variation in community welfare, 61.7% of governance, and 63.2% of community empowerment, respectively, while the remainder is explained by factors external to the research model.

3.3 Hypotheses Testing

Hypothesis tests for (β, γ, and λ) were carried out using the bootstrap resampling method from Geisser and Stone. The statistical test used was the t-test, based on the formulated statistical hypothesis. The bootstrap procedure begins with the generation of B independent bootstrap samples. In this study, the number of bootstrap samples was set at B to 5.000, in accordance with recommendations for obtaining stable and reliable estimates of standard errors, t-statistics, and p-values.

The initial hypothesis test was carried out on the measurement model in order to assess the significance of the relationships between the indicators and their latent constructs. The statistical hypotheses employed are as follows:

$\boldsymbol{H0: \lambda_k = 0}$ ($\boldsymbol{Indicator\ parameter\ for\ k\ significant}$)

$\boldsymbol{H1: \lambda_k \neq 0}$ ($\boldsymbol{Indicator\ parameter\ for\ k\ not\ significant}$)

The decision was made by comparing the calculated t-statistic with the critical t-value.

Table 5 : Hypothesis Testing of the Measurement Model

Latent variable	Indikator	Outer Weight Value	T-statistic	P-Value	Information
Community Welfare	CW_1	0.318	2.983	0.000	Significant
	CW_2	0.508	6.637	0.000	Significant
	CW_3	0.377	5.978	0.000	Significant
Government Governance	GG_1	0.585	11.065	0.000	Significant
	GG_2	0.443	10.636	0.000	Significant
Community Empowerment	CE_1	0.505	17.324	0.000	Significant
	CE_3	0.529	15.365	0.000	Significant
Infrastructure Development	ID_1	0.456	4.012	0.000	Significant
	ID_3	0.711	6.337	0.000	Significant

Table 5 shows that all indicators for community welfare, government governance, community empowerment, and infrastructure development have a value $\boldsymbol{t_{calculated} > t_{critical}(1.96)}$ and $\boldsymbol{p - value < 0.05}$. Thus, hypothesis ($H_0$) is rejected, which means that all indicators have a significant effect on their respective latent constructs.

The second hypothesis test looked at the structural model by examining the path coefficients. Its aim

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was to evaluate the significance of the relationships between latent variables, focusing on the impact of the exogenous latent variables on the endogenous latent variables (γ) as well as the effects that exist among the endogenous latent variables (β). The statistical hypotheses are as follows:

Statistical hypotheses for the relationship between exogenous and endogenous latent constructs:

$\boldsymbol{H0: \gamma_k = 0}$ (***Indicator parameter for k significant***)

$\boldsymbol{H1: \gamma_k \neq 0}$ (***Indicator parameter for k not significant***)

Statistical hypotheses for the relationship between endogenous and endogenous latent constructs:

$\boldsymbol{H0: \beta_k = 0}$ (***Indicator parameter for k significant***)

$\boldsymbol{H1: \beta_k \neq 0}$ (***Indicator parameter for k not significant***)

The decision was made by comparing the calculated t-statistic with the critical t-value.

Table 6 : Hypothesis Testing of the Structural Model

Inner Model	Path Coefficient	Path Coefficient Estimation	T-statistic	P-Value	Information
Government Governance → Community Welfare	β	0.400	1.463	0.143	Not Significant
Infrastructure Development → Community Welfare	γ	0.135	0.294	0.769	Not Significant
Infrastructure Development → Government Governance	γ	0.786	10.741	0.000	Significant
Infrastructure Development → Community Empowerment	γ	0.795	8.714	0.000	Significant.
Community Empowerment → Community Welfare	β	-0.795	2.672	0.008	Significant

The results shown in Table 6 show that infrastructure development has a significant influence on community governance and empowerment, and that this empowerment has a significant effect on community welfare. Of the hypotheses proposed, three were supported and two were not. This suggests that neither governance nor infrastructure development has a significant direct effect on community welfare.

The results of the path coefficient values that have been obtained can formulate the structural model equation as follows:

- A Structural model showing how Government Governance, Infrastructure Development, and Community Empowerment affect Community Welfare

$$\boldsymbol{\eta_1 = 0.400\eta_1 + 0.135\xi_1 - 0.795\eta_2 + \zeta_1}$$

- A Structural Model showing how Infrastructure Development affects Government Governance

$$\boldsymbol{\eta_2 = 0.786\xi_2 + \zeta_2}$$

- A Structural Model showing how Infrastructure Development affects Community Empowerment

$$\boldsymbol{\eta_3 = 0.795\xi_3 + \zeta_3}$$

Here is how to interpret the structural model :

1. The path coefficient for government governance is 0.400, which shows a positive relationship with community welfare. It thus implies that for every one-unit improvement in government governance, community welfare should rise by 0.400 units, all other things remaining the same. Yet the relationship is not statistically significant; as a result, it has not been demonstrated that government governance has a direct effect on community welfare.
2. The path coefficient for infrastructure development is 0.135, which shows a positive link with social welfare. Still, this result is not statistically significant, so infrastructure development does not appear to have a direct effect on social welfare.

3. The path coefficient for infrastructure development is 0.786, showing a significant positive impact on governance. This means a higher level of infrastructure development improves governance quality by 0.786 units. This result indicates that infrastructure development significantly contributes to better governance performance.
4. The path coefficient for Infrastructure development is 0.795, showing a significant positive impact on community empowerment. This indicates that the greater the infrastructure development, the more community empowerment will increase by 0.795 units.
5. The path coefficient for community empowerment is -0.795 and a significant effect on community welfare. This negative coefficient indicates that each one-unit increase in community empowerment is accompanied by a 0.795-unit decrease in community welfare, all else being equal.

Infrastructure development has a positive effect on governance and community empowerment, but no direct impact on community welfare. Furthermore, governance has no significant effect on community welfare. In contrast, community empowerment has a significant but negative influence on community welfare

Community welfare is adversely affected by community empowerment. This condition shows that increases in welfare are not directly reflected in the empowerment measures used, which include the Labor Force Participation Rate (TPAK), the number of Integrated Health Posts (Posyandu), and the number of Beneficiary Families (KPM). According to Hermawati & Winarno (2020) and BPS (2024), the high number of KPM suggests that many households are still considered impoverished or economically vulnerable and hence need social support. Furthermore, since most workers continue to work in the unorganized sector with comparatively poor productivity and pay [31], high TPAK is not always accompanied by higher income. In contrast, a rise in the number of Integrated Health Posts (Posyandu) is more indicative of the accessibility of fundamental healthcare services than it is of a direct improvement in economic welfare [32]. Therefore, an increase in community empowerment indicators does not necessarily lead to an increase in community welfare because program benefits are not fully targeted.

The research shows that the level of community welfare in East Java Province communities at both the district and city levels is affected by infrastructure development, governance, and community empowerment. Although infrastructure development has a positive effect on both governance and community empowerment, its influence on population welfare remains limited. It follows that if welfare is to be improved, policies must place equal emphasis on developing physical infrastructure, improving the quality of human resources, and enhancing the effectiveness of community empowerment initiatives to secure sustainable and targeted benefits.

A single global model was unable to adequately describe the relationships between variables due to probable unobserved heterogeneity within East Java province's regencies and cities, according to the model evaluation results. To identify districts or cities with comparatively homogeneous structural relationship traits, the analysis proceeded using the Partial Least Squares–Prediction-Oriented Segmentation (PLS-POS) method.

3.4 Clustering using PLS-POS

The optimal segment class is determined based on the Average Weighted R-Square value achieved by each segment group. The Average Weighted R-Square values for each segment group are presented in Table 7.

Table 7 : Weighted Average R-Squared Value

Variable	R^2	Number of Segment Classes	Average Weighted R-Square
Community Welfare	0.413	K = 2	0.713
		K = 3	Not Estimated

The results in Table 7 show an overall R^2 of 0.413, while the weighted average R^2 for the two-segment model (K = 2) is 0.713. The weighted average R^2 for the three-segment model (K = 3) could not be estimated because SmartPLS gave an "insufficient sample size" warning. This means the sample size (38 districts/cities) was too small to form three segments. Therefore, the districts/cities of East Java province are classified into two segments based on community welfare characteristics. The number of areas in each segment is listed in Table 8.

Table 8 : Segment Size

Segment	Number of Members	Percentage(%)
1	17	44.737
2	21	55.263

Table 8 shows that segment 1 consists of 17 districts/cities, representing 44.737% of the total observations, while segment 2 consists of 21, representing 55.263%. The distribution of districts/cities within each segment is presented in Table 9.

Table 9 : Regency/City Grouping

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

The segmentation results presented in Table 8 indicate that all regencies/cities are grouped into two segments based on relatively homogeneous characteristics. To identify differences in the relationships among latent variables within each segment, a path coefficient analysis was conducted. The results of this analysis are shown in Table 10.

Table 10 : Path Coefficient Segment 1 and Segment 2

Inner Model	Path Coefficient	Segment 1	Segment 2
Government Governance → Community Welfare	0.400	-0.328	1.013
Infrastructure Development → Community Welfare	0.135	1.401	0.032
Infrastructure Development → Government Governance	0.786	0.846	0.957
Infrastructure Development → Community Empowerment	0.795	0.611	0.938
Community	-0.795	-1.155	-1.514

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Empowerment → Community Welfare

The segmentation results shown in Table 7, which were obtained using the PLS-POS method, show that the values of the path coefficients differ between the global model, segment 1 and segment 2, thus indicating heterogeneity in the relationship between the latent variables among the districts and cities in East Java. In both segments the relationship between community empowerment and community welfare is negative, although this effect is stronger in segment 2. On the other hand, the impact of governance on community welfare is in the opposite direction: it is negative in segment 1 and positive in segment 2. Infrastructure development has a positive effect on both community empowerment and governance in each of the segments, the effect being relatively greater in segment 2. Moreover, the effect of infrastructure development on community welfare is considerably stronger in segment 1 than in segment 2. Altogether, these findings show that the PLS-POS method is able to detect unobserved heterogeneity and gives a more detailed view of the relationship between the variables than the overall PLS-SEM model.

4. Conclusion

This study examines the factors that affect community welfare in East Java by applying the Partial Least Squares Structural Equation Modeling (PLS-SEM) method. It also groups districts based on community welfare characteristics using the Partial Least Squares Prediction-Oriented Segmentation (PLS-POS) method.

The PLS-SEM analysis's results show that community welfare was not directly enhanced by infrastructure development. Nonetheless, it significantly and favorably impacted community empowerment and government performance. On the other hand, community empowerment had a considerable but detrimental impact on community welfare, but government performance had no meaningful effect. This result implies that greater community empowerment, as measured by the study's parameters, did not result in better welfare. Additionally, the structural model evaluation showed that the community well-being variable had a modest explanatory power ($R^2 = 0.413$). This model accounts for 41.3% of the variation in community welfare. Ultimately, 38 districts and cities in the province of East Java were divided into two segments using the PLS-POS analysis: segment 1, which included 22 districts and cities (57.895%), and segment 2, which included 16 districts and cities (42.105%). The segmentation results showed variation in the structural linkages between latent variables among East Java province's districts and cities that had not been seen before.

The study has a number of limitations. The first of these is that the analysis was carried out only in the districts and cities of East Java Province and it therefore cannot be applied to the whole country. Secondly, each of the variables measured is based on just three indicators and this does not fully capture the multidimensional character of community welfare. Thirdly, the segmentation analysis made use of only the PLS-POS approach and as a result the segmentation results cannot be compared with those obtained by means of other methods. It follows that the segments produced in this study should be understood as classifications derived from the indicators employed, and not as a complete reflection of all the factors affecting community welfare.

Further, the research ought to make use of data at the national level and should incorporate a wider variety of variables and indicators in order to obtain a better evaluation of community welfare. It is also suggested that the PLS-POS method be compared with other segmentation methods, for example FIMIX-PLS (Finite Mixture Partial Least Squares). Taking these steps is likely to lead to an improvement in segmentation accuracy. The results of this study could help public authorities and policymakers in formulating more effective and targeted policies aimed at improving community welfare.

CRediT Authorship Contribution Statement

Siti Fadilatul Khasanah: Contributed to conceptualization, Methodology, Software, Formal Analysis, Data Curation, and Writing of the Original Draft. **Rahmawati Erma Standsyah:** Contributed to conceptualization, Methodology, Validation, Writing – Review and Editing, Supervision, and 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 did not obtain any external funding.

The authors would like to thank the Statistics Indonesia (BPS) of East Java Province, the Directorate General of Fiscal Balance (DJPK), and the East Java Province Open Data Portal for supplying the official data that have been used in this study. The secondary data involved span the period 2022 to 2024 and relate to the regencies and cities level in East Java Province, which are the units used for analysis.

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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