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Multidimensional Poverty and its Determinants in Somalia: A Household Level Analysis

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Abstract

Purpose: Poverty is widespread and problematic in least developed countries such as Somalia. The main objective of this study is to analyze the extent and determinants of multidimensional poverty in Somalia.

Methodology: To achieve this objective, this study used the Somali Health and Demographic Survey carried out by the Somali National Statistics Bureau in 2020. Alkire and Foster's methodology was used to measure the extent of multidimensional poverty, and an ordered logistic regression model was employed to identify its determinants at the household level.

Findings: The results of the descriptive analysis show that 84.2 percent of the sampled households are multidimensionally poor, while the intensity of poverty and adjusted headcount ratio were 56.8 percent, and 0.479 respectively. Meanwhile, the study found that the living standard dimension was the major contributor (45 percent) to the overall multidimensional poverty index, followed by education and health dimensions, contributing 28.2 percent, and 26.8 percent, respectively. The ordered logit results indicate that household size significantly increases the likelihood of a household's status being multidimensionally poor. In contrast, household education, employment of at least one household member, livestock ownership, ownership of agricultural land, and having a bank account significantly reduce the probability of being multidimensionally poor.

Unique Contribution to Theory, Practice and Policy: Based on these findings, the study recommends that the government and international partners target the living standards dimension to reduce multidimensional poverty, improve quality and quantity of education, expand employment opportunities, promote financial inclusion, and foster the livelihoods of households involved in agriculture and livestock.

Keywords: *Multidimensional Poverty, Determinants, Somalia, Alkire & Foster, Ordered Logistic, Regression*

1. Introduction

There has been a growing recognition that poverty extends beyond a single dimension such as income and it is now acknowledged that poverty encompasses a broader range of dimensions, increasingly being viewed as a manifestation of limited capabilities (Sen, 1987). Unlike traditional poverty measures that rely solely on income, the multidimensional Poverty Index (MPI) approach is a new paradigm shift in poverty research that considers various factors to assess poverty (Alkire and Foster, 2011a). Globally, there is a population of 485 million individuals afflicted by severe poverty, spanning across 110 nations, and 99 million experience deprivations in all three dimensions, notably living standards, education, and health (OPHI and UNDP, 2023). In Africa, about 58% of households live in multidimensional poverty, characterized by deprivation across three dimensions, particularly health, education, and living standards (ECA, 2021). In Somalia, poverty is widespread and problematic, especially affecting rural households, Internally Displaced people (IDPs), and close to 70 percent of the Somali population lives under the global poverty threshold (World Bank, 2022). Poor households in Somalia face greater exposure to drought, witnessing a substantial decrease in consumption, and increase in poverty levels. Specifically, an increase of one standard deviation in drought exposure during the 2016/17 drought resulted in a 26 percent decline in household consumption (Pape and Wollburg, 2019). The profound impact of the COVID-19 pandemic, soaring commodity prices as a result of Russia's invasion of Ukraine, and repetitive climate shocks such as droughts as the last five sequential periods failed rains, floods, and the impact of locust besiege have caused Somalia to be one of the poorest countries in the region (World Bank, 2023).

Meanwhile, as part of the UNDP's country brief in the 2011 Human Development Report, Alkire et al. (2011) constructed Somali's MPI using UNICEF's Multiple Indicator Cluster Survey (MICS) conducted in 2006. They found that the MPI in Somalia was 0.514, with a headcount poverty rate of 81.2 percent and a poverty intensity of 63.3 percent. More recently, Mustafe (2020) analyzed the determinants of poverty in Somalia and employed logistic regression using the Somali High-Frequency Survey (SHFS) wave 2 as a method of analysis. His study discovered that household size, the presence of a female household head, living or residing in a rural area, ownership of sources of income derived from agriculture and small businesses, literacy, access to power, employment of at least one member of the family, and receipt of remittances are significant determinants of poor households in Somalia. Likewise, Mohamoud and Bulut (2020) followed the same methodology and used the same data; however, they further applied additional variables such as agriculture fishing and hunting

In contrast, empirical studies on the determinants of multidimensional poverty in Somalia are limited, and available poverty studies focus only on a unidimensional approach to measuring poverty (Haaland and Keddeman, 1984; Pape and Wollburg, 2019; Mustafe, 2020; MOHAMOUD and BULUT, 2020). However, measuring poverty using the unidimensional method cannot provide a clear picture of the actual poverty situation of impoverished households, requiring a new method called the multidimensional approach that takes into account different dimensions and indicators that offer precise images that reflect the conditions of poor households (Alkire & Foster. 2011a; Wang et al., 2021; Alkire & Santos, 2013; Babalola & Mohd, 2022 ; Zeeshan et al., 2022; Alkire & Fang, 2019). Additionally, prior poverty studies conducted in Somalia (Mustafe, 2020; MOHAMOUD and BULUT, 2020) used binary models hypothesizing that poverty is a dummy variable (poor and non-poor); however, the poor are not equally poor (moderately poor and severely poor) and anon-poor are not the same (vulnerable and non-poor). Motivated by this area of interest, this study bridged the methodological gap and introduced a new approach in the existing poverty literature in Somalia by applying the Alkire-Foster (AF) methodology and employing an ordered logistic regression model to analyze the extent and major determinants of multidimensional poverty in Somalia.

The next section presents the theoretical and empirical literature reviews. Section three presents the materials and methods. The fourth section provides the results and discussion, and the fifth section presents the conclusions and recommendations.

2. Literature review

2.1 Theoretical Literature Review

The conceptualization and definition of poverty play a significant role in determining the type of measurement to be applied (Dunga, 2019). Poverty has conventionally been regarded only in the income approach, and households have been considered poor if they do not have sufficient money to cover their basic needs (Alkire and Fang, 2019). However, defining poverty depends only on monetary aspects and is unable to provide a true reflection of the problem (Zeeshan et al., 2022). Poverty is a multifaceted and dynamic concept that has transformed throughout human history (Wang et al., 2021). Several concepts of poverty continue to be utilized to describe the multidimensional structure of poverty (Alkire and Foster, 2014). In this study, a household is regarded to be multidimensionally poor if the total of weighted deprivation score of that household equal to or greater than 33.33% (Alkire and Foster, 2011a , 2007)

2.2 Measurements of Poverty

The measurement of poverty has been the subject of debate among scholars and practitioners over the years. Poverty measurement is crucial to recognize poor households and where poor people live to allocate the resources needed to alleviate poverty (Tigre, 2019). However, in the poverty literature, there are two opposing measurement approaches: traditional income measurement, the Welfarist Approach, and the recent multidimensional poverty approach (Alkire and Fang, 2019). Unidimensional poverty measurement can be employed when precisely outlined one-dimensional indicators, such as income are chosen as the reference for poverty assessment (Alkire and Foster, 2011b). Nevertheless, such unidimensional poverty calculations do not cover the capabilities of precious beings and functions, because they are constrained by the capacity to expenditure on basic needs (Zeeshan et al., 2022). The realization of these shortcomings of traditional poverty has paved the way for the enhancement of procedures and ways to measure poverty through a multidimensional approach, which has been promoted by the contemporary presence of national household surveys that facilitate the execution of multidimensional measures (Alkire and Santos, 2013). In recent years, there has been significant focus on the multidimensional nature of poverty and a shift from a one-dimensional to a multidimensional understanding of poverty, which has been influenced by various factors (Alkire and Foster, 2011a). Multidimensional poverty focuses on the non-monetary aspect of poverty by stressing well-being in the framework of expanding choices and opportunities (Babalola and Mohd, 2022). The mathematical approach for measuring multidimensional poverty is known as the adjusted headcount ratio (M_o), introduced by Alkire and Foster (2007). M_o is a suitable measure to be used whenever one or more of the dimensions are deemed ordinal nature (Alkire & Santos, 2010). M_o measured multidimensional poverty in d for a population of n persons. Let $y = [y_{ij}]$ indicate the $n * d$ matrix of accomplishments for i individuals throughout j dimensions. Such an entry in the accomplishments $y_{ij \geq 0}$ represents person i's achievement in j dimension. Each row vector $yi = (yi1, yi2, yi3, \ldots\ldots, yid)$ provides person i's accomplishment in varied dimensions, whereas each column vector $y_j = (y_{j1}, y_{j2}, y_{j3}, \ldots\ldots, y_{nj})$ serves the allocation and distribution of achievements in dimension j throughout individuals. In other words, M_o can be expressed as multidimensional poverty intensity (A) multiplied by the incidence of multidimensional poverty (H). Mathematically, M_o = H×A, where H is the share of multidimensionally poor households in the overall popuslation. The formula of incidence is as follows; $H = \frac{q}{n}$ where q is the number of poor households and n is the total number of populations, whereas the intensity formula is $A = \frac{1}{q}\sum_{i=1}^{q} C_i$, where C_i refers to the fraction of weighted indicators in which poor person i is deprived. Finally, one of the crucial characteristics is to know which dimensions contribute to the overall M_o. Therefore, the formula for the contribution of each j dimension = $\frac{\frac{\sum_{i=1}^{q} C_j}{n}}{Mo}$

2.3 Empirical Literature Review

Prior studies in the global and African contexts analyzed the degree of multidimensional poverty by utilizing the Alkire and Foster methodology and national household surveys and primary datasets. In Taiwan, study carried out by Chen et al. (2019) adopted the Alkire-Foster method of five dimensions and eight indictors to analyze multidimensional poverty profiles in Taiwan using a multilevel modeling approach and utilizing National Health Interview Survey (NHIS). Their study found that age, socioeconomic status, marital status, and household income significantly decreased the degree of multidimensional poverty, while the extent of urbanization and service to manufacturing ratio significantly correlated with the level of multidimensional poverty. Similarly, Najitama et al. (2020) analyzed the causes of multidimensional poverty dynamics in Indonesia using the Indonesian Family Life Survey (IFLS) and employing the Alkire and Foster methodology of three dimensions and tend indicators. Their study utilized a logistic regression model and revealed that the level of education, level of dependency, island of residence, village political system, village government corruption, marital status, size of household, and customary norms are the main drivers of multidimensional poverty in Indonesia.

A study carried out by Charles (2022) in Tanzania, analyzed factors influencing multidimensional poverty using the Tanzania Demographic and Health Survey (TDHS) and adopted the Alkire and Foster methodology of the standard three dimensions and ten indictors. The study further employed a logistic regression model and found that age, education level, sex, marital status, and the use of family planning were significant determinants, with male-headed households being more likely to experience poverty across multiple dimensions. In Rwanda, Bikorimana and Sun (2020) analyzed factors causing multidimensional poverty using the Alkire and Foster method and utilizing Rwanda's Demographic and Health Survey (RDHS). The study further employed an ordered probit regression model, and the regression results indicated that the size of family members, occupation, and land features were the main determinants of multidimensional poverty in Rwanda.

Regarding the contexts closer to Somalia, Eshetu et al. (2022) applied the Alkire-Foster approach, adopting an ordered logistic regression model to analyze the magnitude and main drivers of rural multidimensional poverty in the southern region of Ethiopia. The study's regression results revealed that education, land size, TLU, off-farm participation, savings, dependency ratio, distance from the market, distance from the road, and sickness of family members are the main drivers of rural multidimensional poverty in that region. Similarly, Kassa et al. (2021) utilized the Alkire and Foster methodology and adopted an ordered model to investigate the main factors of rural multidimensional poverty in western Ethiopia. The study found that the kebele dummy, marital status, literacy status, farm size, and membership in cooperatives are the main determinants of rural multidimensional poverty in that region.

3. Materials and Methods

3.1 Description of Study Area

The study was conducted in Somalia, which is located in the Horn of Africa, covering an approximate area of 637,657 square kilometers with hot and tropical climates ranging from 30°C to 40°C. The country experiences limited annual rainfall and is characterized by four distinct seasons: Gu', Deyr (rainy season), Haga, and Jilal (dry season). Ethiopia borders Somalia to the

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west, Kenya to the southwest, Djibouti to the northwest along the Gulf of Aden to the north and the Indian Ocean to the east and south.

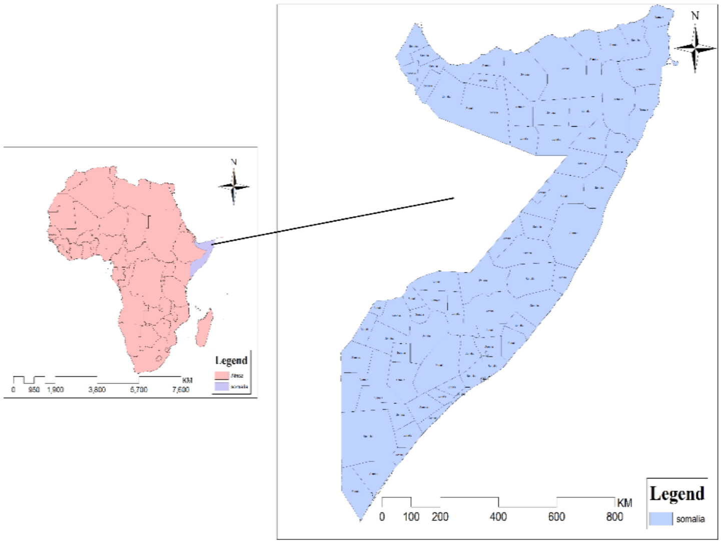

Figure 1: Somalia (study area) map

Source: The author's drawing employing ArcGIS (version 10.8)

3.2 Data Sources

This study used data from the Somali Health and Demographic Survey (SHDS) collected by the Somali National Bureau of Statistics in 2020. The SHDS is a cross-sectional household survey that covers the entire country. The survey contained a sample of 15,826 households, with a total of 55 sampling strata. Each region was stratified into three areas: (urban, rural, and nomadic) using a two-stage stratified cluster sample method for the nomadic stratum and a three-stage stratified cluster sample technique for the rural and urban strata. On the other hand, the SHDS includes all the variables of interest needed for this study, such as child mortality, nutrition, years of schooling, school attendance, source of drinking water, sanitation, access to electricity, housing, cooking fuel, and assets. Furthermore, multidimensional measurements of poverty were analyzed using data from the Demographic and Health Surveys (DHS) in empirical literature from across the world and in regional contexts. For instance, Alkire and Santos (2010) employed DHS in their examination of the multidimensional poverty index of 49 developing countries. Similarly, Pasha (2017) used DHS to explore the multidimensional poverty index from a regional perspective in India. In regional context closer to Somalia, Tigre (2019) studied Ethiopia's multidimensional poverty dynamics using a DHS. Therefore, the empirical studies demonstrate the wide use of DHS data in multidimensional poverty analysis, demonstrating the flexibility of DHS in various socioeconomic and geographic contexts, including Somalia.

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3.3 Alkire-Foster Methodology

This study utilized the multidimensional poverty measurement developed by Alkire and Foster to examine the extent and determinants of multidimensional poverty among households in Somalia. Three global multidimensional poverty measures with ten indicators were also applied and a concise of dimensions, indicators, cutoffs, and weights are presented in Table 1. Multidimensional poverty can be examined by identifying multidimensional poverty indicators based on the global Multidimensional Poverty Index (G-MPI).

Technically, the weighted deprivation score of households can be calculated as follows;

$$C_i = \sum_{j=1}^{d} w_j g_{ij} \qquad (1)$$

where the C_i is the deprivation score, w_j is the weight of each indicator j, and g_{ij} is the deprivation score for household i in indicator j, and d is the total number of indicators. The categorization of households as extremely poor, moderately poor, vulnerable, and non-poor is determined based on the level of multidimensional poverty index, which must be greater than or equal to 50%, greater than or equal to 33.33% but less than 50%, greater than 20% but less than 33.33%, or less than 20%, respectively (S. Alkire & Fang, 2019). To construct MPI indices, the study adopted the following parametric classes; headcount ratio (H), intensity of poverty (A), multidimensional poverty index (a composite index) and formulating the contribution of each dimension.

Incidence of poverty (head count ratio); The multi-dimensionally poverty headcount ratio (H) is share of the multidimensionally poor people to the overall population.

$$H = \frac{q}{n} \qquad (2)$$

Poverty intensity (A); Average proportion of deprivation indicators in which poor people are lacking.

$$A = \frac{1}{q} \sum_{i=1}^{q} C_i \qquad (3)$$

Adjusted Headcount Ratio; The multiplication of the headcount ratio and intensity poverty, commonly referred to as aggregate MPI, which is

$$MPI = H \times A \qquad (4)$$

Contribution of each dimension; contribution of each dimension to the overall MPI

$$\text{Contribution of j dimension to MPI} = \frac{\frac{\sum_{i=1}^{q} C_j}{n}}{MPI} \qquad (5)$$

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where the values of n, C_j, and q represent the total number of households in a certain group, average deprivation in the j^{th} category, and number of poor households, respectively.

Table 1: Dimensions, indicators, cutoffs, and weights.

Dimensions	Indicators	Household deprived if…….	Weigh
Health	Nutrition	Any adult under 70 years of age for whom there is nutritional information is undernourished (destitution).	$\frac{1}{6}$
	Child mortality	A child has died in the family within the five years before the SHDS	$\frac{1}{6}$
Education	Years of education	No household member aged 10 years or older have completed six years of education	$\frac{1}{6}$
	School attendance	At least one school-aged child (up to class 8) is not attending school	$\frac{1}{6}$
Living standard	Cooking fuel	A households use solid fuels, including wood or charcoal for cooking purposes.	$\frac{1}{18}$
	Sanitation	The household's sanitation facility is either not improved or is shared with other households.	$\frac{1}{18}$
	Source of drinking water	The household lacks access to safe drinking water	$\frac{1}{18}$
	Electricity	The household has no access to electricity.	$\frac{1}{18}$
	Housing	Household has roof, floor & walls that it is not low-quality material.	$\frac{1}{18}$
	Assets	The household does not own more than one of the following assets: radio, TV, telephone, computer, bicycle, motorbike, air condition or refrigerator, and lacks ownership of any car.	$\frac{1}{18}$

Source: Own Collection, 2024

3.4 Econometric Model Specification

Various regression techniques, such as binary logistic, binary probit, multinomial logit, and ordered logistic models, have been used in the current body of literature on the drivers of multidimensional poverty. However, there is disagreement about which model is best suited to explain the factors that contribute to multidimensional poverty. The ordered logit model was chosen for this study because it has been successfully applied in similar regional contexts to analyze multidimensional poverty. For example, the ordered logit model has been successfully used to investigate of multidimensional poverty in several regions of Ethiopia by the following studies (Eshetu et al., 2022; Kayeret & Mesfin, 2021; Kassa et al., 2021).

Technically, an ordered logistic regression model can be systematically obtained from the latent variable model by assuming that to depict the process as follows;

$$Y^* = X^T\beta + \varepsilon$$

where Y* is the unobserved outcome variable, X^T is the vector of independent variables, ε is the residual term assumed to follow a standard logistic distribution and finally β is the vector of regression coefficients estimated in this study.

Additionally, suppose Y* cannot be observed but can be observed in the categories of the outcome variable as follows;

$$Y = \begin{cases} 0, & if\ Y* \leq m1 \\ 1, & if\ m1 \leq Y* \leq m2 \\ 2 & if\ m2 \leq Y* \leq m3 \\ 3 & if\ m3 \leq Y* \\ . & \\ . & \\ N & if\ mN \leq Y* \end{cases}$$

Where the parameters m1, m2, m3……., mN are the externally imposed endpoints of the observable categories. The ordered logistic regression model is utilized to fit the parameter vector β using observations of the censored data of Y*, which indicates the continuous latent variable of multidimensional poverty with deprivation cut-off thresholds.

In the population it is as follows; $Y* = \sum_{m=1}^{m} X_{ki} + \epsilon_i = Z_i + \epsilon_i$

Considering these, the model specification is as follows;

$$Y_i = \beta_0 + \beta_1 AGE + \beta_2 SEX + \beta_3 MS + EDUC\beta_4 + \beta_5 HHS + \beta_6 Agri + \beta_7 EMP + \beta_8 Livestock + \beta_9 Bank + U_i$$

In the model, Yi represents the MPI , AGE stands for the age of the household, SEX indicates the sex of the household, EDUC reflects the education level of the household, HHS indicates

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household size, MS represents marital status (a dummy variable: 1 if married, 0 otherwise), Agri is a binary variable for owning agricultural land (1 for having agricultural land, 0 otherwise), EMP is a dummy variable indicating employment status of household (1 if at least one household member is employed, 0 otherwise), Livestock is a binary variable for ownership of livestock (1 if there is livestock, 0 otherwise), and Bank is a dummy variable for having a bank account (1 if having a bank account, 0 otherwise).

Table 2: Summary of name variables, measurements and expected signs

Variable name	Type and measurement	Expected sign	Relevant Literatures
Y_i (Poverty status)	Categorial; 0 = Non poor 1 = Vulnerable 2 = moderately Poor 3 = Severely Poor		Oljira (2022), Kassa et al. (2021), Eshetu et al. (2022) and Kayeret & Mesfin Menza (2021)
Age (in years)	Continuous	Negative	Charles (2022)
Sex	Dummy (1 if male 0 otherwise)	Negative	Dele (2020)
Education (in years)	Continuous	Negative	Najitama et al. (2020)
Marital Status	Dummy (1 if married, 0 otherwise)	Negative	Chen et al. (2019)
Employed	Dummy (1 employed, 0 otherwise)	Negative	Kassa et al. (2021)
Ownership of Agri Land	Dummy (1 if having agriculture land, 0 otherwise)	Negative	Adepoju (2020)
Household Size	Continuous	Positive	Bikorimana & Sun (2020)
Ownership of livestock	Dummy (1 if having livestock, 0 otherwise)	Negative	Eshetu et al. (2022)
Having Bank account	Dummy (1 if having account, otherwise)	Negative	Kayeret & Mesfin Menza (2021)

Source: Own collection

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4. Results and discussion

4.1 The estimation of the multidimensional poverty index

This study utilized the Alkire and Foster methodology to analyze the extent of multidimensional poverty in Somalia using STATA version 18.0. Moreover, it employs three dimensions and ten standard MPI indicators to estimate the Multidimensional Poverty Index (MPI). The poverty cutoff, set at k=3 (which corresponds to one-third of the weighted indicators), serves as the threshold for determining whether an individual is considered multidimensionally poor. As presented in Table 3, the study found that the headcount ratio, intensity of poverty, and MPI are 84.2% ,56.8%, and 0.479, respectively. Parallel to this finding, Alkire et al. (2011) examined Somalia's multidimensional poverty as part of the OPHI country briefing series. They find that the headcount ratio, intensity of poverty, and MPI are 81.2%, 63.3%, and 0.514, respectively.

Table 3:An overview of the estimated MPI, Head count ratio and Intensity of poverty

Poverty Cutoff at K = number of deprived indicators	Head Count ratio	Intensity of Poverty	MPI
K =3 (Ci=0.33)	0.842	0.568	0.479

Source: Own computation based on SHDS (2024)

4.1.2 The contribution of each dimension to the overall MPI in Somalia

As presented in Table 4, the study assessed the contribution of each indicator to the overall MPI to better understand the specific indicators that significantly affect MPI, while simplifying the quantification of the contribution of each dimension to the overall MPI. Table 4 lists the contribution of each indicator and dimension to the overall MPI in Somalia. For instance, health indicators such as nutrition and child mortality contributed 14.5% and 12.3% to the overall MPI, respectively. Educational indicators, namely years of schooling and school attendance, contributed 13.6% and 14.6%, respectively. Within living standards, the contributions are varied; cooking fuel and sanitation contributed 8.6% and 8.3%, respectively. Additionally, source of drinking water contributes 5.6%, electricity makes the largest contribution to living standards 9.1%. Finally, housing and assets contributed 6.3% and 7.1%, respectively.

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Table 4: Contribution of each indicator and each dimension to the overall MPI

Dimensions	Indicators	Weight	Average Deprivation	Contribution of each indicator	Contribution of each Dimension
Health	Nutrition	1/6	41.79 %	14.5 %	26.8%
	Child Mortality	1/6	35.25 %	12.3 %	
Education	Years of Schooling	1/6	39.09 %	13.6%	28.2%
	School Attendance	1/6	41.93 %	14.6 %	
Living Standards	Cooking Fuel	1/18	87.91 %	8.6%	45%
	Sanitation	1/18	77.39 %	8.3%	
	Drinking water	1/18	60.19 %	5.6 %	
	Electricity	1/18	86.92 %	9.1 %	
	Housing	1/18	66.59 %	6.3 %	
	Assets	1/18	73.84 %	7.1%	

Source: Own computation based on SHDS (2024)

The study further decomposed the adjusted headcount ratio (M_o) to analyze the contribution of each dimension to the overall MPI. As show in Table 4, living standards (45%) make the largest contribution, followed by education (28.2%) and health (26.8%). Similarly, the results of this study are closer to those of (Oljira 2022, Kassa et al. 2021, Eshetu et al. 2022, Joshua et al. 2017, Wang et al. 2021) which found that the living standard dimension is the biggest contributor to overall multidimensional poverty aside from other dimensions.

4.2 Ordered logistic regression model

To analyze the major determinant factors of multidimensional poverty in Somalia, this study applied an ordered logistic regression model, as described in the Materials and Methods, to estimate the multidimensional poverty equation. The dependent variable in this analysis was ranked in four levels: non-poor, vulnerable, poor, and extremely poor. Considering the defined categories of the dependent variable, households are categorized as non-poor if the index is below 20%, vulnerable if it's between 20% and 33.33%, moderately poor if it falls between 33.33% and 50%, and severely poor if it's 50% or higher (Alkire and Fang, 2019).

To identify the major determinants of multidimensional household poverty, Table 5 lists the demographic and socioeconomic variables employed in this study. The following variables were found to be statistically significant.

Household Size: The coefficient is positive (0.1542) and significant at 1% level of significance, indicating that an increase in household size is associated with an increase in the likelihood of being in a higher category of multidimensional poverty, ceteris paribus. Consistent with this finding, studies conducted by Michael et al. (2019) and Babalola and Mohd (2022) discovered that household size is significant and positively related to multidimensional poverty. In Somalia, families tend to have many children, men can marry three or four wives, and large households are more likely to fall into poverty traps because they cannot meet the basic needs of all family members.

Education: The coefficient is negative (-0.0566) and statistically significant at 1% level of significance, revealing that higher education levels of the household head are associated with a lower likelihood of the household to be a multidimensional poor, other things equal. In line with this finding, Kassa et al. (2021) and Mare et al. (2022) conducted studies on the determinants of rural multidimensional poverty in different regions of Ethiopia and found that education is negatively related to MPI.

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Table 5: Regression results of ordered logistic regression model

	LR Chi2 (9) = 200.39 Prob>Chi2= 0.0000 Pseudo R^2 = 0.0942		
Ordered logistic regression Log-likelihood= −963.62438			
Variables	**Coefficients**	**Odds Ratio**	**Z-value**
Age	0.0016496(0.009)	1.00165(0.009)	0.18
Household Size	0.1542161(0.027) ***	1.1667(0.032)	5.53
Education	-0.05666(0.008) ***	0.944912(0.008)	-6.35
Sex	-0.02189(0.152)	0.978338(0.149)	-0.14
Marital Status	0.02132(0.111)	1.021559(0.113)	0.19
Employment	-0.747132(0.225) **	0.473723(0.106)	-3.32
Ownership of Agricultural Land	-0.481400(0.089) ***	0.617917(0.055)	-5.40
Ownership of Livestock	-0.989737(0.126) ***	0.371674(0.046)	-7.85
Having Bank Account	-2.10613(0.636) **	0.121707(0.077)	-3.31
/Cut 1	-11.70514	1.428505	
/Cut 2	-10.13206	1.402537	
/Cut 3	-7.399528	1.389335	

Note: *** $p<0.01$ ** $p<0.05$ * $p<0.1$, *Standard errors in brackets*

Results of model diagnostic test:

Parallel line assumption (Brant test): Chi-square (18) = 17.59, Prob> Chi2 = 0.483

Multicollinearity test (Variance inflation factor): VIF = 1.14

Source: Own computation based on SHDS (2024)

Employment: The coefficient is negative (-0.74713) and statistically significant at 5% level of significance, showing that being employed is associated with lower likelihood of being in a multidimensional poverty, ceteris paribus. This happens because as households work and generate income, they have the full capacity to meet basic needs and overall well-being, reducing their vulnerability to multidimensional poverty. Consistent with this, Albis and Elviña (2018) conducted a study on multidimensional poverty in the Philippines and discovered that employment was negatively correlated with multidimensional poverty.

Ownership of Agricultural Land: The coefficient is negative (-0.48140) and statistically significant at 1% level of significance, which implies that owning agricultural land decreases the chances of being multidimensional poor household, other things held constant. Similarly, studies conducted by Kassa et al. (2021) and Adepoju (2020) found that ownership of agricultural land is significant and inversely related to multidimensional poverty.

Ownership of Livestock: The coefficient is negative (-0.9897) and statistically significant at 1% level of significance, implying that having livestock decreases the likelihood of being multidimensionally poor household, ceteris paribus. Similarly, a study conducted by Kumar et al. (2018) discovered that having livestock reduces the probability of being multidimensionally poor. Furthermore, this finding is intuitively true because livestock have been the backbone of Somalia's economy. In the local context, owning a large number of livestock is an indicator or symbol of wealth and pride, something that is far from poverty. Camels, in particular, are highly valued by Somali pastoralists and cherished above all other livestock.

Having Bank Account: The coefficient is also negative (-2.10613) and statistically significant at 5% level of significance, indicating inverse relationship between owning bank account and being multidimensionally poor, all other things being equal. Consistently, Salam and Hermanto (2022) found that having a bank account has a significant and inverse effect on poverty.

The marginal effects of each predicator were estimated after running an ordered logistic regression analysis, and the findings are presented in Table 6. An increase in household size by one person is associated with a 2.83% increase in the probability of being classified as severely poor, ceteris paribus. Under different light, an additional year of education is associated with a decrease of 1.04% in the probability of being severely poor, other things held constant. This indicates that education, measured in years, is a significant tool for reducing or alleviating multidimensional poverty. Similarly, an additional job that household have is associated with a decrease of 1.37%

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in the probability of being severely poor, ceteris paribus. The implication is that when the household receives an additional job, its salary is likely to increase, which means a decrease in multidimensional poverty.

Table 6: Marginal effects after ordered logistic regression model

Variables	Non-poor	Vulnerable	Moderate Poor	Severe Poor
Age	-0.0000124	-0.000041	-0.0002501	0.0003035
Household Size	-0.0011577	-0.0038359	-0.0233848	0.0283783***
Education	0.0004254	0.0014094	0.0085922	-0.0104269***
Sex	0.0001644	0.0005447	0.0033207	-0.0040299
Marital Status	-0.0001601	-0.0005305	-0.0032343	0.003925
Employment	0.0056086	0.0185837	0.1132925	-0.1374849 **
Ownership of Agricultural Land	0.0036138	0.0119741	0.0729979	-0.0885858 ***
Ownership of Livestock	0.0074298	0.0246182	0.1500803	-0.1821283***
Having Bank Account	0.0158104	0.0523867	0.3193662	-0.3875633 **

**** $p<0.01$, ** $p<0.05$ & *$p<0.1$*

Source: Own computation based on SHDS (2024)

Furthermore, an additional ownership of agricultural land decreases the probability of being severely poor by 8.85%, ceteris paribus. The implication is that an increase in fertile land ownership could reduce the probability of being multidimensionally poor. This could be why more land is more productive, ceteris paribus. An increase in livestock that households own also reduces the probability of being severely poor by 18.21%, ceteris paribus. This result may suggest that as livestock ownership increases, the likelihood of a multidimensionally poor person decreases. Likewise, an additional bank account that a household open is associated with a decrease of 38.75% in the probability of being severely poor, ceteris paribus. This finding suggests that having another bank account decreases the likelihood of multidimensional poverty. One reason for this is the fostering of financial inclusion, financial management, risk diversification and mitigation.

5. Conclusions and Policy recommendations

5.1 Conclusions

This study was conducted in Somalia using the latest Somali Health and Demographic Survey (SHDS). The main objective of this study is to analyze the extent and major determinants of multidimensional poverty in Somalia. To this end, this study utilized the Alkire and Foster methodology to calculate multidimensional poverty indices and employed ordered logistic regression to estimate the multidimensional poverty equation. The results of the multidimensional poverty indices revealed that the headcount ratio, intensity of poverty and MPI were 84.2%, 56.8%, and 0.479, respectively. The study also found that the living standard dimension was largest dimension, contributing 45% to the overall MPI in Somalia, followed by education and health dimensions which accounted for 28.2% and 26.8%, respectively. Meanwhile, the regression results indicate that household size significantly increases the likelihood of a household's status being multidimensionally poor. In contrast, household education, households with one member employed, livestock ownership, owning agricultural land, and having a bank account significantly reduced the probability of being multidimensionally poor.

In conclusion, the study findings show the severity and widespread nature of multidimensional poverty in the study area, emphasizing the urgent need to tackle poverty in Somalia using a multidimensional approach. Put simply, the insights from this study have significant implications for both policy and theory because they uncover the multidimensional nature of poverty in Somalia and contribute to the current literature on poverty in the country. In other words, in Somalia, livestock represent the backbone of the economy and remain the key exports. Thus, tackling poverty should be associated with improving the pastoralist's livelihoods. The absence of a livestock is directly correlated with poverty in Somalia (Haaland and Keddeman, 1984). Similarly, a study carried out by MOHAMOUD and BULUT (2020) reported that livestock and agriculture are major sources of income for many poor Somali households.

Based on the study's major findings, it is recommended that the government of Somalia and its international partners prioritize the living standards dimension to reduce multidimensional poverty by targeting cooking fuel, electricity, sanitation, assets, drinking water and housing.

It further proposes improving both the quality and quantity of education, expanding employment opportunities, promoting financial inclusion and fostering the livelihoods of households involved in agriculture and livestock farming.

Future studies, could explore the dynamic analysis of multidimensional poverty across different time periods, and examine additional dimensions such as empowerment, asset ownership, rural livelihoods, food insecurity, and other aspects relevant to poverty.

Abbreviations

OPHI: Oxford Poverty and Human Development Initiative

ECA: Economic Commission for Africa

Author contributions statement

Bukhari Abdiwahab come up the study's idea, reviewed the literature, analyzed the data, wrote results, discussion, and conclusion. Mesfin Menza designed the study, and reviewed the paper. Adam A. Mohamed contributed the STATA dofiles used in this study.

Disclosure Statement

The authors declared no possible conflicts of interest.

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Data Availability Statement

The following link will provide with access to the datasets utilized and/or analyzed in this study: https://microdata.nbs.gov.so/index.php/catalog/50/get-microdata

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