CAUCHY – Jurnal Matematika Murni dan Aplikasi
Volume 10 (2) (2025), Pages 1309-1323
p-ISSN: 2086-0382; e-ISSN: 2477-3344

Development of Multigroup Structural Equation Modeling on Structural and Measurement Models for Waste Management Behavior Patterns

Aldianur Khairani[1], Solimun[1*], Adji Achmad Rinaldo Fernandes [1], Fachira Haneinanda Junianto [1], and Nadia Khairina[2]

[1] *Department of Statistics, Faculty of Mathematics and Natural Science, University of Brawijaya, Indonesia*
[2] *Faculty of Psychology, State University of Malang, Indonesia*

Abstract

An enhanced Structural Equation Modeling (SEM) framework is developed by integrating multigroup analysis with moderation testing at both the structural and measurement (outer) model levels. Data from communities located near and far from tourist areas in Batu City, Indonesia, were used to evaluate how environmental quality, waste bank utilization, and 3R awareness influence community perceptions of the economic benefits of waste management. Measurement model results showed significant differences between groups in loading differences, particularly for Environmental Care (loading difference -0.650, p-value < 0.001), Recycling Effectiveness (loading difference -0.383, p-value < 0.001), and Economic Resource Utilization (loading difference -0.663, p-value < 0.001), indicating context-dependent measurement behavior. In contrast, the structural model showed stability with only one path, Environmental Quality to 3R Awareness, differing significantly (path coefficient difference 0.207, p-value $= 0.009$) between groups. The model demonstrates strong explanatory power, with a determination coefficient of 0.829. Methodologically, this study introduces a novel SEM approach that incorporates a moderated measurement model to evaluate differences in how indicators reflect latent variables when applied to groups with different context characteristics. Substantively, these findings highlight the importance of environmental conditions and 3R behaviors in improving economic outcomes at the community level. This framework offers a replicable SEM strategy for research involving context-sensitive latent variables.

Keywords: Structural Equation Modeling; Multigroup SEM; Measurement Moderation; Outer Model; Waste Management.

1 Introduction

Structural Equation Modeling (SEM) is an extension of path analysis introduced by Wright in 1934 to examine direct and indirect relationships among multiple variables [1]. As a multivariate technique, SEM simultaneously evaluates the relationships between latent constructs and their observed indicators [2]. Latent variables—concepts that cannot be measured directly—are represented through multiple indicators, allowing researchers to model complex theoretical

*Corresponding author. E-mail: solimun@ub.ac.id

Submitted: August 28, 2025 Reviewed: September 26, 2025 Accepted: November 25, 2025
DOI: https://doi.org/10.18860/cauchy.v10i2.34997

structures [3]. SEM consists of two components: the measurement model, which links latent variables to their indicators, and the structural model, which specifies the causal relationships among latent constructs [4], [5]. Indicators within the measurement model may be reflective or formative, depending on whether they represent manifestations of a construct or contribute to its formation [6].

SEM is widely applied across disciplines because it integrates interconnected exogenous and endogenous variables into a unified analytical framework. Path analysis within SEM allows researchers to decompose effects into direct, indirect, and total components [2]. However, limited research has explored these effects within a multigroup moderation context, even though group-level differences frequently arise in empirical studies.

Multigroup SEM addresses this need by dividing samples into predefined categories and estimating models separately for each group. The resulting parameter estimates can then be compared to assess structural and measurement invariance [7]. This approach is particularly useful when data originate from distinct populations, enabling more robust model validation and interpretation [8]. Furthermore, the linearity assumption plays a critical role in SEM because it governs how latent relationships are represented. When linearity holds, parametric path analysis is appropriate; otherwise, nonparametric approaches are required [9], [10].

Given these considerations, this study aims to develop a multigroup SEM framework that simultaneously evaluates structural and measurement models to examine behavioral patterns in waste management. This approach allows for a deeper understanding of how community characteristics—specifically proximity to tourism areas—shape environmental behavior and perceptions.

To operationalize the conceptual framework described in the introduction, this study employs a multigroup Structural Equation Modeling (SEM) approach that simultaneously evaluates the measurement and structural components of the model. The use of multigroup SEM is essential for identifying differences in indicator behavior and structural relationships between communities located far from and near tourism areas. Given the importance of validating linearity, measurement quality, and structural consistency across groups, a systematic methodological procedure is required. The following section outlines the analytical steps undertaken in this study, including model specification, assessment of validity and reliability, evaluation of linearity assumptions, and multigroup estimation procedures.

2 Methods

This section describes the methodological framework adopted in this study. To maintain clarity and a systematic flow, the methods are organized into several subsections that present the conceptual foundation and analytical procedures of the Structural Equation Modeling (SEM) approach. These subsections include explanations of the structure of the measurement (outer) and structural (inner) models, the multigroup analysis used to compare communities near and distant from tourism areas, and the procedures for testing moderation at both the measurement and structural levels. Additionally, this section outlines the model estimation process, evaluation criteria for assessing validity, reliability, and model fit, and the steps undertaken to ensure robustness in interpreting group-specific differences.

2.1 Structural Equation Modeling (SEM)

SEM is a multivariate analytical technique used to assess the relationships between observed indicators and latent variables, as well as the interconnections among latent constructs [11]. This method brings together both the structural and measurement components within a single, unified modeling framework [12]. In SEM applications, the structural (inner) model and the measurement (outer) model are examined concurrently. Within the model representation, variable X functions as an exogenous construct, while variable Y serves as an endogenous construct. Exogenous variables are those whose values arise outside the system, whereas endogenous variables are shaped by other variables within the model [2]. The full, or hybrid, SEM model is expressed in Equation (1) [13].

$$\eta = B\eta^* + \Gamma\xi + \zeta \tag{1}$$

In this model, η represents latent variables that are pure endogenous, while η^* denotes endogenous latent variables that intervene. The matrix B contains the coefficients of intervening endogenous latent variables, and Γ represents the coefficients of exogenous latent variables. The notation ξ refers to latent exogenous variables, and ζ denotes the error model.

2.2 Assumptions

Two fundamental assumptions in Structural Equation Modeling (SEM), particularly in covariance and mean structure analysis, are that the data must be measured on a continuous scale and follow a multivariate normal distribution [14]. These assumptions stem from the large-sample theoretical foundations underlying SEM. Other references also emphasize that SEM requires the relationships among variables to be linear [15]. One method commonly used to evaluate the linearity of these relationships is the Regression Specification Error Test (RESET).

2.3 Moderating Variables

A moderating variable is a variable that strengthens or weakens the influence of exogenous variables (predictor or independent) on endogenous variables (responsive or dependent) [2]. One important characteristic is that the moderator variable is not influenced by the exogenous (explanatory) variable. In general, the effect of a moderator variable is indicated by the product of the exogenous variable indicator and the moderator variable indicator.

2.4 Moderation Effect Test on Structural Model (Inner Model)

In essence, moderating-variable analysis using the multigroup approach involves conducting path analysis separately for two or more groups, for instance, individuals living far from tourism areas (group 1) and those residing near tourism locations (group 2). A variable is considered a moderator when the path coefficients differ significantly between these groups [2]. The significance of the moderating effect can be assessed through bootstrap resampling procedures [7]. The structural model that incorporates a moderating variable can be expressed as follows:

$$\begin{aligned} Y_{1i} &= \gamma_{1.1}X_{1i} + \gamma_{2.1}X_{2i} + \gamma_{1.2}X_{1i}G_i + \gamma_{2.2}X_{2i}G_i + \zeta_{1i} \\ Y_{2i} &= \gamma_{3.1}X_{1i} + \gamma_{4.1}X_{2i} + \beta_{1.1}Y_{1i} + \gamma_{3.2}X_{1i}G_i + \gamma_{4.2}X_{2i}G_i + \beta_{1.1}Y_{1i}G_i + \zeta_{2i} \end{aligned} \tag{2}$$

where $i = 1, 2, \ldots, n$ and $G = 0, 1$.

2.5 Moderation Effect Test on Measurement Model (Outer Model)

Research using a multigroup moderation approach in structural models using SEM is common. However, the moderation approach in the measurement model is a novel research approach, which involves modeling each indicator measuring the latent variable in each group (conducted in a multigroup manner). An illustration of multigroup modeling is presented in Figure 1.

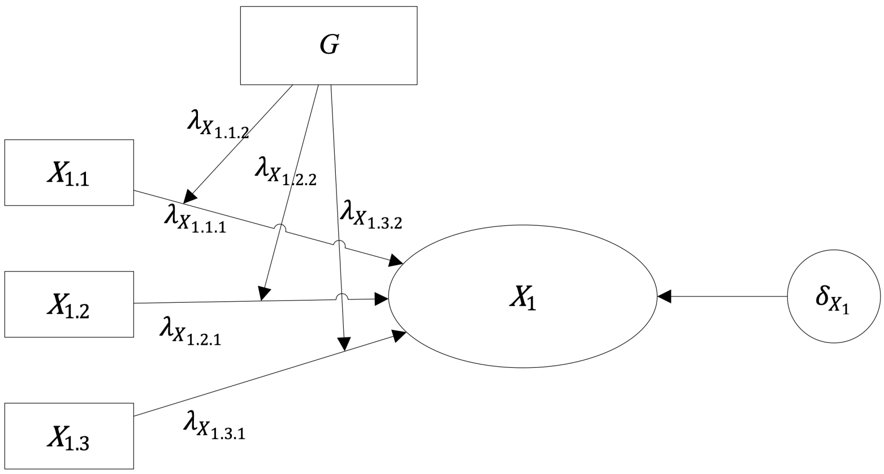

Figure 1: Measurement Model Multigroup

2.6 Linearity Test with Ramsey RESET

According to [9], to test the linearity of the relationship, we use Ramsey RESET. The hypothesis test used in the Ramsey RESET linearity test is carried out with the following steps:

1. A regression is carried out by relating the endogenous variable Y_1 to X_1. The expression for $\hat{Y}_{1i}$, which represents the endogenous variable in the model, is presented in Equation (3), where $i = 1, 2, \ldots, n$.

$$\hat{Y}_{1i} = \hat{\gamma}_0 + \hat{\gamma}_1 X_{1i} \tag{3}$$

The coefficient of determination is then computed based on Equation (3), yielding R_1^2, which is defined in Equation (4).

$$R_1^2 = 1 - \frac{\sum_{i=1}^{n}(Y_{1i} - \hat{Y}_{1i})^2}{\sum_{i=1}^{n}(Y_{1i} - \bar{Y})^2} \tag{4}$$

2. Perform a regression of the variable Y_{1i} along X_{1i} with two additional predictor variables, namely $\hat{Y}_{1i}^2$ and $\hat{Y}_{1i}^3$. Next, the endogenous variables in the model are shown in Equation (5).

$$Y_{1i}^* = \gamma_0^* + \hat{\gamma}_1^* X_{1i} + \hat{\gamma}_2 \hat{Y}_{1i}^2 + \hat{\gamma}_3 \hat{Y}_{1i}^3 + \varepsilon_i^* \tag{5}$$

Calculate the value of the determination coefficient based on Equation (4) as R_2^2, which is formulated in Equation (6).

$$R_2^2 = 1 - \frac{\sum_{i=1}^{n}(Y_{1i}^* - \hat{Y}_{1i}^*)^2}{\sum_{i=1}^{n}(Y_{1i}^* - \bar{Y}^*)^2} \tag{6}$$

3. Perform a linearity test between predictor variables and responses based on the following hypotheses:

$$H_0 : \gamma_2 = \gamma_3 = 0, \qquad H_1 : \text{There is at least one } \gamma_j \neq 0$$

The test statistics used follow the distribution of F as described in Equation (7).

$$F_{\text{hitung}} = \frac{(R_2^2 - R_1^2)/m}{(1 - R_2^2)/(n - k - 1 - m)} \sim F_{(m, n-k-1-m)} \tag{7}$$

where n the number of observations, k the number of early exogenous variables, and m the number of new exogenous variables added.

According to the decision rule, if the resulting p-value is less than α, then H_0 is rejected, indicating that the variables exhibit a non-linear relationship. Conversely, if H_0 is not rejected, the relationship between the variables can be considered linear.

2.7 Bootstrap Resampling Approach Hypothesis Testing

Hypothesis testing in SEM structural models is carried out using a resampling algorithm, beginning with the estimation of parameters, followed by the calculation of variances and p-values. As noted in [11], resampling involves drawing repeatedly from an existing dataset to generate new samples, either with or without replacement. This procedure is performed multiple times until the resulting estimates reach a stable or convergent pattern. Various studies indicate that bootstrap resampling typically achieves convergence after roughly 100 repetitions [2].

The general steps for estimating standard errors through the bootstrap method are as follows:

1. Specify the number of bootstrap iterations B and generate bootstrap samples $(xy_1^*, xy_2^*, \ldots, xy_B^*)$ by randomly selecting n observations from the original dataset with replacement. This process represents the sampling mechanism used in bootstrap resampling.
2. Compute the corresponding bootstrap replicates for each of the B resampled datasets.
3. Estimate the standard error by calculating the standard deviation of the bootstrap estimates across all B iterations, as shown in Equation (8).

$$SE_{\hat{\theta}} = \sqrt{\frac{\sum_{b=1}^{B}(\hat{\theta}_{(b)} - \bar{\theta})^2}{B}} \tag{8}$$

Hypothesis testing with bootstrap resampling uses the Z-statistic, which is then compared to the critical value from the Z table at a chosen significance level. The hypotheses for parameter evaluation are formulated as follows:

1. Statistical Hypothesis for Measurement Model.

$$H_0 : \lambda_{X_{ml}} = 0, \qquad H_1 : \lambda_{X_{ml}} \neq 0$$

Test statistic:

$$Z = \frac{\hat{\lambda}}{SE(\hat{\lambda}_{X_{ml}})} \sim Z_{\alpha/2} \tag{9}$$

2. Statistical Hypotheses for Structural Models.

$$H_0 : \beta_{Y_{jh}} = 0, \qquad H_1 : \beta_{Y_{jh}} \neq 0$$

Test statistic:

$$Z = \frac{\hat{\beta}}{SE(\hat{\beta}_{jh})} \sim Z_{\alpha/2} \tag{10}$$

Standard errors are obtained from bootstrap resampling results. The decision-making criterion is to reject H_0 if the p-value $< \alpha$. If H_0 is rejected, the resulting coefficient is considered suitable for use in the model.

2.8 Model Validity

In SEM, it is essential to assess the adequacy of the model using specific evaluation techniques. One commonly applied approach involves calculating the total coefficient of determination [7]. In model evaluation, the goodness-of-fit index serves as a measure of how well the latent variables relate to one another. One indicator of this fit is the proportion of variance explained, reflected in the coefficient of determination (R^2) for the endogenous latent constructs. The Q-square predictive relevance measure (Q^2) is also employed within the structural model to assess the model's accuracy in predicting observed data. This Q^2 statistic is conceptually equivalent to the total coefficient of determination. The computation of this value is presented in Equation (11).

$$Q^2 = 1 - (1 - R^2_{1,\text{adj}})(1 - R^2_{2,\text{adj}}) \cdots (1 - R^2_{p,\text{adj}}) \tag{11}$$

Using the coefficient of determination (R^2), the adjusted value can be obtained as shown in Equation (12).

$$R^2_{2,\text{adj}} = 1 - \left(\frac{\sum_{i=1}^{n} \frac{(Y_{ji} - \hat{Y}_{ji})^2}{n-m-1}}{\sum_{i=1}^{n} \frac{(Y_{ji} - \bar{Y}_{ji})^2}{n-1}} \right) \tag{12}$$

along: $j = 1, 2, \ldots, J$; $m = 1, 2, \ldots, M$; $i = 1, 2, \ldots, n$. The symbol $R^2_{p,\text{adj}}$ denotes the corrected coefficient of determination in the p-th structural model equation. The term Y_{ji} represents the i-th value of the p-th endogenous variable, while $\hat{Y}_{ji}$ is the corresponding estimated value for that endogenous variable. The notation $\bar{Y}_{ji}$ refers to the mean of the endogenous variable. The parameter n indicates the number of observations, and m denotes the number of exogenous variables included in the model.

2.9 Research Data

This study employs both secondary data and simulated data. The secondary data were sourced from a research grant by [16], which examined community perceptions of the economic benefits of waste in Batu City. The population in this study consists of residents of Batu City, while the sample includes individuals living in Batu District, Bumiaji District, and Junrejo District. A total of 120 respondents were involved, categorized into two groups: those living far from tourism areas (Group 0) and those residing near tourism areas (Group 1). The variables used in this research are presented in Table 1.

Table 1: Research Variables

Variables	Indicators
Environmental Quality (X_1)	Environmental Awareness ($X_{1.1}$) Environmental Maintenance ($X_{1.2}$) Community Attitude towards the Environment ($X_{1.3}$)
Utilization of Waste Banks (X_2)	The Concept of Waste Banks in People's Homes ($X_{2.1}$) Effectiveness of Waste Bank ($X_{2.2}$) Waste Bank Operational Efficiency ($X_{2.3}$)
Awareness of Using 3R (Y_1)	Reduce Effectiveness ($Y_{1.1}$) Reuse Effectiveness ($Y_{1.2}$) Recycle Effectiveness ($Y_{1.3}$) Waste Management Efficiency ($Y_{1.4}$)
Economic Benefits of Waste (Y_2)	Economic Waste Management Efficiency ($Y_{2.1}$) Utilization of Waste as an Economic Resource ($Y_{2.2}$) Prospek Pengelolaan Ekonomi Sampah ($Y_{2.3}$)
Residence Location (G)	Far from Tourism (G_0) Close to Tourism (G_1)

2.10 Research Model

The research model employed in this study is presented in Figure 2.

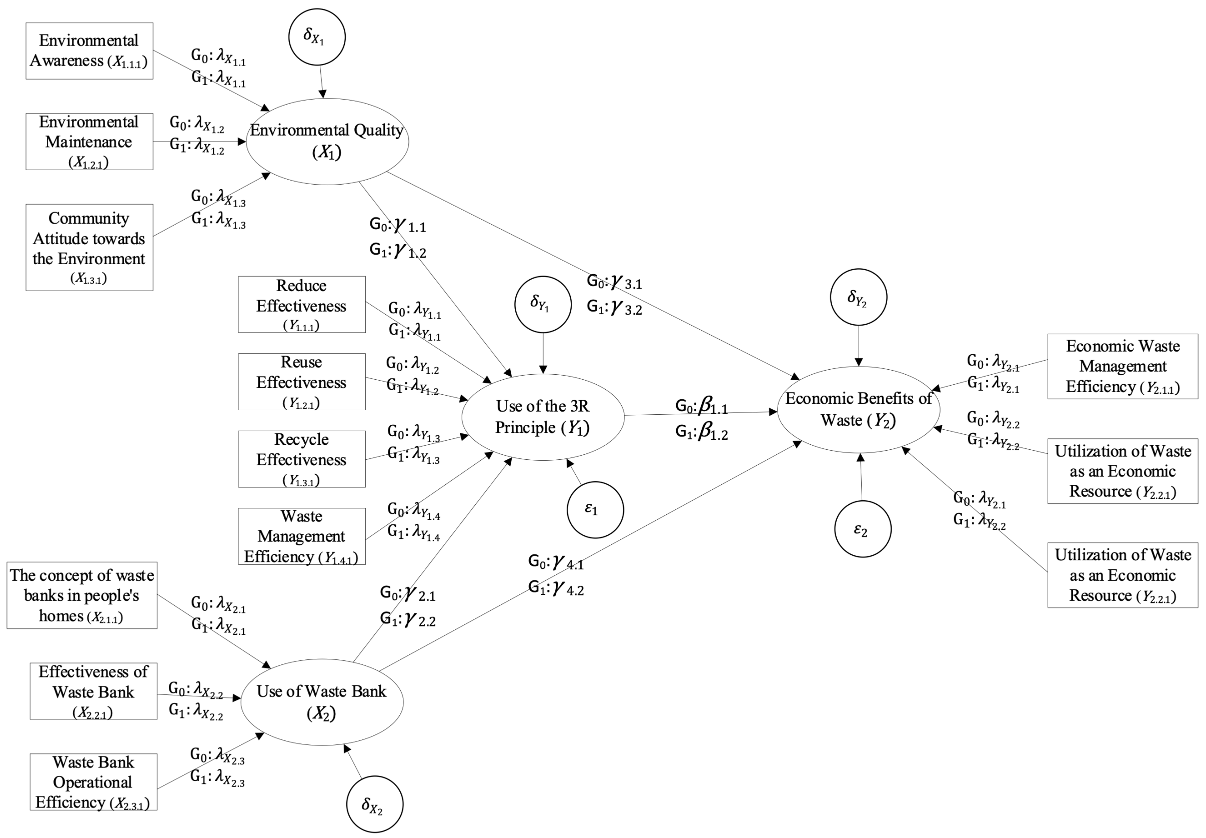

Figure 2: Research Model

2.11 Research Stages

The procedure followed in this study consists of several stages:

1. Preparing the secondary dataset.
2. Constructing a path diagram that reflects the exogenous, endogenous, and moderating variables included in the research.
3. Developing both the measurement model and the structural model.
4. Assessing whether the linearity assumptions are satisfied.
5. Conducting simultaneous estimation of the measurement and structural models to examine the relationships among latent variables, using a multigroup SEM approach.
6. Interpreting the results and formulating the study's conclusions.

3 Results and Discussion

This section presents the research results and provides a discussion interpreting the findings in relation to the theoretical framework and analytical procedures applied in the study. The presentation is structured in stages, beginning with an assessment of the validity and reliability of the measurement instruments, followed by the evaluation of the linearity assumption to ensure the suitability of the SEM approach. Subsequently, the results of the Structural Equation Modeling (SEM) analysis are reported, including the examination of the measurement (outer) model, the structural (inner) model, and the multigroup comparisons involving communities located near and distant from tourism areas. Each set of findings is discussed by emphasizing its statistical and substantive significance, its alignment with or deviation from previous studies, and its methodological implications, particularly concerning the use of moderated multigroup

SEM. With this structure, the Results and Discussion section presents a coherent flow from the empirical evidence to its broader theoretical interpretation.

3.1 Validity and Reliability

Validity testing is conducted by examining the Corrected Item Total Correlation values, which indicate the contribution of each item within the instrument. Following the guidelines in [17], each questionnaire item is evaluated using this statistic. An item is considered valid when its Corrected Item Total Correlation exceeds 0.3. The results of the validity assessment are presented in Table 2.

Table 2: Validity Check Results

Variables	Indicators	Statement Item	Corrected Item Total Correlation	Description
X_1	$X_{1.1}$	$X_{1.1.1}$	0.565	Valid
		$X_{1.1.2}$	0.421	Valid
	$X_{1.2}$	$X_{1.2.1}$	0.513	Valid
		$X_{1.2.2}$	0.455	Valid
		$X_{1.2.3}$	0.478	Valid
	$X_{1.3}$	$X_{1.3.1}$	0.505	Valid
		$X_{1.3.2}$	0.334	Valid
X_2	$X_{2.1}$	$X_{2.1.1}$	0.541	Valid
		$X_{2.1.2}$	0.513	Valid
		$X_{2.1.3}$	0.429	Valid
	$X_{2.2}$	$X_{2.2.1}$	0.589	Valid
		$X_{2.2.2}$	0.306	Valid
		$X_{2.2.3}$	0.515	Valid
	$X_{2.3}$	$X_{2.3.1}$	0.505	Valid
		$X_{2.3.2}$	0.443	Valid
Y_1	$Y_{1.1}$	$Y_{1.1.1}$	0.491	Valid
		$Y_{1.1.2}$	0.325	Valid
	$Y_{1.2}$	$Y_{1.2.1}$	0.469	Valid
		$Y_{1.2.2}$	0.377	Valid
	$Y_{1.3}$	$Y_{1.3.1}$	0.374	Valid
		$Y_{1.3.2}$	0.321	Valid
	$Y_{1.4}$	$Y_{1.4.1}$	0.407	Valid
		$Y_{1.4.2}$	0.579	Valid
Y_2	$Y_{2.1}$	$Y_{2.1.1}$	0.399	Valid
		$Y_{2.1.2}$	0.336	Valid
	$Y_{2.2}$	$Y_{2.2.1}$	0.472	Valid
		$Y_{2.2.2}$	0.427	Valid
	$Y_{2.3}$	$Y_{2.3.1}$	0.406	Valid
		$Y_{2.3.2}$	0.335	Valid

Based on the results presented in Table 2, all items in the instrument have Corrected Item Total Correlation values exceeding 0.3. This indicates that each item is valid and suitably measures the variables included in this study.

In addition to validity, the instrument also requires a reliability assessment to determine whether it consistently measures the intended variables. According to the criteria in [18], an instrument is considered reliable when the Cronbach's Alpha value is greater than 0.6. Reliability reflects the internal consistency of the questionnaire in capturing a construct. The reliability results are displayed in Table 3.

Table 3: Reliability Check Results

Variables	Cronbach's Alpha	Description
X_1	0.728	Reliable
X_2	0.720	Reliable
Y_1	0.641	Reliable
Y_2	0.751	Reliable

Based on the results in Table 3, all instruments used to measure the study variables show Cronbach's alpha values greater than 0.6. Therefore, it can be concluded that the instrument employed in this study demonstrates strong reliability.

3.2 Linearity Assumption Check

One of the fundamental assumptions in SEM is the requirement of linear relationships among variables. To evaluate this assumption, the Regression Specification Error Test (RESET) was applied to each pair of exogenous and endogenous variables. The p-values obtained for both groups are summarized in Table 4.

Table 4: Linearity Test Results

Variables	Group 0 (p-value)	Group 1 (p-value)	Connection
X_1 with Y_1	0.168	0.341	Linear
X_2 with Y_1	0.071	0.084	Linear
X_1 with Y_2	0.113	0.077	Linear
X_2 with Y_2	0.852	0.360	Linear
Y_1 with Y_2	0.154	0.572	Linear

As shown in Table 4, all variable relationships yielded p-values greater than 0.05 for both groups, indicating no evidence of nonlinearity. Thus, the linearity assumption is satisfied, and the SEM analysis can proceed using the standard linear modeling framework.

3.3 Structural Equation Modeling (SEM)

With the linearity assumption confirmed, the next step involves evaluating the measurement and structural components of the SEM. The results of the measurement (outer) model are reported in Table 5, which presents the indicator loadings for each latent variable across both groups along with the corresponding multigroup moderation tests.

The outcomes of the structural (inner) model are summarized in Table 6. These results provide the estimated path coefficients and reveal how the structural relationships between key constructs differ between communities living far from and near tourism areas.

To complement the numerical results, Figure 3 offers a visual representation of the full structural and measurement model for both groups. Significant moderating effects are indicated by a plus sign (+) along specific pathways, highlighting substantial differences in coefficient magnitudes between Group 0 (residents living far from tourism areas) and Group 1 (residents living closer to tourism areas).

Together, Table 5, Table 6, and Figure 3 provide a comprehensive and integrated overview of the SEM results across the two community contexts.

Table 5: Measurement Model Results

Indicators	G_0		G_1		**Moderation Test** $(G_1 - G_0)$	
	Coefficient	**p-value**	**Coefficient**	**p-value**	**Coefficient Difference**	**p-value**
Measurement Model of Environmental Quality Variable (X_1)						
Environmental Awareness $(X_{1.1})$	0,217	0,001*	0,637	<0,001*	0,419	<0,001*
Environmental Maintenance $(X_{1.2})$	0,948	<0,001*	0,299	<0,001*	-0,650	<0,001*
Community Attitude towards the Environment $(X_{1.3})$	0,231	<0,001*	0,711	<0,001*	0,480	<0,001*
Measurement Model of Waste Bank Utilization Variable (X_2)						
The concept of waste banks in people's homes $(X_{2.1})$	0,597	<0,001*	0,613	<0,001*	0,016	0,858ns
Effectiveness of Waste Bank $(X_{2.2})$	0,519	<0,001*	0,327	<0,001*	-0,192	0,021*
Waste Bank Operational Efficiency $(X_{2.3})$	0,611	<0,001*	0,719	<0,001*	0,108	0,200ns
Measurement Model of Awareness of Using 3R Variable (Y_1)						
Reduce Effectiveness $(Y_{1.1})$	0,297	0,354ns	0,453	<0,001*	0,156	0,045*
Reuse Effectiveness $(Y_{1.2})$	0,804	<0,001*	0,831	<0,001*	0,027	0,765ns
Recycle Effectiveness $(Y_{1.3})$	0,514	0,004*	0,131	0,567ns	-0,383	<0,001*
Waste Management Efficiency $(Y_{1.4})$	0,036	0,047*	0,295	<0,001*	0,260	0,004*
Measurement Model of Economic Benefits of Waste Variable (Y_2)						
Economic Waste Management Efficiency $(Y_{2.1})$	0,568	<0,001*	0,640	<0,001*	0,072	0,422ns
Utilization of Waste as an Economic Resource $(Y_{2.2})$	0,681	<0,001*	0,018	0,290ns	-0,663	<0,001*
Prospek Pengelolaan Ekonomi Sampah $(Y_{2.3})$	0,462	0,004*	0,768	<0,001*	0,306	<0,001*

Table 6: Structural Model Results

Relationship between Variables	G_0		G_1		**Moderation Test** $(G_1 - G_0)$	
	Coefficient	**p-value**	**Coefficient**	**p-value**	**Coefficient Difference**	**p-value**
Environmental Quality (X_1) → Awareness of Using 3R (Y_1)	0,401	<0,001*	0,609	<0,001*	0,207	0,009*
Utilization of Waste Banks (X_2) → Awareness of Using 3R (Y_1)	0,543	<0,001*	0,410	<0,001*	-0,133	0,170ns
Environmental Quality (X_1) → Economic Benefits of Waste (Y_2)	0,088	0,131ns	0,226	0,001*	0,139	0,085*
Utilization of Waste Banks (X_2) → Economic Benefits of Waste (Y_2)	0,070	<0,001*	0,081	0,077*	0,011	0,911ns
Awareness of Using 3R (Y_1) → Economic Benefits of Waste (Y_2)	0,574	<0,001*	0,610	<0,001*	0,036	0,610ns

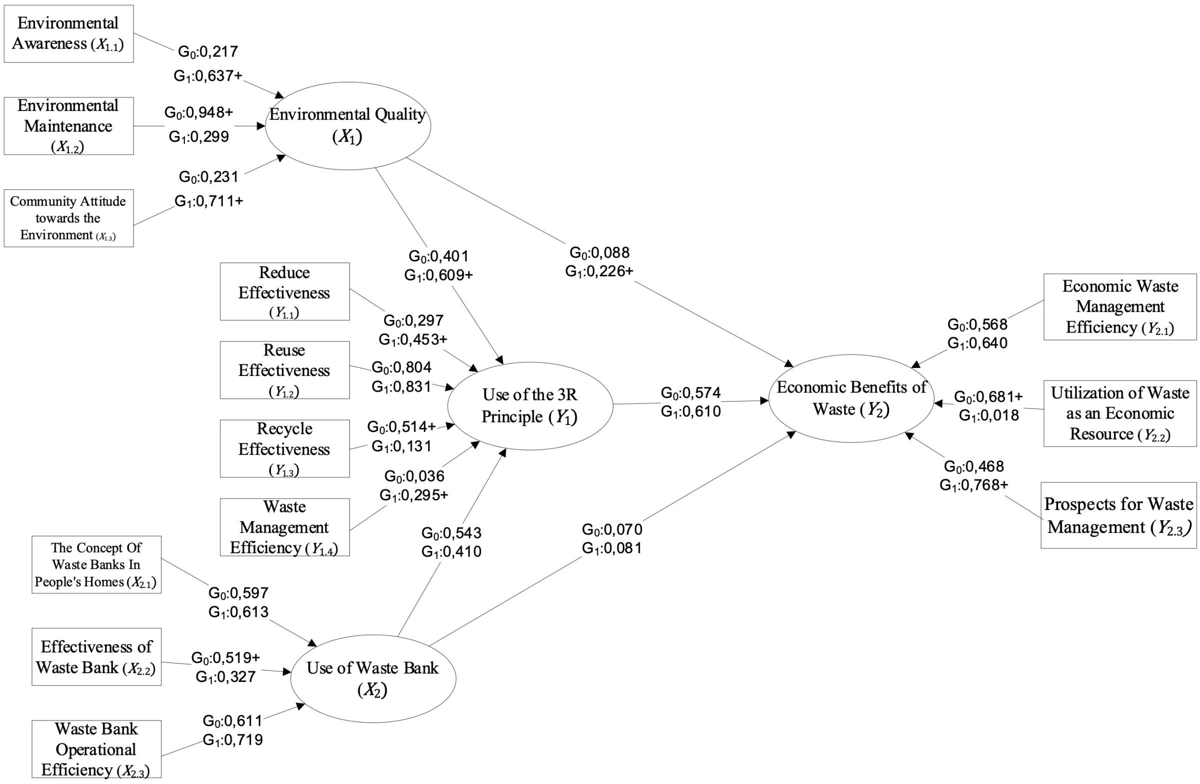

Figure 3: Structural and Measurement Model Results

Figure 3 provides an integrated overview of the structural and measurement relationships for both community groups. The diagram summarizes the estimated indicator loadings, structural path coefficients, and the moderating effects highlighted by the plus sign (+) on several pathways. To further clarify these results, the following sections present a detailed evaluation of the measurement (outer) model and the structural (inner) model, supported by the numerical estimates reported in Tables 5 and 6.

1. Measurement Model (Outer Model) Evaluation

The measurement model was estimated separately for communities living far from (Group 0) and near (Group 1) tourism areas, followed by a multigroup and moderation assessment at the indicator level. Across all latent constructs—Environmental Quality, Waste Bank Utilization, 3R Awareness, and Economic Benefits from Waste—most outer weights were statistically significant (p-value < 0.05), indicating adequate indicator reliability in both groups.

For Environmental Quality, the contribution of each indicator varied between the two groups. Environmental Maintenance remained the most influential indicator for both groups; however, the multigroup moderation analysis showed a significant difference ($\Delta\lambda = -0.650$, p-value < 0.001), suggesting that this indicator is more responsive among communities living closer to tourism sites. The other indicators—Environmental Awareness and Environmental Attitude—also displayed noticeable differences, reinforcing that measurement strength depends on the degree of tourism exposure.

For Waste Bank Utilization, all indicators showed significant loadings in both groups. In Group 0, Operational Efficiency emerged as the most prominent indicator, while in Group 1, Household Waste Bank Adoption carried the highest contribution. The moderation analysis detected a significant difference only for Waste Bank Effectiveness ($\Delta\lambda = -0.192$, p-value $= 0.021$), indicating that operational factors affect the stability of this measurement differently across the two residential contexts.

For 3R Awareness, the indicators Reuse and Recycle consistently provided the strongest contributions. Cross-group differences were identified for Reduce ($\Delta\lambda = 0.156$, p-value = 0.045), Recycle ($\Delta\lambda = -0.383$, p-value < 0.001), and Waste Management Efficiency ($\Delta\lambda = 0.260$, p-value = 0.004), demonstrating that awareness-related measures are highly influenced by contextual conditions.

For Economic Benefits from Waste, Economic Efficiency and Economic Prospects were the leading indicators in Group 1, whereas Waste Utilization as an Economic Resource showed the highest contribution in Group 0. The moderation tests revealed significant differences for two indicators ($\Delta\lambda = -0.663$ and $\Delta\lambda = 0.306$; both p-value < 0.001), indicating that economic perceptions shift systematically depending on how close residents live to tourism areas.

Overall, the integrated multigroup–moderation outer-model analysis demonstrates that indicator-level measurement properties differ significantly across residential locations, validating the methodological contribution of extending SEM with moderated measurement models.

2. Structural Model Results

The structural model was estimated for both groups. Most hypothesized paths were significant, with consistent directional patterns.

In **Group 0** (far from tourism), Environmental Quality ($\gamma = 0.401$, p-value < 0.001) and Waste Bank Utilization ($\gamma = 0.543$, p-value < 0.001) significantly predicted 3R Awareness. 3R Awareness strongly predicted Economic Benefits ($\beta = 0.574$, p-value < 0.001), while Waste Bank Utilization also had a positive effect ($\gamma = 0.070$, p-value < 0.001). Environmental Quality did not have a significant direct effect on Economic Benefits ($\gamma = 0.088$, p-value = 0.131).

In **Group 1** (near tourism), Environmental Quality ($\gamma = 0.609$, p-value < 0.001) and Waste Bank Utilization ($\gamma = 0.410$, p-value < 0.001) also predicted 3R Awareness. Economic Benefits were significantly influenced by Environmental Quality ($\gamma = 0.226$, p-value = 0.001) and 3R Awareness ($\beta = 0.610$, p-value < 0.001).

3. Multigroup Structural Differences

Moderation by residential location showed:

- Significant differences only for Environmental Quality → 3R Awareness ($\Delta\beta = 0.207$, p-value = 0.009).
- Other structural paths were statistically invariant across groups (p-value > 0.05).

This indicates that while structural relationships are generally stable, the magnitude of environmental influence varies by community exposure to tourism.

3.4 Model Validity

The evaluation of the structural model is assessed through the R-Square values, or coefficients of determination, for each endogenous variable in the model. The R-Square values for all endogenous constructs are presented in Table 7.

Table 7: Validity Model Result

Coefficient of Determination Y_1	Coefficient of Determination Y_2	Coefficient of Total Determination
0.586	0.587	0.829

Based on Table 7, the total determination coefficient is 0.829. According to [19], a total determination coefficient ≥ 0.75 indicates that the SEM model demonstrates satisfactory explanatory power. A total determination coefficient of 0.829 implies that the model is able to explain 82.9%

of the variance in the data, while the remaining 17.1% is attributable to other factors outside the scope of this research model.

4 Conclusion

This study not only confirms the substantive relationships among environmental quality, waste bank utilization, 3R awareness, and economic benefits from waste, but also provides a methodological contribution to SEM practice by developing and evaluating the outer measurement model within a multigroup and moderation framework. Statistically, the pattern of direct effects was generally consistent across the two groups (communities located near vs. far from tourism areas). Most hypothesized paths exhibited the same direction and remained significant in both groups, indicating stable indicator contributions to the latent constructs as well as comparable structural relationships across contexts.

A notable exception appears in the path from Environmental Quality to 3R Awareness, which was significantly stronger among residents living closer to tourism areas ($\Delta\gamma = 0.207$, p-value = 0.009). Meanwhile, the difference in the effect of Environmental Quality on Economic Benefits was marginal ($\Delta\gamma = 0.139$, p-value = 0.085), suggesting an amplification effect associated with tourism proximity rather than a fundamental shift in the overall model structure.

Methodologically, integrating multigroup analysis with moderation testing at the outer-model level enabled a comprehensive assessment of whether measurement strength and indicator performance vary across contextual settings. This approach offers richer insights into measurement robustness and contextual sensitivity compared with single-sample SEM. Consequently, this study contributes both substantive empirical findings regarding waste-management behavior and a replicable SEM procedure for researchers seeking to evaluate measurement models under heterogeneous environmental or social conditions.

CRediT Authorship Contribution Statement

Aldianur Khairani: Conceptualization, Data Curation, Formal Analysis, Writing–Original Draft. **Solimun**: Methodology, Supervision, Validation, Resources. **Adji Achmad Rinaldo Fernandes**: Software, Validation, Supervision. **Fachira Haneinanda**: Visualization, Supervision. **Nadia Khairina**: Supervision, Writing–Review & Editing.

Declaration of Generative AI and AI-assisted Technologies

The authors acknowledge the use of OpenAI's GPT-5 language model exclusively for proofreading grammar and enhancing sentence clarity during the preparation of this manuscript. No generative AI or AI-assisted technologies were involved in the conceptualization, data analysis, interpretation of results, or formulation of conclusions. The content, analyses, and conclusions presented in this manuscript remain entirely the responsibility of the authors.

Declaration of Competing Interest

The authors declare no competing interests.

Funding and Acknowledgments

This research received no external funding. The authors would like to thank the respondents who participated in this study and all the constructive comments and support that contributed to the improvement of this work.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request and subject to confidentiality agreements.

References

[1] U. Maisaroh, A. A. R. Fernandes, and A. Iriany, "Structural equation modeling multigroup indirect effects on bank mortgage payment timeliness," *BAREKENG*, pp. 2359–2366, 2023. DOI: 10.30598/barekengvol17iss4pp2359-2366.

[2] Solimun, A. A. R. Fernandes, and Nurjannah, *Metode Statistika Multivariat Pemodelan Persamaan Struktural (SEM) Pendekatan WarpPLS*. Universitas Brawijaya Press, 2017.

[3] G. Dash and J. Paul, "Cb-sem vs pls-sem methods for research in social sciences and technology forecasting," *Technological Forecasting & Social Change*, pp. 1–11, 2021. DOI: 10.1016/j.techfore.2021.121092.

[4] H. Sepriadi, A. Iriany, Solimun, and A. A. R. Fernandes, "Development of cluster integration with varian based structural equation modeling to manage heterogeneous data," *BAREKENG: Journal of Mathematics and Its Applications*, pp. 1193–1202, 2025. DOI: 10.30598/barekengvol19iss2pp1193-1202.

[5] Y. Fan et al., "Applications of structural equation modeling (sem) in ecological studies: An updated review," *Ecological Processes*, vol. 5, p. 19, 2016. DOI: 10.1186/s13717-016-0063-3.

[6] S. Astutik, Solimun, and Darmanto, *Analisis Multivariat: Teori dan Aplikasinya dengan SAS*. Universitas Brawijaya Press, 2018.

[7] Solimun, *Analisis Multivariat Pemodelan Struktural Metode Partial Least Square - PLS*. CV. Citra, 2010.

[8] M. Sarstedt, J. Henseler, and C. M. Ringle, "Multigroup analysis in partial least squares (pls) path modeling: Alternative methods and empirical results," in *Emerald Insight*, 2011, pp. 195–218. DOI: 10.1108/S1474-7979(2011)0000022012.

[9] A. A. R. Fernandes, Solimun, and D. P. Kartikasari, *Analisis Regresi dalam Pendekatan Fleksibel: Ilustrasi dengan Paket Program R*. Universitas Brawijaya Press, 2021.

[10] M. E. Civelek, *Essentials of Structural Equation Modeling*. Lincoln: Zea Books, 2018.

[11] A. A. R. Fernandes, I. N. Budiantara, B. W. Otok, and Suhartono, "Reproducing kernel hilbert space for penalized regression multi-predictors: Case in longitudinal data," *International Journal of Mathematical Analysis*, vol. 8, no. 37-40, pp. 1951–1961, 2014. DOI: 10.12988/ijma.2014.47212.

[12] R. G. Lomax, *A Beginner's Guide to Structural Equation Modeling*. New York: Routledge, 2015. DOI: 10.4324/9781315749105.

[13] R. A. Johnson and D. W. Wichern, *Applied Multivariate Statistical Analysis*. New Jersey: Pearson, 2019.

[14] B. M. Byrne, *Structural Equation Modeling With AMOS: Basic Concepts, Applications, and Programming (3rd ed)*. New York: Routledge, 2016. DOI: 10.4324/9781315757421.

[15] S. Haryono, *Metode SEM untuk Penelitian Manajemen dengan AMOS LISREL PLS*. Jakarta: PT. Intermedia Personalia Utama, 2016.

[16] Solimun, A. A. R. Fernandes, and D. P. Kartikasari, "Pemodelan mindset masyarakat terhadap manfaat ekonomi sampah di kota batu melalui pengembangan structural equation modeling semiparametrik moderasi multigrup," *SINTA*, 2024.

[17] S. Azwar, *Reliabilitas dan Validitas*. Yogyakarta: Pustaka Pelajar, 2015.

[18] H. Taherdoost, "Validity and reliability of the research instrument; how to test the validation of a questionnaire/survey in a research," *International Journal of Academic Research in Management*, pp. 28–36, 2016. DOI: 10.2139/ssrn.3205040.

[19] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis (8th Edition)*. Hampshire: Cengage Learning EMEA, 2019.