Impact of Socioeconomic and Environmental Factors on Energy Poverty and Health Poverty: Evidence from the Bangladesh

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Abstract

This study examines the impact of the environmental and socioeconomic factors on health and energy poverty in Bangladesh. The Bangladesh Demographic and Health Survey (2018-19) were used. Energy poverty, defined as limited access to clean, affordable, and modern energy, significantly affects health, particularly in rural areas where biomass is used, worsening respiratory health. The Alkire-Foster and logistic regression approaches used to identify the critical factors included the socioeconomic and environmental factors. The study results show that energy poverty is closely associated with health and wealth poverty because of limited access to higher education. Therefore, rural areas and those severely affected by climate change face a severe risk of multidimensional poverty. The study results show the need for the proposed policies to assist in sustainable energy. To enhance educational opportunities and address immediate adaptation needs in the affected areas of the specific region. The study suggests that policymakers in Bangladesh should address poverty, climate change, sustainable development, and health.

Keywords: Climate Factors, Rural Households, Socioeconomic Factors, Wealth Index.

Introduction

Energy and health poverty are two significant aspects of household life and key determinants of household wellbeing. They are deeply affected by environmental and socioeconomic factors worldwide. Various third-world countries are facing these severe issues, and Bangladesh is one of them (Dake & Christian, 2023). Therefore, lack of energy access mostly leads to poor health challenges in developing countries. In Bangladesh, energy poverty is a significant issue, as many rural and urban households lack access to affordable, clean, and modern energy. This energy deficiency is associated with significant household outcomes (Gul et al., 2023; Clarke & Erreygers, 2020; Crentsil et al., 2019).

Many homes still rely on wood and coal, standard biomass fuels, for cooking and heating. It contributes to indoor air pollution (IAP) and increases the risk of respiratory infections in a specific country. Socioeconomic factors, such as dwelling, education, age, and wealth, play an important role in the household's vulnerability to both energy and health poverty (Dake & Christian, 2023;

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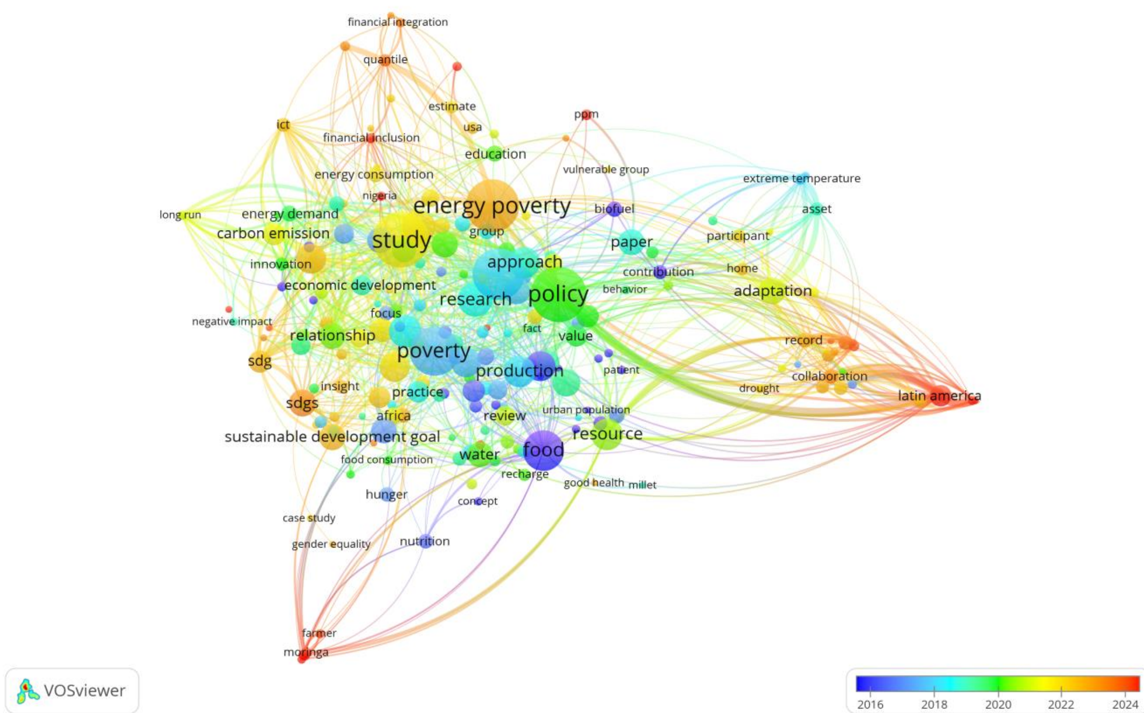
Dell et al., 2020). The significant connection understands the importance of understanding how energy poverty directly affects household-level health.

Households in rural areas are severely denied access to modern energy infrastructure. Besides, individuals with lower educational levels and less wealth are more likely to experience multiple dimensions of poverty (Gul et al., 2022; Iqbal & Nawaz, 2017; Li et al., 2022; Llorca et al., 2020; Mahmood & Shah, 2017). As a result, climate-related environmental disasters such as floods and heatwaves exacerbate health risks, particularly for the most vulnerable. The combined effects of these socioeconomic and environmental factors make it critical for policymakers to address both energy and health poverty in their efforts to reduce overall poverty and improve the well-being of marginalised households (Meierrieks, 2021; Moore, 2012).

Figure 1: Connections between health, energy poverty, and climate variability

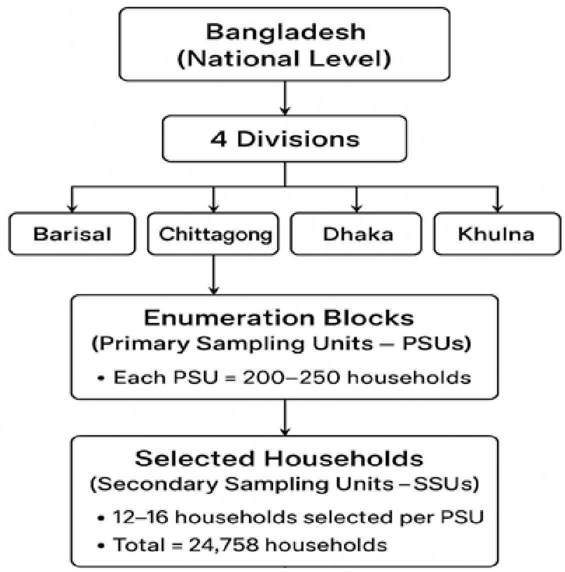


The picture was created from PubMed data (1990-2025). The data show the growing connections between health, energy poverty, and climate variability in the current literature. It shows that topics such as sustainable development, poverty, and energy consumption have shifted to climate adaptation and policy since 2016. The map illustrates interdisciplinary connections among energy access, health, food security, and economic growth, primarily in vulnerable regions such as Latin America and Africa. The trend shows growing attention to the combined effects of energy poverty and climate variability, with a focus on resilience-building solutions and policies, especially in resource-scarce areas.

Methodology

This study examines the links between the energy and health poverty with climate factors of Bangladesh DHS. The two econometric models are developed to examine these relationships. The first model identifies the factors influencing health poverty, focusing on the role of energy poverty, climate change, and household-level socioeconomic characteristics. The second model examines the determinants of energy poverty, prominence the role of residence, age, education, and wealth status. To investigate econometric model, first make mathematical model and then econometric model.

Figure 2: Flowchart



Mathematical Model 1
Model 1: Determinants of Health Poverty
Health Poverty = f (Residence, age, education, energy poverty, wealth index, climate change)

Econometric Model 1
Health Poverty = β1*residence + β2*age + β3*education + β4*energy poverty + β5*wealth index + β6*climate change+ e

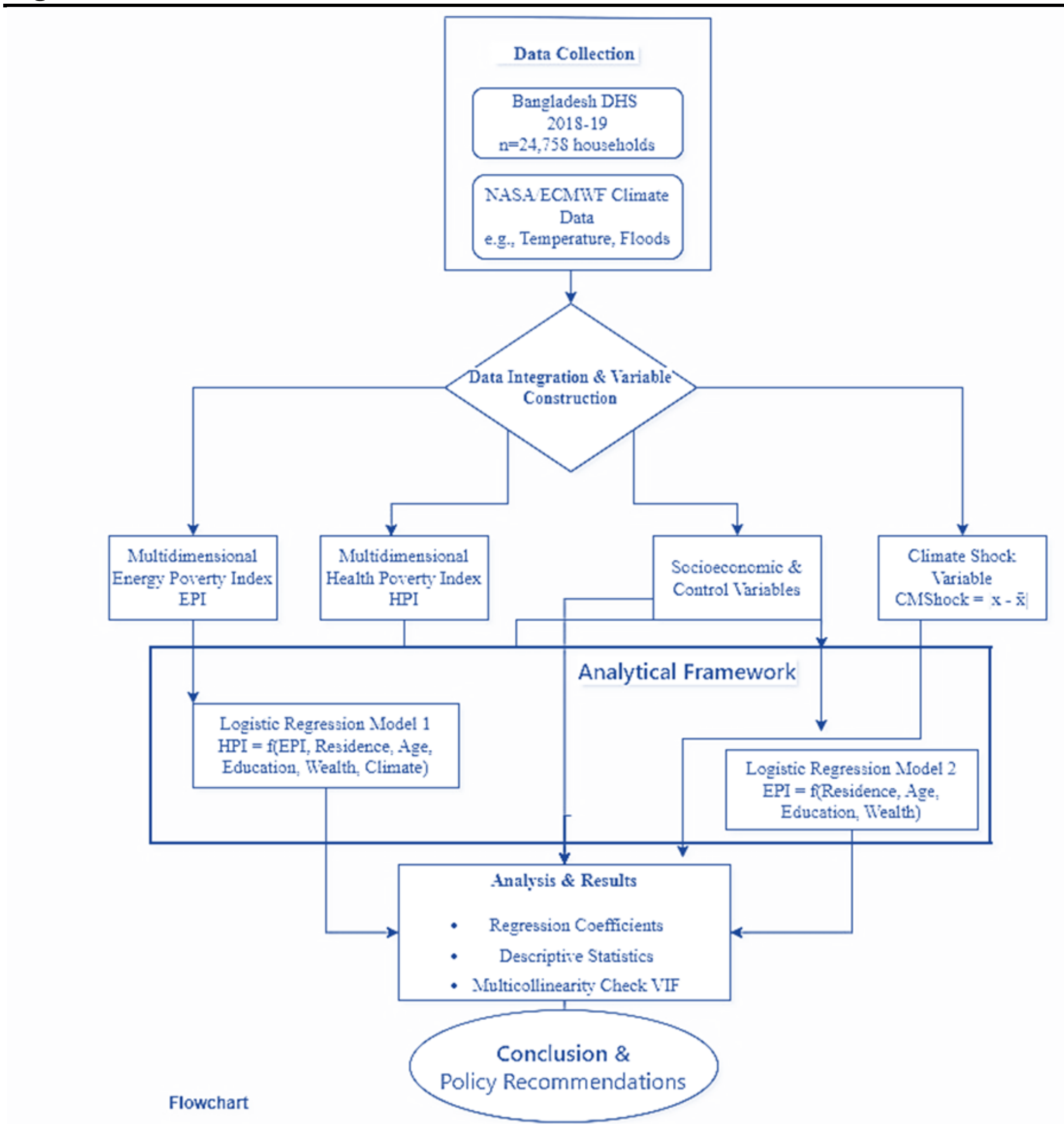
Mathematical Model 2
Model 1: Determinants of Energy Poverty
Energy Poverty = f (Residence, age, education, wealth index)

Econometric Model 2
Energy Poverty = β1*residence + β2*age + β3*education + β4*wealth index + e

Data Sources
This study used data from different sources to achieve the specific objectives. First, discuss the Bangladesh Demographic Health Survey (BDHS) 2018-19 conducted for Bangladesh national institutions. The data gives the bare structure of the demography of the people of Bangladesh's health status in that given period. The Bangladesh Demographic Health Survey (BDHS) involves 24,758 households from the four divisions of Bangladesh, including Barisal, Chittagong, Dhaka, and Khulna. The BDHS collected cross-sectional statistics on social and economic status at the provincial and national levels and stratified by region. The DHS employed a globally

recommended stratified, two-stage cluster sampling procedure to produce representative figures. Thus, in the first stage, the divisions are subdivided into enumeration blocks, each including 200 to 250 households. These enumeration blocks are a random sample from the Primary Sampling Units (PSUs). In the second stage, between 12 and 16 households, through systematic random sampling, are identified from the selected PSU, termed the Secondary Sampling Units or SSUs. These datasets offer the key environmental variables coinciding with BDHS data through a higher-level ID. This integration makes it possible to facilitate the assessments by matching household survey data with climatic factors for policy decision-making.

Figure 3: Flow chart



Energy Poverty

Energy poverty (EP) is defined within the context of using the fuel poverty framework. The centralized training and ordering of supplies and equipment is the theory called EP concept by Santillán et al. (2020), Llorca et al. (2020), Oum (2019), Moore (2012), Bradshaw and Hutton (1983). Fuel poverty is 'inadequate warmth to the home due to inability to pay for fuel (Bradshaw and Hutton., 1983, p. 249). On this basis, the present work is constructed following the notion of the UN Development Programme, which points that: (2010, p. 44) dedicated the definition of EP as a "lack of special in obtaining sufficient, reasonable, dependable, valuable, safe, healthy, and ecologically sustainable to temporary human development." EP happens when a household requires energy to service necessities and cannot afford them (Oliveras et al., 2021). This paper describes EP as a household's unavailability or limited capacity to secure affordable, clean, modern energy services and products for basic energy needs. EP measurement has different levels of objectivity and subjectivity, unidimensionality, and multidimensionality (Awaworyi et al., 2021). Various literature sources pointed out the use of the multiple-dimensional approach in evaluating EP in the recent past (Gul et al., 2020; Sokołowski et al., 2020). This work further uses objective indicators to establish a multidimensional measurement of EP at the household level (Zhang et al., 2021). EP is, therefore, defined as a condition whereby the consumer household cannot obtain adequate energy services or afford the necessary content of the services. So far, a limited body of literature systematically discusses EP in a multidimensional context in Pakistan, including Awan et al. (2013) and Sher et al. (2014). These works offer a research background for including more dimensions and indicators to the EP index, which is under investigation. This study uses the Alkire and Foster (AF) approach to develop the Multidimensional Energy Poverty Index (EPI). Several works have used this technique to construct multiple-domain EPIs based on cross-sectional data collected from households in different countries (Crentsil et al., 2019; Ahmed &Gasparatos, 202). The AF method helps design a practical approach for establishing households without access to safe energy (Crentsil et al., 2019). This paper builds a multidimensional EPI for Bangladesh based on the Bangladesh DHS to operationalize the proposed theoretical framework & Shah (2017).

To assess or quantify the energy-less or energy-starvation of a particular household (Selection of the household implies that it does not constitute the entire household of a nation. Significantly, the policy is decided through this specific household.) The deprivation score is computed for each household depending on its score based on the significant factors in the dataset. To measure the score and choose, use the following formula:

$m_i = \sum(w_i * BV_i)$

The mi indicates the deprivation score for households and is included. Therefore, the BVi shows a binary variable for the same indicators as the i. Besides, BVi=1 shows that the household is derivative in specific indicators, and BVi =0 shows otherwise. Therefore, the weight for each presentation indicator of the data set ensures the summation of all the indicators (Weightsequalor $\sum$ wi = 1). Similarly, a household is classified as energy poverty (sometimes used poorly) if the (mi).

H represents the headcount ratio, and calculated as H = q/n, where q shows household's number identified as energy poor and n represents the all-household’s number. The intensity of deprivation is captured by A, which is calculated as:

$A = (1 / q) \cdot \sum (c\_i \cdot IND\_i)$ for all i, $mi \geq k$

Here, mi is the deprivation score for household i, and k is the threshold for multidimensional energy poverty. The Multidimensional EPI, therefore, reflects both the prevalence (H) and the intensity (A) of energy poverty within a given population.

Table 1: Variable Description

Variable	Description	Code	Sources	Sources
Division	Barisal, Chittagong, Dhaka, Khulna	V25	DHS	(Phiri et al., 2020)
Residence	Type of place where people are living	V025	DHS	(Abbas et al., 2021, Stevens et al., 2023, Abbas et al., 2020)
Age	Age in group of 5	V013	DHS	(Stevens et al., 2023, Abbas et al., 2020)
Education	Highest educational level	V106	DHS	(Abbas et al., 2021, Abbas et al., 2020)
EPI	1= if energy poverty, 0= if no energy poverty	V161	DHS	(Dake& Christian, 2023; Li et al., 2022)
Wealth index	Wealth Index of the all class	V190	DHS	(Anand & Roy, 2016; Megbowon et al., 2018; AJ-Janabi et al., 2021)
	Current marital status	V501	DHS	(Li et al., 2022; Ward & Harlow, 2021)
Climate change$_{DD}$*	Daily climate change	TEM	Kaggle, NASA	(Terfa et al., 2022; Dake& Christian, 2023)
HPI	1=having no health poverty, 0= having energy poverty	Qc801, qc802, qc904e, qc906, qc907, qc101	DHS	(Li et al., 2022; Ward & Harlow, 2021)

*DD refers the daily climate change.

Measuring Health Deprivation (Multidimensional Health Poverty Index (HPI)

The general professional characteristics of self-employed worker by sex, age, and household level use the self-employment health deprivation measure. The multidimensional approach is used in parallel with constructing the Multidimensional EPI and has also been used in the current study. Health poverty is defined mainly as a situation where people have a health status lower than an acceptable level. It indicates a household's inability to procure sufficient health services to meet minimal human needs. Clarke and Erreygers (2020) defined health health poverty "as the state of being in deprived health." Moreover, Iqbal and Nawaz (2017) defined well-being poverty as "the absence of health services, where households are unable to obtain or afford the basic health services required to maintain sound health." This study uses the health variables' principal component analysis (PCA) to quantify health poverty. These two dimensions are also quantized and employed for the particular indicators and the requirements for the deprivation in the specific indicators described above. The deprivation of health index, or the Multidimensional HPI, is computed through the Alkire Foster (AF) method. This approach enabled the identification and quantification of the varying degrees of multidimensional health poverty in households. Strengthening the AF method proved effective in calculating HPI and defining health deprivations' existence and severity level.

Climate Change

For climatic shock, observations are accumulated based on basic climatic parameters, including rainfall, temperature, and flood frequencies, all of which are recorded within a single day. Still, it has a very profound impact on people's socioeconomic status. The literature studies in the previous section explained the effect of climatic variability on social consequences, mainly health and economic wellbeing (Pailler & Tsaneva, 2018; Dell, Berthet, & Schnetzer, 2014). Moreover, this study used climate data from MODIS and ECMWF at the division level to examine climate shocks and able to associate MODIS and ECMWF data with BDHS. Climate shocks are "departures from long-run means; this is common because the climate change literature has characterized it that way" (Dell et al., 2014; Pailler&Tsaneva, 2018). Thus, the following equation is used to quantify the climate shock:

CMShock = |x -x-bar|

The x represents the measure obtained on a climatic factor (for instance, precipitation) when the survey was conducted. In addition, the symbol represents the historical mean for the 30-year accumulating climatic factor. The panels were utilized and built for rains, temperatures, and floods at the tehsil level. These shock measures afford a differentiated perspective regarding climate variability and its tentatively negative effect on health in regions. Mean, standard deviations, and correlation coefficients for the climate shock variables are also shown in Table 2. Regional variations in the severity of climate impacts, such as drought and high temperatures, have been established, and these areas have resulted in higher levels of health deprivation.

Empirical Strategy

In this model, the regressor variable is Multidimensional Health Poverty; therefore, HP = 1 if a household is health-poor, HP = 0 if a household is not health-poor, and vice versa. EP stands for energy poverty, an indicator showing if any household is energy poor and zero otherwise reciprocally. CS also measures climate shock factors like rainfall, temperature, and flood. Y is the overall composite of the dependent variable Y, X stands for the value facts showing different socioeconomic and demographic aspects of the households/consumers' gender, marital status, size of households, and income levels, and e stands for the error term. The coefficients are expressed in odds ratios (Awaworyi et al., 2021; Kose, 2019; Fahad & Wang, 2020; Meierrieks., 2021).

$HP=\alpha+\beta EP+\gamma CS+\theta X+e$

$EPI =\alpha+\beta HP+\gamma CS+\theta X+e$

Analysis and Results

The outcomes of this study reveal a significant association between demographic, socio-economic, and Health Poverty Index (HPI) factors across various age groups, wealth statuses, and education levels. The logistic regression results suggest that rural residence, lower wealth, and energy poverty are strongly associated with high health poverty. Therefore, the diagnostic issues, such as model goodness-of-fit tests and multicollinearity tests, reveal that the model is well-defined, fitting, and robust for clarifying variations in health poverty.

Table 2: Sample Size Distribution

	Type of place of Residence			
Division		Urban	Rural	Total
	Barisal	3,438 [13.89]	1,855 [7.49]	5,293 [21.38]
	Chittagong	2,300 [9.29]	5,121 [20.68]	7,421 [29.97]
	Dhaka	5,917 [23.90]	644 [2.60]	6,561 [26.50]
	Khulna	4,046 [26.34]	1,437 [5.80]	5,483 [22.15]
	Total	15,701[63.42]	9,057 [36.58]	24,758 [100.00]

Table 2 describes the distribution of sample sizes, which are categorized as follows: 63.42% of the sample consists of urban households, and 36.58% are rural, indicating an urban-dominated sample. Khulna and Dhaka (the capital of Bangladesh) have the highest urban population among divisions, with relatively small rural populations. Also, 20.68% of the population resides in rural areas, while 9.29% lives in urban areas. Barisal shows a more balanced distribution; the urban (13.89%) and 7.4% rural, for 21.38%. The urban-rural divide focuses on regional disparities that are significant for examining Bangladesh's health and energy poverty dynamics.

Table 3: Descriptive Statistics with Un-Weight

Variable	Mean	SD	Min	Max	Obs.
Age	4.703288	1.672895	1	7	24,758
Edu. Level	1.314323	.8864055	0	3	24,758
Energy poverty	.2812323	.4496097	0	1	24,734
Wealth index	3.1694	1.398236	1	5	24,758
Marital status	1.141772	.6011386	1	5	24,758
HPI	.5959286	.4907213	0	1	24,758
TEMP	18.9835	12.82925	-26.23	43.37	24,758

Table 3 describes the basic information of the variables used in the particular analysis. The age graph has a moderate SD (1.67) and ranges from 1 to 7. Therefore, the SD of education is 0.89, while energy poverty holds 0.45, respectively. The wealth index and marital status SD have 1.40 and 0.60, respectively. The HPI has 0.49 SD, which means a reliable, even distribution between its binary outcomes. The temperature has the highest variability (SD 12.83), with extreme values (-26.23°C to 43.37°C) showing vital climatic differences across regions.

Table 4: Descriptive Statistics with Weight

Variable	No. of strata	8	No. of obs.	24,734
	No. of PSUs	352	Population size [df]	.02856[344]
	Mean	SD	[95% conf. interval]	
Age	4.666657	.02203	[4.623327-4.709988]	
Edu. Level	1.275986	.0214667	[1.233763-1.318208]	
Energy poverty	.2954507	.0132052	[0.269477-0.321423]	
Wealth index	3.182697	.0461852	[3.091857-3.273538]	
Marital status	1.135698	.0080974	[1.119772-1.151625]	
HPI	.4624516	.0206732	[0.421789-0.503113]	
TEMP	19.93913	.6574264	[18.64605-21.23221]	

Table 4 describes the weighted descriptive statistics. It shows the confidence interval and variability of the significant projected variables. The age groups have a small SD, which means minimal variation with 95% (CI). Education level also has a low SD of 0.02, and energy poverty has a value of 0.013. The wealth index has a high SD. Therefore, marital status also has a low SD. The HPI shows moderate variability with a CI. Temperature has the highest variability, with a CI reflecting regional climatic variability.

Table 5: Description of the sub-group with Un-Weight & Weight

Variable	Sub-group	Freq.	Percent [Un-Weight]	Proportion With Weight
Age	15-19	603	2.44	.025
	20-24	2,197	8.87	.0905
	25-29	3,633	14.67	.1512
	30-34	4,669	18.86	.1934
	35-39	4,689	18.94	.1874
	40-44	4,342	17.54	.1709
	45-49	4,625	18.68	.1815
Edu. Level	no education	4,941	19.96	.2179
	primary	9,211	37.20	.3634
	secondary	8,489	34.29	.3433
	higher	2,117	8.55	.0754
Energy poverty	If have energy poverty	17,778	71.88	.7045
	No energy poverty	6,956	28.12	.2955
Wealth index	poorest	4,080	16.48	.1523
	poorer	4,474	18.07	.1869
	middle	5,121	20.68	.2114
	richer	5,338	21.56	.2238
	richest	5,745	23.20	.2257
Marital status	married	23,332	94.24	.945
	widowed	993	4.01	.0384
	divorced	208	0.84	.0074
	no longer living together/separated	225	0.91	.0091
HPI	If have Health Poverty	10,004	40.41	.5371
	If have no Health Poverty	14,754	59.59	.4629

The table displays the major subgroup characteristics, including both unweighted and weighted proportions. Primary education is more prevalent (37.2%, weight: 36.3%) compared to higher education (8.6%, weight: 7.5%), with the largest age groups being 30-34 (19.3%) and 35-39 (18.7%). Wealth is concentrated in the wealthiest quintiles, while most people struggle with energy poverty. Health poverty is significantly more prevalent in weighted data, and most respondents are married.

Table 6: Logistic Regression Weight

Dependent Variable: HPI					
Independent Variables	No. of strata		8	No of Obs.	24,734
	No. of PSUS		352	Population size [df]	.02856[344]
	F (19, 326)		2.65	Prob > F	0.0003
	Coefficient	SD	t	P>|z|	[95% conf. interval]
Resident	1	1	1	1	1
rural	.2513367	.2008461	1.25	0.212	-.143704 .64637
Age	1	1	1	1	1
20-24	-.0996045	.1192461	-0.84	0.404	-.3341478 .13493
25-29	-.0460059	.1163425	-0.40	0.693	-.2748381 .18282
30-34	.0951343	.1281149	0.74	0.458	-.156852 .34712
35-39	.1850966	.124145	1.49	0.137	-.059082 .42927
40-44	.3919121	.1414371	2.77	0.006	.1137218 .67010
45-49	.4515359	.1510274	2.99	0.003	.1544824 .74858
Edu. Level	1	1	1	1	1
primary	.3784641	.1143266	3.31	0.001	.1535969 .60333
secondary	.6141997	.1553104	3.95	0.000	.3087222 .91967
higher	.9480134	.2023778	4.68	0.000	.5499598 1.3460
Energy poverty	1	1	1	1	1
if have no energy poverty	.0921675	.0314585	2.93	0.003	.03051 .15382
Wealth Index	1	1	1	1	1
poorer	.2180903	.17467	1.25	0.213	-.1254654 .56164
middle	.0771148	.2062466	0.37	0.709	-.3285482 .48277
richer	-.2910981	.2296484	-1.27	0.206	-.7427899 .16059
richest	-.5381543	.259543	-2.07	0.039	-1.048645 -.02766
Marital Status	1	1	1	1	1
widowed	.0428681	.1522059	0.28	0.778	-.2565033 .34223
divorced	.346538	.2482423	1.40	0.164	-.1417258 .83480
no longer living together/separated	-.2998246	.304417	-0.98	0.325	-.8985774 .29892
TEMP	-.0186528	.0010631	-17.55	0.000	-.0207365 -.01656
Cons.	-.3537572	.3397033	-1.04	0.298	-1.021914 .31439

The logistic regression weight results are presented in Table 6. It examines factors influencing health poverty (HPI) with statistically significant variables. A higher HPI has a positive relationship with age groups of 40-44 and 45-49 years old. HPI is strongly affected by educational status, with higher education having the most positive impact. Health poverty is less likely when there is no energy poverty. The HPI often has a negative relationship with wealthier groups, while the most affluent quintile has a strong negative correlation. Temperature affects HPI, suggesting a potential climate-related influence the pragmatic and expected values indicate that the model is appropriately specified.

Table 7: VIF for Multicollinearity

	Variable	Sub-Group	VIF	1/VIF
estat VIF	hv025	-	1.02	0.983541
	Age			
		20-24	4.25	0.235438
		25-29	6.02	0.166041
		30-34	7.16	0.139644
		35-39	7.25	0.137980
		40-44	6.96	0.143623
		45-49	7.37	0.135710
	Edu. Level			
		primary	1.87	0.534846
		secondary	2.20	0.454567
		higher	1.59	0.627909
	Poverty index	-	1.13	0.886850
	Wealth Index	poorer	1.75	0.571372
		middle	1.90	0.526574
		richer	1.99	0.501760
		richest	2.33	0.428479
	Marital status			
		widowed	1.03	0.969771
		divorced	1.00	0.997236
		no longer living together/separated	1.00	0.995244
	T2M		1.01	0.989674

Table 7 presents the variance inflation factor (VIF) research, meaning that multicollinearity is typically not a significant issue in this logistic model. The VIF values of most variables are close to 1, meaning low multicollinearity. However, the sub-group categories show higher VIF values, especially for the 30-34, 35-39, and 45-49 age groups, with values ranging from 6.96 to 7.37, which may suggest a level of relationship between them. The overall VIF values for other variables, such as marriage status, energy poverty status, and educational level, remain low, suggesting that multicollinearity is not a significant issue for most of the model's variables.

Table 8: Logistic Regression Weight

Dependent Variable: EPI					
Independent Variables	No. of strata		8	No of Obs.	24,734
	No. of PSUS		352	Population size [df]	.02856[344]
	F(14, 331)		30.50	Prob > F	0.0000
	Coefficient	SD	t	P>|z|	[95% conf. interval]
Resident					
rural	-.4741429	.1365588	-3.47	0.001	-.7427381 -.2055476
Age					
20-24	-.1871828	.11561	-1.62	0.106	-.4145742 .0402086
25-29	-.3766839	.1138359	-3.31	0.001	-.6005859 -.152782
30-34	-.468235	.1146012	-4.09	0.000	-.6936423 -.2428277
35-39	-.5361284	.1267876	-4.23	0.000	-.7855049 -.2867518
40-44	-.4806202	.1417838	-3.39	0.001	-.7594924 -.2017479
45-49	-.5399301	.1398378	-3.86	0.000	-.8149748 -.2648853
Edu. Level					
primary	-.1276369	.0985547	-1.30	0.196	-.3214827 .0662088
secondary	.0594239	.1233665	0.48	0.630	-.1832238 .3020716
higher	.2408095	.1464799	1.64	0.101	-.0472994 .5289184
Wealth Index					
poorer	-.6287833	.1131637	-5.56	0.000	-.8513632 -.4062034
middle	-1.037107	.1215644	-8.53	0.000	-1.27621 -.7980042
richer	-1.620646	.1358863	-11.93	0.000	-1.887919 -1.353373
richest	-2.57983	.1476445	-17.47	0.000	-2.87023 2.289431
cons	.8740623	.1964052	4.45	0.000	.487756 1.260369

The logistic regression results shown in table 8 for the output variable EPI show a highly significant association with the input variables. The findings suggest that individuals living in rural areas tend to have substantially lower EPI scores than those in urban areas, indicating that geographic location plays a crucial role in determining levels of energy poverty. This intense negative relationship between rural and urban EPIs may reflect disparities in infrastructure development, access to modern energy sources, and economic opportunities across these regions. Age also emerges as an essential determinant, with all age groups over 20 showing negative, statistically significant coefficients. This pattern suggests that energy poverty increases with age, possibly because of reduced income-earning capacity, higher dependency ratios, or lower adaptability to changing energy technologies among older populations. Income, as expected, shows a reliable and robust negative association with EPI across all income brackets. The wealthiest category shows the most significant negative coefficient, confirming that higher income levels are strongly associated with reduced energy poverty. This result underscores the pivotal role of financial resources in securing reliable, affordable energy access, as wealthier households are better able to invest in modern energy solutions and energy-efficient technologies. Educational attainment also shows a differentiated effect. While primary and secondary education is not significantly associated with EPI, higher education has a substantial positive impact. This finding suggests that individuals with advanced education are better positioned to understand, adopt, and sustain efficient energy practices, or to access employment and income opportunities that facilitate improved energy conditions. Thus, the model shows strong explanatory power, suggesting that the set of predictors collectively accounts for significant variation in the EPI. These results highlight the multifaceted nature of energy poverty and underscore the importance of integrated policy approaches that address geographic, socioeconomic, and educational inequalities to enhance equitable energy access.

Table 9: VIF for Multicollinearity

	Variable	Sub-Group	VIF	1/VIF
estat VIF	Resident	-	1.01	0.994385
	Age			
		20-24	4.25	0.235518
		25-29	6.02	0.166189
		30-34	7.15	0.139847
		35-39	7.23	0.138296
		40-44	6.94	0.144009
		45-49	7.32	0.136545
	Edu. Level			
		primary	1.87	0.536015
		secondary	2.19	0.456127
		higher	1.59	0.629473
	Wealth Index	poorer	1.73	0.577124
		middle	1.85	0.541001
		richer	1.89	0.529691
		richest	2.14	0.466461
	Mean VIF		3.80	

Table 9 shows the variance inflation factors (VIF) as a measure of multicollinearity among the independent variables in the logistic regression model. The results reveal that most of the variables have moderate VIF values. The age group has the highest VIF values, ranging from 4.25 to 7.37. The mean VIF value of 3.80 demonstrates a moderate level of Multicollinearity.

Conclusion and Recommendations

The study explores the impact of socioeconomic and demographic variables on the HPI across different areas. The results show that energy poverty, rural residence, education level, and low wealth level have a significant impact on health poverty levels, with age and climate also influencing outcomes. In particular, energy poverty is a serious issue, which means we must develop comprehensive approaches to meet basic energy needs. Similarly, health poverty is positively affected by higher levels of education, highlighting the importance of improving educational quality and access. Based on these findings, two policies are suggested: The government should invest in sustainable energy and enhance infrastructure to combat energy poverty. This is especially important in rural areas and among low-wealth groups, rather than focusing on energy costs and accessibility. Second, a strong focus on education, especially at the elementary and secondary levels, is required to equip future generations with the resources they need to overcome health poverty. Policies should aim to expand educational opportunities in communities with limited resources and integrate health awareness into the curriculum to address both short-term and long-term health and economic well-being issues. Bangladesh can reduce health inequality and improve overall societal wellbeing by addressing energy poverty and enhancing education, paving the way for a more unbiased and prosperous future for all its citizens.

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