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Determinants of multidimensional poverty in Tanzanian households

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Abstract
Despite the international development community's longstanding emphasis on poverty reduction, Tanzania continues to face persistent multidimensional poverty, hindering socioeconomic development and nutritional quality. This study analyzed determinants of multidimensional poverty using the 2017-2018 Tanzania household budget survey dataset (8767 households). The principal component analysis (PCA) was deployed to obtain the outcome indicator by combining those dimensions that contribute the most to multidimensional poverty to capture more information. FGLS method, as an extension of the OLS method, was used to solve the problem of heteroscedasticity by including the predicted weights. The study found that age of the household head, marital status of the household head, location, years of schooling of the headship, household size, income, and employment status were significantly related to multidimensional poverty index. Urban location, official employment status, not married status were better in reducing poverty situation than rural location, not employed status and married status, respectively. In addition, higher household income, years of schooling, age of headship as well as smaller household size, were found to be absolutely improving the household well-being. The findings suggest enhancements in agricultural technology, education, and access to loans for small farmers and small entrepreneurs tackle household poverty effectively.

Keywords: Feasible generalized least square (FGLS), heteroscedasticity, multicollinearity, ordinary least square estimator (OLS) and Tanzania

1. Introduction

[1] Addressing poverty remains a long-standing priority in global development efforts across both developed and developing countries [1, 2]. According to the World Bank's reports, extreme poverty affects 1.2 billion people worldwide, with approximately 700 million living below the extreme poverty line. This represents 10 percent of the global population, a significant decrease from the 36 percent reported in 1990. Notably, 50 percent of those living in extreme poverty are under 18 years old [3].

Attaining sustainable economic growth with a particular emphasis on eliminating extreme poverty and hunger has become the primary development objectives for governments around the world, as reflected in the Sustainable Development Goals and Millennium Development Goals (SDGs) established in 2000. These initiatives aimed to reduce poverty in all its forms across the world [4]. Over the last two decades, from 1999–2009 and 2009–2019, there has been a significant drop in the number of people living below the poverty line. Unfortunately, the COVID-19 pandemic disrupted this positive trend. More than 50 million people are falling into extreme poverty [5]. The World Bank predicts that by the end of 2025, an estimated 71 million individuals will be subjected to extreme poverty.

The COVID-19 pandemic has a substantial influence on the world economy, particularly in underdeveloped countries. In Tanzania, vulnerable people experienced employment losses. Small enterprises experienced lower productivity and capital constraints, resulting in lower

[1] TZS/TShs is Tanzania local currency, equivalent to 0.00038 USD / 0.0028 China Yuan as of 6th June, 2024.

income. These problems underscore the need to rethink and improve poverty reduction policies in developing countries, with an emphasis on assisting vulnerable populations such as women, low-skilled workers, and informal sector workers to promote inclusive economic recovery [1].

Tanzania has made tremendous progress towards poverty reduction since gaining independence in 1961. The poverty index fell from 34.4% in 2007 to 26.4% in 2019 [6]. However, the World Bank expressed concern in 2022 that population growth would outpace poverty reduction initiatives, resulting in an increase in the number of needy people. In 2019, around 14 million individuals lived below the national poverty line, while approximately 26 million (49% of the total population) lived below the international poverty threshold of $1.90 per day. Many non-poor individuals who live just over the poverty line are also at risk of falling into poverty [7].

Existing analytical studies examining the determinants, trends, and reduction of poverty in Tanzania often fall short of comprehensively investigating the problem, as they frequently focus on specific locations [1]. Conducted research on the determinants of rural household poverty in Tanzania a case of Morogoro Region, and their study provided a comprehensive understanding of socioeconomic determinants of poverty. However, they acknowledged that their findings might vary based on location. Moreover, among those studies [2], analyzed the determinates of household poverty and solely used consumption expenditures per adult equivalent as an indicator. The expenditures do not fully capture the entire information about poverty.

This study aims to add to the discussion by examining socio-economic and demographic characteristics as determinants of household poverty in Tanzania. The study uses a nationally representative dataset from the National Household Budget Survey (HBS dataset 2021–2022) and applies a feasible generalized least squares approach for model prediction because the cross-section data has the problem of heteroscedasticity [8]. Additionally, this study deploys a multidimensional poverty index as an outcome indicator to fully capture more information about household poverty.

2. Materials and Methods

2.1 Data Type and Source

The Tanzania National Bureau of Statistics, in collaboration with the Ministry of Finance and Planning, conducted the 2017-2018 Household Budget Survey (HBS). The World Bank, UNICEF, and UN Women provided funding for Tanzania's government and its partners. The survey covered the entire United Republic of Tanzania and employed a two-stage cluster sample design, resulting in a 99 percent response rate from 8767 households. The dataset includes information from agriculture, households, livestock, and communities. However, this analysis solely focuses on the household cross-sectional dataset to capture economic, social, and demographic characteristics and outcomes simultaneously.

2.2 Variables Definitions and Measurements

Table 1: Description of variables

Variables	Description
Dependent variable Multidimensional Poverty Index	This is a continuous variable, calculated by using Principal component Analysis. Only the first principal component was extracted.
Independent variables	
Age of the household head	This is a continuous variable (years)
Size of household	This is a continuous variable (number of household members)
Household head's education level	This is a continuous variable, years of schooling
Sex of the household head	This is a categorical variable, 1 for male and 0 female
Monthly household expenditures	This is a continuous variable, the variable proxy household income.
Credit service	A categorical variable, 1 for access, 0 otherwise
Location (Rural/Urban)	This is a categorical variable (0) rural and (1) urban
Marital status of the household head	This is a categorical variable, 1 for married/living together, 0 for not married
Employment status of the head	This is a categorical variable, (1) employed and (0) otherwise

***Source*:** Author's construction

2.2.1 Construction of Multidimensional Poverty Index (MPI): The Multidimensional Poverty Index (MPI) [2] provides a comprehensive method for assessing poverty by taking into account several factors that affect households' well-being rather than relying on a one-dimensional measure of poverty based on income. Currently, there is no universally accepted criterion for determining the dimensions of the Multidimensional Poverty Index. However, in several studies, the dimensions of education, health, and living standards have been commonly used [16, 17]. This study develops an MPI (Multidimensional Poverty Index) using ten indicators Table 2.

Key indicators include per capita income, which represents a household's economic prosperity, and mean years of schooling, which measures education and knowledge. Vaccination acts as a reliable measure of an individual's health status. Indicators of living standards encompass access to power and gas, the availability of clean drinking water, the kind of housing, the presence of toilets, and the number of rooms per family member. The Multidimensional Poverty Index (MPI) gives a full picture of how poor and well-off households are by combining these different measures. Principal component analysis, which gives more weight to higher levels of variation, is used to make the index.

[2] Household Budget Survey 2017-18 - Tanzania Mainland: Final Report

Table 2: Multidimensional Poverty Index (MPI)

No.	Indicators for Multidimensional Poverty Index	Units
1	Children vaccinations (ever be vaccinated or not)	Dummy Variable
2	Facility of toilet	Dummy Variable
3	Facility of gas	Dummy Variable
4	Facility of electricity	Dummy Variable
5	Number of rooms per family size	Continuous
6	Availability of clean water to drink	Dummy Variable
7	Nature of house wall (brinks or mud)	Dummy Variable
8	Ownership of residence (own house or not)	Dummy Variable
9	Family total years of schooling (in average)	Continuous (years)

Source: Author's construction

2.2.2 Principal Component Analysis (PCA)

PCA [3], is a multivariate statistical approach used to reduce the several correlated variables to the few uncorrelated variables (dimensional reduction) without losing too much information in the process [18]. The PCA technique accomplishes this by establishing a smaller set of variables that explains most of variation in the original variables. The new variables generated are linear combinations of the original variables. The first new variables will explain as much of the variation in the original data as possible [18].

Suppose: $X = [x_1, x_2, \dots x_n]$ is a matrix of n variables and m observations. Prior to using Principal component Analysis, it is usual to first Centre the numerical variables are $\boldsymbol{x}^*$ with elements: $x_{ij}^* = x_{ij} - \bar{x}_j$ where; $\bar{x}_j$ is mean of the variable j. Hence; the new matrix of: $\boldsymbol{x}^* = [x^*{}_1, x^*{}_2, \dots x^*{}_n]$ is constructed with deviation round the mean. Since Principal Component Analysis is primarily account for the variance of the numerical variables, the crucial intention here is to find a linear combination of column vectors of X that maximizes variance. It has turned at that such linear combinations are:

$$\sum_{j=1}^{n} b_j x_j^* = X^* a$$

Where: $b = [b_1, b_2, \dots b_n]^T$ is the normalized eigenvector corresponding to eigenvalue λ of the covariance matrix?

$$M = \frac{1}{t-1} X^{*T} X^*$$

Since M is a symmetrical matrix of order nxn, it has exactly n real eigen values λ_k, $(k = 1,2 \dots n)$ and the corresponding eigen vectors can be applied to generate an orthogonal set vector such as: $b_j^T b_{j'} = 1$ if $j \neq j'$ and zero otherwise.

Accordingly, these n eigen-vectors of M produce n new vectors:

$$y_k = X^* a_k = \sum_{j=1}^{n} a_{ij} X_j^*$$

That maximize variance. These vectors $y_j, (j = 1,2.., n)$ are known as the principal component Analysis (PCs) of the dataset X, with y_1 having the most variance, y_2 the second most, and so on down to y_n having the least. Also, the new coordinate system is represented by the matrix:

$Y = [y_1, y_2 \dots y_n]$. Thus, there is a matrix $Y^* = [y_1, y_2, \dots y_p]$ of the first p eigenvectors that correspond to the p largest eigenvalues of the matrix S that can be to move n-dimensional data of X to p-dimensional space.

2.3 Linear Regression Model

The study initially used the Ordinary Least Squares Method (OLS) [4] to estimate the linear regression model of determinants of multidimensional poverty among households in Tanzania. The method was used as the dependent variable was a continuous variable [19]. The linear regression model states as:

$$Y_i = X_i \beta + u_i \;\; N(0, \sigma_\varepsilon^2)$$

Where; Y_i, is the multidimensional poverty index at a point of time, X_i is a vector of covariates, β is a vector of parameters of the model, u_i is the error term. The model assumes that the mean and variance of the error are zero and constant, respectively. When assumptions are violated, the estimates tend to be biassed, inconsistent, and inefficient. Therefore, the feasible generalised least square estimator will be applied instead of the OLS estimator to resolve the problem of heteroscedasticity.

2.4 Diagnostic tests for linear regression model

2.4.1 Multicollinearity test and remedial measure

Multicollinearity arises when there is a substantial statistical relationship between independent variables [19]. While multicollinearity does not hinder the Ordinary Least Squares (OLS) estimations, it does lead to imprecise/inaccurate estimates due to the large variances of the calculated coefficients.

The study utilized variance inflation factors (VIF) to evaluate the presence of multicollinearity. If the variance inflation factor (VIF) exceeds ten (10), it signifies a strong correlation among the predictors. In such cases, eliminating a collinear variable with a high correlation coefficient can rectify the issue:

$$VIF(\widehat{\beta_\iota}) = \frac{1}{1-R_i{}^2}$$

Whereas; VIF $(\widehat{\beta_\iota})$ = Variance Inflation Factors for Coefficients, R_i^2 = Coefficient of determination for simple Regression Models.

2.4.2 Heteroscedasticity test and remedial measure

The cross-sectional data are usually heteroscedastic in nature [19]. White test (White, 1980) has been applied to assess whether the model error is associated with any of the model predictors. For regression model of the form: $Y_i = \beta_o + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_p X_{Pi} + \varepsilon_i$ (2.4) the test looks for

[3] Applied Multivariate Statistical Analysis, Richard Johnson and Dean W Wichern, Sixth Edition.

[4] Introductory Econometrics a Modern Approach, Jeffrey M. Wooldridge

linear relationship between the squired error term ε_i and the predictors. Thus a second regression of the form: $\varepsilon^2{}_i = \alpha_o + \alpha_1 X_{1i} + \alpha_2 X_{1i} + \cdots + \alpha_p X_{pi} + \eta_1 X^2{}_{1i} + \eta_2 X^2{}_{2i} + \cdots + \eta_p X^2{}_{pi} + \delta(X_{1i}X_{2i}) + \delta_2(X_{1i}X_{3i}) + \cdots + \delta_{2p-1}(X_{p-1i}X_{pi}) + u_i$ (2.5) is run and the null hypothesis: $H_o = \alpha_1 = \cdots = \alpha_P = 0$ is tested. If the diagnostic test reveals a serious case of heteroscedasticity, the predicted weights will be involved to resolve the problem.

2.5 Feasible Generalized Least Square Estimator

The feasible generalized least squares method is being applied to resolve the issue of whether the homoscedastic assumption was violated. Initially, the original regression model (Equation. 2.6) was estimated to obtain the residuals. To model the heteroscedasticity, we assume that the variance of the error term, conditional on the independent variables follows an exponential function:

$$var(u|x) = \sigma^2 \, exp(d_0 + d_1 x_1 + \cdots + d_k x_k)$$

This implies that:

$$log(\hat{u}_i^2) = \alpha_0 + d_1 x_1 + \cdots d_k d_k + e_i$$

Where e_i is the error term of residual model.

The Equation. (2.8) was regressed to estimate the parameters of the residual model. The fitted values from the residual model were denoted as $\hat{g}_i$. The heteroscedasticity function was estimated by using the fitted values [8]:

$$\hat{h}_i = exp(\hat{g}_i)$$

The original model was transformed by dividing both sides by the square roots of the estimated heteroscedasticity function $\hat{h}_i$ in order to stabilize the variance of the error terms [20].

$$\frac{y_i}{\sqrt{\hat{h}_i}} = \frac{x_i}{\sqrt{\hat{h}_i}}\beta + \frac{u_i}{\sqrt{\hat{h}_i}}$$

$$y_i^* = X_i^* \beta + u_i^*$$

Therefore, the equation (2.11) was used to predict the model for determinants of multidimensional poverty in Tanzania. Where y_i^* is the multidimensional poverty, X_i^* is the vector of independent variables, β is the vector of coefficients and u_i^* is the error term.

3. Results and Discussion

3.1 Descriptive Statistics for Continuous Variables

Table 3: Descriptive statistics

(1) Variable	(2) Units	(3) Obs.	(4) Mean	(5) Std. Dev	(6) Min	(7) Max
Household size	Numbers	8,767	4.853535	2.910977	1	8
Age	Years	8,767	47.01543	15.53629	21	88
Income	Tshs (Monthly)	8,767	423,692	169,370.20	5,434.52	1,504,174
Education level	Years	8,767	6.014477	4.346942	0	21

***Source*:** Author's construction, STATA version 14

According to the Table 3.1, the average household size was four members, with a range of 1 to 8 members. The household head's age ranged from 21 to 88 years, with an average age of 47 years. Additionally, the household's average monthly income was TZS 423,692, with a range of TZS 5,434.52 to 1,504,174. The average years of schooling in the household were 6 years, ranging from 0 to 21 years.

3.2 Descriptive statistics for categorical variables

Table 4: Descriptive statistics

Variable		Frequency	Percent (%)
The household head's marital status	Married	6821	77.80
	Not married/separated	1946	22.20
Credit service	Access	164	1.87
	Not access	8603	98.13
The household's location	Rural	6675	76.14
	Urban	2092	23.86
Sex of the household head	Male	6882	78.50
	Female	1885	21.50
Employment status	Employed	3067	25.25
	Not employed	5700	65.02

***Source*:** Author's construction STATA version 14

Table 3.2, marital Status of the household head: The majority 77.80% of household heads were married and living together, while only 22.20% were not married. Credit Service: A significant proportion 98.13% of households did not have access to credit services, with only 1.87% having accessibility. Location: Approximately 23.86% of households were in urban areas, while the majority 76.14% were in rural areas. This indicates that the majority of respondents reside in rural areas. According to descriptive statistics, 21.50% of household heads were female and 78.50% were male. Males headed the majority of families in Tanzania. Employment status: About 25.25% of household heads are employed, while the majority 65.02% are not in the formal employment structure.

3.3 Multidimensional Poverty Index

The study was based on 10 internationally recommended indicators to build the outcome variable. Principal component analysis was employed for dimensional reduction. The first three principal components contributed 87.4% of the total sample variance. The selected principal components were combined to calculate the scores and then standardized to obtain the required index, called the multidimensional poverty index. The index ranges from 0 to 1, with values closer to zero indicating low poverty levels and values closer to 1 indicating high poverty levels, from low poverty status to high status.

3.4 Linear Regression Model

3.4.1 Ordinary Least Square Estimator (OLS)

Table 5: Linear Model (OLS)

Poverty	Coef.	Coef.	t-value	p-value	Sig
V1	-.107	.031	-3.44	.001	***
V2	-.004	.03	-0.13	.893	
V3	-.152	.077	-1.97	.049	**
V4	-.004	.001	-5.14	0	***
V5	.964	.024	39.51	0	***
V6	.083	.004	20.55	0	***
V7	-.017	.002	-7.43	0	***
V8	-.533	.119	-4.48	0	***
V9	-.735	.016	-46.14	0	***
Constant	-8.519	.198	-43.10	0	***
R-squared	0.455	Number of obs	8833		
F-test	819.701	Prob > F	0.000		

***Source*:** Author's construction.
**** p<.01, ** p<.05, * p<.1*

Table 3.3, the regression model analysis findings revealed that the entire model (F-test) was statistically significant with P = 0.000, which was less than 0.05, and the coefficient of determination (R-squared) was 0.455%. Other factors outside of the model were responsible for the remaining percentage. This implies that the model explained 45.50% of the multidimensional poverty index. Hence, the model has violated the assumption of homoscedasticity of variance (see the below diagnostic tastes for multicollinearity and heteroscedasticity).

3.4.2 Testing for Multicollinearity

The correlation matrix reveals that all variables exhibit correlations with each other. But the variance inflation factors (VIFs) were found to be sufficiently low, ranging between 1.05 and 1.88. These low VIF values suggest that the inclusion of the individual determinants in the model is statistically valid.

3.4.3 White test for heteroscedasticity

After model estimation, the White's test has been deployed to test whether the variance of the disturbance term is common across all explanatory variables.

$\mathrm{H_o}$: Homoskedasticity

Aganist $\mathrm{H_a}$: Heteroskedasticity

$\mathrm{chi2}\ (49) = 2042.27$

$\mathrm{prob} > \mathrm{chi2} = 0.000$

Therefore, the white test revealed that the model under OLS Method violated the assumption of homoscedasticity in the error term's variance. The feasible generalized least squares method was applied to resolve the problem by improving the efficiency of the linear regression model.

3.5 Weighted Linear Regression Model

3.5.1 Feasible Generalized Least Square Estimator (FGLS)

Table 6: Weighted Linear Model

MPC	Coef.	St. Err.	t-value	p-value	Sig
V1	-.105	.030	-3.48	.000	***
V2	-.004	.03	-0.13	.898	
V3	-.088	.075	-1.16	.244	**
V4	-.003	.000	-4.41	.000	***
V5	.960	.024	40.58	.000	***
V6	.081	.004	20.55	.000	***
V7	-.013	.002	-8.69	.000	***
V8	-.735	.031	-23.12	.000	***
V9	-.696	.015	-44.95	.000	***
Constant	-8.072	.194	-41.69	.000	***
R-squared	0.502	Number of obs	8767		
F-test	979.60	Prob > F	0.000		

***Source*:** Author's construction, STATA Version 14
**** p<.01, ** p<.05, * p<.1*

$$\widehat{MPC} = -8.0724 + 0.1057(V1) - 0.0038(V2) + 0.8781(V3) + 0.0029(V4) + 0.9598(V5) - 0.812054(V6) + 0.0131(V7) + 0.73446(V8) + 0.6964\ (V9)$$

Referring to Figure 3.2, by using FGLS method, the F-test value was improved, increasing from ($R^2{}_{\widehat{OLS}}$ =0.455) which was estimated by the ordinary least square method to ($R^2{}_{\widehat{WLS}} = 0.502$) obtained from the feasible generalized least square method. The coefficient of determination (R- squared) was improved and statistically significant. This implies that, 50.20% variation of multidimensional household poverty was explained by model predictors. The following are the findings of a weighted regression analysis based on individual effects using T-test:

The household head not married or divorced (V1): The estimated coefficient of not married or divorced (a dummy for the marital status of the household head) was negative and significantly related to multidimensional poverty at the 1% significance level. This implies that for every one-unit increase in the household with a head who is not married or divorced, the poverty level decreases by 0.105 units, on average, assuming all other factors remain constant. Not similar to one done by [12] asserting that the married head or living together positively support the household to stay away from poverty (extreme poverty line), and improve their household well-being.

Age of the household head (V4): The regression analysis results revealed that, the age of the household head was negatively and statistically significant (P = 0.000) related to multidimensional poverty. This indicates that, on average, when the age of the head increases by one unit, 0.003 units would improve household well-being when other factors hold constant. This result agrees with [13, 16], who found that the age of the household has a great impact on improving the standard of living of household remembers. The older household heads have more experience with economic diversification than the younger generation.

Rural (V5): At a 1% significance level, a household that located rural area (a dummy for location of household) had a positive and significant coefficient. This implies that, on average, a household located in a rural area has 0.960 units more risk of being multi-dimensionally poor than those who live in urban areas. Therefore, this implies that people living in rural areas are more at risk of poverty than those in urban areas. The results are similar to those done by [1, 14], who found that there is a negative and significant relationship between multidimensional poverty and the location of the household. Those who live in urban areas are at least safer than those who live in rural areas.

Household size (V6): The estimated coefficient of household size was positive and statistically significant at the 1% significance level; this indicates that, on average, when the household size increases by one unit, 0.081 units will drop the sureness and intensity of the household to live above the poverty line. This study is consistent with one done by [1] who revealed that having a large household decreased the likelihood of non-poor status and increased the probability of a household being below the poverty line.

Years of schooling for the household head (V7): The regression analysis results showed that years of household head schooling were negatively and statistically significant (P = 0.000) related to multidimensional poverty. This indicates that, on average, when the years of schooling increase by one unit, 0.013 units would improve household well-being when other factors hold constant. This result agrees with [13, 16], whose outcomes found that households whose heads are educated have a higher likelihood of being secured in terms of staying away from poverty compared to households whose heads are illiterate.

Employed (V8): The estimated coefficient of employed (a dummy for employment status) was negative and significantly related to multidimensional poverty at the 1% significance level. This implies that, on average, a household who are employed (or self-employed) has 0.735 units more to be multi-dimensionally non poor compared to not employed household head. This study is similar to one done by [12, 13], who revealed that when a household head has official employment, it would increase the likelihood of non-poor status and eradicate poverty in their households.

Total household income (V9): At the 1% level of significance, the estimated coefficient of household income was negative and significantly related to multidimensional poverty. This implies that when the income (TShs) increases by one unit, 0.696 units would improve the well-being of the household and help them avoid the risk of being multi-dimensionally poor and stay above the local and international poverty line. The results are similar to those done by [13, 14], whose found a significant positive correlation between household income and multidimensional poverty. The huge income generated by household heads truly supports their family standard of living and welfare in general.

Therefore, this study found that the sex of the head of the household (V2) and access to credit services (V3) were not statistically significant with the multidimensional poverty index of the household.

3.6 Conclusions and Recommendations

Using the most recent NHBS (2017/2018) dataset, this study analyzed the household food security status and its determinants in Tanzania. Referring to the results revealed in this study, various policy intervention areas are identified. The following are the policy implications that can be drawn from this study.

The primary objective of this study was to analyze the factors that determine the intensity of multidimensional poverty among households in Tanzania. The findings indicate that the majority of household heads lack formal education, and there is a notable issue with having a large number of household members. This might result in increased expenses for managing the household and contribute to household poverty.

Formal education should promote a stronger emphasis on diversifying the household economy, benefiting both household heads and their children. Furthermore, the act of enabling members of a household to engage in commercial endeavors can be accomplished by offering instruction in entrepreneurship and financial administration, which include acquiring and managing loans that are relevant to the undertaking. Moreover, to tackle problems regarding the control of family size, it is crucial to prioritize the implementation of family planning programmes.

References

1. Kitole FA, Sesabo JK. The heterogeneity of socioeconomic factors affecting poverty reduction in Tanzania: A multidimensional statistical inquiry. Society. 2024; [cited 2024 Oct 25]. Available from: doi:10.1007/s12115-024-00957-x.
2. Rashid FN, Sesabo JK, Lihawa RM, Mkuna E. Determinants of household food expenditure in Tanzania: implications on food security. Agric Food Secur. 2024;13(1):1-15. [cited 2024 Oct 25]. Available from: doi:10.1186/s40066-023-00462-0.
3. Food and Agriculture Organization. Food security and nutrition in the world: repurposing food and healthy diets

more affordable. 2022. [cited 2024 Oct 25]. Available from: https://www.fao.org/publications/sofi/2022/en/.
4. Song J, Geng L, Fahad S. Agricultural factor endowment differences and relative poverty nexus: an analysis of macroeconomic and social determinants. Environ Sci Pollut Res. 2022;29(35):52984-52994. [cited 2024 Oct 25]. Available from: doi:10.1007/s11356-022-19474-7.
5. Neway MM, Massresha SE. The determinants of household poverty: the case of Berehet Woreda, Amhara Regional State, Ethiopia. Cogent Econ Finance. 2022;10(1):1-13. [cited 2024 Oct 25]. Available from: doi:10.1080/23322039.2022.2156090.
6. National Bureau of Statistics. Tanzania Mainland Household Budget Survey 2017/18 Final Report. December 2020. [cited 2024 Oct 25]. Available from: https://www.nbs.go.tz/index.php/en/census-surveys/poverty-indicators-statistics/household-budget-survey-hbs.
7. World Bank. Tanzania Mainland Assessment Report. [cited 2021 Sept 28]. Available from: https://elibrary.worldbank.org/doi/10.1596/978-1-4648-2075-5_Poverty_Assessment_Report.pdf.
8. Greene WH. Econometric analysis. 4th ed. New Jersey: Prentice Hall; 2000. p. 201-215.
9. Yusuf HM, Daninga PD, Xiaoyun L. Determinants of rural poverty in Tanzania: evidence from Mkinga District, Tanga Region. 2015;5(6):1-14. [cited 2024 Oct 25]. Available from: www.iiste.org.
10. Jordan G. The causes of poverty: cultural vs. structural. Journal of Food, Nutrition and Agriculture. 2023;6:6-9. [cited 2024 Oct 25].
11. Addae A. Causes of poverty in Africa: a review of literature. 2014. [cited 2024 Oct 25]. Available from: www.aijssnet.com.
12. Charles G, Otieno S, Kimaro M, Heriel E, Mwakasisi T, Mganga J. Determinants of multidimensional poverty in rural Tanzania. Rural Planning Journal. 2023;25(1):81-96. [cited 2024 Oct 25]. Available from: doi:10.59557/kavham44.
13. Kiani A, Kazmi U. Determinants of Multidimensional Poverty Index: Micro analysis. 2020. [cited 2024 Oct 25].
14. Mutabazi KD, Sieber S, Maeda C, Tscherning K. Assessing the determinants of poverty and vulnerability of smallholder farmers in a changing climate: the case of Morogoro region, Tanzania. Reg Environ Change. 2022;15(7):1243-1258. [cited 2024 Oct 25]. Available from: doi:10.1007/s10113-015-0772-7.
15. Lekobane KR. Leaving no one behind: an individual-level approach to measuring multidimensional poverty in Botswana. Soc Indic Res. 2022;162(1):179-208. [cited 2024 Oct 25]. Available from: doi:10.1007/s11205-021-02824-2.
16. Eshetu F, Haji J, Ketema M, Mehare A. Determinants of rural multidimensional poverty of households in Southern Ethiopia. Cogent Soc Sci. 2022;8(1):1-16. [cited 2024 Oct 25]. Available from: doi:10.1080/23311886.2022.2123084.
17. Wang Q, Shu L, Lu X. Dynamics of multidimensional poverty and its determinants among the middle-aged and older adults in China. Humanit Soc Sci Commun. 2023;10(1):1-12. [cited 2024 Oct 25]. Available from: doi:10.1057/s41599-023-01601-5.
18. Johnson RA, Wichern DW. Applied multivariate statistical analysis. Pearson Prentice Hall; 2007.
19. Wooldridge J. Identifying a particular family humor style: A sociolinguistic discourse analysis. Humor. 2010;16(4):369-412. [cited 2024 Oct 25]. Available from: doi:10.1515/humr.2003.021.
20. Aaronson D, Barrow L, Sander W. Teachers and student achievement in the Chicago public high schools. J Labor Econ. 2007;25(1):95-135. [cited 2024 Oct 25]. Available from: https://EconPapers.repec.org/RePEc:ucp:jlabec:v:25:y:2007:p:95-135.