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Ordinal Logistic Regression Model in Determining Factors Associated with Household Food Insecurity in Namibia

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Abstract

Food insecurity is a global issue, and households in a society can experience food insecurity at different levels that could range from being mildly food insecure to severely food insecure. The severity of food insecurity is an ordinal categorical variable in nature and different types of ordinal logistic regression models could be used to model such variables. The purpose of this study is to identify the socioeconomic and demographic factors associated with household food insecurity in Namibia by fitting an ordinal logistic regression model using the 2015/2016 Namibia Household Income and Expenditure Survey. The proportional odds model (POM) and the partial proportional odds model (PPOM) were fitted and the performance of the two models was also compared. The PPOM was found to be the better model and based on the PPOM result, the study found factors such as the age of the household head, the household size, the source of income of a household, the annual income of the household, the education level attained by a household head and the geographical location of a household to be significant factors associated with severity of household food insecurity in Namibia.

Keywords

Food Insecurity, Ordinal Logistic Regression, Partial Proportional Odds Model

1. Introduction

Food insecurity can be described as a condition in which households are unable to access adequate safe food because of insufficient money and other resources for normal growth, development, and healthy life. Food insecurity at the household level is associated with several factors, including poverty, low income, level of education, household size, employment status, age, the gender of the household head, and food price [1]. Such factors increase the risks of anaemia, lower nutrient intake, behavioural problems, aggression, poorer general health, higher risks of being hospitalized, depression, and suicide ideation [2]. Furthermore, factors associated with household food insecurity vary from time to time and can be suddenly influenced by geographical locations, natural disasters, political instability, global disease outbreaks, and economic instability [3].

Namibia has a population of around 3.02 million [4]. Geographically, it is a large country with a 1500 km-long coastline on the South Atlantic Ocean and shares a boarder with Zambia, Angola, South Africa, and Botswana. In 2020, 17% of the Namibian population faced a high level of food insecurity from July to September 2020 [5]. Food insecurity is, thus, a real threat in Namibia. Socio-economic and demographic factors were reported by different authors as contributors to household food insecurity in Namibia, see [6]. Mbongo [6] fitted a binary logistic regression model to assess food insecurity in the informal settlements of Katutura, Windhoek. However, the author avoided the ordinal nature of the response variable which could result in a biased estimate of the parameters and hence lead to a biased conclusion.

Households in a society can experience food insecurity at different levels that could range from being food secure to severely food insecure [7]. Therefore, food insecurity has natural order categories, and it is a polytomous response variable. In such a situation, the ordinal logistic regression models can be utilized to determine the magnitude and significance of the relationship between the ordinal dependent variables such as severity of food insecurity, and the set of predictor variables [8] [9]. There are various cumulative logistic regression models available in the literature. Some of these include the proportional odds model, two versions of the partial proportional odds model (with and without restrictions), the continuation ratio model, and stereotype model [10]. In this study, the proportional odds and partial proportional odds regression model was utilized to identify factors associated with food insecurity in Namibia.

The cumulative logistic regression model, also known as the proportional odds model (POM), is commonly used for analyzing ordinal data because of its effectiveness in providing generalizing visualizations that assess the effect of explanatory variables at the class level [9]. When the assumption of parallelism is violated, the partial proportional odds model (PPOM) can be employed as an alternative to model an ordinal response variable. The current study is, therefore, aims to fit both POM and PPOM to assess the socio-economic and demographic factors associated with household food insecurity using the 2015/2016 Namibia Household Income and Expenditure Survey (NHIES).

Measurement of Household Food Insecurity

Household food insecurity can be measured with different indicators that assist in determining the severity groups in which a household can fall. The number of categories of household food insecurity severity varies according to different household food insecurity indicators. For example, indicators such as the Coping Strategies Index (CSI), Reduced Coping Strategies Index (RCSI), and Household Food Insecurity Access Scale (HFIAS) classify household food insecurity severity into 4 severity groups. The first group is food secure when the household is generally not food insecure. The second group is mildly food insecure when a household is not certain about obtaining food, doesn't eat preferred food, and sometimes eats undesirable foods. The third group is moderately food insecure when a household often reduces the quantity of food, often skips meals, and mostly eats undesirable foods. The last group is severely food insecure when the household goes a whole day and night without eating any meals more often and eats undesirable food [11].

The RCSI indicator consists of 5 questions about the coping strategies that a household had used 7 days before the survey and the number of days it had used each strategy in the past 7 days. The frequency of occurrence of each coping strategy runs from 0-7 days. In addition, each of the 5 coping strategies is associated with a universal severity weight score of 1, 2, 1, 3, and 1 corresponding to Question 1 to Question 5, respectively (see **Table A1** in Appendix A). The frequency occurrence of each strategy is multiplied by the corresponding coping strategy weight score to obtain each coping strategy score of each household. These coping strategy scores were then added together to determine the RCSI score for each household. The household was classified to be in the food insecurity severity group: Food secure, mildly food insecure, Moderately food insecure, or Severely food insecure if the RCSI score of a household is between 0 - 3, 4 - 18, 19 - 42, or >43, respectively [12]. Because of the availability of the questions for RCSI indicators in the 2015/16 Namibia household income and expenditure survey, the current study utilized the RCSI indicator to measure and categorize household food insecurity in Namibia.

2. Data and Methodology

2.1. The Data

The study employed a quantitative cross-sectional study design and utilized secondary data from the 2015/16 Namibia Household Income and Expenditure Survey (NHIES) that was conducted by the Namibia Statistics Agency (NSA). The 2015/16 NHIES data covered information such as household head's demographic characteristics, education, health, the main source of income, household ownership, and annual consumption. Household Primary Sampling Units (PSUs) were selected using probability proportional to size sampling, based on the 2011 Population and Housing Census data. This survey covers all 14 regions in Namibia by using a sample of 10368 households from 864 PSUs. An enumerator conducted interviews with the family member who was most familiar with the household's affairs. The NHIES is a household-based survey therefore it excluded those living in institutions such as hospitals, nursing homes, school hotels, etc. However, private households found within institutions were included. In addition, homeless people and people who usually live in private households, but were in the institution during the time of data collection were also excluded from 2015/16 NHIES.

The main response variable is the household food insecurity level, computed using the Reduced Coping Strategies Index (RCSI), which measures household food insecurity. The household food insecurity level is an ordinal categorical variable with four categories namely food secure, mildly food insecure, moderately food insecure, and severely food insecure. Household food insecurity levels were categorized based on food consumption scores: 1 - 3 (food secure), 4 - 18 (mildly food insecure), 19 - 42 (moderately food insecure), and ≥43 (severely food insecure) [13]. However, due to the fewer households in the category of severely food insecure, households categorized in this category were combined with moderately food insecure. As a result, this study considered the response variable household food insecurity levels with three categories (food secure, mildly food Insecure, and moderately/severely food insecure).

2.2. Statistical Models

The study applied the ordinal logistic regression model since the household food insecurity level is a categorical variable with three ordered categories. The cumulative logistic regression model which is well known as the proportional odds model (POM) is the most widely used type of ordinal logistic model. In this study, the POM was used to estimate the cumulative probability of a household being in a certain category or below that category of the household food insecurity levels given a set of covariates. The POM works under the assumption of the parallel line. Therefore, if the proportional odds assumption for the ordinal logistic models is violated then the partial proportional odds model (PPOM) is a better alternative which is a generalization of the POM and it allows the covariates that violated the assumption of proportionality, to vary across the categories of the household food insecurity level [14]. The current study did not consider other cumulative logistic regression models, such as the stereotype and continuation ratio models. The continuation ratio model is mainly suitable for a response variable involving a clear sequential decision process over time, which is not ideal for the current data. In contrast, the stereotype model is more complex and less interpretable due to the presence of scaling parameters in the model used to account for the ordinal nature of the dependent variable.

2.2.1. Proportional Odds Model (POM)

Let Y_k be the household food consumption scores for the k^{th} household with J categories and $\boldsymbol{x}$ be a $p \times 1$ vector of the explanatory variables associated with household food insecurity. Then the $P(Y_k \le j \mid \boldsymbol{x})$ is the cumulative probability of Y_k being in a specific category $j = 1, \cdots, J-1$ or lower. The odds of being in lower or equal to a particular category are defined as

$$\frac{P(Y_k \le j \mid \boldsymbol{x})}{P(Y_k > j \mid \boldsymbol{x})} \tag{1}$$

and the cumulative logit of POM is defined as

$$\operatorname{logit}\left[P\left(Y_k \leq j \mid \boldsymbol{x}\right)\right]=\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}, \tag{2}$$

where α_j is the regression constants corresponding to the j^{th} categories and $\boldsymbol{\beta}$ is a $p \times 1$ regression coefficients vector corresponding to the independent variables.

The cumulative probability in Expression (2) can be stated as

$$P\left(Y_k \leq j \mid \boldsymbol{x}\right)=\frac{\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}{1+\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}. \tag{3}$$

The probability of each j^{th} category is defined as [15]

$$\pi_j(\boldsymbol{x})=\frac{\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}{1+\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}-\frac{\exp\left(\alpha_{j-1}+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}{1+\exp\left(\alpha_{j-1}+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}. \tag{4}$$

The parameter estimation was conducted using the Fisher's scoring method which numerically solves the maximum likelihood non-linear equations. The POM likelihood function is formulated as

$$L=\prod_{k=1}^{n} \prod_{j=1}^{3}\left(\frac{\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}{1+\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}-\frac{\exp\left(\alpha_{j-1}+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}{1+\exp\left(\alpha_{j-1}+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}\right)^{y_{kj}}. \tag{5}$$

Expression (5) can be re-expressed as a log – likelihood function given by [8]

$$\mathcal{L}=\sum_{k=1}^{n} \sum_{j=1}^{3} y_{kj} \ln\left(\frac{\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}{1+\exp\left(\alpha_j+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}-\frac{\exp\left(\alpha_{j-1}+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}{1+\exp\left(\alpha_{j-1}+\boldsymbol{x}^{\mathrm{T}} \boldsymbol{\beta}\right)}\right). \tag{6}$$

The Fisher's scoring algorithm is given by

$$\boldsymbol{b}^{m}=\boldsymbol{b}^{m-1}+\left[\beth^{m-1}\right]^{-1} \boldsymbol{U}^{m-1}, \tag{7}$$

where $\boldsymbol{b}^{m}$ is the estimated regression coefficients vector observed at m^{th} iteration, $\boldsymbol{U}^{m-1}$ is the score statistic vector observed at $(m-1)^{\text{th}}$ iteration and $\left[\beth^{m-1}\right]^{-1}$ is the information matrix observed at the $(m-1)^{\text{th}}$ iteration [16].

2.2.2. Proportional Odds Assumption (Parallel Lines Assumption)

The parallel lines assumption states that the effect of an explanatory variable in the fitted model is the same for all categories of the response variable [17]. The Brant's Wald test is used to test the proportionality assumption for each covariate and all together in the proportional odds model. The Brant's Wald test is simply conducted by comparing the coefficients of POM and PPOM. Then it tests the significance of the difference in the model's regression coefficients by producing a chi-square statistic [18]. When the assumption of proportionality of POM is violated, the PPOM is then utilized as an alternative model.

2.2.3. Partial Proportional Odds Model (PPOM)

The PPOM allows non-proportional odds for a subset of q of the p-covariates ($q \leq p$). The cumulative logit of the PPOM is formulated as

$$\text{logit}\left[P\left(Y_k \le j \mid \mathbf{x},\mathbf{z}\right)\right] = \alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j \quad \text{for } j = 1,\cdots,J-1, \tag{8}$$

where $P\left(Y_k \le j \mid \mathbf{x},\mathbf{z}\right)$ is the cumulative probability of Y_k being in a specific category $j = 1,\cdots,J-1$ or lower. The α_j is the regression intercept corresponding to the j^{th} categories. Furthermore, $\mathbf{x}$ is a $p \times 1$ covariates vector that satisfies the assumption of proportionality and $\boldsymbol{\beta}$ is the $p \times 1$ corresponding regression coefficients vector, $\mathbf{z}$ is the $q \times 1$ vectors of covariates that violated the proportionality assumption and $\boldsymbol{\gamma}_j$ is the $q \times 1$ associated regression vector of coefficients.

The cumulative probability in Expression (8) can be stated as

$$P\left(Y_k \le j \mid \mathbf{x},\mathbf{z}\right) = \frac{\exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)}{1+\exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)}. \tag{9}$$

The probability of each j^{th} category is defined as [15]

$$\pi_j\left(\mathbf{x},\mathbf{z}\right) = \frac{\exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)}{1+\exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)} - \frac{\exp\left(\alpha_{j-1} + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_{j-1}\right)}{1+\exp\left(\alpha_{j-1} + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_{j-1}\right)}. \tag{10}$$

Similar to POM, the parameter estimation can be computed using the Fisher's Scoring Method which numerically solve the maximum likelihood non-linear equations. The PPOM likelihood function were formulated as

$$L = \prod_{k=1}^{n}\prod_{j=1}^{3}\left(\frac{\exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)}{1+\exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)} - \frac{\exp\left(\alpha_{j-1} + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_{j-1}\right)}{1+\exp\left(\alpha_{j-1} + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_{j-1}\right)}\right)^{y_{kj}}. \tag{11}$$

Expression (11) can be re-expressed as a log – likelihood function [8]

$$\mathcal{L} = \sum_{k=1}^{n}\sum_{j=1}^{3} y_{kj} \ln\left(\frac{\exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)}{1+exp\left(\alpha_j + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_j\right)} - \frac{\exp\left(\alpha_{j-1} + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_{j-1}\right)}{1+exp\left(\alpha_{j-1} + \mathbf{x}^{\mathrm{T}}\boldsymbol{\beta} + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}_{j-1}\right)}\right). \tag{12}$$

2.2.4. Comparison of Models

In order to choose the best performing ordinal logistic regression models, the POM and PPOM models were compared based on model fit, coefficients, and significance level of the covariates. The Akaike's Information Criterion (AIC) was used to select the best model.

Akaike's information criterion (AIC)

The AIC is a statistical method that is used to measure the quality of the estimated statistical models. The AIC is estimated by considering the complexity and goodness of fit of the model at the same time. AIC does not provide any information about the fitness of the estimated model and therefore it can only be used to compare different models [19]. The AIC is computed as:

$$\text{AIC} = 2p - 2\ln\left(L\right) \tag{13}$$

where p is the number of parameters in the model, L is the maximum likelihood value of the fitted model, and $2p$ is a penalty term paid for overfitting the models as a result of adding too many variables. The best fitted model is the one with the smallest value of the AIC [16].

2.2.5. Model Adequacy

To assess the model adequacy, the multinomial methods of testing the goodness of fit likelihood ratio test and McFadden's Pseudo R^2 were used. The model goodness of fit refers to the measure of the discrepancy between the model fitted and the data [20].

Likelihood Ratio Test

The likelihood ratio test is defined as the hypothesis that assists in selecting the best model between two nested models. When testing the overall significance of the model involves the ratio of the likelihood functions of the null model and fitted model [21].

H_0: The null model is the better fit vs H_1: The fitted model is the better fit. The likelihood ratio test is formulated as

$$\text{LRT} = -2\left[\mathcal{L}_{null} - \mathcal{L}_{fitted}\right], \tag{14}$$

where $\mathcal{L}_{fitted}$ is log likelihood of the fitted model and $\mathcal{L}_{null}$ is log likelihood of the null model. Rejecting the null hypothesis indicates the overall significance of the covariates or of the fitted model.

McFadden's Pseudo R^2

The McFadden's Pseudo R^2 accesses the contribution of the covariates in the fitted model to the overall correlation between the dependent variable and the individual covariates [22]. The McFadden's Pseudo R^2 expression is given by

$$R^2 = 1 - \frac{\mathcal{L}_{fitted}}{\mathcal{L}_{null}},$$

where $\mathcal{L}_{fitted}$ is log likelihood of the fitted model and $\mathcal{L}_{null}$ is log likelihood of the null model. The R^2 lies between $[0,1]$ and the values closer to one indicate the better fit and the R^2 that is greater than 0.2 indicates the excellent fit. Furthermore, the R^2 value can be also negative.

3. Results

3.1. Descriptive Results

The study considered 10090 households, and the result of the survey revealed that on average the household head age was 47 years ranging from 12 to 107 years and 5474 (54.3%) of the household heads were male (see **Table 1**). Most of the households 5535 (54.1%) were from the rural areas with the northern part and central part of Namibia having the larger sample of the households of 5664 (56.1%) and 3306 (32.8%), respectively. The average household size was 4 members per household and the household size ranged from 1 to 35 members. The households that had members less than or equal to 5 people were the highest with 7259 (72.1%) followed by the households that had members of 6 - 10 people with 2412 (23.9%), and the households that had more than 10 people were only 400 (4.0%). Furthermore, the survey showed that 4994 (49.5%) households that depended on salary or wages were the highest, followed by 2715 (26.9%) households that depended on pensions, social grants, or drought reliefs. In addition, the computed annual income was N$100,000 or below for most households 7078 (70.1%) and only 369 (3.7%) households had a computed annual income of above N$500,000. For the education level attained by a household head, the survey indicated that 4630 (45.9%) household heads had no formal education or only had a primary level of education. In addition, 946 (9.4%) household heads had a tertiary level of education while 344 (3.4%) household heads did not state their education level attained. The above results are presented in Table 1.

The results of the chi-square statistics in Table 1 show that the explanatory variables: geographical location, the settlement type, the source of income of a household, the annual income of a household, the sex of the household head, the highest level of education level attained by a household head, and the household size had a statistically significant (p-value < 0.001) association with the household food insecurity severity levels. Due to this, all the above explanatory variables were included to fit the proposed models.

Table 1. The cross-tabulation of the household food consumption score levels and the categorical variables.

Variables	Categories	Total N (%)	Food Secure	Mildly Food Insecure	Moderately/Severely Food Insecure	p-value*
Geographical Location	Southern part	1120 (11.1)	1000 (89.3)	85 (7.6)	35 (3.1)	<0.001
	Central part	3306 (32.8)	2777 (84)	369 (11.2)	160 (4.8)	
	Northern part	5664 (56.1)	4007 (70.7)	1000 (17.7)	657 (11.6)	
Settlement Type	Urban	4555 (45.1)	3784 (83.1)	561 (12.3)	210 (4.6)	<0.001
	Rural	5535 (54.1)	4000 (72.3)	893 (16.1)	642 (11.6)	
Source of Income of the Household	Salaries or wages	4994 (49.5)	4211 (84.3)	538 (10.8)	245 (4.9)	<0.001
	Pension/grants/drought relief	2715 (26.9)	1886 (69.5)	491 (18.1)	338 (12.4)	
	Farming	1243 (12.3)	869 (69.9)	223 (17.9)	151 (12.1)	
	Business and others	1138 (11.3)	818 (71.9)	202 (17.8)	118 (10.4)	
Sex of a Household Head	Female	4616 (45.7)	3484 (75.5)	705 (15.3)	427 (9.3)	<0.001
	Male	5474 (54.3)	4300 (78.6)	749 (13.7)	425 (7.8)	
Highest Level of Education Attained by the Household Head	Primary/No formal education	4630 (45.9)	3197 (69)	831 (17.9)	602 (13)	<0.001
	Secondary	4170 (41.3)	3395 (81.4)	545 (13.1)	230 (5.5)	
	Tertiary	946 (9.4)	899 (95)	34 (3.6)	13 (1.4)	<0.001
	Not stated	344 (3.4)	293 (85.2)	44 (12.8)	7 (2)	
Household Size	5 and below people	7259 (72.1)	5830 (80.3)	985 (13.6)	444 (6.1)	<0.001
	6 - 10 people	2412 (23.9)	1711 (70.9)	371 (15.4)	330 (13.7)	
	11 and above people	400 (4.0)	230 (57.5)	93 (23.3)	77 (19.3)	
Annual Income of a Household	≤ N$100,000	7078 (70.1)	5128 (72.4)	1204 (17)	746 (10.5)	<0.001
	N$ 100,001 to N$ 500,000	2643 (26.2)	2315 (87.6)	230 (8.7)	98 (3.7)	
	Above N$500,000	369 (3.7)	341 (22.9)	20 (2.3)	8 (2.2)	

*The p values are for the Chi-square statistics.

The household food insecurity severity level was divided into 3 levels according to the reduced coping strategies index indicators (Food Secure (FS), Mildly Food Insecure (MFI), and Moderately/Severely Food Insecure (MSFI)). The study found that 7784 (77.1%) households in Namibia were food secure, 1454 (14.4%) households were mildly food insecure, and 852 (8.4%) households were moderately/severely food insecure as presented in Figure 1.

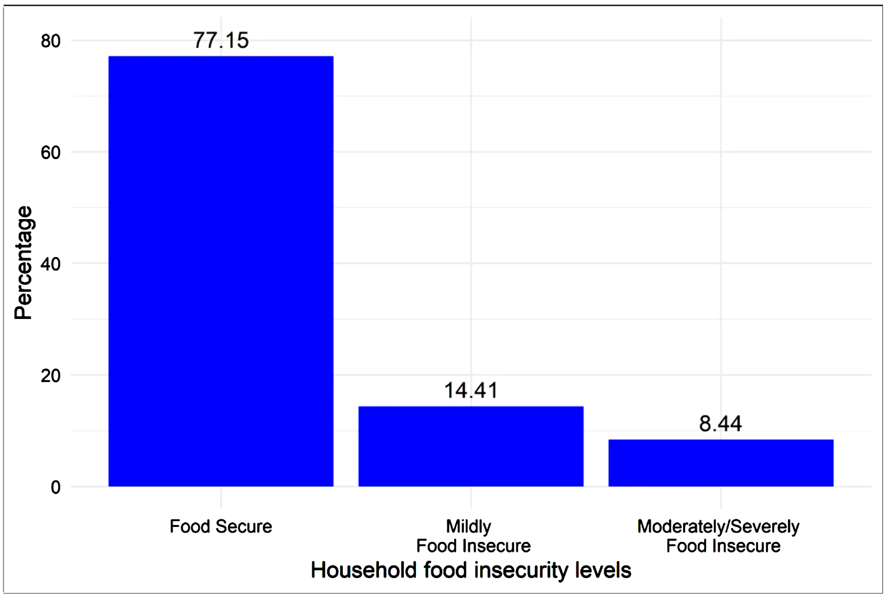

Figure 1. The level of household food insecurity in namibia.

Table 1 also provides the cross-tabulation results between the categories of the 7 categorical explanatory variables and the 3 household's food insecurity levels. Due to the distribution of the numbers of households within household food insecurity levels, for each category of the specific explanatory variable, the number of households that were food secure was large followed by the mildly food insecure, and moderately/severe food insecure respectively. For example, 3484 (75.5%) female household heads were food secure and 705 (15.3%) female household heads were mildly food insecure while only 427 (9.3%) female household heads were moderately/severely food insecure.

The map presented in Figure 2 shows the percentage distribution of the 4 household food insecurity levels across Namibia for the households that were included in the survey. The yellow colour indicates the regions with the highest percentages within each household food insecurity severity level while the dark blue indicates the regions with the lowest percentages within each household food insecurity severity level. In general, the four maps indicate that two regions in north-eastern Namibia (Kavango and Caprivi) were less food secure (Figure 2(a)), and more food insecure (Figures 2(b)-(d)) as compared to the other regions of Namibia. Moreover, the regions in the southern part of Namibia were more food secure, particularly (Hardap & Karas regions).

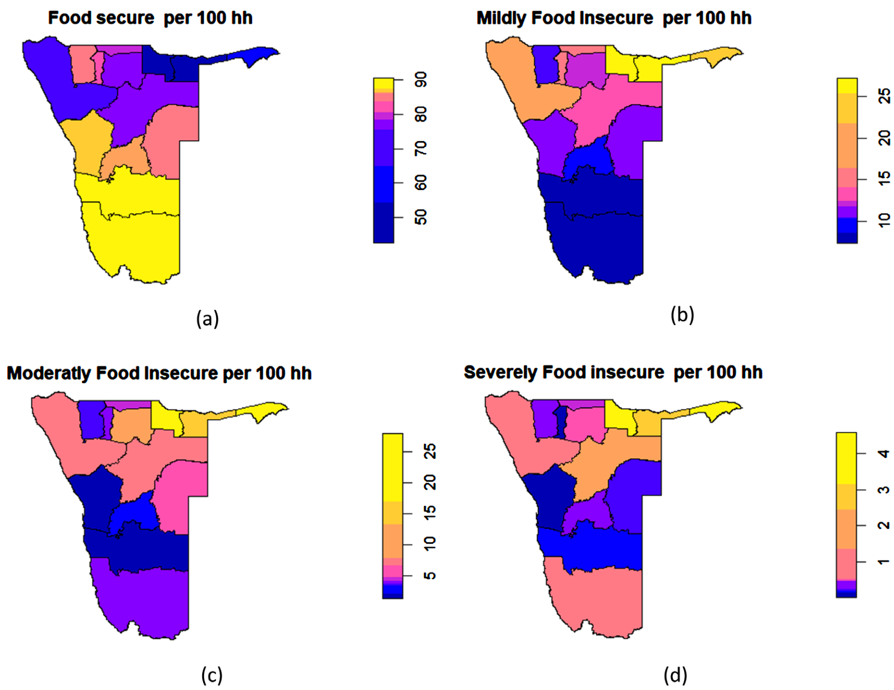

Figure 2. Distribution of household food insecurity by regions.

3.2. Results of the Models Fitted

3.2.1. The Proportional Odds Model (POM)

The proportional odds model was fitted to the data and the covariate's geographical location, the source of income of a household, the annual income of the household, the sex of the household head, the highest education level attained by a household, and the household size was statistically significant at 5% level of significance (see Table B1 in Appendix B). However, the gender of the household head and the settlement type had no significant effect on household food insecurity levels. In order to continue with the results of the proportional odds model, the proportional odds model must meet the assumption of parallelisms. The Brant test for the proportional odds assumption was conducted using a "brant" package in R. The Brant test indicates whether the proportional odds model assumption for all covariates or individual covariates was violated or not. The results of Brant test results are presented in Table 2.

Table 2. The brant test for proportional odds assumption.

Variables	Chi-sq Values	df	p values
Omnibus (Overall Model)	64.54	15	< 0.001
Central Parts	0.00	1	0.98
Northern Parts	0.10	1	0.75
Rural	16.96	1	< 0.001
Pension/Grants/Drought Reliefs	0.07	1	0.79

Continued

Farming	0.88	1	0.35
Business and Others	0.00	1	0.96
Secondary	4.39	1	0.04
Tertiary	0.00	1	0.98
Not Stated	5.82	1	0.02
6 - 10 People	25.6	1	<0.001
11 and above People	1.86	1	0.17
Age	0.67	1	0.41
Male	0.12	1	0.73
N$ 100,001 to N$ 500,000	0.91	1	0.34
N$ 500001 and above	0.02	1	0.88

The results in Table 2 show that the overall test of the proportional odds assumption was highly significant at a 5% level of significance (p-value < 0.001) and, therefore, the parallel line assumption does not hold. Furthermore, the covariates (rural, secondary, not stated, and household size (6 - 10 people)) violated the assumption of proportionality. Since the assumption of parallelism of the proportional odds model is violated, the proportional odds model is not valid. Thus, the partial proportional odds model was fitted and the result of this model was presented in the next subsection.

3.2.2. Partial Proportional Odds Model

The partial proportional odds model was fitted because the parallel lines assumption of the proportional odds model was violated. In order to support the choice of the partial proportional odds model, Akaike's Information Criterion (AIC) of the proportional odds model and partial proportional odds model was computed. The AIC for proportional odds and partial proportional odds models were 12861.18 and 12799.7, respectively. Since the partial proportional odds model had the smallest AIC value, this model was a better model and the results of the partial proportional odds model were utilized for this study.

The results of the fitted partial proportional odds model were presented in Table 3 with two panels that contrast the three-household food insecurity severity levels. The first panel contrasted Food Security (FS) versus Mildly Food Insecure (MFI) and Moderately/Severely Food Insecure (MSFI) while the second panel contrasted FS & MFI versus MSFI.

From the first panel in Table 3, the effect of a specific covariate on FS VS MFI & MSFI and FS & MFI VS MSFI were the same for the covariates that did not appear in panel 2. For the specific covariates that appear in both panels, their effects vary according to FS VS MIFI & MSFS and FS & MIFI VS MSFS. Additionally, for a given category of categorical factor, the negative signs of the coefficients/logs odds indicated that the chance of a household being in the higher categories of a household food insecurity level is lower as compared to the reference category.

Table 3. The fitted partial proportional odds model results.

Variables	Coefficients:	Std.Error	z value	Pr(>|z|)	Odds ratios	95% CI	
						Lower	Upper
FS VS MFI & MSFI							
(Intercept): 1	1.2514	0.1397	8.961				
Central Parts	−0.4760	0.1099	−4.332	<0.001	0.621	0.501	0.771
Northern Parts	−0.8974	0.1063	−8.446	<0.001	0.408	0.331	0.502
Rural: 1	0.0100	0.0626	0.16	0.873	1.010	0.894	1.142
Pension/Grants/Drought Reliefs	−0.4724	0.0703	−6.719	<0.001	0.624	0.543	0.716
Farming	−0.2722	0.0845	−3.222	<0.001	0.762	0.645	0.899
Business and Others	−0.5241	0.0804	−6.522	<0.001	0.592	0.506	0.693
Secondary	0.5169	0.0598	8.641	<0.001	1.677	1.491	1.885
Tertiary	1.5159	0.1628	9.312	<0.001	4.554	3.310	6.265
Not Stated	0.9019	0.1653	5.456	<0.001	2.464	1.782	3.407
6 - 10 People: 1	−0.3926	0.0587	−6.693	<0.001	0.675	0.602	0.758
11 and above People: 1	−1.0295	0.1136	−9.067	<0.001	0.357	0.286	0.446
Age	0.0126	0.0017	7.228	<0.001	1.013	1.009	1.016
Male	−0.0254	0.0510	−0.498	0.61824	0.975	0.882	1.077
N$ 100,001 to N$ 500,000	0.6892	0.0706	9.765	<0.001	1.992	1.735	2.288
N$ 500,001 and above	0.8253	0.2107	3.917	<0.001	2.283	1.510	3.450
FS & MFI VS MSFI							
(Intercept): 2	2.7859	0.1565	17.796	<0.001			
Rural: 2	−0.3135	0.0919	−3.41	<0.001	0.731	0.610	0.875
Secondary: 2	0.6857	0.0883	7.769	<0.001	1.985	1.670	2.360
Tertiary: 2	1.5287	0.2851	5.363	<0.001	4.612	2.638	8.064
Not Stated: 2	1.7998	0.3899	4.616	<0.001	6.048	2.817	12.987
6 - 10 People: 2	−0.7305	0.0802	−9.11	<0.001	0.482	0.412	0.564
11 and above People: 2	−1.1733	0.1410	−8.324	<0.001	0.309	0.235	0.408

The results from the partial proportion model in **Table 3** showed that the age of a household head was statistically significant at a 5% level of significance ($p < 0.001$). The estimated odds ratio (OR = 1.013; 95% CI: 1.009 - 1.016) showed that for every one-year increase in the age of a household head, the chance of the households being food secure increases by 1.3% holding all other covariates constant.

The results also revealed that the source of income of a household was significantly associated with household food insecurity levels. The estimated odds ratio (OR = 0.624; 95% CI: 0.543 - 0.716) suggested that the odds of a household that depended on pension, social grants, or drought reliefs being in higher categories of household food insecurity levels lower by 37.6% as compared to a household that depended on salaries or wages. Besides that, the chance of the households that were depending on subsistence farming and commercial farming to be in higher household food insecurity levels was lower by 24% as compared to the reference category. In addition, a household that depended on business as a source of income was 40.8% less likely to be higher household food insecurity levels as compared to a household that depended on salaries or wages.

The results of the study also showed that the annual income of the household was another significant factor that influences the household food insecurity levels. The odds ratio (OR = 1.992; 95% CI: 1.735 - 2.288) indicated that a household that earned an annual income of between N$ 100,001 to N$ 500,000 was approximately 2 times more likely to be in higher food insecurity status as compared to a household that earned an annual income of N$ 100,000 or below. In addition to that, the odds of a household that earned at least an annual income of N$500,001 was 2.28 times more likely to be in higher food insecurity levels as compared to a household that earned an annual income of N$ 100,000 or below.

Furthermore, the type of settlement was a significant factor associated to the household food insecurity levels. The odds ratio (OR = 0.731; 95% CI: 0.610 - 0.875) in panel 2, suggested that the households in rural areas were 26.9% less likely to be mildly food insecure or food secure as compared to households in urban areas. Apart from that, the geographical location of a household was also another significant factor associated with household food insecurity levels. The estimated odds ratio (OR = 0.621; 95% CI: 0.501 - 0.771) showed that a household located in the central parts of Namibia was 37% less likely to be in higher food insecurity levels as compared to a household located in the southern parts of Namibia. For a household that was located in the northern parts of Namibia was 59.2 % less likely to be in higher food insecurity levels than a household located in the southern parts of Namibia.

The education level attained by a household head was another significant factor associated to household food insecurity levels. The odds ratio (1.677; 95% CI: 1.491 - 1.885) suggested that the odds of a household being food secure was 67.7% higher for a household head with a secondary level of education than a household head who had no education or had a primary level of education. In addition to that, the odds ratio (1.985; 95% CI: 1.67 - 2.36) in panel 2 showed that the odds of a household to be mildly food insecure or food secure was 98.5% higher for a household head with a secondary level of education than a household head who had no education or had primary level of education. Moreover, for a household head that did not state his/her education level, the odds of a household were 2.46 times more likely to be food secure and 6.04 times more likely to be mildly food insecure or food secure. Furthermore, for a household head with a tertiary level of education, the odds of the household were 4.6 times more likely to be in lower food insecurity levels as compared to a household head who had no education or had a primary level of education.

Finally, the results of the study showed that the household size was significantly associated to the household food insecurity levels. The estimated odds ratio (0.675; 95%: CI: 0.602 - 0.758) indicated that the household with 6 - 10 members was 32.5% less likely to be food secure as compared to a household with less than 6 members but the odds of that household was 51.8 % less likely to be mildly food insecure or food secure than a household with less than 6 members. Furthermore, the odds of a household with more than 10 members were 71.4% less likely to be food secure but the odds of that household were 69% less likely to be mildly food insecure or food secure.

3.2.3. The Predicted Probability

Figure 3 shows the predicted probability of a household falling into individual categories: 1) food security, 2) mildly food insecure, and 3) moderately/severely food insecure respectively. This is when the age of a household head increases and the categorical explanatory variables are set to their respective reference categories. The estimated probability of a household being food secure was above 75% and increasing. In contrast, the predicted probability of a household being mildly food insecure was below 25% and decreases as the household head gets older.

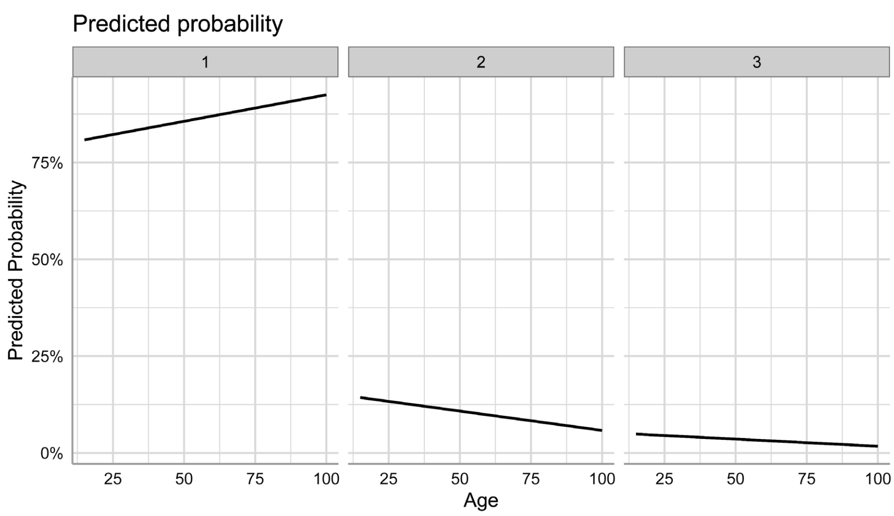

Figure 3. The predicted probability.

Figure 4 displays the estimated cumulative probability of a household being in the category mildly food insecure or moderately/severely food insecure (P[Y> = 2]) and category severely food insecure (P[Y> = 3]) respectively. This is when the age of a household head increases while the independent factors are set to their respective reference categories. The cumulative predicted probability of a household being mildly food insecure or moderately/severely food insecure was less than 20% and declining. In contrast, the cumulative estimated probability of a household being moderately/severely food insecure was less than 7.5% and also decreased as the age of a household increased.

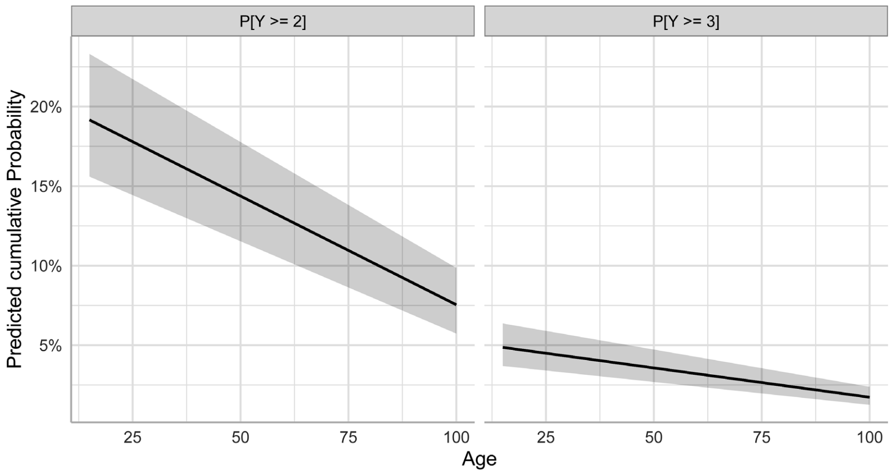

Figure 4. The cumulative predicted probability.

3.2.4. The Model Goodness of Fit

In order to evaluate the model goodness of fit of the partial proportional odds model fitted, McFadden's Pseudo R^2 and the likelihood ratio test were carried out. For the fitted model to be considered a better fit McFadden's Pseudo R^2 value should be between 0.2 and 0.4.

Table 4. The likelihood ratio test and the McFadden Pseu*do* R^2.

df	Log Likelihood	Chi sq	p-value	McFadden
21	−549.99	1100	<0.001	0.0794

The estimated McFadden Pseudo R^2 value presented in Table 4 was only 0.0794. However, for the log-likelihood ratio test, since the p-value < 0.001, it indicated that the covariates in the partial proportion model were significant, and hence the overall partial proportional odds model was statistically significant.

3.3. Discussions

The main purpose of this study was to use an ordinal logistic regression model to identify the socio-economic and demographic factors that affect the household food insecurity level in Namibia. The partial proportional odds model was more adequate for this study as the proportional odds model significantly violated the assumption of a parallel line. In addition, three independent variables—type of settlement, household size, and education attained by a household head—did not meet the proportional odds assumption. Moreover, the AIC and the likelihood-ratio test of the partial proportional model outperformed the proportional odds model and therefore the partial proportional model was selected as the best model in this study.

Based on the fitted partial proportional model results, the study revealed that the age of the household head, the household size, the source of income of a household, the annual income of the household, and the education level attained by a household head were found to be statistically significant socio-economic and demographic factors associated with the severity of household food insecurity levels in Namibia.

Previous research by Amrullah *et al.* [23] found that the age of the household head significantly influences food insecurity levels, which aligns with the findings of this study. The study showed that an increase in the age of a household head improves household food security levels. Notably, the household head sex was not a significant contributor to household food insecurity. However, this finding is not in line with the result reported by Mbongo [6] that demonstrated the association between household food insecurity and the gender of the household head. This could be because the population considered by Mbongo [6] was only a specific part of Namibia which was very small in contrast to the study area considered in this study.

The education level attained by a household head was also a major factor linked with household food insecurity levels. The study found that secondary and tertiary levels of education among household heads assist households in being food secure or mildly food insecure. Similar findings reported by Maharjan & Joshi [24] and Maziya *et al.* [25] found that an improvement in the education level of a household head improves the household food security status. Typically, household heads with higher qualifications have a greater opportunity to get the higher paying jobs and developed financial security—a critical factor in reducing food insecurity [26].

Moreover, the size of a household was found to be a key factor associated with household food insecurity levels. The study found that a household with 6 to 10 people or 11 and above people tends to be more food insecure as compared to a household with fewer than 6 members. Previous studies by Amrullah *et al.* [23] and Maharjan & Joshi [24] reported that the larger the household size, the more likely the household was to be food insecure, which aligns with the findings of this study. This high level of food insecurity could among a household with large family size could be due to the increased food demand and higher dependency ratios in such households [27].

Regarding the source of income of the household, households that depended on other sources of income rather than salaries or wages tend to be more food insecure as compared to the household that depends on salary or wages. This could be due to income instability which could become a barrier for a household to consistently afford food. The present study also found that household with annual computed income of N$ 100,000 or less tends to be more food insecure than those with annual computed income of above N$100,000. This could be because lower income lead to lower household food consumption, which could results with higher level of household food insecurity [28]. Similar results were reported by Nyangasa *et al*. [29] who found a significant association between low monthly income and poor food consumption scores and higher levels of food insecurity among households in Zanzibar.

Concerning the type of settlement, the study found that households in rural areas tend to be more food insecure as compared to households in urban areas. This is often because of inequality of income between the household in rural and urban areas [25]. Similar result by Shedenova & Beimisheva [30] pointed out that rural households often face lower income levels and limited access to essential services compared to their urban counterparts, and hence reason for higher food insecurity. Furthermore, the current study result indicates that households in the northern and central parts of Namibia tends to be more food insecure compared to the household in the southern part of Namibia. This could be especially because households in the northern part of Namibia were mostly in rural areas and those households that were in urban areas, most of them were situated in an informal settlement with limited infrastructures that could contribute to food insecurity.

3.4. Conclusions and Recommendations

3.4.1. Conclusions

This study used the 2015/16 Namibia Household Income and Expenditure Survey (NHIES) data to identify socio-economic and demographic factors that are significantly associated with household food Insecurity in Namibia. The proportional odds model was fitted, and the assumption of proportional odds was violated. As a result, the partial proportional odds model was fitted. The performance of the two models was compared using AIC and the partial proportional odds model outperformed the proportional odds model. The key factors found to be associated with household food insecurity in Namibia were the age of the household head, the household size, the source of income of a household, the annual income of the household, the education level attained by a household head, and the geographical location of a household.

3.4.2. Recommendations

Based on the results and findings of this study, to ensure household food security, the following set of recommendations to the policy makers and future researchers in this area could be considered to reduce household food insecurity. Firstly, since larger household sizes were more likely to be food insecure, the promotion of family planning programs that could make people aware of modern contraceptives, especially in remote areas could help in reducing the impact of large family sizes. Secondly, to improve food security in remote areas, the government should increase local food production especially by supporting and assisting smallholder farmers with agricultural machinery, training skills, and access to the markets. Thirdly, for future work, researchers should also consider using other indicators of household food insecurity levels classifications other than coping strategies of food insecurity such as food consumption score which is based on food frequency, dietary diversity, and nutritional significance of different food categories. Furthermore, the data set used in this study might be outdated since the survey was conducted in 2015/16. Taking into consideration the fact that the Namibia economy has changed over time and the effects of the COVID-19 pandemic, the food insecurity situation within the country might have changed and hence new research using the current situation of the country is recommended to deepen and improve the result of the current study. Lastly, as can be observed from the descriptive results of the study, there could be some spatial autocorrelation between regions and further study by employing the spatial models is recommended.

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Author Contributions

DBG conceptualized and designed the study. DBG and LOME contributed equally to drafting of the manuscript. DBG edited the manuscript. Both authors read and approved the final version.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

References

[1] Santos, M.P., Brewer, J.D., Lopez, M.A., Paz-Soldan, V.A. and Chaparro, M.P. (2022) Determinants of Food Insecurity among Households with Children in Villa El Salvador, Lima, Peru: The Role of Gender and Employment, a Cross-Sectional Study. *BMC Public Health*, **22**, Article No. 717. https://doi.org/10.1186/s12889-022-12889-4

[2] Gundersen, C. and Ziliak, J.P. (2015) Food Insecurity and Health Outcomes. *Health Affairs*, **34**, 1830-1839. https://doi.org/10.1377/hlthaff.2015.0645

[3] Coleman-Jensen, A., Gregory, C. and Singh, A. (2014) Household Food Security in the United States in 2013. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2504067

[4] Namibia Statistics Agency (2024) 2023 Population and Housing Census Main Re-

port. Namibia Statistics Agency.

[5] Integrated Food Security Phase Classification [IPC] (2020) Global Report on Food Crises 2020. IPC Global Partners. https://www.ipcinfo.org

[6] Mbongo, L.T. (2017) Food Insecurity and Quality of Life in Informal Settlements of Katutura, Windhoek, Namibia. https://repository.unam.edu.na/handle/11070/2326

[7] FAO (2021) FAO Publications Catalogue 2021. https://doi.org/10.4060/CB4402EN

[8] Agresti, A. (2012) 16.1 Delta Method. Categorical Data Analysis, 587-591. https://www.wiley.com/en-us/Categorical+Data+Analysis%2C+3rd+Edition-p-9780470463635

[9] Lelisho, M.E., Wogi, A.A. and Tareke, S.A. (2022) Ordinal Logistic Regression Analysis in Determining Factors Associated with Socioeconomic Status of Household in Tepi Town, Southwest Ethiopia. *The Scientific World Journal*, **2022**, Article ID: 2415692. https://doi.org/10.1155/2022/2415692

[10] Das, S. and Rahman, R.M. (2011) Application of Ordinal Logistic Regression Analysis in Determining Risk Factors of Child Malnutrition in Bangladesh. *Nutrition Journal*, **10**, Article No. 124. https://doi.org/10.1186/1475-2891-10-124

[11] Tuholske, C., Andam, K., Blekking, J., Evans, T. and Caylor, K. (2020) Comparing Measures of Urban Food Security in Accra, Ghana. *Food Security*, **12**, 417-431. https://doi.org/10.1007/s12571-020-01011-4

[12] Vulnerability Analysis and Mapping Unit (2008) FSC Indicators Handbook. https://fscluster.org/handbook/Section_two_rcsi.html

[13] Maxwell, D., Vaitla, B. and Coates, J. (2014) How Do Indicators of Household Food Insecurity Measure up? An Empirical Comparison from Ethiopia. *Food Policy*, **47**, 107-116. https://doi.org/10.1016/j.foodpol.2014.04.003

[14] Abreu, M.N.S., Siqueira, A.L., Cardoso, C.S. and Caiaffa, W.T. (2008) Ordinal Logistic Regression Models: Application in Quality of Life Studies. *Cadernos de Saúde Pública*, **24**, s581-s591. https://doi.org/10.1590/s0102-311x2008001600010

[15] Zuhdi, S., Sari Saputro, D.R. and Widyaningsih, P. (2017) Parameters Estimation of Geographically Weighted Ordinal Logistic Regression (GWOLR) Model. *Journal of Physics*: *Conference Series*, **855**, Article ID: 012064. https://doi.org/10.1088/1742-6596/855/1/012064

[16] Peterson, B. and Harrell, F.E. (1990) Partial Proportional Odds Models for Ordinal Response Variables. *Applied Statistics*, **39**, Article No. 205. https://doi.org/10.2307/2347760

[17] Sasidharan, L. and Menéndez, M. (2014) Partial Proportional Odds Model—An Alternate Choice for Analyzing Pedestrian Crash Injury Severities. *Accident Analysis & Prevention*, **72**, 330-340. https://doi.org/10.1016/j.aap.2014.07.025

[18] McNulty, K. (2021) Handbook of Regression Modeling in People Analytics. Chapman and Hall/CRC, 256. https://doi.org/10.1201/9781003194156

[19] Williams, R. (2006) Generalized Ordered Logit/Partial Proportional Odds Models for Ordinal Dependent Variables. *The Stata Journal*: *Promoting Communications on Statistics and Stata*, **6**, 58-82. https://doi.org/10.1177/1536867x0600600104

[20] Angiro, B. (2015) Multinomial Logit Modeling of Factors Associated with Multiple Sexual Partners from the Kenya Aids Indicator Survey 2007. *American Journal of Theoretical and Applied Statistics*, **4**, Article No. 170. https://doi.org/10.11648/j.ajtas.20150403.23

[21] Andriani, P. and Chamidah, N. (2019) Modelling of Hypertension Risk Factors Using

Logistic Regression to Prevent Hypertension in Indonesia. *Journal of Physics: Conference Series*, **1306**, Article ID: 012027. https://doi.org/10.1088/1742-6596/1306/1/012027

[22] Mittlböck, M. and Heinzl, H. (2001) A Note on R2 Measures for Poisson and Logistic Regression Models When Both Models Are Applicable. *Journal of Clinical Epidemiology*, **54**, 99-103. https://doi.org/10.1016/s0895-4356(00)00292-4

[23] Amrullah, E.R., Ishida, A., Pullaila, A. and Rusyiana, A. (2019) Who Suffers from Food Insecurity in Indonesia? *International Journal of Social Economics*, **46**, 1186-1197. https://doi.org/10.1108/ijse-03-2019-0196

[24] Maharjan, K.L. and Joshi, N.P. (2011) Determinants of Household Food Security in Nepal: A Binary Logistic Regression Analysis. *Journal of Mountain Science*, **8**, 403-413. https://doi.org/10.1007/s11629-011-2001-2

[25] Maziya, M., Mudhara, M. and Chitja, J. (2017) What Factors Determine Household Food Security among Smallholder Farmers? Insights from Msinga, Kwazulu-Natal, South Africa. *Agrekon*, **56**, 40-52. https://doi.org/10.1080/03031853.2017.1283240

[26] Mutisya, M., Ngware, M.W., Kabiru, C.W. and Kandala, N. (2016) The Effect of Education on Household Food Security in Two Informal Urban Settlements in Kenya: A Longitudinal Analysis. *Food Security*, **8**, 743-756. https://doi.org/10.1007/s12571-016-0589-3

[27] Nkoko, N., Cronje, N. and Swanepoel, J.W. (2024) Factors Associated with Food Security among Small-Holder Farming Households in Lesotho. *Agriculture & Food Security*, **13**, 1-10. https://doi.org/10.1186/s40066-023-00454-0

[28] Rahman, A. and Mishra, S. (2019) Does Non-Farm Income Affect Food Security? Evidence from India. *The Journal of Development Studies*, **56**, 1190-1209. https://doi.org/10.1080/00220388.2019.1640871

[29] Nyangasa, M.A., Buck, C., Kelm, S., Sheikh, M. and Hebestreit, A. (2019) Exploring Food Access and Sociodemographic Correlates of Food Consumption and Food Insecurity in Zanzibari Households. *International Journal of Environmental Research and Public Health*, **16**, Article No. 1557. https://doi.org/10.3390/ijerph16091557

[30] Shedenova, N. and Beimisheva, A. (2013) Social and Economic Status of Urban and Rural Households in Kazakhstan. *Procedia—Social and Behavioral Sciences*, **82**, 585-591. https://doi.org/10.1016/j.sbspro.2013.06.314

Abbreviations

AIC	Akaike's Information Criterion (AIC)
CI	Confidence Interval
CSI	Coping Strategies Index
FS	Food Security
HFIAS	Household Food Insecurity Access Scale
MFI	Mildly Food Insecure
MSFI	Moderately/Severely Food Insecure
NHIES:	Namibia Household Income and Expenditure Survey
NSA	Namibia Statistics Agency
OR	Odds Ratio
POM	Proportional Odds Model
PPOM	Partial Proportional Odds Model
RCSI	Reduced Coping Strategies Index

Appendix A

Table A1. The reduced coping strategies index (RCSI) indicators questions.

Questions	Frequency (0 - 7 Number of Days per Week)	Severity Weight	Weighted Score Frequency * Wight
Q1 Rely on less preferred and less expensive foods?		1	
Q2 Borrow food or rely on help from others?		2	
Q3 Limit portion size at meal time?		1	
Q4 Restrict consumption by adults for small children to eat?		3	
Q5 Reduce the number of meals eaten in a day?		1	
Total Household Score			

Appendix B

Table B1. The proportional odds model result.

Variables	Coefficients	Std.Error	z value	Pr(>|z|)
(Intercept): 1	1.2615	0.1395	9.0420	
(Intercept): 2	2.5105	0.1421	17.6730	<0.001
Central Parts	−0.4774	0.1102	−4.3330	<0.001
Northern Parts	−0.8981	0.1065	−8.4340	<0.001
Rural: 1	−0.0287	0.0620	−0.4620	0.8730
Pension/Grants/Drought Reliefs	−0.4710	0.0703	−6.7010	<0.001
Farming	−0.2685	0.0842	−3.1880	<0.001
Business and Others	−0.5210	0.0805	−6.4750	<0.001
Secondary	0.5379	0.0592	9.0900	<0.001
Tertiary	1.5230	0.1625	9.3700	<0.001
Not Stated	0.9549	0.1665	5.7350	<0.001
6 - 10 People:1	−0.4493	0.0574	−7.8270	<0.001
11 and above People :1	−1.0482	0.1087	−9.6460	<0.001
Age	0.0129	0.0017	7.4140	<0.001
Male	−0.0251	0.0509	−0.4930	0.6182
N$ 100,001 to N$ 500,000	0.6851	0.0705	9.7190	<0.001
N$ 500,001 and above	0.8149	0.2106	3.8700	<0.001