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ANALYSIS OF FOOD SECURITY FACTORS WITH PATH MODELING SEGMENTATION TREE (PATHMOX) METHOD IN PARTIAL LEAST SQUARES IN WEST KALIMANTAN

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ABSTRACT

Food security is essential for ensuring community well-being by guaranteeing sufficient, safe, and nutritious food, particularly in regions with complex socio-economic conditions. This study analyzes food security in West Kalimantan Province by identifying key influencing factors, constructing a structural equation model, and segmenting regions based on their food security characteristics. Utilizing secondary data from the 2023 Food Security and Vulnerability Atlas (FSVA), the research employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) method with the Path Modeling Segmentation Tree (PATHMOX) approach. The study incorporates ten indicators across four latent variables: food availability, food access, food absorption, and overall food security. The results reveal that regional segmentation using the PATHMOX approach effectively identifies data heterogeneity, categorizing West Kalimantan's 14 districts/cities into two distinct groups based on the Human Development Index (HDI). The first group (10 regions) exhibits higher food consumption despite socio-economic challenges, whereas the second group (4 areas) demonstrates better food security yet lower intake levels. These findings highlight that food security is influenced by access, distribution, and policy implementation rather than solely by the Normative Consumption Production Ratio (NCPR). The insights from this study provide a foundation for developing targeted policies to enhance food security strategies in West Kalimantan Province, ensuring a more sustainable and equitable food system. By applying PATHMOX segmentation, policymakers can address regional disparities more effectively, fostering strategic interventions that improve food availability, accessibility, and utilization across different population groups.

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1. INTRODUCTION

Food security is fundamental to sustainable development, ensuring everyone can access sufficient, safe, and nutritious food to maintain a healthy and active life. It plays a crucial role in stability, social and economic development, and public welfare, aligning with the Sustainable Development Goals (SDGs) [1]. However, achieving food security remains a significant challenge, particularly for developing countries like Indonesia, which faces fluctuating food prices, import dependence, economic disparities, malnutrition, climate change, and natural disasters [2]. Indonesia is ranked 77 out of 125 countries, with 68 out of 514 districts/cities still vulnerable to food security with moderate levels of hunger and severe malnutrition in 2023. Natural disasters and climate change, such as floods and droughts, will further worsen the food security situation in 2023, one of which is in West Kalimantan Province [3]. Nearly 5,000 disasters affected more than 8.7 million people [4]. Recognizing the urgency of this issue, the Government of Indonesia has collaborated with the World Food Programme (WFP) to enhance food security in high-risk areas such as Yogyakarta, West Kalimantan, and East Nusa Tenggara. This highlights the importance of addressing food security in West Kalimantan as a priority area [2].

West Kalimantan Province is strategically located, sharing a border with Malaysia and possessing significant agricultural potential [5]. However, West Kalimantan Province is experiencing obstacles in achieving optimal food security. It is evident from 20 sub-districts out of 174 sub-districts in West Kalimantan that they are still experiencing food insecurity [6]. Limited access to food is a challenge when optimizing strategic areas for food distribution. Food productivity is hampered by the lack of agricultural technology, land conversion, and land diversification, so agricultural potential cannot be managed optimally [7]. The existence of food security between districts/cities due to challenges such as geography, infrastructure limitations, and poverty affects food security in an area. Food security has three important aspects to facilitate identification and provide a comprehensive picture, including availability, access, and absorption of food [8]. These three aspects are the determining factors for food security in a region. These food security factors cannot be measured directly. An indicator is needed that can determine the variable (latent variable). An effective analysis method is required to determine the inequality and factors affecting West Kalimantan Province’s food security and to overcome these problems. One of the adequate methods is the Partial Least Squares Structural Equation Modeling (PLS-SEM) method.

The PLS-SEM method is a flexible approach that accommodates data that does not meet the normality assumption and enables researchers to analyze relationships between variables even with small sample sizes [9]. The PLS-SEM method can also relate non-measurable variables to support modeling complex relationships between variables. Other researchers have often discussed previous research on food security with the PLS-SEM method. For instance, a study investigating factors influencing climate change through adaptation practices and their effects on horticultural crops and food security in Qazvin Province utilized the PLS-SEM method [10]. Additionally, a study exploring the relationship between obesity and food security in West Java Province employed the PLS-SEM method [11]. Another study discusses the factors that affect food security in Indonesia in the face of a global economic recession using the SEM method with the GSCA approach based on Alternating Least Squares (ALS) [12].

Several researchers have discussed research related to SEM-PLS. However, research has never been conducted using the Path Modeling Segmentation Tree (PATHMOX) approach to analyze patterns of food security differences. The PATHMOX method offers path modeling with decision tree-based segmentation based on specific moderation factors [13]. This method allows for more detailed analysis by dividing the data into homogeneous segments and analyzing the relationships between variables in each segment [14]. Using PATHMOX, this study aims to fill the existing research gap by demonstrating how decision tree-based segmentation can provide valuable insights into food security patterns. This will support sustainable food security planning and help efficiently allocate resources, ensuring that food availability, accessibility, and absorption are optimized across diverse socio-economic and geographical contexts.

2. RESEARCH METHODS

This study uses the Partial Least Squares Structural Equation Modeling (PLS-SEM) method with the Path Modeling Segmentation Tree (PATHMOX) approach. The conceptual model of food security, as outlined in the journal “Analysis of Food Security Factors in Indonesia using SEM-GSCA with the Alternating Least Squares Method” [12], is illustrated in Figure 1.

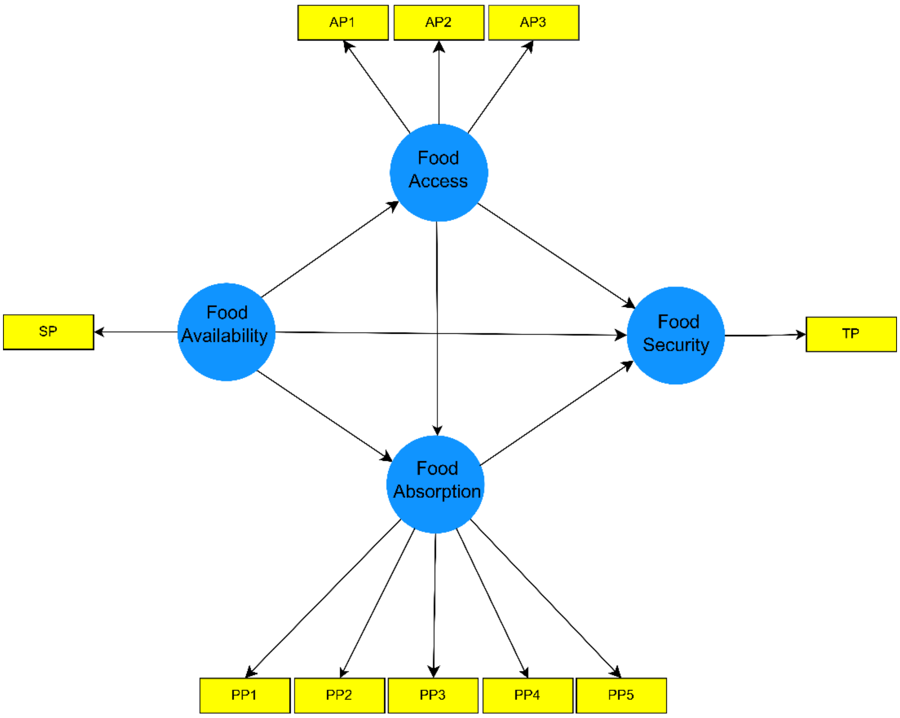

Figure 1. Conceptual Model of Food Security

The data analysis procedure and the research stages are carried out as follows:

a. Data Collection.

The data used in this study are secondary data obtained from the Publication of the 2023 Food Security and Vulnerability Map, which is based on food security indicators in West Kalimantan Province [15].

b. Data Analysis Process

The data analysis process uses SmartPLS to build the SEM-PLS model and RStudio to analyze the PATHMOX approach.

c. Measurement Model Evaluation

This stage aims to ensure the validity and reliability of the indicators used. The evaluation includes the Convergent Validity Test, which is checked using outer loading values greater than 0.7 and an Average Variance Extracted (AVE) greater than 0.5 [16]. The Discriminant Validity Test ensures that the constructs are distinctly different from each other, while the Reliability Test is conducted using Composite Reliability values greater than 0.7 to confirm the consistency and dependability of the constructs [16].

d. Structural Model Evaluation

The evaluation of the structural model includes testing the coefficient of determination (R^2) to measure the explanatory power of independent variables, and the path coefficient test to evaluate the strength of relationships between constructs.

e. SEM-PLS Test Results Analysis

The results of the SEM-PLS test are then analyzed to conclude the relationships between the hypothesized variables, based on the relationships previously tested.

f. PATHMOX Model and Segmentation Variables Selection

The PATHMOX approach selects segmentation variables that support the research by identifying variables relevant to segmenting regions based on their characteristics.

g. Segmentation Based on Regional Nodes

The segmentation variables are categorized based on the Regency/City area nodes in West Kalimantan Province to identify the characteristics of each region according to the nodes defined in the PATHMOX model.

h. Integration of All Analysis Results

All analysis results from SEM-PLS and PATHMOX are integrated to provide recommendations that support the research objectives.

2.1 Data

The variables and indicators used in the study can be described as follows.

Table 1. Research Variables

Latent Variables	Code	Indicators (Manifest Variable)
Food Availability (ξ_1)	SP	Normative Consumption Production Ratio (NCPR)
Food Access (η_1)	AP1	Percentage of Poor People
	AP2	Prevalence of Food Expenditure
	AP3	Percentage of Households Without Electricity Access
Food Absorption (η_2)	PP1	Percentage of Households Without Access to Clean Water
	PP2	Average Length of Schooling for Girls Over 15 Years
	PP3	Ratio of Health Workers
	PP4	Percentage of Life Expectancy
	PP5	Stunting Percentage
Food Security (η_3)	TP	Food Security Index (FSI)

Table 1 is secondary data from the Food Security and Vulnerability Atlas (FSVA) 2023 publication in West Kalimantan Province. This study uses four main food security variables measured based on nine corresponding indicators from 14 cities/regencies in West Kalimantan Province. The latent variables include food availability, access, absorption, and security. The variable is divided into two types of latent variables: one exogenous latent variable, food availability (ξ_1), and three endogenous latent variables, namely food access (η_1), food absorption (η_2), and food security (η_3). The Exogenous Latent Variable (Food Availability) is chosen because it is independent and is a predictor for the other latent variables. Its role as the starting point in the causal chain of food security is widely supported by theoretical models and empirical evidence. On the other hand, the Endogenous Latent Variables (Food Access, Food Absorption, and Food Security) depend on food availability. They are selected based on their roles as outcomes or consequences of food availability within the food security framework.

2.2 Partial Least Squares Structural Equation Modeling (PLS-SEM)

This study uses the SEM method, one of the multivariate analysis techniques, to model the structural equation between path analysis and factor analysis with latent variables [17]. The SEM method is used in analyzing complex relationship patterns between latent variables and indicators (outer models) as well as the relationships between latent variables and other latent variables (inner models) [18]. SEM methods are divided into Partial Least Squares-based SEM (PLS-SEM) and covariance-based SEM (CB-SEM) [19]. PLS is part of a variance-based SEM approach that tests predictive relationships between constructs by examining existing influence relationships [20]. PLS-SEM is an alternative model to CB-SEM because it overcomes the limitations set by the CB-SEM method, such as using a relatively small data sample size. When data cannot normally be distributed and can be used for very complex models, PLS-SEM can be used [21]. PLS-SEM divides the model into outer and inner models, which can be expressed as **Equation (1)** based on endogenous variables and **Equation (2)** based on exogenous variables.

$$\boldsymbol{y} = \boldsymbol{\Lambda_y \eta} + \boldsymbol{\varepsilon} \tag{1}$$

$$\boldsymbol{x} = \boldsymbol{\Lambda_x \xi} + \boldsymbol{\delta} \tag{2}$$

From **Equation (1)**, $\boldsymbol{y}$ is the vector of the endogenous latent variable $(p \times 1)$. The measurement model matrix is $\boldsymbol{\Lambda_y}$ $(p \times m)$, the vector of the endogenous latent variable is $\boldsymbol{\eta}$, and $\boldsymbol{\varepsilon}$ is the vector of the measurement error $\boldsymbol{y}$. Then, from **Equation (2)**, the vector of the exogenous latent variable is $\boldsymbol{x}$ $(q \times 1)$, $\boldsymbol{\Lambda_x}$ is the measurement model matrix $(q \times n)$, the exogenous latent variable vector is $\boldsymbol{\xi}$, and $\boldsymbol{\delta}$ is the measurement error vector $\boldsymbol{x}$. Furthermore, the structural equation is expressed in **Equation (3)**.

$$\boldsymbol{\eta}_j = \boldsymbol{\beta}_{j0} + \sum_i \boldsymbol{\beta}_{ji}\boldsymbol{\eta}_i + \boldsymbol{v}_j \tag{3}$$

The vector of the endogenous latent variable is $\boldsymbol{\eta}$, and $\mathbf{B}$ is the matrix of structural coefficients. Then, $\sum_i \boldsymbol{\beta}_{ji}\boldsymbol{\eta}_i$ is a linear combination of exogenous latent variables that affect $\boldsymbol{\eta}_j$. Notation $\boldsymbol{v}_j$ it is a linear combination of exogenous latent variables that affect.

2.3 Path Modeling Segmentation Tree (PATHMOX)

Path Modeling Segmentation Tree (PATHMOX) is a segmentation method like a decision tree to analyze research data with many segmentation variables without requiring prior knowledge of the factors involved [22]. PATHMOX builds a path model as a decision tree to classify observations that only allow each node to be divided into two branches for a different segment model (binary segmentation tree) [23]. **Figure 2**, sourced from [24], is the segmentation tree.

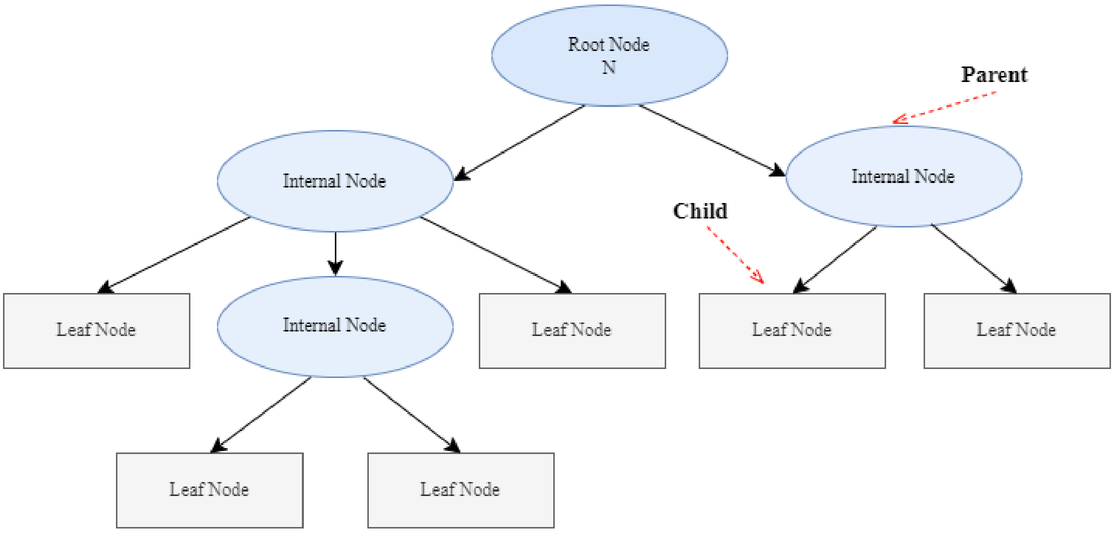

Figure 2. **PATHMOX Segmentation Tree Structure**

3. RESULTS AND DISCUSSION

In SEM-PLS, there are two types of models to describe the relationship between construction or latent variables and indicators (measurement variables): formative models and reflective models. This study uses a reflective model in which the indicators reflect the construction. **Figure 3** illustrates the initial conceptual model design.

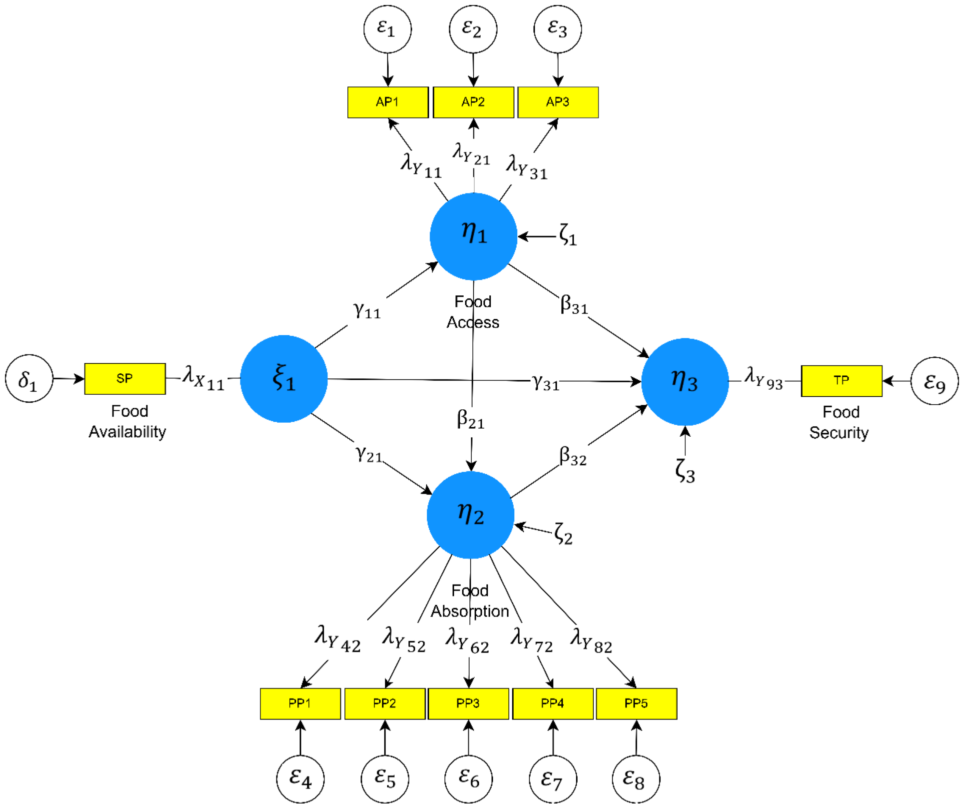

Figure 3. Initial Structural Model of Food Security

The model's formation is based on research sources [12], as shown in Figure 3. The model explains the relationship between food security and the variables influencing it. Figure 4 depicts the relationship with a path diagram with a factor loading value.

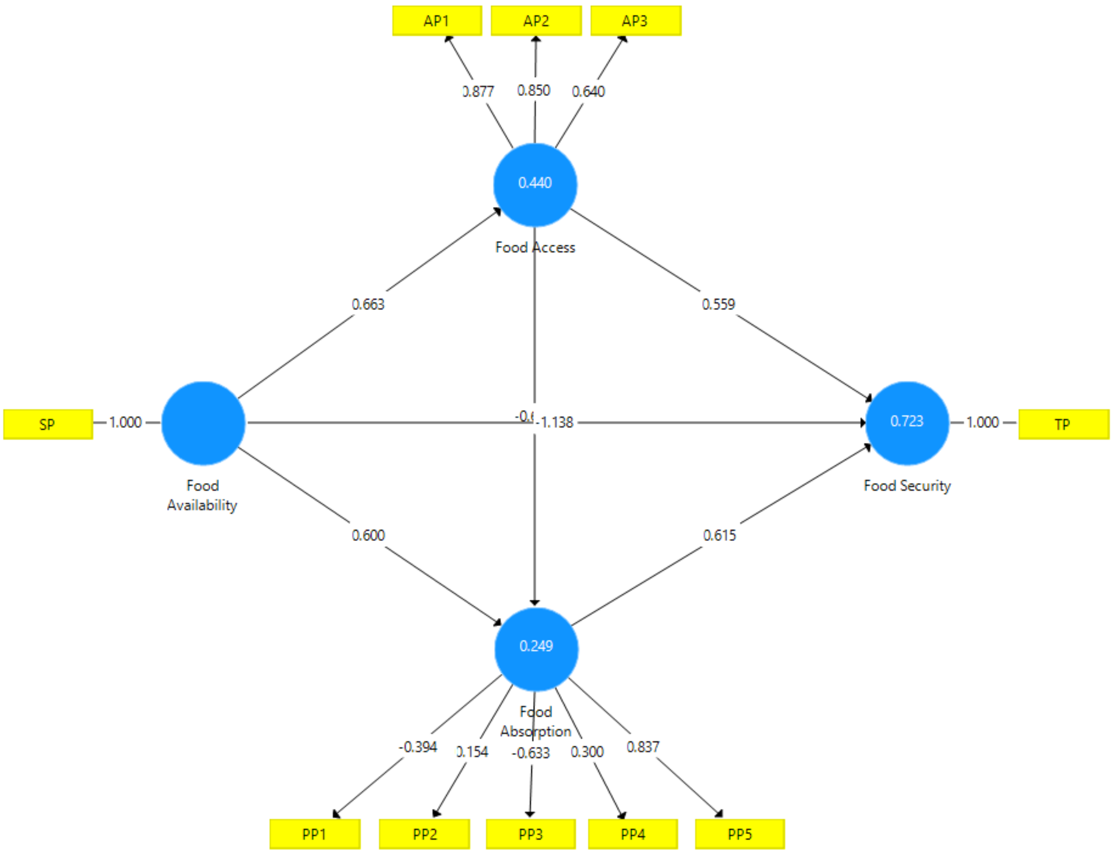

Figure 4. Results of the Structural Model of Food Security

3.1 Measurement Model Evaluation (Outer Model)

By assessing convergent validity, discriminant validity, and reliability, as explained earlier in the data analysis procedure under the Measurement Model Evaluation section, it was determined that a value of outer loading less than 0.7 indicates that the construct is considered invalid. This is to ensure that the relationship between the latent variable and its indicators is valid and suitable to be used as a measurement model [25].

Table 2. Outer Loadings and Convergent Validity

Latent Variables	Indicators	Outer Loading	P-Value	AVE	Information
Food Availability	SP	1.000	-	1.000	Valid
	AP1	0.877	0.003		Valid
Food Access	AP2	0.850	0.031	0.634	Valid
	AP3	0.640	0.121		**Invalid**
	PP1	-0.394	0.520		**Invalid**
	PP2	0.154	0.790		**Invalid**
Food Absorption	PP3	-0.633	0.285	0.274	**Invalid**
	PP4	0.300	0.622		**Invalid**
	PP5	0.837	0.277		Valid
Food Access	TP	1.000	-	1.000	Valid

In Table 2, however, the indicator with an outer loading value < 0.7 (invalid) was neither adjusted, re-evaluated, nor removed, as its exclusion did not significantly impact the Average Variance Extracted (AVE) value. This is based on the outer loading value and p-value, which indicate that the indicator is strong enough to represent a latent variable based on a predetermined threshold value. Based on the values above, there are five valid indicators. Although there are some statistically invalid data (p-value ≥ 0.05), the indicator can still be considered practically valid if it focuses on the strength of the relationship and follows the PLS-SEM approach, even though it will affect the final model results. The p-value ensures that the relationship is not formed by chance.

Based on Table 2, the measurement model equation is obtained as follows.

Food Availability Variables (ξ_1)

$$X_{11} = 1.000\xi_1 + \delta_1 \tag{4}$$

Food Access Variables (η_1)

$$Y_{11} = 0.877\eta_1 + \varepsilon_1 \tag{5}$$

$$Y_{21} = 0.850\eta_1 + \varepsilon_2 \tag{5}$$

$$Y_{31} = 0.640\eta_1 + \varepsilon_3 \tag{7}$$

Food Absorption Variables (η_2)

$$Y_{42} = \text{-}0.394\eta_2 + \varepsilon_4 \tag{8}$$

$$Y_{52} = 0.154\eta_2 + \varepsilon_5 \tag{9}$$

$$Y_{62} = \text{-}0.633\eta_2 + \varepsilon_6 \tag{10}$$

$$Y_{72} = 0.300\eta_2 + \varepsilon_7 \tag{11}$$

$$Y_{82} = 0.837\eta_2 + \varepsilon_8 \tag{12}$$

Food Availability Variables (η_3)

$$Y_{93} = 1.000\eta_3 + \varepsilon_9 \tag{13}$$

Furthermore, the AVE value can be assessed where the AVE value in the food absorption variable of 0.274 < 0.5 does not meet the requirements for convergent validity. The food absorption variable has limitations in adequately explaining the variance of the indicators. However, this variable is retained in the structural model due to its essential theoretical relevance, and the reliability of latent variables remains adequate based on the discriminant validity in Table 3 and reliability in Table 4.

Table 3. Discriminant Validity (Fornell-Larcker Criterion)

Latent Variables	Food Access	Food Security	Food Availability	Food Absorption
Food Access	**0.796**			
Food Security	-0.329	**1.000**		
Food Availability	0.663	-0.648	**1.000**	
Food Absorption	-0.218	0.275	0.192	**0.524**

The Fornell-Larcker Criterion is considered satisfactory if the latent variable exhibits a higher value than it is correlated with other latent variables in the same column [26]. In Table 3, the √AVE values for each latent variable show good correlation and fulfill the specified criteria. Thus, the model has a good discriminatory validity value and can be continued in reliability testing.

Table 4. Reliability

Latent Variables	Cronbach's Alpha	Composite Reliability	Information
Food Availability	1.000	1.000	Reliable
Food Access	0.723	0.836	Reliable
Food Absorption	**-0.795**	**0.019**	**Unreliable**
Food Security	1.000	1.000	Reliable

The Cronbach's alpha and composite reliability values in Table 4 are more significant than 0.6 for the variables of Food Availability, Food Access, and Food Security, so they are eligible and have a good score. However, the value of the Food Absorption variable did not meet the threshold value, with a composite reliability of 0.019 and a Cronbach's alpha value of -0.795. Although the Food Absorption variable exhibited low reliability metrics, it was retained in the model due to its strong theoretical foundation and essential role in the food security conceptual framework. This decision aligns with the flexibility of the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which emphasizes predictive capability over strict measurement reliability [27]. Furthermore, research on food security determinants underscores the interconnectedness of food availability, access, and utilization, reinforcing the inclusion of variables like Food Absorption in comprehensive models [28].

3.2 Structural Model Evaluation (Inner Model)

The inner model ensures that the relationship between the latent variables is significant and follows the hypothesis [29]. The results of the internal model still use all the variables that exist, and the predictive relationship between latent variables has good predictive ability, as described in the internal model. The evaluation was carried out by assessing the determination coefficient (R^2, T-statistics, and path coefficient through p-value [30].

Table 5. Value of Coefficient Determination

Endogenous Variables	R^2
Food Access	0.440
Food Absorption	0.723
Food Security	**0.249**

Based on Table 6, the food security variable has the lowest value among food access and absorption variables. The model on the food security variable can only explain 24.9% of the variance. As much as 75.1% of the variables are greatly influenced by factors other than the model that have not been considered in this analysis.

Table 6. Path Parameter Coefficients

Inner Model	Original Sample	T-Statistic	P-Value
Food Access → Food Security	0.559	0.960	0.337
Food Access → Food Absorption	-0.616	0.793	0.428
Food Availability → Food Access	**0.663**	**2.143**	**0.033**
Food Availability → Food Security	**-1.138**	**2.075**	**0.039**
Food Availability → Food Absorption	0.600	0.879	0.380
Food Absorption → Food Security	0.615	0.959	0.338

Based on Table 7, a structural equation can be obtained, namely:

Structural model of Food Access variable:

$$\eta_1 = 0.663\xi_1 + \zeta_1 \tag{14}$$

Structural model of Food Absorption variable:

$$\eta_2 = -0.616\eta_1 + 0.600\xi_1 + \zeta_2 \tag{15}$$

Structural model of Food Security variable:

$$\eta_3 = 0.559\eta_1 + 0.615\eta_2 - 1.138\xi_1 + \zeta_3 \tag{16}$$

Table 7 shows two significant relationships (alpha value < 0.05): food availability affects food access and security. The other relationships do not show significance in this model. The coefficient value (0.663) and statistical significance (0.033) of the relationship between food availability and food access suggest that improving food availability will effectively enhance food access. However, food security and food availability showed a negative relationship (-1.138) and were statistically significant (0.039). This indicates a real negative influence that can be caused by other factors, such as food security decreases even though food availability increases.

Table 7. Specific Indirect Effect

Inner Model	Original Sample	T-Statistic	P-Value
Food Availability → Food Access → Food Absorption	-0.408	0.746	0.456
Food Access → Food Absorption → Food Security	-0.379	0.708	0.479
Food Availability → Food Access → Food Security	0.371	0.955	0.340
Food Availability → Food Absorption → Food Security	0.369	0.836	0.403
Food Availability → Food Access → Food Absorption → Food Security	-0.251	0.691	0.490

Table 8 shows that none of the pathways met the statistically significant criteria (p-value < 0.05) and (t-statistic values > 1.96). The results indicate no indirect influence or mediation between latent variables, allowing the analysis to proceed by evaluating the total effects of the latent variables.

Table 8. Total Effect

Inner Model	Original Sample	T-Statistic	P-Value
Food Access → Food Security	0.181	0.396	0.692
Food Access → Food Absorption	-0.616	0.793	0.428
Food Availability → Food Access	**0.663**	**2.143**	**0.033**
Food Availability → Food Security	-0.663	1.641	0.101
Food Availability → Food Absorption	-0.648	0.592	0.554
Food Absorption → Food Security	0.615	0.959	0.338

Based on Table 9, the total effect illustrates one variable's influence on another. The relationship significantly influences food access and availability in a model that reflects a combination of direct and indirect effects through the mediator (if any) of a single variable on the latent variable. Food availability significantly positively influenced (0.663) food access (0.033). So, increasing food availability can substantially improve food access.

3.3 Segmentation with the PATHMOX Model

The PATHMOX method divides the data into groups based on one segmentation variable with a dataset separation process (binary partition) [31]. The segmentation variable is assumed to be the primary source of observed heterogeneity [14]. Grouping is carried out by determining the segmentation variables that are most effective and relevant to the research, as shown in Table 10.

Table 9. Selection of Segmentation Variables

Segmentation Variables	F-Statistic	P-Value	Binary Splits
Poverty	3.936	0.005094	1
HDI	**8.511**	**0.000019**	1
PHDI	4.179	0.003606	1

Table 10 shows that in a binary segmentation tree, the acceptable split set for each node depends on the segmentation variables present in the data. Poverty, the Public Health Development Index (PHDI), and the Human Development Index (HDI) are binary variables with two values, so they have one binary partition or are only divided by one possibility. These variables were selected due to their strong theoretical relevance to disparities in food security, public health, and human development [32]. PATHMOX selects each node's most significant segmentation variable and the highest F-statistic for statistical significance evaluation [33]. In this study, HDI emerged as the most significant segmentation variable compared to the others, allowing a PATHMOX tree to be formed.

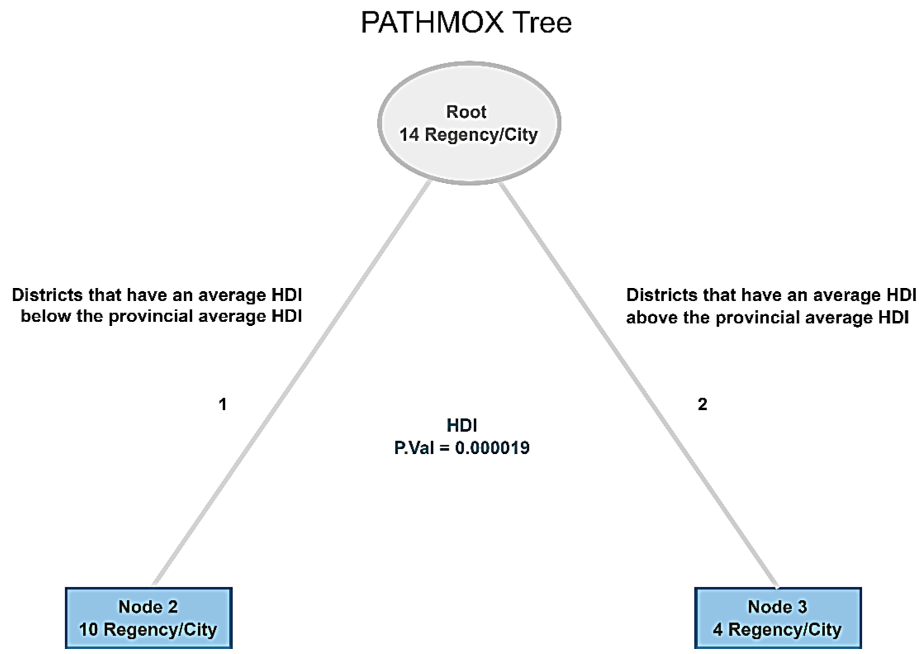

Figure 5. PATHMOX Segmentation Tree

Figure 5 shows that the HDI has already divided the tree significantly, so the other variables are not considered further, and the segment division stops after the third node. The segmentation results show that the HDI successfully separated the sample into two groups (nodes), namely Node 2, which has as many as 10 samples, and Node 3, which has as many as four samples, as seen in Table 11.

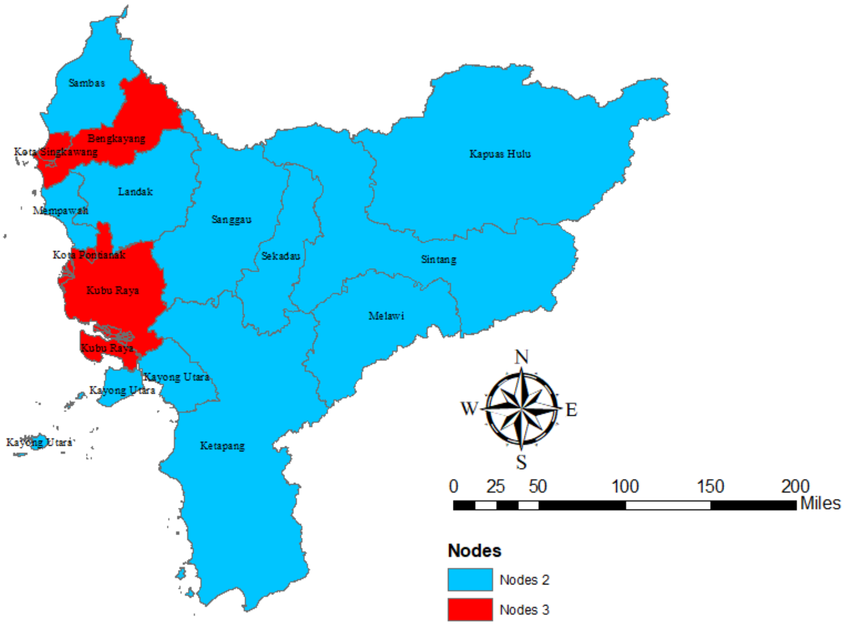

Figure 6. Food Security Map with the PATHMOX Method

Table 10. Region Grouping by Node

Nodes	Districts /Cities	
	Qty	Names
2	10	Kayong Utara, Kapuas Hulu, Ketapang, Landak, Mempawah, Melawi, Sanggau, Sambas, Sekadau, and Sintang
3	4	Bengkayang, Kubu Raya, Pontianak City, and Singkawang City

Based on Table 11, the division of Nodes 2 and 3 explains the number of regencies/cities included in each segmentation group using the PATHMOX method. Node 2 comprises 10 districts: Kayong Utara, Kapuas Hulu, Ketapang, Landak, Mempawah, Melawi, Sanggau, Sambas, Sekadau, and Sintang. It shows that most of West Kalimantan is included in this group. Node 3 consists of 4 cities/regencies, representing areas with significantly different HDI characteristics from Node 2: Bengkayang, Kubu Raya, Pontianak City, and Singkawang City. As seen in Figure 6, a map of food security distribution in Regencies/Cities in West Kalimantan Province can be formed based on Nodes 2 and 3.

This difference represents a distinct pattern of relationships between food security variables, such as food availability, food security, food absorption, and food access, in regions with different levels of HDI. As shown in Table 12, the characteristics of each node can be assessed based on indicators.

Table 11. Characteristics of Each Segment

Code	Indicators (Manifest Variable)	Node 2	Node 3
SP	Normative Consumption Production Ratio (NCPR)	1.32	**0.52**
AP1	Percentage of Poor People	**7.96**	4.82
AP2	Prevalence of Food Expenditure	**2.,51**	17.76
AP3	Percentage of Households Without Electricity Access	**3.90**	1.10
PP1	Percentage of Households Without Access to Clean Water	58.54	**60.54**
PP2	Average Length of Schooling for Girls Over 15 Years	8.08	**8.82**
PP3	Ratio of Health Workers	**0.75**	0.89
PP4	Percentage of Life Expectancy	**71.63**	72.72
PP5	Stunting Percentage	**28.31**	27.20
TP	Food Security Index (FSI)	**72.15**	72.31

In **Table 12**, the bolded value is the negative influence of each indicator on the node. Node 2 has a better NCPR and food security index than Node 3. This shows that, on average, food consumption in Node 2 is better regarding food needs. However, if you look closely, the Node 2 area tends to have socio-economic problems, such as a high percentage of poverty, a significant prevalence of spending, a high percentage of households without access to electricity, a low ratio of health workers, and a reasonably high life expectancy and stunting rate. Although socio-economic problems in Node 3, such as poverty and infrastructure access, are not as bad as in Node 2, the food security of the Node 3 region remains below normative standards. This difference shows that food security is not only a matter of socio-economic indicators such as poverty but also depends on other factors such as distribution efficiency, physical and economic access to food, and policy interventions. Node 2 shows better food security despite facing various social problems, while Node 3 still lags in food consumption despite having relatively better social conditions.

4. CONCLUSIONS

Based on the research that has been conducted, it can be concluded that out of 10 indicators, five indicators affect the food security model, including NCPR, Percentage of Poor Population, Prevalence of Food Expenditure, Percentage of Stunting, and FSI. Within the framework of structural equations, six paths are formed. Two of them have a real influence, namely food availability, a positive impact on food access, and food availability, which negatively impacts food security. Only food availability can significantly increase food access if we focus on direct and indirect relationships (the total number of influences).

The segmentation produced by the PATHMOX method was formed into two regional groups from 14 HDI-based cities/regencies. The first regional group comprises 10 cities/regencies: Kapuas Hulu, Kayong Utara, Ketapang, Landak, Melawi, Mempawah, Sambas, Sanggau, Sekadau, and Sintang. The second regional group comprises four districts/cities: Bengkayang, Kubu Raya, Pontianak City, and Singkawang City. Each regional group has different characteristics, where the first regional group tends to be able to consume more food than the normative need, despite facing various socio-economic problems. Meanwhile, the second regional grouping tends to have good food security conditions and socio-economic support, even though the community's food intake is below the normative need. This difference shows that food security is influenced by various factors such as physical and economic access to food, distribution efficiency, and policy interventions to declare food security good, and it does not depend only on the NCPR problems. Therefore, the local government of West Kalimantan needs to prioritize food security programs that focus on the needs of each regional group, such as maintaining stability and equity balanced by increasing normative food consumption, strengthening local food production, improving distribution infrastructure, controlling food prices, and developing sustainable food stocks. For further research, it is possible to use further segmentation algorithms by involving more variables to find out additional factors that affect food security.

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