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RETHINKING MULTIDIMENSIONAL POVERTY IN BANGLADESH: HOW DO WEIGHTS INFLUENCE THE MAPPING?

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The complexity of poverty is widely acknowledged, as it involves various contributing factors. This study centers on implementing the modified Alkire-Foster methodology to establish a multidimensional poverty index. Utilizing data from the 2019 Multiple Indicator Cluster Survey, encompassing three dimensions and ten well-being indicators, the analysis demonstrates that considering all indicators ($n = 10{,}352$) with no missing cases yields a multidimensional poverty index of 0.150. However, when incorporating missing cases as non-deprived individuals ($n = 59{,}066$), the index decreases to 0.104. Furthermore, utilizing modified principal component analysis, the poverty index is assessed at 0.260 ($n = 10{,}352$). The study's findings suggest that individuals in rural areas, particularly those headed by males, experience heightened deprivation compared to their counterparts.

Keywords: Multidimensional poverty index, Decomposition, Multiple Indicator Cluster Survey, Principal component analysis, Bangladesh
JEL Classification: B21, C01, I32

1. INTRODUCTION

Bangladesh has achieved notable success in reducing poverty from a single-dimensional perspective, with the poverty rate dropping from 48.9% in 2000 to 24.3% in 2016, indicating consistent advancement toward meeting the Sustainable Development Goal (SDG) of poverty alleviation by 2030 (GED, 2020). As of 2021, Bangladesh's extreme poverty rate stands at 4%, while the single-dimensional monetary poverty rate is 20.5% (ADB, 2022). However, poverty is a dynamic and evolving phenomenon. For example, Sakamoto et al. (2020) underscored the impact of COVID-19 on Bangladesh's progress toward various SDGs, while Benedek et al. (2021) illustrated how the pandemic impeded global SDG achievements. Therefore, to maintain the progress in poverty reduction, it's vital to regularly and comprehensively evaluate poverty across diverse population groups and using varied samples. Additionally, it's crucial to transcend a single-dimensional view and examine poverty within a multidimensional framework.

In recent years, there has been a growing recognition of poverty as a multidimensional concept, encompassing not only a lack of income but also inadequate access to food, child malnutrition, illiteracy, lack of sanitation, safe water, and other factors (UNDP, 2000). Several attempts have been made to quantify and measure poverty. Sen (1976) emphasized the numerical measurement of poverty and proposed an ordinal approach, but it faced criticism for its lack of decomposability principles. Foster et al. (1984) later introduced the FGT measure, a cardinal unidimensional poverty measure that satisfied the principles of monotonicity and transfer. Anand and Sen (1997) expanded on this by proposing the marginal poverty measure, which led to the development of the Human Poverty Index (HPI), aggregating the marginal dimensions of multiple indicators. Atkinson (2003) introduced the study of multiple indicators through union and intersection approaches to measuring poverty. The union approach defined someone as poor if they were deprived in any dimension, while the intersection approach defined someone as poor if they were deprived in all dimensions. However, these approaches had drawbacks of overestimating and underestimating poverty, respectively (Alkire and Seth, 2009). Bourguignon and Chakravarty (2003) proposed a unidimensional identification approach to measure poverty, but the weighting factor for aggregating dimensions remained unresolved.

To overcome the limitations of measuring poverty through a single dimension, Alkire and Foster (2007, 2011) introduced the multidimensional poverty index (MPI). This index incorporates deprivation cutoffs within and across dimensions, assigning appropriate weights. The MPI can be seen as a middle ground between the concepts of union and intersection. Alkire and Jahan (2018) conducted a significant reconstruction of the global MPI, examining the theoretical foundation, data accessibility, and policy relevance of five indicators out of ten (nutrition, child mortality, school years, housing, and ownership of assets). Alkire and Fang (2019) utilized Chinese data to demonstrate the MPI's stability across different time periods and regions. Alkire and Kanagaratnam (2020) proposed adjusting indicators for globally comparable multidimensional poverty measures approximately once every decade. In addition to measurement, determining the optimal weights for the MPI is also crucial. Despite the numerous advantages associated with implementing the Alkire Foster (AF) weights, significant criticisms also exist (Pratama and Rahadiana, 2023). A notable critique comes from Catalán and Gordon (2020), who scrutinized the reliability and construct validity of the AF version within the MPI. Focusing on the MPI for Latin America developed by Santos and Villatoro (2018) as a case study, they contended that AF weights are statistically unreliable, and its predefined dimensional structure is invalid. In response, this study introduces an adjustment to the AF method through a statistical approach while maintaining the originally proposed indicators and dimensions. Njong and Dschang (2008) utilized techniques such as principal component analysis (PCA), multiple correspondence analysis, and fuzzy logic to derive data-driven weights for estimating the MPI. Also the worldwide Demographic and Health Survey (DHS) wealth-index is measured by the PCA weights (BDHS, 2022). Consequently, it is anticipated that this study will address the limitations of the AF method. PCA weights for the individual indicators are estimated through a statistical procedure, whereas AF weights are rather equal and arbitrary.

Over time, MPI measurements have gained widespread usage in assessing poverty, both on national and international scales. Numerous studies have employed MPI to analyze poverty dynamics in various countries. For instance, it has been utilized to examine poverty in China (Yu, 2013), India (Dotter and Klasen, 2014; Dehury and Mohanty, 2015), South Africa (Rogan, 2016), Colombia (Angulo et al., 2016), and Germany (Suppa, 2018). Santos and Villatoro (2018) employed MPI to study poverty in 17 Latin American countries, while Alkire et al. (2015) applied it for global poverty tracking. Beyond poverty measurement, research by Bersisa and Heshmati (2021) found that MPI is more effective in monitoring and addressing poverty across its various dimensions, particularly as the Sustainable Development Goals (SDGs) encompass additional dimensions of well-being. Masset and García-Hombrados (2021) identified several advantages of MPI over other poverty measures, including its simplicity in construction, its ability to summarize diverse information in a single metric, and its capacity for explicit comparative analysis among different groups.

Moreover, Burchi et al. (2022) conducted a study examining long-term and mid-term trends in multidimensional poverty in low- and middle-income countries. Their findings revealed that interventions successful in reducing income poverty may not necessarily be effective in reducing multidimensional poverty. Jung (2022) showcased how MPI could be instrumental in directing attention towards outlier population cohorts in countries where there is a weak alignment between poverty diagnosis and aid distribution. Furthermore, Pandey et al. (2022) employed PCA to construct MPI at the household level, making comparisons between urban and rural areas. Overall, MPI has proven to be a valuable tool in assessing poverty and has been employed in diverse contexts, contributing to a deeper understanding of poverty dynamics and informing efforts towards poverty alleviation.

The official poverty index of Bangladesh, as measured by the Bangladesh Bureau of Statistics (BBS), currently adopts a unidimensional approach based on per capita consumption expenditure (HIES, 2022). However, Alkire et al. (2011) conducted a study in 2007 revealing that 58% of the population in Bangladesh experienced multidimensional poverty, with an MPI score of 0.292. Their findings indicated that living standards were the primary indicator of poverty, followed by nutrition and education. Another study in 2013 reported an MPI score of 0.1480 for Bangladesh (UPPR, 2015). In 2020, Alkire and Kanagaratnam (2020) reported an MPI score of

0.104 for Bangladesh. However, their study assumed that households without children under the age of five were non-deprived in the nutrition indicator, leading to an underestimation of the MPI index. Furthermore, the nutrition indicator was given greater weight compared to other dimensions.

Apart from the work done by Alkire and Kanagaratnam (2020), there have been few recent studies examining multidimensional poverty in Bangladesh. Islam et al. (2020) reviewed the nature of poverty and social inequality in Bangladesh, while Kamruzzaman (2021) conducted a qualitative analysis on the perception of poverty among the extremely impoverished population. Omar and Hasanujzaman (2021) focused on studying multidimensional energy poverty in Bangladesh, and Aziz et al. (2021) demonstrated how women empowerment contributed to poverty reduction in rural areas of Bangladesh. Dutta (2021) analyzed the impact of multidimensional poverty on children in India and Bangladesh, while Tauseef (2022) examined the importance of income, relative income, and non-monetary aspects of poverty in individual well-being.

To fill the void in recent MPI estimation and explore the influence of subjective and random weights of indicators, this study endeavors to calculate the MPI for Bangladesh by utilizing data from the Multiple Indicator Cluster Surveys (MICS) conducted in 2019. The research paper also aims to examine the poverty indices of diverse population groups and subgroups to analyze the distribution and dynamics of poverty. Thus, the study has two primary objectives: firstly, to estimate the weighted MPI index for Bangladesh using the MICS 2019 data, and secondly, to analyze different population groups and subgroups in order to comprehend the distribution and changes in poverty.

The paper is structured as follows. Section 2 offers a comprehensive discussion of the data and variables employed in this study. In section 3, we present our methodology and the outcomes of our analysis. Finally, section 4 concludes by summarizing the key findings of this study and section 5 includes discussion and conclusion for policy implications.

2. DATA AND VARIABLES

The data used in this study were collected from the Bangladesh Multiple Indicator Cluster Survey (MICS) conducted in 2019. The survey was conducted jointly by the Bangladesh Bureau of Statistics (BBS) and UNICEF Bangladesh as part of the Global MICS Program. The survey involved in-person interviews with a total of approximately 59,066 households, conducted between January 19 and June 1, 2019. The selection of households followed a two-stage stratified cluster sampling approach. Enumeration areas were randomly chosen from the 2011 census list, and within each selected enumeration area, households were listed, and a sample of households was then selected as the second stage.

In this study, we analyzed data from a total of 10,352 households that had complete information on three dimensions and ten indicators. The selected indicators covered a wide range of aspects, including educational and health status, access to electricity, availability of safe water, condition of floors and roofs, type of cooking fuel used, and measurement of household assets. These indicators were extracted from the dataset and served as the foundation for our analyses.

3. METHODOLOGY

3.1. The Alkire-Foster MPI

The estimation of multidimensional poverty can be broken down into two main steps: identification and aggregation (Sen, 1976; Bourguignon and Chakravarty, 2003). In this study, we utilize the AF (2011) method, which incorporates a dual cut-off threshold to measure multidimensional poverty and provides enhanced flexibility. This method allows for the aggregation of deprivation across different dimensions, enabling us to determine the percentage of the average poor individuals experiencing deprivation in each dimension. To establish the identity function, the first step involves defining an achievement matrix for the population.

Let $y = [y_{ij}]$ denotes an $n \times d$ achievement matrix where i denotes the individual achievement and j denotes the poverty dimensions, n is total population and $d$indicates dimension. The identity function is defined as

$$\rho_k(y_i|z) = \begin{cases} 1 & c_i \geq k \\ 0 & c_i < k. \end{cases} \tag{1}$$

Here, z is our deprivation threshold for each dimension, c_i represents the number of deprivations suffered by person i and k is our poverty cut-off threshold. The dimensional deprivation threshold vector defined as $z = (z_1, \cdots, z_d)$, is fixed for each dimension and determines whether an individual is regarded as deprived in an indicator. The variable $k = 1, \cdots, d$ acts as the dynamic poverty cut-off threshold. Values of from $k = 1$ and $k = d$ are special cases of union and intersection (Atkinson, 2003) method of poverty identification. Increasing values of k increases the censoring of non-poor individuals and this censored deprivation matrix is denoted as,

$$g_{ij}^{\alpha}(k) = g_{ij}^{\alpha}\rho_k(y_i|z), \tag{2}$$

where α is the elasticity of individual poverty with respect to the normalized gap, so that a 1% increase in the gap of a poor person leads to an α% increase in the individual's poverty level. Afterwards, FGT based poverty measure is used for aggregation. This is defined as,

$$M_0 = HA = \frac{q(y|z)}{n} \times \left|\frac{c(k)}{qd}\right| = \mu(g^0(k)). \tag{3}$$

Here, $H = \frac{q(y|z)}{n}$ is the headcount ratio, n is the total population, $q(y|z) = \sum_{i=1}^{n} \rho_k(y_i|z)$denotes the total deprived individualsand $A = \left|\frac{c(k)}{qd}\right|$ denotes the average deprivation shared across the poor. MPI represents the percentage of deprivations poor people experience, as a share of the possible deprivations that would be experienced if all people were deprived in all dimensions. In Table 1, we present the dimensions and their deprivation criteria used in this study.

Table 1. Dimensions and Indicators

Dimensions	Indicators	Deprived if
Education	Years of schooling	No household members have completed six years of schooling.
	School attendance	Any child of school-age (6-14 years) is not attending school up to class 8.
Health	Nutrition	Any child under-5 years of age is underweight
	Child mortality	Any child of the household has died in the span of five years prior to the survey.
Living standards	Electricity	Household members have no access to electricity.
	Water	No household member has access to clean water (following the MDG guidelines).
	Improved sanitation	No household member has access to improved sanitation. Sharing a latrine is considered deprived by the global MPI standard.
	Housing	The household has a mud, clay, earth, sand, or dung floor; the roof or walls are made of natural or rudimentary materials such as mud, dirt, grass, carton, plastic and so on or has no roof or walls.
	Cooking fuel	The household cooks with dung, agricultural crops, shrubs, wood, charcoal, coal or no food are cooked in the household.
	Assets	No household members own a car or truck or more than one of the following assets: radio, television, telephone, computer, bicycle, motorbike, or refrigerator.

Source: OPHI (2017) and MICS (2019)

3.2. PCA-based Weights

The above-mentioned Equation 3 assumes each dimension to be of equal importance. However, this study introduced the relative weights to each dimension. These weights reflect the relative importance of each dimension.

$$M_0 = HA = \frac{q(y|z)=\sum_{i=1}^{n} w_i \rho_k(y_i|z)}{n} \times w_i \left|\frac{c(k)}{qd}\right| = \mu(g^0(k)). \quad (4)$$

In Equation 4, w_i represent the dimension specific weights. These weights can be set either statically or dynamically as long as they satisfy the criteria of $\sum_{i=1}^{n} w_i = 1$.

Weighting in multidimensional poverty analysis can be determined through static assignment by domain experts or through dynamic methods (Dschang, 2008; BDHS, 2022). In this study, we employed PCA to derive the weights. We compared the PCA weights with the AF constant weights obtained from OPHI 2017. The results demonstrated that the PCA weights were data-driven, in contrast to the subjective nature of the standard AF weights. Table 2 presents the weights for both approaches. To extract the weights for the PCA model, we evaluated the polychoric correlation matrix using the poverty indicators. It was essential to verify the positive semi-definiteness of the correlation matrix. In cases where the matrix did not meet this criterion, negative eigenvalues were encountered and subsequently set to zero. The analysis revealed that the first principal component accounted for 35.4% of the variance in the data. According to the PCA weights, housing elements, assets, and access to electricity were identified as the primary determinants of poverty.

Table 2. Indicator Weights from Principal Component Analysis

Dimension	Indicator	AF weights*	Normalized weights from PCA
Health	Child mortality	0.167	0.024
	Nutrition	0.167	0.037
Education	School attendance	0.167	0.066
	Years of schooling	0.167	0.113
Living standard	Electricity	0.056	0.146
	Water	0.056	0.098
	Sanitation	0.056	0.086
	Housing	0.056	0.150
	Cooking Fuel	0.056	0.131
	Assets	0.056	0.149
Total		1.00	1.00

Note: For each dimension $1/3$ weight, for indicators of health, education $(1/3 \times 1/2)$. As most of the weights are very low, we use 3 decimal points

It is depicted from the Table 2 that AF approach assign more weights for child mortality, nutrition, school attendance and year of schooling, the procedure was subjective. While data-driven PCA approach puts more weights for housing, assets, electricity and cooking fuel sequentially, matched with the developing country like Bangladesh. If we scrutinize carefully the AF and PCA weights, an interesting fact reveals that the highest weighted indicator in one approach becomes the least weighted indicator for the other.

3.3. The Bootstrap Method for Robustness Checking

The bootstrap method uses the resampling procedure to measure the properties or of a given statistic, θ. It first resamples the original dataset X for B times with replacement. The b^{th} resample gives us the measure $\hat{\theta}^{*b}$ for all $b = 1, 2, \cdots, B$; which produces a set of B resample estimates $\hat{\theta}^{*1}, \hat{\theta}^{*2}, \cdots, \hat{\theta}^{*B}$. Let $\hat{\theta}^{*b}$ be the arithmetic mean over the resample parameters. After computing the set of B statistics, we can generate the standard errors for $\widehat{M}_0$, $\widehat{H}$ and $\hat{A}$.

3.4. Selection Bias in Standard Alkire-Foster Method

The AF method utilizes ten indicators to estimate the multidimensional poverty index. However, if a household lacks eligible members to provide data for a specific indicator, this method assumes that the household is non-deprived in that particular indicator. In our dataset, information on the nutrition indicator in the health dimension was only collected for households with children under the age of five. Consequently, data for the nutrition indicator was unavailable for households without children of that age group. According to the standard AF technique, households with no children under the age of five are considered non-deprived in the nutrition indicator. However, this assumption of the standard AF method is impractical and introduces selection bias, leading to potential inaccuracies. Moreover, depending on the subjective selection of weights, there is a risk of overestimating or underestimating poverty levels.

To address the bias introduced by the standard AF method, we propose implementing a bias-corrected approach. This approach involves treating households that lack the necessary information for a specific indicator as missing data for that particular indicator. Consequently, households without children under five years of age, which would be missing data in the nutrition indicator, are excluded from the analysis.

In addition, the standard AF method assumes equal weighting for all dimensions (health, education, and living standards). However, this normative weighting technique is subjective and may not fully capture the multidimensionality of deprivation and well-being (Pasha, 2017; Catalán and Gordon, 2020). As an alternative, we can apply a more data-driven weighting scheme to address this issue. In this study, we have derived the weights assigned to each indicator using PCA. Consequently, we will refer to the standard AF method as SAF, the bias-corrected AF method as BCAF, and the

PCA-derived dynamically weighted AF method as PCAAF. To further assess the robustness of our results, we have conducted point-wise bootstrap sampling, with 1000 replications, for all three methods.

4. ANALYSIS AND RESULTS

4.1. MPI estimation

In this section, we will discuss the results of our study. As previously stated, the primary objective of this research is to estimate the multidimensional poverty index based on the AF methodology and analyze the levels of poverty among various subgroups in Bangladesh using the nationally representative MICS 2019 data.

Table 3 displays the comparative results between SAF, BCAF, and PCAAF. As previously mentioned, SAF (Alkire et al., 2020) calculates poverty indices by assuming households without children under the age of five as non-deprived instead of treating them as missing values. This assumption results in approximately 63% of households in the MICS 2019 dataset being considered non-deprived in the nutrition poverty indicator, leading to an estimated MPI value of 10 and a headcount ratio of 25%. However, by treating households without children under five as missing values, the sample size decreases from 59,066 to 10,352 households, leading to different estimates. The BCAF approach estimates the MPI at 15 with a headcount ratio of 35%, while the PCAAF approach estimates the MPI at 26 with a headcount ratio of 51%.

It is important to highlight that assuming a large number of households with missing data as non-deprived in the SAF approach may introduce selection bias and lead to an underestimation of poverty. The disparities in the estimates underscore the significance of carefully addressing missing values in poverty analysis to avoid potential biases and ensure accurate assessments. The key indicators contributing to poverty in Bangladesh vary across the SAF, BCAF, and PCAAF approaches. In SAF, school attendance is the most significant contributor to poverty, followed by malnutrition. In BCAF, malnutrition takes precedence as the primary contributor, followed by school attendance. However, in PCAAF, housing emerges as the major contributing factor, followed by cooking fuel. Indicators with higher weight values have a greater influence on poverty. The contribution strengths of each indicator in different approaches can also be observed in Figure 1, which provides a visual representation of these findings.

Table 3. Headcount Ratio and MPI

Poverty Indicator	SAF	BCAF	PCAAF
Total Households (n)	59066	10352	10352
Deprived Households (n)	16202	3693	5701
Headcount Ratio (%)	25.00	35.00	51.00

SAF uses the whole sample taking the nutritional missing cases as non-deprived, eventually the MPI estimates come across with underestimation. BCAF and PCAAF approaches utilize only 18% of the sample data with subjective and data-driven weights accordingly.

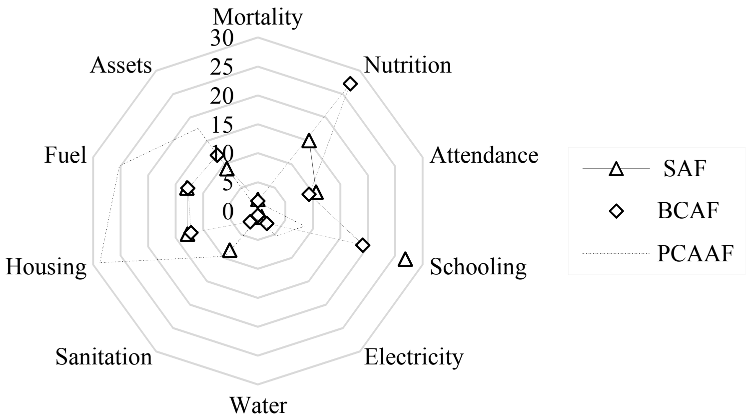
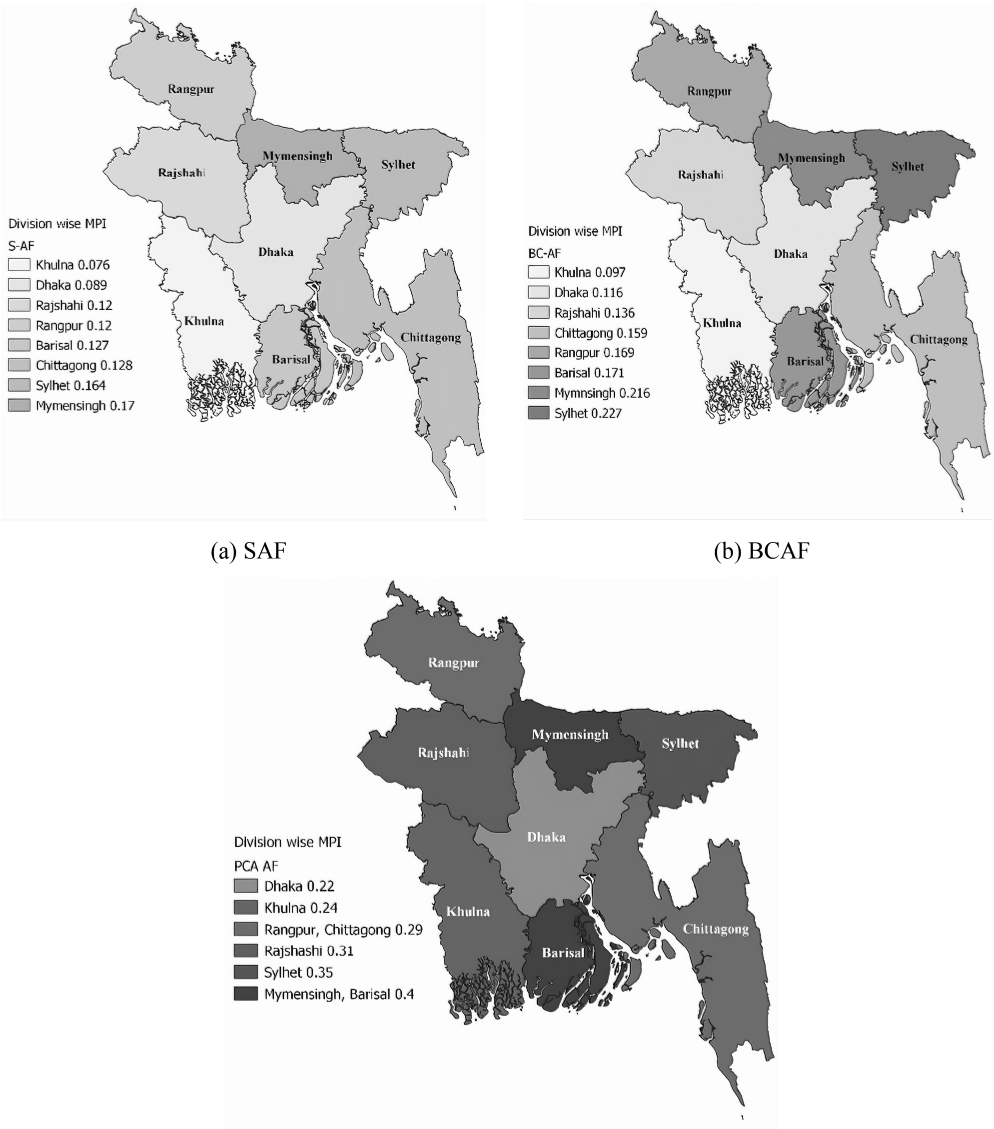


Figure 1. Indicators Contributing to Poverty

In Figure 1, SAF delineates that the higher weighted indicators contribute the most to the MPI estimates, the major contributor indicators are years of schooling and nutrition, same picture is shown for BCAF approach, because of the similar weights of indicators. Whereas PCAAF approach shows that housing and cooking fuel have the major impact on the MPI estimates.

Figure 2 is the most crucial finding of this study, portraying the drastic disparities of MPI estimates according to the administrative divisions of Bangladesh for different weights and approaches. According to the SAF approach with subjective weights, the administrative division/area Khulna shows the least MPI (0.08), Sylhet and Mymensingh show the highest MPIs 0.16 and 0.17 respectively. BCAF approach with subjective weights, depicts Khulna as the least MPI (0.09), Mymensingh and Sylhet as the highest MPI possessed districts (0.22 and 0.23, respectively). The overall MPIs are found to be higher in BCAF approach than that of SAF approach. The lowest MPI of PCAAF approach with data-driven weights, is estimated as 0.22 for Dhaka division, a way high compare to the other two approaches. Mymensingh and Barisal both scores 0.40 MPIs, are depicted as the poorest administrative divisions, that matches with the nationally representative survey estimates (HIES, 2022).



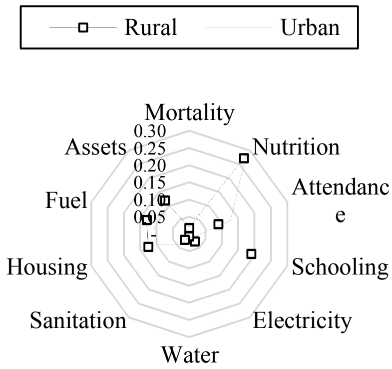
(a) SAF (b) BCAF

(c) PCAAF

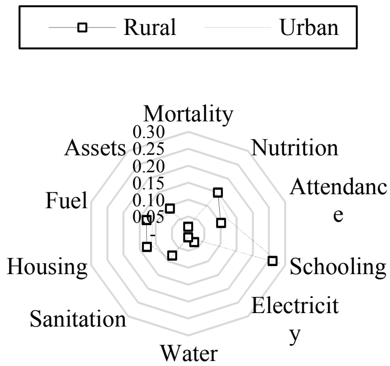
Figure 2. MPI Decompositions by Administrative Divisions of Bangladesh

4.2. Rural vs Urban MPI

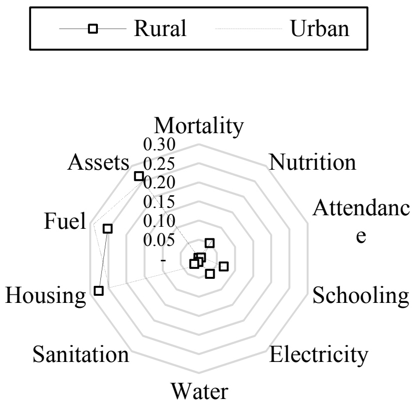
In Figure 3, the contributions of each poverty indicator in urban and rural areas are visualized. The pattern of indicator contributions is generally similar between urban and rural areas, except for the top three indicators. Both the SAF and BCAF approaches shows that schooling and nutrition indicators impacting on the poverty more to urban area. It becomes apparent that the poverty estimate related to nutrition and assets is significantly more alarming for the rural population compared to the urban population, according to PCAAF approach. Conversely, urban households face greater poverty challenges in terms of sanitation. Additionally, approximately 29% of the poor rural population is deprived in terms of cooking fuel, while the corresponding figure for the urban population is 26%. These findings align with the observations of Aziz et al. (2022). Overall, the figures highlight the disparities in poverty between rural and urban areas, emphasizing the specific indicators where each population segment faces particular challenges.



(a) SAF



(b) BCAF

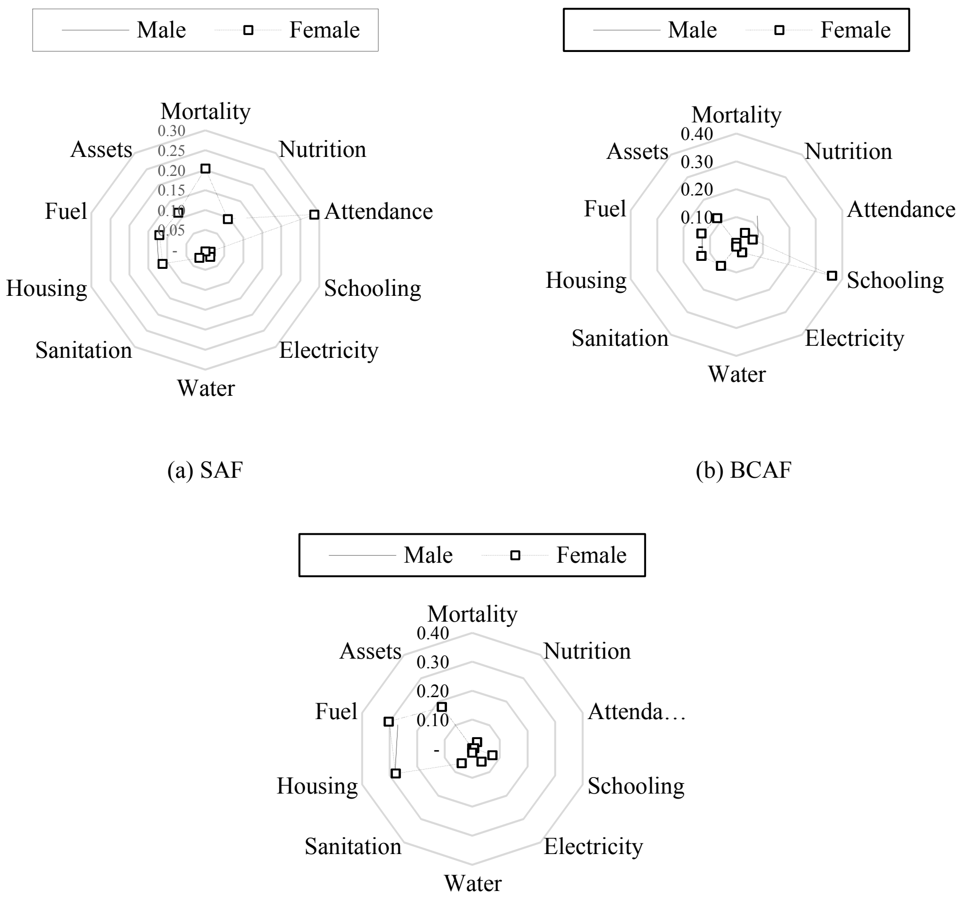


(c) PCAAF

Figure 3. Indicators Contributing to Rural-Urban MPI

4.3. Household head specific MPI

Figure 4 shows that households with male heads are poorer compared to female heads. For SAF, schooling indicator impact to MPI is higher for the female headed households than male headed households, whereas it is the opposite for nutrition. For BCAF approach, we can say that male headed households are deprived higher in number of indicators compare to female-headed households, regardless of the schooling and nutrition indicators. Hence, female-headed households seem to manage poverty comparatively better. According to the PCAAF approach housing indicator shows that female headed households are less poor compare to the male headed households, while cooking fuel indicator differs slightly.



(c) PCAAF

Figure 4. Indicators Contributing to Male-Female Headed Households MPI

5. DISCUSSION AND CONCLUSION

This study underscores that multidimensional deprivation is more prevalent in rural areas than in urban areas, consistent with findings reported by Wahed et al. (2017) and Hossen et al. (2018). Furthermore, male-headed households are shown to experience higher levels of multidimensional poverty compared to female-headed households, with rates of 36% and 27%, respectively. Barisal, Mymensingh, and Sylhet administrative divisions consistently demonstrate the highest rates of multidimensional poverty among the eight divisions, as observed in previous studies by Uddin and Huda (2016) and Alkire and Kanagaratnam (2020). Additionally, the rural population is identified as being more multidimensionally impoverished than their urban counterparts, as highlighted by the World Bank (2019).

Utilizing the MPI index with PCAAF weight helps mitigate selection bias and provides data-driven weights for each indicator via a robust simulation approach. Previous research further indicates that the weights assigned in PCAAF offer valuable insights into poverty. For instance, studies have established correlations between poverty and housing issues (Stephens and Leishman, 2017; Tunstall et al., 2013; Dewilde and Keulenaer, 2003), the association between cooking fuel and poverty (Olang et al., 2018), the relationship between assets and poverty (Hoque, 2014; Brandolini et al., 2010; Carter and Barrett, 2006), and the significance of energy access and usage for poverty alleviation in China (Geall and Shen, 2018) and Bangladesh (Barnes et al., 2011).

The reduced weight attributed to nutrition in PCAAF, in comparison to SAF, is likely influenced by sample size considerations. As PCAAF operates on a data-driven basis, it is significantly impacted by sample sizes. Tasnim et al. (2017) uncovered that housing conditions were contributing factors to malnutrition in rural Indonesia. However, there is a dearth of studies exploring the extent of causality and the relationship between poverty and its associated indicators. Additionally, it's noteworthy that poverty intensity has marginally increased with the PCAAF approach. The PCAAF method allocates greater emphasis to housing, assets, electricity, and cooking fuel successively, aligning with the context of a developing country like Bangladesh.

It is imperative to acknowledge that the precision and accuracy of our PCAAF results are constrained by the absence of nutritional status information. Incorporating anthropometric nutritional measurements for all household members would be beneficial to attain a statistically robust and accurate poverty estimate. Moreover, broadening the MPI to encompass additional dimensions such as expenditure poverty measures, gender equity, and employment rates (Masset and García-Hombrados, 2021) could enhance the precision and relevance of poverty assessment. Additionally, adopting statistically validated PCA weights rather than equal weights for the components could further refine the MPI. Drawing on the adaptation of the Alkire-Foster method to the context of Bangladesh, this study suggests that policymakers address poverty across various multidimensional segments with relative weights, considering regional disparities and accounting for neighborhood dynamics. This comprehensive approach is crucial for poverty eradication and the promotion of environmental, economic, and social well-being.

APPENDIX

Table A1. Households' deprivation in different indicators

Dimensions	Indicators	Contribution to MPI for SAF	Contribution to MPI for BCAF	Contribution to MPI for PCAAF
Health	Child mortality	02.02	01.71	00.17
	Nutrition	15.11	27.22	01.31
	School attendance	10.62	09.35	01.91
Education	Years of schooling	26.87	19.13	08.49
Living standard	Electricity	01.18	02.64	05.37
	Water	01.08	00.78	01.33
	Sanitation	08.31	02.29	09.68
	Housing	12.81	12.18	28.83
	Fuel	12.91	12.74	25.23
	Assets	09.09	11.96	17.68

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