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# Latent Household Food Security in Raja Ampat Marine Protected Areas: A Binary CFA Approach

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**Abstract**

This study examines household food security in four marine protected areas in Raja Ampat using repeated cross-sectional household survey data. Data were collected between 2010 to 2024, grouped into five monitoring periods. This study aims to provide a measurement framework for household food security as a latent construct based on binary indicators representing dimensions of food access and to estimate latent household food security scores in the four analyzed areas. In addition to applying confirmatory factor analysis to new empirical data, this study also presents a systematic estimation framework for measuring the latent construct using binary household indicators in repeated cross-sectoral survey data. The framework includes indicator threshold estimation, tetrachoric correlation estimation, parameter estimation using the robust diagonally weighted least squares method, and derivation of latent scores based on posterior expectations using the Gauss–Hermite quadrature approach. The analysis results indicate that the one-factor model provides acceptable fit and adequate construct reliability across the analyzed area-period groups. Estimates of factor loadings and thresholds provide information on the relative contribution and severity of each indicator in representing variations in household food access conditions. Overall, the goodness-of-fit indices indicate that the one-factor structure provides a reasonable representation of the relationships among the observed indicators under the fitted measurement model.

**Keywords:** robust DWLS; tetrachoric correlation; threshold



## 1. Introduction

In statistics, many important constructs cannot be directly measured. These constructs are latent and can only be observed through a number of indirect indicators, which are generally categorical or binary in nature. States that the latent variable modeling approach can use factor analysis, especially confirmatory factor analysis (CFA), which models the relationship between observed indicators and the underlying latent constructs. The CFA model is formed using either a covariance-based or variance-based approach. The assumption is that the indicators follow a multivariate normal distribution. This implicitly requires continuous data. When observed variables are categorical but treated as continuous data, this can result in biased parameter

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estimates. This condition has the potential to reduce the precision and accuracy of the estimates and may lead to misleading scientific conclusions [1].

The CFA approach for categorical data requires modifications to the input matrix, namely, by replacing the covariance matrix with a correlation matrix that matches the characteristics of the data. The assumption made when using a correlation matrix is that each categorical variable originates from a latent variable that is continuous and normally distributed [2]. When the indicator is ordinal with two categories, tetrachoric correlation is used [3]. Several previous studies have used tetrachoric correlation as input for factor analysis when such conditions occur [4, 5] The assumption when using tetrachoric correlation is that both binary variables are the result of dichotomizing latent continuous variables that follow a bivariate normal distribution. This estimation considers the threshold and covariance structure of the underlying latent variables. If the sample size is relatively small or if the category distribution in the binary variables is unbalanced, the estimation of the tetrachoric correlation may become unstable. This instability can result in a variance that is either very large or very small, thus reducing the accuracy of the standard error calculation. Parameter estimation methods for CFA when categorical indicators have been provided by previous researchers [6–10]. One widely recommended method, owing to its stability for small sample sizes, is the diagonally weighted least squares. A more robust approach for small sample sizes and handling unbalanced categories is the robust DWLS. This method corrects the test statistics and their standard errors. This method has been widely used by previous researchers [11, 12]. However, it is often found in psychometric problems, whereas it has not yet been applied to food security issues. In this study, the observed indicators are binary household-level variables collected across multiple marine protected area sites and monitoring periods. Several site–period cells contain relatively small numbers of households, and some indicators exhibit unbalanced category distributions. These data characteristics may affect the stability of tetrachoric correlation estimates and reduce the reliability of conventional maximum likelihood estimation. Therefore, the robust DWLS estimator is selected because it is specifically designed for ordinal or binary indicators and provides adjusted standard errors and test statistics under conditions of small cell sizes and non-normal data structures.

As one of the goals of sustainable development, food security is a multidimensional concept that cannot be measured directly [13]. One of the main dimensions of this concept is access to food, which uses various indicators. Many empirical studies measure food security using a simple additive index by summing or assigning fixed weights to several indicators. This implies that all indicators contribute equally, without considering the latent relationships among them. However, no single indicator can fully represent the actual conditions. In practice, measuring household food security through interviews often faces social bias, such as respondents' desire to maintain their self-image. For example, a family lacking food might give answers that make their situation seem better. This can lead to errors that reduce data validity. Although food security encompasses availability, access, utilization, and stability, the analysis in this study explicitly focuses on the household-level access dimension. The indicators used reflect households' ability to obtain sufficient and nutritious food rather than representing the full multidimensional structure of food security. Therefore, the latent construct estimated in this study should be interpreted as access-related household food security and not as a comprehensive food security index.

Based on the 2024 Food Security and Vulnerability Atlas, it is evident that most regencies in the Papua region are categorized as having the highest to moderate priority levels of food insecurity vulnerability. One of the marine protected areas or MPA included in this category is several zones in Raja Ampat. Marine protection and sustainable resource management in Raja Ampat are a high priority for the national, provincial, and district governments [14]. Therefore, these areas are protected and managed through a zoning system to ensure the sustainability of fisheries resources and the marine environment. Although designed for conservation purposes, this policy is often seen as potentially affecting the economic aspects of local communities, especially those whose livelihoods depend on marine natural resources to meet their food requirements.

A latent construct-based approach allows for the integration of various indicators into a more consistent composite measure while accounting for measurement errors inherent in each indicator. The approach used in this study offers a more precise framework for accurately and contextually measuring household food security, particularly in coastal areas.

In addition to applying binary CFA to new empirical data, this study also provides a methodological contribution by presenting a systematic and transparent estimation framework for measuring latent constructs using binary household indicators in repeated cross sectional survey data. This framework integrates several estimation stages: threshold estimation, tetrachoric correlation estimation, parameter estimation using the robust diagonal weighted least squares method, and latent score derivation based on posterior expectations using the Gauss–Hermite quadrature approach. By explicitly documenting these estimation stages, the study aims to improve the transparency and reproducibility of latent construct measurement using binary indicators in repeated cross sectional household surveys

The next section of this paper is organized as follows. Section 2 describes the data sources and methods used, including the functions of the algorithms developed during the analysis. Section 3 presents the empirical results. Finally, Section 4 summarizes the main conclusions and outlines the directions for future work.

## 2. Methods

This section presents the methodological framework used in the study. The discussion begins with the data source and indicator definition, and then proceeds to the CFA model specification, estimation procedure, construct reliability, goodness-of-fit assessment, and latent score derivation.

### 2.1. Data

This study used primary data from a household survey conducted by the S4C, LPPM Papua University. The survey design uses a quasi-experimental approach with a Before After Control Impact (BACI) framework, employing repeated cross-sectional sampling rather than a true panel design. The indicators used are based exclusively on the access dimension, with a particular focus on food insecurity and hunger arising from households lacking sufficient food or financial resources for procurement. This is in line with the method previously applied by [15] and is presented comprehensively in Table 1.

**Table 1:** Household food security indicators

| Indicator | Description | Category |
|---|---|---|
| $Y_1$ | In the last 12 months, did [you/you or other adults in your household] ever reduce the size of your meals or skip meals because there wasn't enough food to eat? | [0] no [1] yes |
| $Y_2$ | [I/We] couldn't eat balanced meals (a balanced meal is one that contains multiple types of food (e.g., carbohydrate, protein and vegetables)) | [0] no [1] yes |
| $Y_3$ | [My/Our] food just didn't last, and we were not able to get more in the past twelve months | [0] no [1] yes |
| $Y_4$ | In the last 12 months, did you ever eat less than you felt you should because there wasn't enough food | [0] no [1] yes |
| $Y_5$ | How often did ever reduce the size of your meals or skip meals because there wasn't enough food to eat? | [0] never [1] often |
| $Y_6$ | In the last 12 months, were you ever hungry but didn't eat because there wasn't enough food | [0] no [1] yes |

*Source:* S4C, LPPM Papua University

Observations with missing responses on the food security indicator were excluded from the estimation process.This research was limited to four regions based on available data. These four regions are Teluk Mayalibit, Kofiau Boo, Selat Dampier, and Kepulauan Misool. A total of 5,430 households participated in these four regions, with the number of households interviewed at each period varying. The survey was conducted from 2010 to 2024 and was divided into five periods. The survey years for each period were as follows: Teluk Mayalibit (2010, 2012, 2014, 2017, and 2021), Kofiau Boo (2011, 2013, 2015, 2018, 2021), Selat Dampier (2012, 2014, 2016, 2019, 2024), and Kepulauan Misool (2011, 2013, 2015, 2018, 2023).

The analytical procedure consisted of several stages. *First*, threshold parameters were estimated for each binary indicator to represent the cut-point on the underlying latent response variable that separates the two observed response categories. *Second*, the association among the underlying continuous variables was approximated using the tetrachoric correlation matrix. *Third*, the CFA model parameters were estimated using the RDWLS estimator. Parameter estimation was implemented through custom-written functions in the R statistical environment, which were developed to perform threshold estimation, tetrachoric correlation and RDWLS-based CFA. When relatively small or unstable factor loadings occurred, those indicators were retained because they represented conceptually relevant aspects of household food access. Futhermore, factor loading values greater than 1 will be reviewed for goodness of fit index. If the model fit index is appropriate, no indicator reduction is performed. According to [16], this condition in CFA is generally referred to as a Heywood case and can arise due to sampling fluctuations or estimation characteristics. Importantly, the occurrence of a Heywood case does not necessarily invalidate the entire model, especially when other model fit indices indicate adequate representation of the data. CR value are also calculated to evaluate the internal consistency of the indicators in measuring the latent construct. *Fourth*, model adequacy is evaluated using several fit indices. *Finally*, a latent score representing household food security is calculated from the adjusted CFA model using the estimated factor loadings and threshold parameters. This score provides a continuous representation of the latent construct underlying the observed binary indicators. The convergence of the estimation procedure was assessed based on the stability of the parameter estimates during the iterative optimization process.

## 2.2. CFA Model

The first order CFA model used in this study is

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

with $\mathbf{y}$ is a random vector with a mean vector $\mu$ and the variance-covariance matrix $\Sigma, \boldsymbol{\eta}$ is a random vector of size $k \times 1 (k < p)$ with an element $\eta_1, ..., \eta_k$ referred to as a common factor, $\mathbf{L}$ is a constant matrix of unknown value with the size of p×k called factor loading and $\boldsymbol{\varepsilon}$ is a random vector called a specific factor. The assumptions used are $E(\eta) = 0$, $E(\varepsilon) = 0$, $cov(\eta, \varepsilon) = 0$, $var(\eta) = \Delta$ definite positive and $var(\varepsilon) = \Psi = diag(\Psi_1, \ldots, \Psi_p)$ with $\Psi_i > 0$. For the purpose of model identification, the scale of the latent factor is set by fixing $var(\eta) = 1$, thus, all factor loading parameters are estimated freely. Parameter estimation is performed using a tetrachoric correlation matrix. Therefore, model fitting is not conducted on the full covariance matrix, but only on the off-diagonal correlation elements. Specifically, the one-factor structure is expressed as $\rho_{jk} \approx \lambda_j \lambda_k, j < k$. Diagonal elements (variety of indicators) are not included in the objective function of the estimation, therefore $var(\varepsilon)$ not explicitly estimated. The first-order CFA modeling of binary indicators was conducted through three stages [17]. The initial stage was the estimation of the threshold using a two-step maximum likelihood (ML). So, threshold parameters were estimated for each binary indicator. This was followed by the estimation of the tetrachoric correlation using a ML estimator. The final aspect was the estimation of the parameters by minimizing the likelihood function.

### *2.2.1. Threshold*

The threshold divides the standard normal distribution into areas corresponding to the proportions of categories in the data. The latent variable $y_j^*$ can't be observed, only the ordinal variable $y_j$

can be observed.

**Algorithm 1** Threshold estimate

**Require:**
Observation data matrix $Y = (y_{ij}) \in \{0,1\}^{n\times p}$
Determine the number of indicators: $p \leftarrow$ number of columns in $Y$
Create an empty vector: $\tau \in \mathbb{R}^p$
**while** $j = 1, 2, \ldots, p$ **do**
  Compute the empirical proportion of category 1: $\bar{y}_j = \frac{1}{n}\sum_{i=1}^{n} y_{ij}$
  Numerical correction (boundary protection):
  for $\Phi^{-1}(\cdot)$ to be defined: $\tilde{y}_j = \min(1-\varepsilon, \max(\varepsilon, \bar{y}_j))$, $\varepsilon = 10^{-8}$
  where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.
  Threshold estimation with MLE: $\hat{\tau}_j = \Phi^{-1}(1-\tilde{y}_j)$
  where $\Phi(\tau) = \Pr(y_j^* \leq \tau)$, $y_j^* \sim \mathcal{N}(0,1)$
**end while**
**return** Final $\hat{\tau}_j$

**Algorithm 2** Tetrachoric correlation

**Require:** Two binary vectors $x, y \in \{0,1\}^n$; $\texttt{maxcor} \in (0,1)$ (limit for $|\rho|$); $\varepsilon > 0$ (boundary protection for proportions); $\delta > 0$ (convergence tolerance)
**Ensure:** $\hat{\rho}$ (tetrachoric correlation, constrained to $[-\texttt{maxcor}, \texttt{maxcor}]$)
Build $2\times 2$ contingency table $T = (n_{ab})$ with $a, b \in \{0,1\}$: $n_{00}, n_{01}, n_{10}, n_{11}$
**if** any $n_{ab} = 0$ **then**
  Continuity correction: $n_{ab} \leftarrow n_{ab} + 0.5$ for all $a, b \in \{0,1\}$
**end if**
$n \leftarrow \sum_{a,b\in\{0,1\}} n_{ab}$
Marginal proportions: $\bar{x} \leftarrow \Pr(x=1) = \dfrac{n_{10}+n_{11}}{n}$, $\bar{y} \leftarrow \Pr(y=1) = \dfrac{n_{01}+n_{11}}{n}$
Boundary protection: $\tilde{x} \leftarrow \min(1-\varepsilon, \max(\varepsilon, \bar{x}))$, $\tilde{y} \leftarrow \min(1-\varepsilon, \max(\varepsilon, \bar{y}))$
Threshold (univariate MLE): $\hat{\tau}_x \leftarrow \Phi^{-1}(1-\tilde{x})$, $\hat{\tau}_y \leftarrow \Phi^{-1}(1-\tilde{y})$
Initialize $\rho \leftarrow 0$
**while** $|\Delta| \geq \delta$ **do**
  Compute model cell probabilities using bivariate standard normal CDF $\Phi_2(\cdot,\cdot;\rho)$:

$$\pi_{00}(\rho) = \Phi_2(\hat{\tau}_x, \hat{\tau}_y; \rho), \quad \pi_{10}(\rho) = \Phi(\hat{\tau}_y) - \Phi_2(\hat{\tau}_x, \hat{\tau}_y; \rho),$$

$$\pi_{01}(\rho) = \Phi(\hat{\tau}_x) - \Phi_2(\hat{\tau}_x, \hat{\tau}_y; \rho), \quad \pi_{11}(\rho) = 1 - \Phi(\hat{\tau}_x) - \Phi(\hat{\tau}_y) + \Phi_2(\hat{\tau}_x, \hat{\tau}_y; \rho).$$

  Log-likelihood: $\ell(\rho) \leftarrow \sum_{a,b\in\{0,1\}} n_{ab} \log\big(\pi_{ab}(\rho)\big)$
  Compute score and Hessian: $g(\rho) \leftarrow \dfrac{\partial \ell(\rho)}{\partial \rho}$, $H(\rho) \leftarrow \dfrac{\partial^2 \ell(\rho)}{\partial \rho^2}$
  Newton step: $\Delta \leftarrow -\dfrac{g(\rho)}{H(\rho)}$, $\rho_{\text{new}} \leftarrow \rho + \Delta$
  Clamp: $\rho_{\text{new}} \leftarrow \min(\texttt{maxcor}, \max(-\texttt{maxcor}, \rho_{\text{new}}))$
  **while** $\ell(\rho_{\text{new}}) < \ell(\rho)$ **do**
    Step halving (line search): $\Delta \leftarrow \Delta/2$
    $\rho_{\text{new}} \leftarrow \rho + \Delta$
    Clamp: $\rho_{\text{new}} \leftarrow \min(\texttt{maxcor}, \max(-\texttt{maxcor}, \rho_{\text{new}}))$
  **end while**
  Update: $\rho \leftarrow \rho_{\text{new}}$
**end while**
**return** $\hat{\rho} \leftarrow \rho$

For a binary variable $y_j \in \{0,1\}$, the category can only be determined based on where $y_j^*$ passes the threshold $y_j$ or not. Thus, the relationship between the binary observation variable $y_j$

and the latent variable $y_j^*$ is

$$y_j = \begin{cases} 0 & \text{if } y_j^* \leq \tau_j \\ 1 & \text{if } y_j^* > \tau_j \end{cases} \tag{2}$$

The threshold value is estimated from the univariate marginal distribution [2]. The threshold estimation algorithm follows Algorithm 1.

### *2.2.2. Tetrachoric correlation*

The tetrachoric correlation $\hat{\rho}$ is estimated through several steps: creating a likelihood function from the probabilities of the four cells, finding the derivative of the log likelihood function with respect to $\rho$ and find the $\hat{\rho}$ that maximizes the likelihood function [3]. The tetrachoric estimate algorithm follows Algorithm 2.

### *2.2.3. Robust diagonally weighted least square*

The DWLS is an iterative least squares method in CFA which uses diagonal weights of the asymptotic covariance V estimated from the tetrachoric correlation. The matrix $\mathbf{V}$ is the weighting element of the matrix $\mathbf{W}$ through the relationship $\mathbf{W} = (diag\mathbf{V})^{-1}$ [9]. The tetrachoric correlation matrix $\mathbf{R}$ and the model correlation matrix $\rho(\mathbf{L}, \boldsymbol{\Delta})$ are symmetric matrices of size p×p based on the submission that the information above the diagonal is the same as those below.

**Algorithm 3** RDWLS estimate

**Require:** $s$: vector of upper-triangular (off-diagonal) sample correlations; $W$: DWLS weight matrix; $p$: number of observed indicators
**Ensure:** $\hat{\lambda}$: estimated factor loadings; $T_{\text{DWLS}}$: DWLS fit statistic

```
Variables: λ (initialized loading vector); μ (model-implied correlations); r (residual vector); J (Jacobian matrix); Δ (parameter update)
q ← length(s); require q = p(p−1)/2
initialize λ
repeat
    μ ← vech_u(λλ′)
    r ← s − μ
    Construct Jacobian J with J_ij = λ_k and J_ik = λ_j for each (j < k)
    A ← J′WJ
    g ← J′Wr
    Δ ← solve(A, g)
    λ_new ← λ + Δ
    if ∑(λ_new) < 0 then λ_new ← −λ_new
until max |Δ| < ε
r̂ ← s − vech_u(λλ′)
T_DWLS ← r̂′Wr̂
return λ̂, T_DWLS
```

Furthermore, the latent indicator variance of one value leads to diagonal elements with no information for the parameter estimation. This shows that only unique elements below (or above) the diagonal $\rho_{j,k}, j < k$ are used and expressed as $\mathbf{r} = vech_{off}(\mathbf{R})$, $\mathbf{h}(\boldsymbol{\theta}) = vech_{off}(\rho(L, \Delta))$ and

$$\boldsymbol{\theta} = \begin{bmatrix} \text{vec}(L) \\ \text{vech}(\Delta) \end{bmatrix}.$$

The DWLS fit function directly compares two equivalent vectors as follows:

$$F(r, \boldsymbol{\theta}) = [r - h(\boldsymbol{\theta})]^\top W [r - h(\boldsymbol{\theta})], \tag{3}$$

The optimization solution was obtained using the Newton–Raphson method. The robust diagonally weighted least square (RDWLS) adjusts the standard error and corrects the chi-square statistic. The correction of the chi-square was achieved by applying a scaling factor (c) based on the asymptotic variance of the correlation. The formula used by Satorra-Bentler (1988) in is $c_3 = \frac{d}{h}(N-1)\min F(r^*, L, \Delta)$, with $d$ is the degree of freedom, $h = tr([\Delta_c^{'} V^{-1}\Delta_c)^{-1}\Delta_c^{'} W\Delta_c)]$. $\Delta_c$ applied as the orthogonal complement of $\Delta$ at $\Delta_c^{'}\Delta = 0$, and $N$ is sample size. Meanwhile, standard error correction was conducted on the estimated parameter variance which was the variance matrix of the estimated $\hat{\theta}$. This showed that the standard error of each parameter $\hat{\theta}_j$ was $\mathrm{SE}(\hat{\theta}_j) = \sqrt{\frac{1}{N}\left[A\ \mathrm{Cov}(\hat{\boldsymbol{\theta}})\right]_j}$. The RDWLS estimate algorithm follows Algorithm 3.

## 2.3. Construct reliability

Construct reliability (CR) is a measure used to assess the reliability of a latent factor by examining how well its indicators consistently represent the construct. CR can be calculated using the following formula:

$$\mathrm{CR} = \frac{\left|\sum_{i=1}^{p} \hat{\lambda}_i\right|^2}{\left|\sum_{i=1}^{p} \hat{\lambda}_i\right|^2 + \left|\sum_{i=1}^{p} \hat{\varepsilon}_i\right|^2} \tag{4}$$

with $\hat{\lambda}_i$ is the standardized factor loading obtained from $\hat{\lambda}_i = \lambda_i/\sigma_{y_i}$ and $\varepsilon_i$ is the diversity of error indicators obtained from $\hat{\varepsilon}_i = 1 - \lambda_i$. CFA is a qualitative and statistical process that involves construct reliability. The measurement of an indicator is considered reliable if CR⩾0,7 [18]. According to [19], it is still acceptable if CR⩾0.6.

## 2.4. Goodness of Fit Index

After estimating the model parameters, the adequacy of the CFA model was evaluated using a goodness-of-fit assessment. Goodness of fit is used to measure the suitability of observational inputs with the predictions of a proposed model. The overall goodness of fit of the model is called the model fit test. The goodness of fit method in this study is to compare the proposed model with the baseline model or so-called null model or independence model. This study is based on repeated cross-sectoral survey data and not longitudinal panel observations, so formal measurement invariance across periods and regions was not tested.

### *2.4.1. Comparative Fit Index (CFI)*

The CFI is used to assess whether a proposed one-factor measurement model adequately represents the observed relationships among indicators. CFI values range from 0 to 1, with value greater than or equal to 0.90 generally indicating acceptable model fit. The CFI is calculated using the following formula [20].

$$\mathrm{CFI} = 1 - \frac{\chi^2_M - df_M}{\chi^2_0 - df_0} \tag{5}$$

with $\chi^2_M$: chi-square value of the hypothesized model, $\chi^2_0$: chi-square value of the null model (model without relationships between variables), $df_M$: degrees of freedom of the hypothesized model and $df_0$: degrees of freedom of the null model.$\chi^2_0$ obtained when the predicted correlation vectors are all zero ($\rho^*(L, \Delta) = 0$).

### *2.4.2. Tucker-Lewis Index (TLI)*

Same as CFI value, the TLI value ranges from 0 to 1. TLI value $\geqslant 0.90$ indicates goodness if fit, whereas if $0.80 \leqslant \mathrm{TLI} \leqslant 0.90$ is often called marginal fit. The TLI is calculated using the following formula

$$TLI = \frac{\left(\frac{\chi^2_0}{df_0} - \frac{\chi^2_M}{df_M}\right)}{\left(\frac{\chi^2_0}{df_0}\right) - 1} \tag{6}$$

### 2.5. Latent score

The latent score for each observation was obtained using the expected value of the posterior (EAP) distribution [21]. The probit model was used due to its relation to the tetrachoric correlation.

**Algorithm 4** Gauss–Hermite Quadrature Nodes and Weights

**Require:** $K$: number of quadrature points (e.g., $K = 21$)
**Ensure:** $\{(\eta_k, w_k)\}_{k=1}^{K}$: nodes and weights of Gauss–Hermite quadrature for the standard normal distribution

1: **Function:** gh_quadrature($K$)
2: Check if the quadrature package/implementation is available
3: Compute $K$ Gauss–Hermite quadrature points for the normal distribution: generate nodes $\eta_k$ and weights $w_k$, for $k = 1, 2, \ldots, K$
4: Form grid vectors: $\eta_{\text{grid}} = (\eta_1, \ldots, \eta_K)$
5: $w = (w_1, \ldots, w_K)$
6: **return** $\eta_{\text{grid}}, w$

**Algorithm 5** Conditional Log-Likelihood $\log p(y_i \mid \eta_k)$

**Require:** $y_i = (y_{i1}, \ldots, y_{ip}) \in \{0,1\}^p$ (response vector of individual $i$)
$\eta_{\text{grid}} = (\eta_k)_{k=1}^{K}$ (quadrature nodes)
$\lambda = (\lambda_1, \ldots, \lambda_p)$ (factor loadings)
$\tau = (\tau_1, \ldots, \tau_p)$ (thresholds)
**Ensure:** $\ell_k = \log p(y_i \mid \eta_k)$ for $k = 1, \ldots, K$

1: **Model (binary probit):**

$$y_{ij} = \begin{cases} 1 & \text{if } \lambda_j \eta - \tau_j + \varepsilon_{ij} > 0, \\ 0 & \text{otherwise} \end{cases} \qquad \varepsilon_{ij} \sim \mathcal{N}(0,1)$$

$$P(y_{ij} = 1 \mid \eta) = \Phi(\lambda_j \eta - \tau_j)$$

2: **for** $k = 1, 2, \ldots, K$ **do**
3: Compute linear predictor per indicator:

$$a_{kj} = \lambda_j \eta_k - \tau_j$$

4: Compute probabilities:

$$p_{1,kj} = \Phi(a_{kj}), \quad p_{0,kj} = 1 - \Phi(a_{kj})$$

5: Compute conditional log-likelihood:

$$\ell_k = \sum_{j=1}^{p} \left[ y_{ij} \log(p_{1,kj} + \varepsilon_0) + (1 - y_{ij}) \log(p_{0,kj} + \varepsilon_0) \right]$$

where $\varepsilon_0 = 10^{-12}$ (numerical stability)
6: **end for**
7: **return** $(\ell_1, \ldots, \ell_K)$

The prior used was $\phi(\eta) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\eta^2}{2}\right)$ and the marginal probability was obtained through the approximation of Gauss-Hermite Quadrature (GHQ) because the integral produced did not have a closed-form solution. Three stages were used to estimate the latent scores. *First* select a point $\eta_k$ optimal and gives weight $w_k$ so that $\int (f(\eta)\Phi(\eta) d\eta \approx \sum_k^K w_k f(\eta_k)$. *Second*, calculate the conditional likelihood of the individual's response $i$ at a certain latent value $\eta_k$ namely $p(y_i|\eta_k, \lambda, \tau)$. *Final*, calculates each individual's latent score. The algorithm of the three stages shown in Algorithm 4 to Algorithm 6.

**Algorithm 6** Latent score (binary probit, one factor)

**Require:** $Y = (y_{ij}) \in \{0,1\}^{N\times p}$ (binary data)
$\lambda \in \mathbb{R}^p$ (factor loadings)
$\tau \in \mathbb{R}^p$ (thresholds)
$K$ (number of quadrature points)
**Ensure:** $\hat{\eta} = (\hat{\eta}_1, \dots, \hat{\eta}_N)$
$\widehat{se} = (\widehat{se}_1, \dots, \widehat{se}_N)$

**Function:** eap_scores_probit_binary($Y, \lambda, \tau, K$)
Ensure $Y$ is a matrix and $p = \mathrm{ncol}(Y)$
Ensure $\mathrm{length}(\lambda) = \mathrm{length}(\tau) = p$
Obtain Gauss–Hermite nodes and weights: $\{(\eta_k, w_k)\}_{k=1}^{K}$ (Stage 1)
$N \leftarrow$ number of rows of $Y$
Initialize $\hat{\eta}$ and $\widehat{se}$ of length $N$
**for** $i = 1, 2, \dots, N$ **do**
  Extract response vector $y_i = (y_{i1}, \dots, y_{ip})$
  Compute $\ell_{ik} = \log p(y_i \mid \eta_k)$ for all $k$ (Stage 2)
  Stabilize exponentials:
$$\ell_i^{\max} = \max_k \ell_{ik}, \quad L_{ik} = \exp(\ell_{ik} - \ell_i^{\max})$$
  Unnormalized posterior weights:
$$\tilde{L}_{ik} = w_k L_{ik}$$
  Posterior normalization:
$$\mathrm{den}_i = \sum_{k=1}^{K} \tilde{L}_{ik}$$
  First and second posterior moments:
$$\mathrm{num1}_i = \sum_{k=1}^{K} \tilde{L}_{ik}\eta_k, \quad \mathrm{num2}_i = \sum_{k=1}^{K} \tilde{L}_{ik}\eta_k^2$$
  EAP estimate:
$$\hat{\eta}_i = \frac{\mathrm{num1}_i}{\mathrm{den}_i}$$
  Posterior variance:
$$\widehat{\mathrm{Var}}(\eta_i \mid y_i) = \frac{\mathrm{num2}_i}{\mathrm{den}_i} - \hat{\eta}_i^2$$
  Posterior standard error:
$$\widehat{se}_i = \sqrt{\max\Big(\widehat{\mathrm{Var}}(\eta_i \mid y_i), 0\Big)}$$
**end for**
**return** $(\hat{\eta}, \widehat{se})$

## 3. Results and Discussion

Because the data are based on repeated cross-sectional surveys and measurement invariance across periods and regions has not been formally tested, the results are interpreted primarily as within region–period measurement summaries rather than as definitive temporal or regional comparisons.

Prior to conducting the CFA analysis, the proportion of each response category was examined for every indicator to assess category balance and determine the corresponding threshold positions. The descriptive statistics show that the prevalence of category 1 varies across regions and survey periods. However, these variations should be interpreted as descriptive patterns within each region–period group rather than as conclusive evidence of temporal change. In presenting the descriptive statistics, this study focuses on the proportion of category 1 because it reflects the occurrence of food vulnerability conditions captured by the indicators and provides the main information used for threshold estimation. Details are presented in Table 2.

**Table 2:** The proportion of category 1 for each indicator, region, and period

| Indicator | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 |
|---|---|---|---|---|---|
| Teluk Mayalibit | | | | | |
| Adult skip | 0.35 | 0.36 | 0.31 | 0.19 | 0.37 |
| Balanced diet | 0.87 | 0.88 | 0.85 | 0.86 | 0.47 |
| Did not last | 0.42 | 0.33 | 0.12 | 0.31 | 0.47 |
| Eat less | 0.33 | 0.23 | 0.29 | 0.14 | 0.35 |
| Freq adult skip | 0.11 | 0.15 | 0.07 | 0.06 | 0.10 |
| Hungry | 0.12 | 0.04 | 0.10 | 0.04 | 0.06 |
| Kofiau Boo | | | | | |
| Adult skip | 0.47 | 0.29 | 0.34 | 0.13 | 0.22 |
| Balanced diet | 0.97 | 0.97 | 0.97 | 0.69 | 0.51 |
| Did not last | 0.43 | 0.38 | 0.01 | 0.36 | 0.30 |
| Eat less | 0.56 | 0.26 | 0.11 | 0.13 | 0.23 |
| Freq adult skip | 0.18 | 0.11 | 0.07 | 0.06 | 0.09 |
| Hungry | 0.13 | 0.07 | 0.02 | 0.04 | 0.11 |
| Selat Dampier | | | | | |
| Adult skip | 0.34 | 0.23 | 0.26 | 0.16 | 0.32 |
| Balanced diet | 0.87 | 0.88 | 0.87 | 0.77 | 0.77 |
| Did not last | 0.39 | 0.13 | 0.20 | 0.21 | 0.63 |
| Eat less | 0.34 | 0.25 | 0.13 | 0.11 | 0.31 |
| Freq adult skip | 0.16 | 0.11 | 0.09 | 0.04 | 0.25 |
| Hungry | 0.11 | 0.05 | 0.06 | 0.03 | 0.12 |
| Kepulauan Misool | | | | | |
| Adult skip | 0.37 | 0.23 | 0.26 | 0.16 | 0.32 |
| Balanced diet | 0.90 | 0.89 | 0.97 | 0.76 | 0.84 |
| Did not last | 0.51 | 0.45 | 0.04 | 0.40 | 0.65 |
| Eat less | 0.34 | 0.21 | 0.13 | 0.10 | 0.30 |
| Freq adult skip | 0.24 | 0.11 | 0.07 | 0.09 | 0.23 |
| Hungry | 0.11 | 0.09 | 0.02 | 0.09 | 0.31 |

Table 2 shows that the proportion of category 1 is unbalanced and varies significantly across indicators and over time. This condition limits the use of estimation methods that rely on the assumption of a multivariate normal distribution. To address this limitation, this study conceptualizes household food security as a latent construct that cannot be directly observed and estimates it using CFA with binary indicators. Parameter estimation is performed using the robust DWLS approach, which is specifically designed for categorical data and is more robust to category imbalance and violations of the normality assumption. This approach allows for unbiased estimation and a more stable and reliable latent food security score for further analysis.

We will discuss the results of the model parameter estimates for each MPA. The parameters displayed include the estimated loading factors $\hat{\lambda}_j$, standard error (SE) and threshold $\hat{\tau}_j$ for each indicator. CFI, TLI and CR are also given every period. We also present descriptive latent scores obtained. This aims to describe the characteristics of food security in each period and each region that have been obtained.

## 3.1. Teluk Mayalibit

The estimated results of the model for each period in Teluk Mayalibit are shown in Table 3. The results indicate that the one-factor model provides a reasonable representation of the food security construct in the estimated model, although the strength of several indicators varies across region–period groups. The estimated models show CFI and TLI values above 0.90 and CR values above 0.80, indicating acceptable model fit and internal consistency. These findings suggest that the access dimension of household food security is reasonably represented by the fitted model within each survey period in Teluk Mayalibit.

**Table 3:** Parameter estimates, CR, SE and Goodnes of fit index in Teluk Mayalibit

| Periode | Parameter | Adult skip | Balanced diet | Did not last | Eat less | Freq adult skip | Hungry |
|---|---|---|---|---|---|---|---|
| 1 | $\hat{\lambda}_j$ | 0.67 | 0.27 | 0.99 | 0.99 | 0.77 | 0.61 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.19 | -1.13 | 0.38 | 0.45 | 1.26 | 1.18 |
| CFI = 0.99, TLI = 0.98 and CR = 0.88 | | | | | | | |
| 2 | $\hat{\lambda}_j$ | 0.48 | 0.12 | 0.98 | 0.96 | 0.69 | 0.54 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.44 | -1.19 | 0.35 | 0.73 | 1.05 | 1.73 |
| CFI = 0.99, TLI = 0.94 and CR = 0.82 | | | | | | | |
| 3 | $\hat{\lambda}_j$ | 0.49 | 0.15 | 1.04 | 0.93 | 0.79 | 0.56 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 1.16 | -1.03 | 0.50 | 0.56 | 1.47 | 1.26 |
| CFI=0.99, TLI = 0.97 and CR=0.85 | | | | | | | |
| 4 | $\hat{\lambda}_j$ | 0.74 | 0.24 | 0.92 | 1.01 | 0.84 | 0.63 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.50 | -1.08 | 0.89 | 1.07 | 1.58 | 1.74 |
| CFI=0.92, TLI = 0.97 and CR=0.89 | | | | | | | |
| 5 | $\hat{\lambda}_j$ | 0.91 | 0.45 | 1.01 | 0.91 | 0.67 | 0.64 |
| | SE | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.09 | 0.07 | 0.34 | 0.39 | 1.28 | 1.59 |
| CFI=0.92, TLI = 0.94 and CR=0.89 | | | | | | | |

In most estimated models, the indicators “did not last” and “eat less” show relatively high factor loadings, indicating a strong association with the latent access dimension of food security. The “did not last” indicator represents insufficient household food supplies or a limited ability to obtain additional food when supplies run out. Meanwhile, the “eat less” indicator reflects household consumption adjustments in response to food shortages, namely by reducing the amount of food consumed. Together, these two indicators directly capture household experiences of food shortage and reduced food intake. Therefore, they are more strongly linked to the access dimension of food security and tend to produce higher factor loadings than the other indicators.

In contrast, the “balanced diet” indicator shows a relatively lower factor loading. This may be because the indicator reflects the quality and diversity of food consumption rather than the direct experience of food shortages. In some situations, households may still meet basic energy needs even when their diets are less diverse or not fully balanced. Nevertheless, this indicator remains conceptually relevant because it represents an important aspect of food access, particularly the ability of households to obtain sufficiently diverse and nutritious food. Several indicators were found to have factor loadings slightly greater than 1. However, the overall model fit indices remained acceptable, indicating that the measurement model still provided an adequate representation of the observed data.

The standard errors associated with the estimated parameters are very small, indicating that the parameter estimates obtained from the model are stable. The estimated threshold values describe the level of the latent food insecurity condition at which each indicator is likely to occur. Indicators such as “freq adult skip” and “hungry” show relatively high threshold values. This suggests that these conditions generally emerge when household food insecurity levels are relatively high. Therefore, these indicators represent more severe manifestations of limited food access. In contrast, the “balanced diet” indicator shows negative threshold values. This suggests that households may report difficulty consuming a balanced diet even when the level of food insecurity is relatively low.

The number of households varies from period to period. From periods 1 to 5, respectively, they are 260, 270, 243, 261, and 247. The descriptive statistic of latent food security scores for each period is shown in Table 4.

Descriptive statistics show that the latent food security score has a minimum value of 0, representing the best food security condition in the observed data. The maximum values are close to 3, indicating the presence of households experiencing relatively high levels of food insecurity.

**Table 4:** Descriptive statistic latent score in Teluk Mayalibit

| | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 |
|---|---|---|---|---|---|
| Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Max | 2.87 | 2.88 | 2.88 | 2.23 | 2.97 |
| Mean | 0.81 | 0.76 | 0.60 | 0.38 | 0.85 |
| Median | 0.62 | 0.53 | 0.15 | 0.08 | 0.67 |

This range of scores reflects the variation in household food security conditions in Teluk Mayalibit. The median value is significantly lower than the maximum value. This indicates that the majority of households are concentrated at relatively better levels of food security, while only a small proportion experience higher levels of food insecurity. Overall, the distribution of latent scores reflects heterogeneity in household food security conditions, but is dominated by households with relatively good levels of food security.

### 3.2. Kofiau Boo

The estimated results of the model for each period in Kofiau Boo are shown in Table 5. The CFA results indicate that the one-factor model provides an acceptable representation of the household food security construct in Kofiau Boo. CFI values consistently exceed the recommended threshold of 0.90, indicating that the proposed measurement model adequately captures the covariance structure among the six indicators and supports their representation within a single latent dimension. TLI values are generally close to the recommended level of 0.90. In several model estimations, slightly lower TLI values suggest a marginally acceptable fit. However, values within the range of approximately 0.80–0.90 are still considered acceptable in many applied studies. CR values indicate that the internal consistency of the indicators measuring the latent construct is generally adequate. Although some estimates fall slightly below the commonly recommended threshold of 0.70, values within the range of 0.60–0.70 are still considered quite acceptable.

**Table 5:** Parameter estimates, CR, SE and Goodnes of fit index in Kofiau Boo

| Periode | Parameter | Adult skip | Balanced diet | Did not last | Eat less | Freq adult skip | Hungry |
|---|---|---|---|---|---|---|---|
| 1 | $\hat{\lambda}_j$ | 0.47 | 0.36 | 1.11 | 0.74 | 0.76 | 0.20 |
| | SE | 0.00 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.19 | -1.83 | 0.08 | -0.16 | 0.91 | 1.11 |
| CFI = 0.94, TLI = 0.90 and CR = 0.80 | | | | | | | |
| 2 | $\hat{\lambda}_j$ | 0.31 | 0.25 | 1.04 | 0.97 | 0.77 | 0.68 |
| | SE | 0.00 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.19 | -1.83 | 0.08 | -0.16 | 0.91 | 1.11 |
| CFI = 0.99, TLI = 0.97 and CR = 0.85 | | | | | | | |
| 3 | $\hat{\lambda}_j$ | 0.11 | 0.10 | 0.60 | 0.95 | 0.24 | 0.81 |
| | SE | 0.02 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 2.28 | -1.93 | 0.43 | 1.25 | 1.49 | 2.00 |
| CFI=0.90, TLI = 0.84 and CR=0.66 | | | | | | | |
| 4 | $\hat{\lambda}_j$ | 0.83 | 0.52 | 1.02 | 1.00 | 0.92 | 0.61 |
| | SE | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.37 | -0.49 | 1.15 | 1.11 | 1.59 | 1.74 |
| CFI=0.99, TLI = 0.99 and CR=0.93 | | | | | | | |
| 5 | $\hat{\lambda}_j$ | 0.65 | 0.45 | 0.98 | 0.91 | 0.87 | 0.79 |
| | SE | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.51 | -0.01 | 0.77 | 0.73 | 1.35 | 1.25 |
| CFI=0.99, TLI = 0.99 and CR=0.91 | | | | | | | |

From a structural perspective, the indicators "did not last," "eat less," and "freq adult skip" show relatively high factor loadings, indicating a strong association with the latent food security construct. These indicators reflect direct experiences of food shortages and reduced food consumption at the household level, which represent central manifestations of limited food access. In contrast, the indicators "balanced diet" and "adult skip" exhibit relatively smaller factor loadings, suggesting a weaker statistical association with the latent construct. Nevertheless, these indicators remain conceptually relevant as they represent additional aspects of household food conditions. We found several indicators with factor loadings slightly exceeding 1. However, the resulting model fit indices indicated adequate representation, so the resulting model was not invalidated.

The estimated standard errors for the parameters are generally very small, indicating that the parameter estimates obtained from the model are stable and estimated with relatively high precision. The estimated threshold values describe the level of the latent food insecurity condition at which each indicator is likely to occur. Indicators such as “freq adult skip” and “hungry” show relatively high threshold values, indicating that these conditions generally appear when the level of household food insecurity is relatively high. These indicators therefore represent more severe manifestations of limited food access at the household level. In contrast, the “balanced diet” indicator shows negative threshold values. This indicates that households may report difficulty consuming a balanced diet even when the level of food insecurity is relatively low.

The number of households in the sample for periods 1 to 5 was 139, 140, 138, 139, and 189, respectively. The descriptive statistic of latent food security scores for each period is shown in Table 6.

**Table 6:** Descriptive statistic latent score in Kofiau Boo

| | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 |
|---|---|---|---|---|---|
| Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Max | 2.71 | 2.83 | 1.62 | 2.77 | 2.89 |
| Mean | 1.02 | 0.50 | 0.08 | 0.68 | 0.48 |
| Median | 0.95 | 0.08 | 0.00 | 0.42 | 0.23 |

The minimum latent score was 0.00, indicating that households with the lowest latent food security scores were observed in the data. The maximum latent scores ranged between 1.62 and 2.89, suggesting that some households still exhibited relatively high latent scores. A lower latent score indicates greater food security. The difference between the mean and median values indicates an asymmetric distribution of latent scores. In particular, the median being lower than the mean suggests that most households have relatively low latent scores, while a smaller proportion of households exhibit higher scores.

### 3.3. Selat Dampier

The estimated results of the model for each period in Selat Dampier are shown in Table 7. The CFA results indicate that the one-factor model provides an adequate representation of the household food security construct in Selat Dampier. CFI and TLI values above 0.90 indicate that the one-factor model provides a good fit to the data. In addition, CR values above 0.80 indicate good internal consistency in measuring the underlying construct.

Structurally, the indicators “did not last”, “eat less” and “freq adult skip” exhibit relatively high factor loadings. This is indicating that experiences of reduced consumption and limited food availability form the core components of the latent construct. The “hungry” indicator also shows a relatively high threshold, representing a more severe condition of food insecurity.

The balanced diet indicator exhibits a very small loading in one estimation. This is suggesting a weak association with the latent construct. This may reflect differences in household perceptions of what constitutes a balanced diet, which may not always align with direct experiences of food shortages. However, this does not substantially affect the overall adequacy of the measurement model.

The estimated standard errors for the model parameters are generally very small. This indicates that the estimated parameters are obtained with a high level of precision and that the estimation procedure produces stable results within the fitted CFA models. The threshold parameters indicate the point on the latent food insecurity scale at which households are likely to

**Table 7:** Parameter estimates, CR, SE and Goodnes of fit index in Selat Dampier

| Periode | Parameter | Adult skip | Balanced diet | Did not last | Eat less | Freq adult skip | Hungry |
|---|---|---|---|---|---|---|---|
| 1 | $\hat{\lambda}_j$ | 0.50 | 0.53 | 0.86 | 0.88 | 0.86 | 0.64 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.29 | -1.12 | 0.41 | 0.40 | 1.00 | 1.24 |
| CFI = 0.96, TLI = 0.93 and CR = 0.87 | | | | | | | |
| 2 | $\hat{\lambda}_j$ | 0.38 | -0.04 | 1.08 | 0.91 | 0.78 | 0.64 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 1.12 | -1.17 | 0.62 | 0.69 | 1.24 | 1.60 |
| CFI = 0.98, TLI = 0.97 and CR = 0.83 | | | | | | | |
| 3 | $\hat{\lambda}_j$ | 0.31 | 0.49 | 0.96 | 0.91 | 0.88 | 0.72 |
| | SE | 0.02 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.83 | -1.12 | 1.11 | 1.14 | 1.32 | 1.55 |
| CFI=0.90, TLI = 0.97 and CR=0.87 | | | | | | | |
| 4 | $\hat{\lambda}_j$ | 0.56 | 0.18 | 0.98 | 0.94 | 0.70 | 0.68 |
| | SE | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.81 | -0.72 | 1.07 | 1.23 | 1.73 | 1.85 |
| CFI=0.98, TLI = 0.97 and CR=0.85 | | | | | | | |
| 5 | $\hat{\lambda}_j$ | 0.62 | 0.01 | 0.97 | 0.99 | 0.81 | 0.68 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | -0.34 | -0.74 | 0.25 | 0.51 | 0.67 | 1.19 |
| CFI=0.99, TLI = 0.98 and CR=0.87 | | | | | | | |

report each condition represented by the indicators. Indicators such as "hungry" and "freq adult skip" are associated with relatively high threshold values. This indicates that these situations tend to occur when households experience a higher level of food insecurity and therefore reflect more severe manifestations of limited food access. In contrast, the "balanced diet" indicator is associated with negative threshold values. This indicates that households may report difficulty maintaining a balanced diet even when the overall level of food insecurity is not yet high. Such a pattern suggests that dietary quality may deteriorate earlier than other manifestations of food insecurity. This is thought to be a reason for the continued use of this indicator.

The descriptive statistic of latent food security scores for each period is shown in Table 8. The number of households in the sample for periods 1 to 5 was 305, 319, 313, 338, and 234, respectively. The minimum latent score observed in the data was 0.00, indicating that households with the lowest latent food security scores were present in the sample. The maximum latent scores ranged between 2.69 and 3.06, suggesting that some households exhibited relatively high latent scores. A lower latent score indicates greater food security.

**Table 8:** Descriptive statistic latent score in Selat Dampier

| | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 |
|---|---|---|---|---|---|
| Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Max | 3.05 | 2.91 | 3.06 | 2.99 | 2.69 |
| Mean | 0.94 | 0.58 | 0.54 | 0.39 | 0.82 |
| Median | 0.77 | 0.18 | 0.37 | 0.17 | 0.47 |

The difference between the mean and median values suggests an asymmetric distribution of latent scores. In particular, the median values tend to be lower than the means, indicating that most households have relatively low latent scores, while a smaller proportion of households exhibit higher scores.

### 3.4. Kepulauan Misool

The estimated results of the model for each period in Kepulauan Misool are shown in Table 9. The CFA results indicate that the one-factor model provides an adequate representation of the household food security construct in Kepulauan Misool. CFI and TLI values above 0.95 indicate that the model provides an excellent fit to the empirical data. In addition, CR values above 0.80

indicate good internal consistency among the indicators used to measure the latent construct. Overall, the measurement model can be considered appropriate and reliable.

**Table 9:** Parameter estimates, CR, SE and Goodnes of fit index in Kepulauan Misool

| Periode | Parameter | Adult skip | Balanced diet | Did not last | Eat less | Freq adult skip | Hungry |
|---|---|---|---|---|---|---|---|
| 1 | $\hat{\lambda}_j$ | 0.71 | 0.36 | 1.02 | 0.94 | 0.86 | 0.70 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | -0.03 | -1.27 | 0.34 | 0.42 | 0.71 | 1.21 |
| CFI = 0.99, TLI = 0.983 and CR = 0.91 | | | | | | | |
| 2 | $\hat{\lambda}_j$ | 0.41 | 0.03 | 0.98 | 0.86 | 0.80 | 0.66 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.14 | -1.23 | 0.74 | 0.80 | 1.24 | 1.33 |
| CFI = 0.98, TLI = 0.97 and CR = 0.82 | | | | | | | |
| 3 | $\hat{\lambda}_j$ | 0.05 | -0.21 | 1.05 | 0.88 | 0.83 | 0.69 |
| | SE | 0.00 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 1.80 | -1.83 | 0.66 | 1.11 | 1.48 | 1.99 |
| CFI=0.98, TLI = 0.96 and CR=0.79 | | | | | | | |
| 4 | $\hat{\lambda}_j$ | 0.75 | 0.52 | 0.88 | 0.86 | 1.00 | 0.54 |
| | SE | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | 0.26 | -0.69 | 1.02 | 1.29 | 1.37 | 1.37 |
| CFI=0.99, TLI = 0.97 and CR=0.90 | | | | | | | |
| 5 | $\hat{\lambda}_j$ | 0.59 | -0.12 | 0.98 | 0.91 | 0.90 | 0.72 |
| | SE | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\hat{\tau}_j$ | -0.40 | -1.00 | 0.47 | 0.54 | 0.74 | 1.15 |
| CFI=0.99, TLI = 0.99 and CR=0.86 | | | | | | | |

Structurally, the indicators “did not last,” “eat less,” and “freq adult skip” exhibit relatively high factor loadings. This is indicating that experiences of reduced food consumption and limited food availability represent core components of the latent construct. The “hungry” indicator also contributes meaningfully, with a relatively high threshold representing a more severe condition of food insecurity. In contrast, the “balanced diet” indicator exhibits relatively small and occasionally negative loadings, suggesting a weaker statistical association with the latent construct. This pattern may reflect differences in household perceptions of what constitutes a balanced diet, which may not always correspond to direct experiences of food shortages. This is thought to be a reason for the continued use of this indicator. Nevertheless, the overall model fit and reliability indices indicate that the household food security construct can be adequately represented by a one-factor model. We found several indicators with factor loadings slightly exceeding 1. However, the resulting model fit indices indicated adequate representation, so the resulting model was not invalidated.

The standard errors associated with the estimated parameters are generally very small. This indicates that the estimated parameters are obtained with a high degree of precision and that the estimation procedure provides stable results for the fitted measurement model. The threshold estimates indicate the level of the latent food insecurity condition at which each indicator tends to be observed. Indicators such as “hungry” and “freq adult skip” are associated with relatively high threshold values. This suggests that these situations tend to occur when households experience a more serious level of food insecurity and therefore represent more severe conditions of limited food access. In contrast, the “balanced diet” indicator is characterized by negative threshold values. This indicates that households may report difficulties in consuming a balanced diet even when the overall level of food insecurity is not yet high. This pattern suggests that problems related to dietary quality may emerge earlier than other forms of food insecurity.

The descriptive statistic of latent food security scores for each period is shown in Table 10. The number of households in the sample for periods 1 to 5 was 234, 239, 243, 244, and 219, respectively.

**Table 10:** Descriptive statistic latent score in Kepulauan Misool

| | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 |
|---|---|---|---|---|---|
| Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Max | 2.97 | 2.68 | 2.44 | 3.05 | 2.76 |
| Mean | 1.18 | 0.58 | 0.29 | 0.76 | 0.89 |
| Median | 0.86 | 0.35 | 0.00 | 0.43 | 0.59 |

The minimum latent score observed in the data was 0.00, indicating the presence of households with the lowest food security scores. The maximum latent scores ranged between 2.44 and 3.05, suggesting that some households exhibited relatively high latent scores. A lower latent score indicates greater food security. The difference between the mean and median values suggests an asymmetric distribution of latent scores, with a tendency toward higher values at the upper end of the distribution. This pattern reflects heterogeneity in household food security conditions in the Kepulauan Misool.

## 4. Conclusion

This study proposes an empirical framework for measuring household food security in marine protected areas using latent variable modeling applied to repeated cross-sectional survey data. Within the analyzed region–period groups of the Raja Ampat Marine Protected Areas, the confirmatory factor analysis model provides an acceptable measurement representation of household food security based on binary indicators derived from the household survey data. The estimated factor loadings and thresholds describe the relative contribution and severity of each indicator within the latent construct. The results show that several indicators contribute more strongly to the construct, while others exhibit relatively small or occasionally negative factor loadings in some region–period groups. This variability suggests that the contribution of certain indicators to the latent construct may differ across empirical contexts. Overall, the goodness-of-fit indices suggest that the one-factor structure provides a reasonable representation of the relationships among the indicators under the fitted model.

Because the analysis relies on repeated cross-sectional data rather than a longitudinal panel, the findings are interpreted primarily as measurement results within each analyzed region–period group rather than as evidence of temporal stability or cross-regional equivalence. Future research should incorporate measurement invariance testing or longitudinal modeling approaches to assess comparability across periods and regions. Expanding latent score estimation to additional conservation areas would also help evaluate the broader applicability of the proposed measurement framework.

## CRediT Authorship Contribution Statement

**Indah Ratih Anggriyani:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing original draft **I Made Sumertajaya:** Supervision, Investigation, Review, and Editing **Khairil Anwar Notodiputro:** Conceptualization, Supervision, Review and Editing **Yenni Angraini:** Data curation, Supervision, review, and Editing.

## Declaration of Generative AI and AI-assisted technologies

During the preparation of this manuscript, the author used ChatGPT (OpenAI) to improve the grammar and clarity of several paragraphs. The content is reviewed and edited afterward as needed and the author takes full responsibility for the published article

## Declaration of Competing Interest

The authors declare no competing interests or personal relationships that could have influenced the work reported in this study.

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## Data and Code Availability

The dataset analyzed in this study is not publicly available but was provided by Science for Conservation (S4C), LPPM of the Papua University.

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