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Unveiling Multidimensional Poverty in Jammu and Kashmir: Insights from Alkire Foster Method and NFHS-5 Data

Umar Ali[1]*, Rossanto Dwi Handoyo[2], Lilik Sugiharti[3], Nasir Ahmad Zargarr[4]
[1] Department of Economics, Universitas Airlangga, Surabaya, Indonesia
[2] Department of Economics, Kashmir University, Srinagar, India

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A B S T R A C T

This study seeks to examine the multidimensional poverty in Jammu and Kashmir, aiming to illuminate its nature and extent beyond traditional monetary measures. Utilizing the Alkire Foster method and drawing on data from NFHS-5, the research uncovers a prevalence of multidimensional poverty surpassing that of monetary poverty in the region. Within surveyed districts, the study identifies Ramban as experiencing the highest incidence, contrasting with Srinagar, which exhibits the lowest headcount. Anantnag emerges as the district facing the most intense multidimensional poverty. In exploring the factors influencing multidimensional poverty, binary logistic regression reveals the significant roles of education, occupation, and land ownership. Conflict is identified as an amplifier of multidimensional poverty, and a predictive model achieves an accuracy rate of approximately 82.80%. The study underscores the critical importance of local factors in shaping poverty experiences, emphasizing the roles of nutrition, sanitation, housing, and education. Gender, age, and conflict are highlighted as pivotal determinants in the latter stages of the study. The research concludes with a managerial perspective, offering actionable insights for policy recommendations, development initiatives, and specific steps for government agencies and stakeholders. These proposed interventions aim to address identified determinants and contribute to the overarching goal of reducing poverty in Jammu and Kashmir.

1. INTRODUCTION

In recent decades, poverty analysis has transcended the conventional focus on income alone, recognizing that the true extent of poverty is better captured through a multidimensional lens. This paradigm shift has led to the emergence of the concept of "*multidimensional poverty*," which acknowledges that poverty is a complex phenomenon encompassing various interconnected deprivations that extend beyond income inadequacy. This shift is particularly pertinent in the context of developing countries like India, where diverse socio-economic, cultural, and geographic factors interact to shape the experience of poverty (Scheidel, 2013). The assessment of poverty frequently commences by considering fundamental human necessities, as illustrated in the works of (Rowntree, 1902). Poverty denotes a condition of having a minimal standard of living, either in absolute or relative terms within society. Absolute poverty entails that a destitute household (or individual) falls below a subsistence level of livelihood, while relative poverty centers on segments of society that are relatively disadvantaged (Sen, 1985). The notion of absolute poverty finds greater applicability and relevance in impoverished and developing economies, whereas the concept of relative poverty aligns better with developed nations. Sen (1981) posits that absolute poverty pertains to a state of deprivation, highlighting aspects like hunger and malnutrition. Sen contends that individuals in poverty often fail to meet the essential caloric and nutritional requisites, a perspective sometimes called the 'biological approach.' This stance, however, has faced criticism. Another method to gauge poverty revolves around 'Capability Failure.' This refers to the incapacity of individuals or communities to access certain valuable activities or conditions crucial to human life, constituting a 'Capability Failure' for them.

Sen (1976) emphasize that the recognition of absolute poverty can be achieved independently of the relative context. Within 'Commodities and Capabilities. Sen (1983) also highlight that poverty can be viewed as a complete inability to pursue specific valuable functions. The lack of capabilities stems from a dearth of opportunities, indicating that society has not furnished individuals with the means to cultivate or sustain fundamental human capabilities. This correlation facilitates the establishment of a connection between development and privation. The expansion of capabilities defines human development, with individuals constituting both the method and objective in all developmental processes. Diverging from income, capabilities are not manifest in inputs but rather in human outcomes, signifying the quality of individuals' lives. Deprivation becomes apparent in the absence of essential capabilities, indicating that individuals fail to attain a certain threshold of vital human accomplishments or functioning (UNDP, 1996). Sen et al. (1983) contends that a more effective approach to conceptualizing poverty is through the lens of 'Capability Failure.'

The state of Jammu and Kashmir, situated in the northernmost part of India, presents a unique and compelling case study to examine the dynamics of multidimensional poverty within the Indian subcontinent. Historically celebrated for its breathtaking landscapes, rich cultural heritage, and geopolitical significance, Jammu and Kashmir has also been grappling with multifaceted challenges linked to socio-economic development, political instability, and regional disparities. The region's multidimensional poverty is deeply rooted in historical and contemporary factors. Historical conflicts, socio-political disturbances, and territorial disputes have shaped the economic trajectories of Jammu and Kashmir. These issues have led to infrastructural challenges, reduced access to basic services, and limited economic opportunities, all of which contribute to the complexity of poverty beyond just income deprivation. Additionally, the region's demographic diversity, including various ethnicities, religious groups, and linguistic communities, further amplifies the multidimensionality of poverty by creating differential experiences of disadvantage and vulnerability (Aijaz, 2014) Decades of political unrest, armed conflict, and the persistent dispute over its territorial status have engendered a unique set of challenges that extend beyond income insufficiency. The resulting disruption of economic activities, hampered access to public services, and displacement of populations have compounded the multidimensional nature of poverty in the region. Moreover, the heterogeneous composition of Jammu and Kashmir's population, comprising diverse ethnic, linguistic, and religious groups, introduces additional layers of complexity to the poverty landscape. These variations often intersect with gender disparities, further accentuating the vulnerability of specific subgroups within the population (Haroon, 2018).

This paper embarks on an exploration of the multidimensional poverty landscape in Jammu and Kashmir. It seeks to unravel the various dimensions of poverty, which include but are not limited to education, health, housing, sanitation, access to basic services, and overall living standards. Through a meticulous analysis of relevant data, this study intends to shed light on the distinct aspects of deprivation that converge to perpetuate poverty in the region. Moreover, it aims to critically assess the existing policies and interventions aimed at poverty reduction, considering their effectiveness in addressing the complex layers of disadvantage present in Jammu and Kashmir. The significance of studying multidimensional poverty in Jammu and Kashmir extends beyond academic inquiry. Effective poverty alleviation strategies demand a comprehensive understanding of the interconnected dimensions of deprivation that households and communities face. Such insights can inform the design and implementation of targeted interventions, tailored to the specific challenges faced by the region's population. By delving into the intricacies of multidimensional poverty in Jammu and Kashmir, this study aims to contribute both theoretically and practically to the discourse on poverty alleviation and sustainable development in India.

This research not only aims to understand the determinants of multidimensional poverty in Jammu and Kashmir but also adopts a managerial perspective by focusing on strategies to address these determinants. These strategies encompass a range of interventions, including policy recommendations, development initiatives, and specific actions that can be taken by government agencies, non-governmental organizations, and other stakeholders in the region. By delving into not only the root causes but also the potential solutions, this study seeks to provide actionable insights for reducing multidimensional poverty in Jammu and Kashmir.

This research will make a novel contribution to understanding multidimensional poverty in Jammu and Kashmir. Firstly, it will focus on specific dimensions of poverty that have not been adequately addressed before, such as education, health, housing, sanitation, access to basic services, and overall living standards. This will help uncover inequalities and vulnerabilities in different aspects of life. Secondly, the study will analyze existing policies and interventions aimed at reducing poverty in the region. By evaluating their effectiveness, the research aims to provide critical insights for further improvements. Thirdly, the research will consider demographic diversity, including ethnicity, religion, and language, and how these factors interact with poverty. This will provide unique insights into overlooked inequalities. Additionally, the research will not only analyze the causes of poverty but also emphasize strategies and solutions that can be implemented by stakeholders. This managerial focus aims to provide practical guidance for actions on the ground. Lastly, the research aims to bring theoretical and practical relevance to the issue of multidimensional poverty in Jammu and Kashmir. By delving into the complexities of poverty in the region, the study seeks to contribute to academic literature and offer implementable insights for more effective poverty alleviation strategies. Overall, this research aims to make a valuable contribution to understanding and mitigating multidimensional poverty.

However, it is crucial to acknowledge certain limitations and potential obstacles that may impact the scope and findings of the study. Its exclusive focus on the Jammu and Kashmir State in India necessitates caution in generalizing findings to other regions, as the dynamics of poverty can vary significantly across diverse geographical and socio-economic contexts. The selective incorporation of specific dimensions and indicators within each dimension, though providing depth, may inadvertently overlook other influential factors contributing to the intricate phenomenon of multidimensional poverty. Furthermore, the use of cross-sectional data, while offering a snapshot of poverty at a specific moment, lacks the nuanced understanding provided by longitudinal data, potentially limiting the assessment of trends and changes over time. The chosen indicators and their weighting, while carefully considered, may impact the overall assessment of poverty levels, potentially omitting relevant dimensions specific to the local context. External factors, such as macroeconomic conditions and government policies, are not extensively addressed in this study, thereby limiting a comprehensive understanding of the broader poverty landscape in Jammu and Kashmir.

2. METHOD

Model Specification

This study employed the Alkire and Froster (AF) method to examine the socio-economic profile of households in the Jammu and Kashmir and Binary Regression Model are employed to examine the determinants of multidimensional poverty in the study area.

AF Method

To estimate the nature and extent (socioeconomic profile) of household in the study area the following model is used. In order to examine multidimensional poverty, the current study employed the Alkire and Foster Methodology, which was developed in 2010 and endorsed by the United Nations Development Program (UNDP). This methodology combines the counting approach with the unidimensional FGT class, resulting in a set of measures that effectively assess and connect various dimensions of poverty. The method consists of two main steps: identifying the poor and then aggregating their poverty status. The AF-methodology was employed in this study to identify individuals living in poverty based on three dimensions: education, health, and standard of living. In order to maintain consistency and align with the Sustainable Development Goals (SDGs), the study utilized the same indicators for each dimension. The health dimension encompassed indicators such as child mortality and nutrition, while the education dimension included indicators such as years of schooling and child school attendance. The standard of living dimension consisted of six indicators, including the lack of adequate housing, sanitation facilities, cooking fuel, access to clean water, electricity, and household assets. Each indicator was assessed against specific thresholds, and individuals were classified as poor based on whether they fell below these predetermined norms. The Dual Cutoff method is employed in the Alkire and Foster methodology to identify individuals living in poverty. This method involves two cutoff points. The first one, known as the Deprivation cutoff, determines whether a person is deprived in each dimension. If an individual is deemed deprived based on the specified norms or cutoff values for the indicators within a dimension, a value of 1 is assigned. Conversely, if the person is non-deprived according to the predetermined cutoff, a value of 0 is assigned. The foundation of multidimensional poverty measurement lies in the achievement matrix X, which has dimensions of n x d. In this matrix, each entry Xij represents the achievement of person i in dimension j. For each dimension, a threshold zj is established as the minimum achievement required for an individual to be considered non-deprived. This threshold is referred to as the Deprivation Cutoff.

The deprivation cutoffs, represented as a vector z = (z1, ..., zd), are collected for each of the d dimensions. When comparing an individual's achievement level xij in dimension j to the respective cutoff zj, if xij is below zj, the person is considered deprived in that specific dimension (i.e., xij < zj). By utilizing the achievement matrix x and the deprivation cutoff vector z, a deprivation matrix g0 can be generated. In this matrix, gij0 is assigned a value of 1 whenever xij < zj, indicating deprivation, and assigned a value of 0 otherwise. The matrix gij provides a summary of the deprivation status across all individuals and dimensions in the achievement matrix x. Similarly, the vector gi0 summarizes the deprivation status of an individual i across all dimensions, while the vector gj0 summarizes the deprivation status of all individuals in dimension j. The importance of deprivation may vary across different dimensions. To account for this, a vector w = (w1, ..., wd) consisting of weights or deprivation values is used to indicate the relative significance of deprivation in each dimension. The weight assigned to dimension j is represented by wj, where wj > 0. In the Alkire and Foster methodology, each dimension is given equal weight, which is typically 1/3. For example, in the health dimension, child mortality and nutrition are assigned a weight of 1/6 each. Similarly, in the education dimension, both years of schooling and child school attendance are given a weight of 1/6. As the standard of living dimension consists of six indicators, each indicator is assigned a weight of 1/18.

Table 1. Dimensions, indicator, deprivation cutoff and weights of the global MPI (Multidimensional Poverty Index)

Dimension	Indicator	Deprivation cutoff	weight
Health	Nutrition	If any member in the household is undernourished	$^1/_6$
	Child mortality	One or more children have died	$^1/_6$
Education	Year of schooling	No one completed five years of schooling	$^1/_6$

Living Standard	School attendance	At least one school aged child not enrolled in school	$^1/_6$
	Cooking Fuel	The household cooking with dung, wood or charcoal	$^1/_{18}$
	Sanitation	The sanitation facility is not improved of the household	$^1/_{18}$
	Drinking water	The household does not have access to safe drinking water	$^1/_{18}$
	Electricity	The household has no electricity	$^1/_{18}$
	Floor	The household has a dirt, sand or dung floor	$^1/_{18}$
	Assets	The household owns at most on the following; radio, television, bike, refrigerator, and doesn't own a car or truck	$^1/_{18}$

Source; Alkire and Santos (2010,2014), cf. Alkire, Roche, Santos and seth (2011) and Alkire, Conconiand Roche (2013).

The deprivation score assigned to each individual is a measure of the extent of their deprivations across all dimensions, based on their deprivation profile. This deprivation score is calculated by summing the weighted deprivations. Mathematically, it can be expressed as:

$$\mathbf{C}=\sum_{j=1}^{d} w_j g_{ij}{}^{0} \quad \textbf{(1)}$$

To identify individuals who are experiencing multidimensional poverty, an additional cutoff or threshold known as the poverty cutoff is established and represented by the value k, where k equals 1/3. If a person's deprivation score equals 1/3, according to Alkire et al. (2015) approach, they are classified as poor. This criterion helps determine the poverty status of individuals based on the severity of their deprivations across multiple dimensions. Once the poverty cutoff is established, a censored deprivation score vector is derived by multiplying each entry of the deprivation score vector by the identification function. Alternatively, this censored deprivation score vector can be directly obtained from the censored deprivation matrix, and it can be calculated as follows:

$$\mathbf{Ci(k)}= \sum_{j=1}^{d} \mathbf{w_j g_{ij}{}^{0}\,(k)} \quad \textbf{(2)}$$

The censored deprivation score vector is represented as c(k). In the aggregation step, the deprivation scores of individuals who are not classified as poor are censored, and the proportion of individuals identified as experiencing multidimensional poverty in the population is computed. This proportion is known as the headcount ratio of multidimensional poverty (H), which indicates the incidence of multidimensional poverty. The calculation for the headcount ratio of multidimensional poverty can be determined using the following formula:

$$\mathbf{H}= \frac{q}{n} \quad \textbf{(3)}$$

The intensity of poverty (A) in the AF methodology is calculated by determining the average share of weighted indicators in which individuals classified as poor are deprived. This calculation provides a measure of the extent to which poor individuals experience deprivation across various dimensions. It is obtained by dividing the sum of the weighted deprivations of the poor by the sum of the weights assigned to the indicators. Mathematically, it can be expressed as:

$$\mathbf{A}=\frac{\sum_{I=1}^{N} Ci(K)}{q}$$
$$=\frac{\sum_{i=1}^{n}\sum_{j=1}^{d} w_j g_{ij}{}^{0}(k)}{q} \quad \textbf{(4)}$$

The censored deprivation score of individual 1, denoted as ci(k), is part of the overall calculation for individuals experiencing multidimensional poverty. In this context, q represents the number of people who are classified as multidimensional poor. Once the incidence (H) and intensity (A) of multidimensional poverty have been calculated, the multidimensional poverty index (MPI) is constructed by taking the product of H and A (MPI = H x A). The MPI represents the weighted deprivation experienced by individuals classified as poor, divided by the total population. In other words, it quantifies the overall level of multidimensional poverty by combining information on both the proportion of people living in poverty and the severity of their deprivations.

The AF methodology extends the FGT approach used for unidimensional poverty measures and produces a parametric set of measures. One of these measures is the Adjusted Multidimensional Headcount Ratio, denoted as M0 or MPI (Multidimensional Poverty Index). It is calculated as the average of the censored deprivation score vector, represented as:

$$\mathbf{M0}=\frac{1}{n}\,x\sum_{i=1}^{n} c_i(k) \tag{5}$$

The calculation of the percentage share of each indicator in the overall measure of multidimensional poverty was performed using the following function:

$$\phi_j^0(k) = \frac{w_j h_j(k)}{MPI} \tag{6}$$

The term $\phi_j^0(k)$ represents the contribution of dimension j to the Multidimensional Poverty Index (MPI). For each dimension j, ranging from 1 to d, if a specific indicator's contribution to poverty significantly surpasses its weight, there will be a relatively high censored headcount ratio associated with that indicator. This observation is outlined by Alkire, Roche, et al. (2015).

Binary Logistic Regression Model

The study employs the Binary Logistic Regression Model to investigate the factors influencing multidimensional poverty. The dependent variable in this analysis is a binary variable that indicates whether a household falls into poverty or not, with a value of 1 indicating poverty and 0 indicating non-poverty. The model considers various socioeconomic and demographic variables at either the household or village level. The model can be described by the following equation:

$$Logit(p) = In\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_i Edu_i + \beta_2 OCC_i + \beta_3 Owcl_i + \beta_4 EM_i + \beta_5 Gen_i + \beta_6 Age_i + \beta_7 HHS_i + \beta_8 HDR_i + \beta_9 Oc_i + \varepsilon \tag{7}$$

In this equation, X1, X2, … Xn represent the predictor variables, β0 is the overall intercept, β1, β2, β3, … βn are the regression coefficients, and Pj indicates the likelihood that the j-th household is living in poverty (or below the poverty line). The independent variables encompass three types: continuous variables, binary variables, and categorical variables. When dealing with categorical variables, a positive coefficient signifies that, while holding all other factors constant, the probability of experiencing poverty is higher compared to the reference category, and vice versa (Hashmi et al., 2008)

The logistic regression method will be employed to analyze the key determinants of poverty, considering both qualitative and quantitative variables. Specifically, the model aims to identify the factors that influence the probability of a household being in poverty. This binary logistic regression model is fitted with all available data, where the dependent variable represents household multidimensional poverty status, with two possible outcomes: "Poor" or "Non-Poor." The resulting model is represented as follows:

$$Logit(p) = In\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_i Edu_i + \beta_2 OCC_i + \beta_3 Owcl_i + \beta_4 EM_i + \beta_5 Gen_i + \beta_6 Age_i + \beta_7 HHS_i + \beta_8 HDR_i + \beta_9 Oc_i + \varepsilon \tag{8}$$

The fitted model will be evaluated to identify its strengths in terms of accuracy in predicting the outcome variable from each of the study's imputes/predictor variables. The model will be run using the R statistical software, and the parameters estimates are calculated using maximum likelihood estimation techniques.

Operational Definition

Table 2. Operational Definition of Variables

Variable Name	Operational Definition	Measurement	Categories	Scale
Household's poverty status	Households' status is whether poor or noon poor.	NFHS-5	1 = Poor 0 = non-Poor	Ordinal
Education of the Household head	Education is a way to get out of poverty (Todaro,2010). According to Dartanto & Nurkholis (2013), higher levels of education raise the probability of being less poor because it widens the opportunities for good job and income.	NFHS-5	0 = Illiterate 1 = Up to primary	Ordinal
Gender of Household head	Sex of household head is women or men. It is assumed that households headed by women are likely poorer than headed by men (Barros et al.1997; Buvinic and Gupta, 1977; Lampietti and Stalker, 2000)	NFHS-5	0 = Male 1 = Female	Nominal

Occupation of the Household head	It refers to what is the main occupation of household head	NFHS-5	1 = Service 2 = Business 3 = Farmer 4 = Daily wage 5 = Skilled labour	Nominal
Age of the Household head.	Age and productivity at work are related, and poverty in households is strongly correlated with the age of the household head (UNDP, 2015).	NFHS-5	1 = < 40 Years 2 = 40 - 60 Years 3 = > 60 Years	Numerical
Household Size	The number of people living in a family includes the children, their parents, and any other people who live with them (Becker, 2009).	NFHS-5	0 = Up to 4 1 = 5 - 6 2 = 7 and more	Numerical
Dependency Ratio	It refers to the household members who are not working.	NFHS-5	Continuous	
Number of Earning members	It refers to the total number of members who earn in the family.	NFHS-5	0 = Only member 1 = More members	
Ownership of Cultivated Land	Ownership of cultivated land pertains to the agricultural land that a household possesses and utilizes for cultivation purposes		0 = No 1 = Yes	
Occurrence of Conflict	It signifies the geographical regions, often categorized as districts, where conflict incidents take place.		0 = Not conflicted 1 = Conflicted	

Type and Source of Data

This study used secondary data. Further, the present study utilized the unit data from the fifth round of the National Family Health Survey (NFHS-5). NFHS is a nationwide cross-sectional demographic health survey conducted periodically (after each four years) under the stewardship of the Ministry of Health and Family Welfare, Government of India. NFHS 1 was conducted in 1992–93 and the NFHS-5 were conducted during 2019–21. For the collection of data,17 Field Agencies conducted NFHS-5 fieldwork in India in two stages, the first from 17 June 2019 to 30 January 2020 and the second from 2 January 2020 to 30 April 2021, collecting data from 636,699 households. In the first phase of the survey conducted in (2019-20), they collect the data from 318350 households. In the second phase of the survey conducted in (2020-21), collect the data from 318349 households across the country.

Descriptive Analysis

To analyze the data, two software packages were employed: SPSS (Statistical Package for the Social Sciences) and R. The analysis was conducted in two stages. Initially, households were classified into two groups, namely, those considered "poor" and those classified as "non-poor" based on their deprivation scores. Subsequently, the second stage of the analysis involved inferential analysis, where a binary logistic regression model was utilized to examine the factors influencing poverty status, taking into account the household's socioeconomic and demographic characteristics.

Nature and extent of multidimensional poverty

In calculating the overall Multidimensional Poverty Index (MPI), an individual was considered poor if they experienced deprivation in at least one-third of the indicators or if their deprivation score was equal to 0.333 ($k \geq 33.3\%$). The outcomes of multidimensional poverty, including incidence (H), intensity (A), and the Adjusted Multidimensional Poverty Index (MPI), are presented in Table 3. These results are based on the responses of households to ten fabricated indicators used for measuring multidimensional poverty.

Incidence of Multidimensional Poverty (H)

In the study area of Jammu and Kashmir, based on Table 3, the multidimensional headcount ratio stands at 15.24 percent, indicating that 15.25 percent of household's experience acute poverty. These findings align with the results obtained during the estimation of district-wise multidimensional headcount ratio. Notably, Ramban district exhibits the highest multidimensional headcount ratio at 37.21 percent, followed by Doda at 29.02 percent, Rajouri at 26.94 percent, Udhampur at 27.31 percent and Kishtwar at 25.91percent. In contrast, the Srinagar district of Jammu and Kashmir displays the lowest multidimensional headcount ratio at 2.26 percent, as shown in Table 3 and Figure 1.

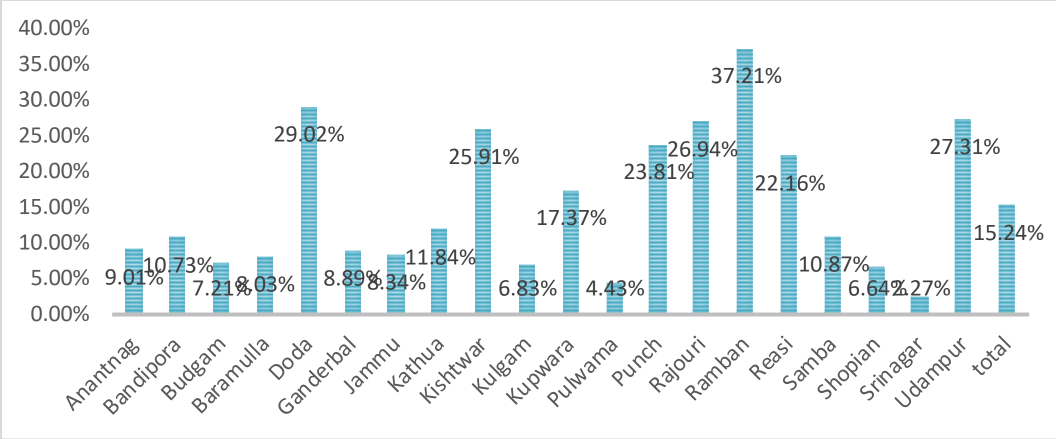

Figure 1. Incidence of multidimensional poverty

Table 3. Indices of Multidimensional poverty

Districts	H	A	M0
Anantnag	0.925	0.4821	0.445
Bandipora	0.1073	0.4493	0.048
Budgam	0.721	0.4217	0.304
Baramulla	0.803	0.4285	0.344
Doda	0.2902	0.4691	0.136
Ganderbal	0.883	0.4279	0.377
Jammu	0.834	0.4282	0.357
Kathua	0.1184	0.4401	0.052
Kishtwar	0.2591	0.4624	0.119
Kulgam	0.683	0.4437	0.303
Kupwara	0.1737	0.4223	0.073
Pulwama	0.434	0.4187	0.181
Poonch	0.2381	0.4299	0.102
Rajouri	0.2694	0.4525	0.121
Ramban	0.3721	0.4597	0.171
Reasi	0.2216	0.4384	0.097
Samba	0.1087	0.4347	0.047
Shopian	0.665	0.4277	0.284
Srinagar	0.227	0.4031	0.091
Udhampur	0.2731	0.4436	0.121
Total	**0.1524**	**0.4391**	**0.067**

Source: Author's Estimation

Intensity of Multidimensional poverty (A)

The poverty headcount ratio alone does not provide insight into the severity or intensity of poverty experienced by poor individuals. To gain a comprehensive understanding of poverty, it becomes crucial to compute the intensity of poverty in conjunction with the headcount ratio. The intensity of poverty refers to the average proportion of dimensions in which impoverished individuals experience deprivation. It measures the extent to which the poor are deprived. In the A.F. model, the intensity of multidimensional poverty is determined by the proportion of weighted indicators in which people are deprived. As shown in Table 3, the study area Jammu and Kashmir exhibits a 43.91 percent intensity of multidimensional poverty, which is almost equal to the national average of 43.9 percent (Sebidi & Vollmer, 2018). The study reveals that 15.24 percent of the multidimensionally poor population in the area experience deprivation in 43.91 percent of the weighted indicators.

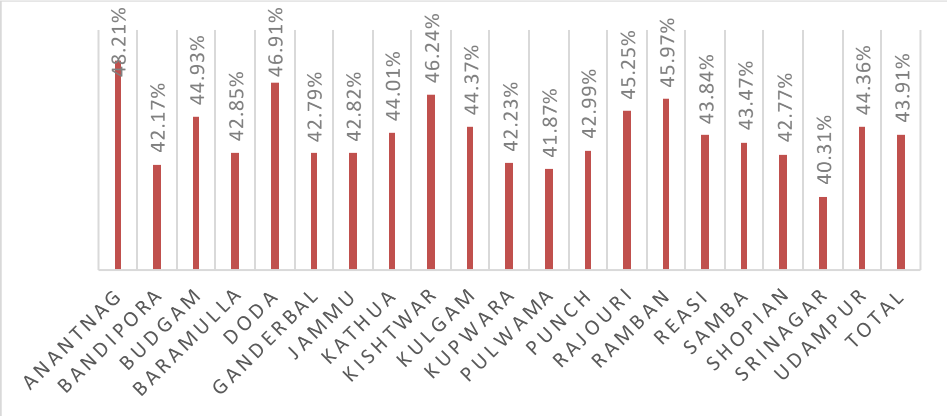

Figure 2. Intensity of multidimensional poverty

Based on the overall average in Figure 2, the Anantnag district exhibits the highest intensity of multidimensional poverty. It secures the 1st rank with an intensity of 48.21%. In contrast, the Doda district obtains the 2nd rank in the intensity of multidimensional poverty (46.91%), while achieving the 2nd rank in the headcount ratio for multidimensional poverty. The intensity of multidimensional poverty in Kishtwar district is found to be 46.24%, whereas Bandipora, Budgam, Baramulla, Ganderbal, Jammu, Kathua, Kulgam, kupwara, Pulwama, Poonch, Ramban, Reasi, Samba, shopian, Srinagar and Udhampur shows a ratio of (44.93%), (42.17%), (42.85%), (42.79%), (42.82%), (44.01%) and (44.37%) respectively. The presentation of intensity of multidimensional poverty is depicted in Figure 2.

Adjusted headcount ratio or MPI (M0)

The multidimensional headcount ratio (H) remains unchanged if an impoverished household experiences deprivation in an additional dimension, as it does not adhere to the dimensional monotonicity property. To address this limitation, an adjusted headcount ratio or MPI (Multidimensional Poverty Index) is introduced by Alkire, Roche, et al. (2015). The MPI is calculated as the mean of a censored deprivation score vector and can be expressed as follows:

$$\mathbf{M0} = \frac{1}{n}\, x \sum_{i=1}^{n} c_i(k) \tag{9}$$

Alternatively, the MPI (Multidimensional Poverty Index) can be formulated as the product of two partial indices, H and A (MPI = H x A). This implies that the MPI represents the proportion of the population that is multidimensionally poor, taking into account the intensity of deprivation experienced. This adjustment is crucial to determine whether the individuals identified as poor in the headcount ratio are equally impoverished or not. If all the people counted in the headcount ratio are deprived in all indicators, then the intensity (A) will be equal to 1, and consequently, the MPI will be equal to H. The MPI is referred to as an adjusted headcount ratio because it factors in the intensity of poverty (Alkire & Foster, 2011). When examining the estimation of the multidimensional poverty index across districts, it is observed that the Anantnag, Ganderbal, Jammu and Baramulla districts of Jammu and Kashmir have higher values compared to the calculated aggregate multidimensional poverty index. The values are 0.445 in Anantnag, 0.377 in, Ganderbal, 0.375 in Jammu and 0.344 in Baramula. On the other hand, Bandipora, Budgam, Kathua, Kulgam, Kishtwar, Pulwama, Poonch, Ramban, Reasi, Samba, and Shopian, districts in Jammu and Kashmir have values of 0.254, 0.165, and 0.129, respectively. The district-wise multidimensional poverty index of the study area is depicted in Figure 3. Therefore, the study reveals a high incidence and intensity of multidimensional poverty in Jammu and Kashmir. These results align with previous research conducted by Santos & Ura (2008), Thimmaiah (2015) and Megbowon (2018).

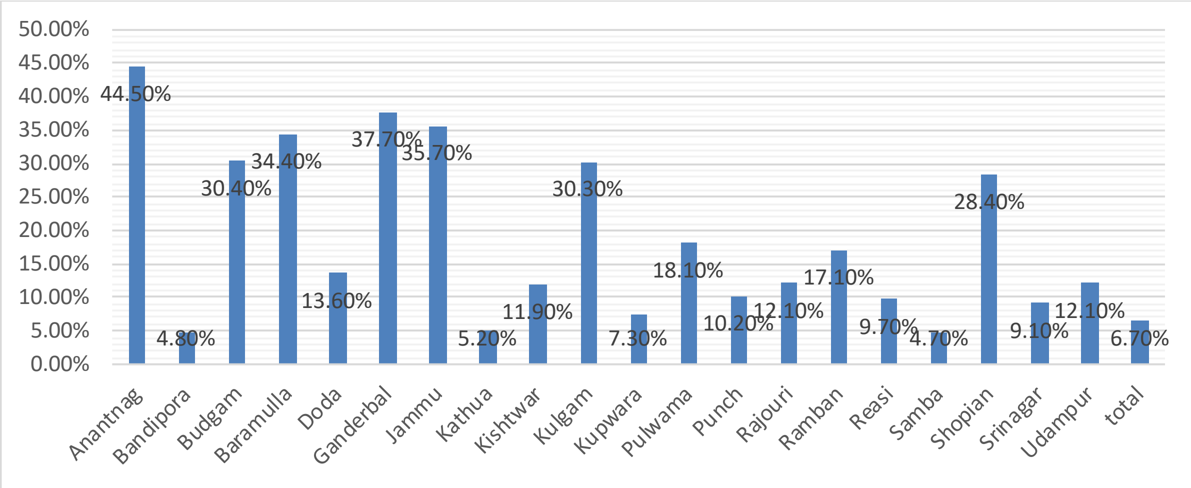

Figure 3. District wise MPI

Analysis of the decomposition of multidimensional poverty by indicators

One of the crucial characteristics of the multidimensional poverty index is its ability to satisfy the dimensional breakdown property. The MPI can be broken down into its individual censored indicators. This approach counts people who are both multidimensionally poor and deprived in each indicator. However, individuals who experience deprivation in some indicators but do not meet the poverty threshold are considered multidimensionally non-poor and are excluded when estimating the indicator-wise censored headcount ratio. Analyzing the indicator-wise distribution of the population in MPI provides valuable poverty-related information, which is beneficial for monitoring the impact of policy shifts and program changes.

Table 4. Indicator-wise Censored headcount Ratio

Districts	Nutrition	Child mortality	Year of schooling	School attendance	Sanitation	Electricity	Housing floor	Cooking fuel	Drinking water	Assets
Anantnag	0.06	0.01	0.06	0.02	0.07	0.02	0.04	0.07	0.02	0.05
Bandipora	0.05	0.01	0.04	0.02	0.06	0.01	0.04	0.05	0.01	0.03
Budgam	0.06	0.01	0.06	0.04	0.10	0.02	0.05	0.09	0.04	0.06
Baramulla	0.06	0.02	0.03	0.02	0.04	0.01	0.04	0.05	0.02	0.04
Doda	0.21	0.01	0.09	0.09	0.23	0.05	0.26	0.28	0.07	0.21
Ganderbal	0.07	0.02	0.04	0.02	0.07	0.01	0.03	0.06	0.02	0.03
Jammu	0.05	0.01	0.04	0.01	0.06	0.01	0.04	0.06	0.02	0.01
Kathua	0.11	0.01	0.04	0.02	0.12	0.01	0.12	0.13	0.07	0.08
Kishtwar	0.16	0.01	0.10	0.05	0.20	0.06	0.22	0.24	0.06	0.15
Kulgam	0.04	0.02	0.05	0.03	0.06	0.01	0.05	0.06	0.01	0.03
Kupwara	0.13	0.02	0.03	0.04	0.15	0.04	0.10	0.15	0.04	0.09
Pulwama	0.03	0.01	0.02	0.01	0.03	0.01	0.02	0.03	0.01	0.01
Poonch	0.21	0.02	0.05	0.02	0.19	0.02	0.20	0.24	0.13	0.16
Rajouri	0.22	0.01	0.06	0.04	0.25	0.04	0.23	0.25	0.18	0.15
Ramban	0.22	0.01	0.15	0.10	0.27	0.08	0.32	0.35	0.12	0.26
Reasi	0.18	0.01	0.06	0.03	0.18	0.05	0.21	0.21	0.10	0.10
Samba	0.07	0.01	0.04	0.01	0.10	0.02	0.09	0.09	0.04	0.06
Shopian	0.04	0.01	0.03	0.02	0.05	0.02	0.03	0.06	0.04	0.03
Srinagar	0.01	0.01	0.01	0.01	0.01	0.01	0.001	0.01	0.01	0.001
Udhampur	0.21	0.02	0.08	0.04	0.24	0.02	0.25	0.26	0.18	0.15
Total	0.11	0.01	0.05	0.03	0.12	0.02	0.11	0.13	0.05	0.08

Table 4 clearly indicates that concerning the indicator for years of schooling, the ratio of deprived individuals stands at (5%) within the study area. Among the districts, the highest ratio of deprived individuals in terms of years of schooling is observed in Ramban district at (15%), followed by Kishtwar at (10%), Doda at (9%), Udhampur district at (8%), Budgam and Rajouri at (6%) each, Reasi, Kulgam and Poonch are at (5%) each, Anantnag, Bandipora, Ganderbal, Jammu and Kathua are at (4%) each, Kupwara, Shopian, Baramula and Samba are at (3%) each. In the Pulwama and Srinagar districts, the corresponding ratios are (02%) and (01%), respectively. For the indicator of child mortality, (01%) of total households have experienced the passing away of a child in the last five years. At the district level, a higher headcount ratio is found in Baramulla, kulgam, Kupwara, Poonch and Udhampur districts (02%), followed by Anantnag, Bandipora, Budgam, Doda, Gandrbal, Jammu, Kathua, Kishtwar, Pulwama, Rajouri, Ramban, Reasi, Samba and Shopian districts are at (01%) each. District Srinagar have experienced only (0.005%) of child mortality in the last five years.

Table 4 also clearly indicates that concerning the indicator for Nutrition, the ratio of deprived individuals stands at (11%) within the study area. Among the districts, the highest ratio of deprived individuals in terms of years of schooling is observed in Rajouri and Ramban districts at (22%) and (22%), followed by Poonch and Udhampur districts at (21%) each, Doda at (21%), Reasi at (18%), Kishtwar at (16%), Kupwara at (13%), Kathua at (11%), Ganderbal and Samba at (07%) each Anantnag, Budgam, Baramulla at (06%) each, Bandipora, and Jammu at (05%) each, Kulgam and Shopian at (04%). In the Pulwama and Srinagar districts, the corresponding ratios are (03%) and (01%), respectively. Table 5.2 also illustrates that (11%) of households possess floors made of dung, clay, mud or dirt or sand.

Among all districts, the highest proportion of deprived households in terms of having an improved housing floor is noticed in district Ramban (32%) followed by Doda (26%), Udhampur (25%), Rajouri (23%), Kishtwar (22%), Reasi (21%), Poonch (20%), Kathua (11%), Kupwara (10%), Samba (9%), Budgam and Kulgam each (05%), Anantnag, Bandipora, Baramulla and Jammu each (4%), Ganderbal (3%), Pulwama (2%). The lowest percentage is in district Srinagar (0.1%). The percentage of households lacking access to improved sanitation facilities is determined to be (12%), within the study area. Across the districts the highest percentage of households experience this deprivation is in district Ramban (27%) followed by Rajouri district (25%), Udhampur (24%), Doda (23%), Kishtwar (20%), Poonch (19%), Reasi (18%), Kupwara (15%), Kathua (12%), Samba (10%), Budgam (10%), Anantnag (07%), Bandipora and Jammu each (06%), Shopian (05%), Baramulla (04%). The lowest percentage is in district Srinagar (01%). Concerning the indicator for cooking fuel usage, approximately (13%) of households utilize firewood or dung for cooking. Among all the districts the highest percentage is district Ramban (35%) followed by district Doda (28%), Udhampur (26%), Rajouri (25%), Poonch (24%), Kishtwar (24%), Reasi (21%), Kupwara (15%), Budgam and Samba each (09%), Anantnag (07%), Shopian, Ganderbal, Jammu, and Kulgam each (06%), Bandipora and Baramulla each (05%), Pulwama (03%). The lowest percentage is in district Srinagar (01%). Within the study area, households lacking access to safe drinking water comprise (05%).

Among the entire districts the larger proportion of households without access to safe drinking water facilities are in Rajouri (18%) and Udhampur (18%) followed by Poonch (13%), Ramban (12%), Reasi (10%), Doda and Kathua each (07%), Kishtwar (06%), Budgam, Kupwara, Samba and Shopian each (04%), Anantnag, Baramulla, Ganderbal and Jammu each (02%), Conversely, the smallest proportion of households experiencing deprivation in accessing safe drinking water is found in districts Srinagar, Bandipora and Kulgam each (01%). Regarding the household asset indicator, it is revealed that (08%) of household's face deprivation. Among all households, a greater percentage of those deprived of possessing at least one asset, such as a radio, mobile phone, TV, bike, refrigerator, etc., is evident in the district. Ramban (26%) followed by Poonch (16%), Doda (21%), Kishtwar, Rajouri and Udhampur each (15%), Reasi (10%), Kupwara (09%), Kathua (08%), Budgam and Samba each (06%), Anantnag (05%), Baramulla (04%), Bandipora, Ganderbal, Kulgam and Shopian each (03%). Conversely, lower percentages of households deprived of access to assets are found in Jammu and Srinagar (01%) and (0.01%) respectively. The graphical representation of the indicator-wise headcount ratios of households can be observed in Fig 5.3. The proportion of households lacking access to electricity facilities is determined to be (02%). The highest proportion of households lacking access to electricity is Ramban (08%) followed by Kishtwar (06%), Doda and Reasi each (05%), Kupwara and Rajouri each (04%), Anantnag, Budgam, Poonch, Samba, Shopian and Udhampur each (0.2%). The lowest percentage of households deprived to access to electricity are in districts Bandipora, Baramulla, Ganderbal, Jammu, Kathua, Kulgam, Pulwama and Srinagar (01%).

Percentage contribution of each indicator to the Multidimensional poverty index (MPI)

The censored headcount ratio aptly reveals the extent of deprivation within impoverished populations, it fails to illustrate the relative significance of individual indicators. Despite two indicators sharing the same censored headcount ratio, their respective contributions to the overall poverty landscape might differ due to the interplay between the censored headcount ratio and the assigned weight for each indicator. Consequently, to enhance our understanding beyond the censored headcount ratio, an additional analytical approach involves assessing the percentage contribution of each indicator to the broader multidimensional poverty context. This can be mathematically articulated as the contribution of dimension j to the Multidimensional Poverty Index (MPI). Which is shown in Table 5.

$$\text{Thus, } \boldsymbol{\phi_j^0(k)} = \frac{\boldsymbol{w_j h_j(k)}}{\boldsymbol{MPI}} \tag{10}$$

Table 5. Percentage contribution of each Indicator to MPI

Districts	Nutrition	Child mortality	Year of schooling	School attendance	Sanitation	Electricity	Housing floor	Cooking fuel	Drinking water	Assets
Anantnag	27.22	2.13	21.19	9.34	8.94	3.09	5.07	7.96	1.67	5.89
Bandipora	20.94	2.01	19.83	13.98	10.22	2.43	5.23	8.49	4.12	5.47
Budgam	30.09	1.52	25.21	11.01	10.07	1.34	5.18	7.93	2.01	3.08
Baramulla	33.14	2.47	13.96	13.00	7.21	0.08	5.96	9.01	3.44	5.03
Doda	24.87	1.01	10.94	10.43	8.35	2.03	8.94	10.18	3.02	6.86
Ganderbal	33.09	2.35	17.79	8.06	9.48	0.47	5.00	7.99	3.12	5.03
Jammu	29.01	1.56	23.07	4.96	9.13	0.27	6.89	8.59	3.37	2.47
Kathua	33.06	1.23	11.13	6.07	9.96	0.02	10.05	11.21	6.13	6.07
Kishtwar	25.15	2.07	16.01	8.35	9.14	2.63	8.89	9.93	2.28	7.11
Kulgam	23.02	1.23	22.85	11.48	9.06	1.90	8.13	9.00	1.54	3.47
Kupwara	33.09	2.06	7.21	6.49	11.06	2.63	7.13	11.03	3.21	5.97
Pulwama	29.21	1.07	16.32	12.01	10.06	3.04	6.03	9.13	2.00	4.16
Poonch	32.89	1.50	7.64	4.05	9.23	1.00	9.12	11.07	6.21	6.88
Rajouri	31.97	1.15	9.16	4.89	10.07	1.31	9.03	10.05	7.09	6.21
Ramban	23.08	1.02	14.95	11.03	8.13	2.46	8.97	9.93	3.47	7.49
Reasi	30.94	1.21	9.12	5.07	9.21	2.12	10.15	10.29	4.89	4.97
Samba	30.23	0.67	13.01	4.96	10.87	0.67	9.54	11.21	4.32	7.06
Shopian	24.99	0.58	21.01	8.89	9.10	2.97	6.10	9.39	4.00	5.13
Srinagar	34.21	2.34	32.07	22.91	5.99	0.57	1.46	0.78	0.57	0.21
Udampur	32.05	1.05	10.95	6.24	10.23	1.00	10.37	11.05	7.39	6.37
Total	**30.06**	**1.5**	**16.17**	**8.86**	**9.27**	**1.6**	**7.30**	**9.21**	**3.69**	**5.24**

Table 5 indicates that, when analyzing the allocation of each indicator's percentage contribution to the Multidimensional Poverty Index (MPI), it becomes evident that deprivation in nutrition holds a greater share (30.06) in the study area, surpassing the shares of other indicators. Subsequently, the next most substantial contributing indicator is the year of schooling (16.17), followed by access to improved sanitation (9.27), availability of adequate cooking fuel (9.21), school attendance (8.86), improved housing floor (7.30), ownership of assets (6.92). access to safe drinking water (5.24), and conversely, the smallest contributions to MPI are registered for access to electricity (1.6) and child mortality indicators (1.5). Looking at the districts within the sample, as per Table 4.6, for nutrition indicator, a higher share is discernible in Srinagar district (34.21percent) followed by Baramulla (33.14 percent), Ganderbal (33.09 percent), Kupwara (33.09 percent), Kathua (33.06 percent), Poonch (32.89percent), Udhampur (32.05 percent), Rajouri (31.97percent), Reasi (30.94 percent), Samba (30.23 percent), Budgam (30.09 percent), Pulwama (29.21 percent), Jammu (29.01 percent), Anantnag (27.22 percent), Kishtwar (25.15 percent), Shopian (24.99 percent), Doda (24.87 percent), Ramban (23.08 percent). The least share is found in the districts of Kulgam and Bandipora are (23.02 percent) and (20.94 percent) respectively. The child mortality indicator's contribution to the MPI is notably high in Baramula (2.47 percent) followed by Ganderbal (2.35 percent), Srinagar (2.34 percent), Anantnag (2.13 percent), Kishtwar (2.07 percent), Kupwara (2.06 percent), Bandipora (2.01 percent) Jammu (1.56 percent), Budgam (1.52 percent), Poonch (1.50 percent), Kathua (1.23 percent), Kulgam (1.23 percent), Reasi (1.21 percent), Rajouri (1.15 percent), Pulwama (1.07

percent), Udhampur (1.05 percent). District Ramban and Doda contribute the least share (1.02 percent) and (1.01 percent) respectively. The highest share of year of scholing indicator is found in Srinagar district (32.07 percent) followed by Budgam (25.21 percent), Jammu (23.07percent), Kulgam (22.85 Percent), Anantnag (21.19 percent), Shopian (21.01 percent), Bandipora (19.83 percent), Ganderbal (17.79 percent), Pulwama (16.32 percent), Kishtwar (16.01 percent), Ramban (14.95 percent), Bramulla (13.96 percent), Samba (13.01 percent) Kathua (11.13 percent), Udhampur (10.95 percent), Doda (10.94 percent), Rajouri (9.16 percent). Reasi and Poonch district contribute the least share (9.12 percent) and (7.64 percent) respectively.

The highest share for the indicator of children not attending school is evident in Srinagar district (22.91 percent), Bandipora (13.98 percent), Baramulla (13 percent), Pulwama (12.01 percent), Kulgam (11.48 percent), Ramban (11.03 percent), Budgam (11.01 percent), Doda (10.43), Anantnag (9.34 percent), Shopian (8.89 percent), Kishtwar (8.35 percent), Kupwara (6.49 percent), Udhampur (6.24 percent), Kathua (6.07 percent), Reasi (5.07 percent), Samba (4.96 percent), Jammu (4.96percent), Rajouri (4.89 percent). The least percentage share is registered in district Poonch (4.05 percent). Concerning the indicator of deprivation in access to improved sanitation, the higher share to the MPI is witnessed in Kupwara district (11.06 percent) followed by Samba district (10.87 percent), Udhampur (10.23 percent), Bandipora (10.22 percent), Budgam and Rajouri contribute the same share (10.07 percent) and (10.07 percent) respectively. Kupwara (10.06 percent), Kathua (9.96 percent), Ganderbal (9.48 percent), Poonch (9.23 percent), Reasi (9.21 percent), Kishtwar (9.14 percent), Jammu (9.13 percent), Shopian (9.10 percent), Kulgam (9.06 percent), Anantnag (8.94 percent), Doda (8.35 percent), Jammu and Ramban share each (8.13 percent), Baramulla (7.21 percent). The least contribution share is in district Srinagar (5.99 percent). Examining the percentage share of deprivation in accessing electricity facilities within the MPI, the highest share is in district Anantnag (3.09 percent) followed by Pulwama (3.04 percent), Shopian (2.97 percent), Kishtwar and Kupwara shares same (2.63 percent) each, Bandipora (2.43 percent), Reasi (2.12 percent), Kulgam (1.90 percent), Budgam (1.34 percent), Rajouri (1.31 percent), Poonch and Udhampur shares same each (1 percent), Samba (0.67 percent), Srinagar (0.57 percent), Ganderbal (0.47 percent), Jammu (0.27 percent). District Baramulla and Kathua shares least (0.08 percent) and (0.02 percent) respectively. In terms of the share of deprivation in the improved housing floor indicator a higher share is in district Udhampur (10.37 percent) followed by Reasi (10.15 percent), Kathua (10.05 percent), Samba (9.54 percent), Poonch (9.12 percent), Rajouri (9.03 percent), Ramban (8.97 percent), Doda (8.94 percent), Kishtwar (8.89 percent), Kulgam (8.13 percent), Kupwara (7.13 percent), Jammu (6.89 percent), Samba (6.54 percent), Pulwama (6.03 percent), Baramulla (95.96 percent), Bandipora (5.23 percent), Budgam (5.18 percent), Anantnag (5.07 percent), Ganderbal (5 percent). The least contribution share is in district Srinagar (1.46 percent).

When examining the percentage share of deprivation in access to adequate and improved cooking fuel in relation to the MPI, district Kathua and Samba shares the highest percentage each (11.21 percent) followed by districts Poonch (11.07 percent), Udhampur (11.05 percent), Kupwara (11.03 percent), Reasi (10.29 percent), Doda (10.18 percent), Rajouri (10.05 percent), Ramban and Kishtwar shares same each (9.93 percent), Shopian (9.39 percent), Pulwama (9.13 percent), Baramulla (9.01 percent), Kulgam (9 percent), Jammu 98.59 percent), Bandipora (8.49 percent), Ganderbal (7.99 percent), Anantnag (7.96 percent). The least percentage share is found in district Srinagar (0.78 percent). The contribution of deprivation in accessing safe drinking water indicators to the MPI is notably higher in district Udhampur (7.39 percent) followed by Rajouri (7.09 percent), Poonch (6.21 percent), Kathua (6.13 percent), Reasi (4.89 percent), Samba (4.32 percent), Bandipora (4.12 percent), Shopian (4 percent), Ramban (3.47 percent), Baramulla (3.44 percent), Jammu (3.37 percent), Kupwara (3.21 percent), Ganderbal (3.12 percent), Doda (3.03 percent), Kishtwar (2.28 percent), Budgam (2.01 percent), Pulwama (2 percent), Anantnag (1.67 percent), Kulgam (1.54 percent). Srinagar district contibutes the least percentage to MPI (0.57 percent).

Concerning the deprivation in accessing assets indicator, a greater share within the MPI is evident in district Ramban (7.49 percent) followed by Kishtwar (7.11 percent), Samba (7.06 percent), Poonch (6.88 percent), Doda (6.86 percent), Udhampur (6.37 percent), Rajouri (6.21 percent), Kathua (6.07 percent), Kupwara (5.97 percent), Anantnag (5.89 percent), Bandipora (5.47 percent), Shopian (5.13 percent), Ganderbal (5.03 per cent), Reasi (4.97 per cent), Pulwama (4.16 per cent), Kulgam (3.47 per cent), Budgam (3.08 per cent) district Jammu and Srinagar contributs the least percentage (2.47 per cent) and (0.21 per cent) respectively.

3. RESULT AND DISCUSSION

Results The findings of this section are that in the study area of Jammu and Kashmir, there is notable evidence of elevated multidimensional poverty when contrasted with national averages. The research illustrates that Jammu and Kashmir experience 15.24 per cent multidimensional poverty. Among the districts, Ramban, Doda, Udhampur and Rajouri districts exhibit a higher prevalence of multidimensional poverty, while Srinagar and Pulwama district in Jammu and Kashmir demonstrates the lowest occurrence. The intensity of multifaceted poverty is identified to be 44 per cent, which is slightly lower than the national (47.13 percent) average. When examining various districts higher intensity of multidimensional poverty is found in the district of Anantnag and

Doda, and the least intensity of multidimensional poverty is found in the district of Srinagar. The study's calculated Multidimensional Poverty Index for the study area is 0.067. Comparatively, a greater index value is recorded in the Anantnag district, while a lower value is noted in the Kathua district of Jammu and Kashmir.

Again, this study uses the Multidimensional Poverty Index (MPI) as a method of measuring poverty that considers more than one dimension or aspect of poverty. It is designed to provide a more comprehensive overview of poverty, not solely focusing on income or consumption but also taking into account other factors that influence human well-being. Developed by the Oxford Poverty and Human Development Initiative (OPHI) and proposed by economists Amartya Sen and Sabina Alkire, the MPI combines various dimensions of poverty, such as health, education, and living standards, to offer a more complete and accurate picture of poverty.

The calculation process of MPI involves several steps:

1. Selection of Dimensions: Poverty dimensions are chosen based on international consensus and the specific characteristics of each country. For instance, the health dimension may include access to healthcare services and nutritional status, while the education dimension may encompass access to and participation in education.
2. Selection of Indicators: Key aspects of each dimension are represented by selected indicators. For the health dimension, indicators may include infant mortality rates and access to clean water.

2) Assessment of Individual or Household Status: Data is obtained from surveys or other data sources to assess the status of individuals or households regarding each indicator. Each individual or household is then classified as either multidimensionally poor or not poor for each indicator.
3) Multidimensional Poverty Classification: Individuals or households are considered multidimensionally poor if they are deprived in one or more dimensions. This allows for the identification of people or families who may be overlooked by traditional poverty measurements that focus solely on income.
4) Index Calculation: MPI is calculated by combining the proportion of the population that is poor in one or more dimensions. The MPI value ranges from 0 (no poverty) to 1 (full poverty).

The significance of MPI in the context of poverty assessment lies in its ability to provide a more holistic and inclusive view of societal conditions. By incorporating multiple dimensions, MPI aids governments and stakeholders in designing more effective and comprehensive policies to reduce poverty. MPI also facilitates comparisons between countries or regions, helping to assess global or regional poverty levels by considering various aspects of human well-being.

In the examination of the composition of multifaceted poverty components, which is based on three dimensions and ten indicators, it is observed that the higher proportion of nutrition indicators in the entire study region contributes more to the Multidimensional Poverty Index (MPI), followed by indicators related to year of schooling, sanitation, cooking Fuel, school attendance, housing fuel, assets, and drinking water. Conversely, a relatively smaller share of the MPI is attributed to the child mortality dimension and the electricity indicator. In the current chapter, the exploration of the extent and characteristics of multidimensional poverty underscores the variability of poverty status across the districts. Multiple factors could potentially account for the occurrence of multidimensional poverty among the sampled households. While statistics depicting the prevalence of poverty are undoubtedly valuable as they inform us about the evolving trends of poverty over time, they do not, however, shed light on the interconnectedness of the factors associated with poverty. The study found that the share of nutrition indicator to multidimensional poverty is higher as compared to the rest of the indicators. The result is consistent with the result of the Planning Commission Government of India (2018). Thus, an answer to the first research question, the study shows a higher percentage share of nutrition indicators to multidimensional poverty in the entire study area of Jammu and Kashmir as well as across all the districts.

Determinants of multidimensional poverty of household

The previous section delved into an examination of the nature and scope of multidimensional poverty. The estimations regarding the prevalence of multidimensional poverty provide valuable insights into the trajectory of poverty over time. Analyzing the breakdown of poverty's evolution over time is crucial to understanding whether poverty has seen an increase or decrease. However, this understanding is insufficient for a comprehensive grasp of the underlying reasons behind multidimensional poverty. A range of factors, including socio-economic and demographic ones, could potentially influence the multidimensional poverty experienced by individuals. This section aims to unveil the factors that might be associated with the multidimensional poverty faced by the population of Jammu and Kashmir. Additionally, the relative significance of these variables is assessed to formulate targeted strategies for addressing the challenges in the study area.

Specification of the Empirical Model and Expected sign of the independent variables

Creating an equation to estimate multidimensional poverty, which illustrates the correlation between household poverty levels and a range of potential determinants, could confront the challenge of endogeneity. This arises due to the direct inclusion of exogenous variables in constructing multidimensional poverty. A common strategy to address endogeneity is to employ non-indicator measurement variables, such as certain demographic and supplementary socio-economic characteristics of the household (Alkire, Foster, et al., 2015). In this study, an effort has been made to minimize the reliability on variables that might be prone to reverse causation. Instead, internal factors distinct from the average attainment of all household members have been utilized (Osmani & Latif, 2013). Utilizing this rationale, the current study employs a binary logistic regression model to identify the factors influencing multidimensional poverty among households in Jammu and Kashmir. The variable of interest is the incidence of multidimensional poverty among the households in the sample, represented dichotomously as 1 for those categorized as multidimensionally poor and 0 for those designated as multidimensionally non-poor. This classification is based on the deprivation score assigned to each sampled household, distinguishing them as either poor or non-poor. The inherent nature of this dependent variable precludes the use of a linear functional form, which could yield misleading interpretations when applied to dummy dependent variables. Consequently, to address this issue, researchers have turned to a binary logistic regression model. In line with this approach, the logistics function (Gujarati, 2009) has been employed as presented below.

$$\boldsymbol{P_i = E\left(Y = \frac{1}{X_i}\right) = \frac{1}{1+\varepsilon^{-(\beta 0+\beta ixi)}}} \tag{11}$$

Pi defines the probability of a household being in a state of poverty. In this equation, when Y equals 1, it signifies that the household is experiencing multidimensional poverty. The equation incorporates the various factors that impact a household's multidimensional poverty status. The symbols β0 and βi are the coefficients obtained from regression analysis, while 'e' stands for the mathematical constant known as the base of the natural logarithm. Thus, the expression can be represented as follows:

$$\boldsymbol{1 + \frac{1}{1|e^{-Z_i}}} \tag{12}$$

Where $Z_i = \beta_0 + \sum \beta_i X_i + \varepsilon$

Here, ε is the disturbance term.

So, if Pi represents the likelihood of a household experiencing multidimensional poverty, then 1-Pi represents the likelihood of the household not experiencing multidimensional poverty. Thus

$$\boldsymbol{P = \frac{1}{1+e^{Z_i}}} \tag{13}$$

Thus, can write the equation as

$$\boldsymbol{\frac{P}{1-P_i} = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{Z_i}} \tag{14}$$

In this context, $\frac{P}{1-P_i}$ represents the quotient of the probability that a household might encounter multidimensional poverty against the probability that it won't experience such poverty. This signifies the odds ratio that leans towards the occurrence of multidimensional poverty.

The natural logarithm of expression (11) can be written as,

$$\boldsymbol{L_i = In(\frac{P_i}{1-P_i} = Z_i = \beta_0 + \sum \beta_i X_i + \varepsilon} \tag{15}$$

Here, $\boldsymbol{L_i}$ is the log of odd ratio and term as logit and the model is a logistic regression model.

thus, the model is expressed in the following equation.

$$\boldsymbol{Logit(p) = In\left(\frac{Pi}{1-Pi}\right) = \beta_0 + \beta_i Edu_i + \beta_2 OCC_i + \beta_3 Owcl_i + \beta_4 EM_i + \beta_5 Gen_i + \beta_6 Age_i + \beta_7 HHS_i + \beta_8 HDR_i + \beta_9 Oc_i + \varepsilon} \tag{16}$$

Thus, the expression represents the binary logistic model employed to assess the determinants affecting multidimensional poverty among households within the study region.

Table 6 presents a compilation of potential independent variables that could contribute to the occurrence of multidimensional poverty among the sampled households, along with the anticipated directions of their effects on multidimensional poverty.

Table 6. Specification of Independent Variable and Expected Sign for Multidimensional Poverty

Independent variable	Description and Measurement	Expected Sig
Education of the Household Head (Edu)	0 = illiterate 1 = up to primary	-
Occupation of the Household Head (Occ)	1 = service 2 = business 3 = farmer 4 = daily wage 5 = skilled labor	-
Ownership of cultivated Land (Owcl)	0 = No 1 = Yes	-
Number of Earning members (EM)	0 = Only member 1 = more members	+
Gender of the Household Head (Gen)	1 = Male 0 = Female	-/+
Household Head Age (Age)	1 = < 40 Years 2 = 40-60 Years 3 = > 60 Years	-/+
Household Size (HHS)	0 = up to 4 1 = 5-6 2 = 7 and more	-/+
Household Dependency Ratio (HDR)	Continuous	+
Occurrence of Conflict (Oc)	0 = not conflicted 1 = conflicted	+

In the Table 6 the specification, measurement and expected sig for multidimensional poverty status is shown binary logistic regression model to determine the significant factors of multidimensional poverty is run in SPSS software after testing the assumption and found no assumptions have been violated. There is no multicollinearity problem in the data set as the Variable Inflation Factor (VIF) is found to be less than ten (VIF<10) All the predicted variables, except dependency ratio are taken as categorical as it is well fitted in the model than taking as continuous. The estimated result of the regression analysis on multidimensional poverty is shown in Table 7.

As can be observed in Table 7, the key determinants of multidimensional poverty are as follows: The coefficient pertaining to the education level of the household head exhibits a negative correlation with multidimensional poverty and demonstrates significance at the 10 per cent level. Specifically, households led by individuals possessing at least a primary level of education are 41 per cent less likely to experience multidimensional poverty when compared to households led by those lacking formal education. Education serves to enhance awareness and amplify the skills and capabilities of individuals, thereby augmenting their earning potential and contributing to their overall well-being. Educated individuals are better positioned to access gainful employment opportunities, consequently elevating productivity and fostering a prolonged and healthy life.

Table 7. Results of Binary Logistic Regression for Multidimensional Poverty of the Households

Predictor Variables		Coefficient (β)	SE	OR	Sig
Education					
	No formal Edu	-0.515	0.223	.596*	0.018
	Up to primary				
Occ					
	Service	-0.764	0.395	.469**	0.055
	Petty business	-1.196	0.403	.305*	0.005
	Farmer	-0.589	0.397	0.558	0.139
	Daily wage	-0.413	0.46	0.665	0.371
	Skilled labour				
Owel					
	Owned land	-2.418	0.22	.091*	.000
	Not owned land				
EM					
	Only earner	-1.679	0.291	.189*	.000
	Other earner				
Gen					
	Male	0.227	0.321	1.255	0.482

	Female				
Age					
	Less than 40 yrs	-3.331	0.465	.038*	.000
	40-60 yrs	-0.005	0.243	1.005	0.992
	60 and above				
HHS					
	Up to 4	-0.282	0.252	0.758	0.265
	7 and above	-0.719	0.416	.490***	0.086
	HDR	0.065	0.132	1.067	0.629
Ooc					
	Conflicted	2.34	0.28	0.39	.004
	Not conflicted				
	Constant	2.943	0.537		.000
	Model Prediction Success		82.80%		
	-2log likelihood		671.084		
Hosmer-Lemeshow model sig. test (df-8)			12.839 (p=.119)		
	Cox and Snell R^2		0.426		
	Nagelkerke R^2		0.586		

*,** and *** implies 10, 5 and 1 percent level of significance

The acquisition of education facilitates increased earnings, which in turn aids in the mitigation of poverty (M. Tariq Majeed & Malik, 2015). Thus, an escalation in education levels corresponds to a reduction in the incidence of multidimensional poverty. The occupation of the household head emerges as a noteworthy determinant of multidimensional poverty within the surveyed region. Notably, individuals employed in the service sector exhibit a significant association with multidimensional poverty at the 5 per cent level of significance. Specifically, service workers are observed to have a 48 per cent reduced likelihood of experiencing multidimensional poverty compared to those engaged in skilled labour. Similarly, household heads involved in petty business also display a significant link with reduced multidimensional poverty, exhibiting a 69 per cent decreased likelihood when contrasted with the reference group of skilled labour. In the context of this study, the occupations of farming and daily wage labour do not demonstrate significant implications for multidimensional poverty within the sampled region (Osmani & Latif, 2013).

The ownership of cultivated land emerges as a noteworthy and significant predictor of multidimensional poverty within the scope of this study. Significantly, at the 10 per cent level of significance, the observed negative coefficient value implies that household heads who possess cultivated land are 91 per cent less likely to experience multidimensional poverty in comparison to those who do not own cultivated land. This finding aligns with the outcomes reported by Bogale et al. (2005) and Muhammad Tariq Majeed & Malik (2016). The presence of supplementary income earners within a household contributes to the overall household income. The outcome reveals a notable and statistically significant negative correlation between poverty and the existence of additional income earners within the household, observed at the 10 per cent level of significance. Within the context of this study, household heads benefiting from the presence of additional income earners are shown to be 81 percent less likely to experience multidimensional poverty, in comparison to households lacking such additional earners. This result is in accordance with the research findings of Deressa & Sharma (2014) and M. Tariq Majeed & Malik (2015). The gender of the household head, as indicated by the coefficient, is not identified as a significant predictor of multidimensional poverty within the study region. The age of the household head emerges as a significant determinant of multidimensional poverty within the study locale. The negative coefficient value associated with younger household heads, significant at a 5 per cent level, indicates that households led by younger individuals are 96 per cent less likely to experience multidimensional poverty when compared to those headed by older individuals. This disparity may be attributed to factors like increased work efficiency and labor mobility within the younger household head demographic. In this study, household size exhibits a negative correlation with multidimensional poverty. The negative coefficient value, significant at 1 per cent level, signifies that larger families are 42 per cent less prone to experiencing multidimensional poverty in contrast to smaller families. A larger household size potentially entails a greater number of earning members, thereby diminishing the likelihood of poverty within a larger family context. The dependency ratio doesn't emerge as a significant predictor of multidimensional poverty in the study area. In this study occurrence of conflict exhibits a positive coefficient which implies that there is a positive relationship between conflict and probability of falling in poverty. Those districts which have witnessed conflict as seen, their poverty increases by this coefficient. The provided analysis of the findings indicates that education, occupation, land ownership, secondary earners, age, conflict and household size are crucial indicators of multidimensional poverty within the study region. Therefore, in response to the second research question, it can be concluded that socioeconomic and demographic factors including education, occupation (specifically in the service and petty business sectors), ownership of cultivated land, presence of additional earners, age, and household size significantly influence multidimensional poverty in the study area.

4. CONCLUSION

This research investigates multidimensional poverty in Jammu and Kashmir, focusing on its characteristics and determinants, hypothesizing that it exceeds one-dimensional monetary poverty. The findings reveal coexistence of income and multidimensional poverty, with a higher prevalence of the latter, particularly in Ramban district. Factors like education, occupation, and land ownership significantly influence poverty, and conflict escalates multidimensional poverty likelihood. The logistic regression model predicts poverty with 82.80% accuracy. Indicator analysis underscores the importance of nutrition, sanitation, housing, and school attendance. The study emphasizes the local context's role in shaping poverty experiences, and in addressing these determinants, a managerial approach is advocated, stressing the need for practical, result-oriented actions by various stakeholders to reduce poverty in the region, including government agencies, non-governmental organizations, and other entities dedicated to economic development.

This study has limitations as it focuses solely on Jammu and Kashmir State in India, necessitating caution in generalizing its findings to other regions. The selective incorporation of specific dimensions and indicators within each dimension may overlook other influential factors in the complex phenomenon of multidimensional poverty. The use of cross-sectional data presents a snapshot of poverty at a particular moment, lacking the dynamic understanding provided by longitudinal data. The chosen indicators and their weighting may impact the assessment of poverty levels, potentially omitting relevant dimensions in the local context. External factors such as macroeconomic conditions and government policies are not extensively addressed, limiting a comprehensive understanding of the poverty landscape. Future research is recommended to conduct longitudinal studies, incorporate qualitative methods for richer insights, explore intersections of poverty in vulnerable groups, assess the effectiveness of existing policies, conduct comparative analyses in other regions, and employ advanced econometric techniques to establish causal relationships between determinants and multidimensional poverty outcomes.

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