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What Determines Household Multidimensional Energy Poverty? A Study of the Rural Jagatsinghpur District of Odisha

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Abstract

Energy Poverty, a contemporary global challenge, acts as a major hindrance in attaining Sustainable Development Goals (SDGs) by accelerating carbon emissions, adversely affecting the quality of the environment, gender equality, and people's health and education. To address this problem, although prominent schemes, such as PMUY and PAHAL, have been in operation in India at the national and state levels, as of 2021, around 44 percent of households at the country level and 66 percent in Odisha lack access to clean cooking fuels. Against this backdrop, the present study tries to undertake a household-level analysis of multidimensional energy poverty in Odisha's second topmost multidimensionally non-poor district, i.e., Jagatsinghpur, which is the novelty of this study. The Alkire Foster Methodology has been adopted to construct the Multidimensional Energy Poverty Index (MEPI), considering five dimensions and five indicators. Binomial logistic regression has been used to study the impact of different socio-economic and demographic factors on household energy poverty level. The study's major finding reveals that about 69 percent of the study households are multidimensionally energy-poor. The study also observed negative impact of the educational level of the head of household and income level of the household and positive impact of household size on household multidimensional energy poverty. The existence of regional disparities in multidimensional energy poverty among all the blocks in the district is another finding of this study. Suitable policy interventions and support mechanisms are, therefore, desired to address multidimensional energy poverty and foster sustainable development.

Keywords: Alkire-Foster Approach, Binomial Logistic Regression, MEPI, Multidimensional Energy Poverty, Odisha.

Introduction

Energy –renewable or non-renewable, viz., wind, sunlight, coal, uranium, crude oil, and natural gas, that are used to generate power are including electricity– serves as the key input in farming and industrial activities and supports the gadgets working for education, health, communication, and daily household activities, including cooking, lighting, heating, and many more. Based on environmental impact, energy is categorized as traditional energy, viz., coal, firewood, biomass, cow-dung, crop residue, and clean energy, viz., hydro, solar, and wind. Considering the detrimental impacts of the usage of traditional energy that emits harmful gases like Carbon Monoxide (CO) and Carbon Dioxide (CO_2), and the importance of clean energy that emits little to no greenhouse gases, curbs air pollution, lessens deforestation, combat climate change, and improves overall life on land, United Nations Development Programme (UNDP), United Nations Department of Economic and Social Affairs (UNDESA), and World Energy Council jointly in their report "World Energy Assessment" developed the concept of 'Energy Poverty', as "the absence of sufficient choice in accessing adequate, affordable, reliable, high quality, safe, and environmentally benign services to support economic and human development" (1). Prior to that, Boardman, in her pioneering work 'Fuel poverty: from cold homes to affordable warmth,' introduced the income-based criterion in measuring the fuel poverty of a person adopting the Ten-Percent-Rule (TPR), i.e., a person incurring an expenditure of more than 10 percent of his income on energy will be considered as fuel poor (2). Afterward, several other researchers also used the same approach in their energy poverty study (3-5). This one-dimensional approach to energy poverty was primarily applicable to developed economies and focused on affordability aspects of the household by arguing that the expenditure on energy by the energy-poor households takes a relatively a larger share of their income but fail to capture the simultaneous energy deprivations

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relating to availability, affordability, and accessibility to clean energy faced by households in developing economies (6). In response to the limitations associated with the traditional approach to energy poverty, an alternative perspective has emerged through the application of the capability approach, originally developed by Amartya Sen, to the study of energy poverty. The capability approach emphasizes individuals' substantive freedoms—their capabilities to achieve valued ways of being and doing—over the mere possession of goods or services (7). Within this framework, energy is conceptualized not as an end in itself, but as a means to enable a range of essential human functioning, which includes, but is not limited to, being adequately nourished, maintaining good health, accessing education, engaging in productive work, and participating in social and cultural life. As such, energy deprivation should be understood in terms of the constraints it imposes on individuals' capability sets, rather than solely in terms of material scarcity (8). This approach is preferred over the traditional approach because of its ability to integrate energy policy with broader debates on poverty, justice, and development, highlight energy's instrumental role in supporting multiple facets of well-being, and encourage innovative, targeted, and sustainable interventions (9). Capability-based framework into the study of energy poverty thus foregrounds the need for policies that prioritize the enhancement of human capabilities, particularly among marginalized populations and enables a broader conceptualization of energy access as integral to the expansion of human freedoms and the pursuit of well-being, thereby providing a normative foundation for more inclusive and equitable energy policies.

Thus, as opposed to the one-dimensional measurement of household energy poverty, numerous researchers focused on multiple dimensions, such as availability, accessibility, and affordability, in measuring the energy poverty level of a household (10-12). The existence of modern energy services at an appropriate distance from the household in same geographic location specifies the availability dimension of energy poverty (11, 13); households' access to clean energy sources indicates the accessibility dimension (8, 12, 14-17), and the financial burden faced by the household caused by the energy-related expenses measures the affordability dimension (13, 18-20). Therefore, the multidimensional approach to energy poverty adopts composite indices in understanding, measuring, and monitoring the issue of multidimensionality and its possible implications on the overall well-being of the household.

Energy poverty in India is not homogeneously distributed; it varies sharply across states due to differences in infrastructure and socio-economic development. Over 65 percent of Indian households fall into the "more" or "most energy poor" categories, with Bihar, Odisha, and Jharkhand among the worst-affected, and these states not only lack access but also suffer from poor energy quality and affordability (21). High incidence of multidimensional energy poverty is also observed in the rural districts of Uttar Pradesh, Assam, and Madhya Pradesh, where energy poverty overlaps significantly with other development deprivations such as income and education (8, 22). The state-level mapping of Residential Energy Poverty Index, considering multiple aspects of energy access and usage and taking into account various factors like clean energy access, electricity access, energy appliance access, and energy efficiency, revealed high vulnerability in energy poverty in the eastern and north-eastern regions of India, performing poorly in dimensions of clean and green energy, electricity access, and reliability, with relatively better performance of the western states due to stronger grid access and cleaner energy uptake (23). Furthermore, the structural barriers to energy access, particularly in rural India, include not only a lack of electrification but also intermittent supply and unaffordability of clean cooking fuels— the challenges that remain largely unresolved in the most energy-poor states (24, 25). These interstate findings underscore the need for geographically tailored energy interventions.

Distinct research studies relating to energy poverty also reveal that energy deprivation resulting from lack of availability, accessibility, or affordability of clean energy compels households to continue with routine traditional energy such as firewood, cow-dung, agricultural waste, and crop residue that adversely affects household member's educational level, health status, and living standards, lessening their job opportunities available and income levels (13, 23). The collection and usage of traditional energy, mostly firewood, involve massive deforestation and a multipronged rise in greenhouse gas emissions, leading to overall environmental degradation and climate change (6, 23, 26). It is assessed that use of a 14.2kg LPG cylinder for cooking is equivalent to burning 176 kilograms of firewood on a traditional cookstove, and transitioning from the use of firewood to LPG can result in a 74 percent reduction in net climate effect (27). Thus, using LPG cylinders for cooking not only reduces deforestation but also contributes to environmental protection. Further, household members' exposure to poisonous gases such as CO and CO_2 arising from the combustion of traditional energy significantly affects the health condition of the family members through various lung-related diseases like Tuberculosis, Asthma, and Bronchitis (16, 28). Prolonged contact with poisonous gases also exacerbates prevalent health issues such as lung cancer, heart disease, and asthmatic attacks among household members, leading to reduced life expectancy and premature deaths (29, 30). Poor health also restricts the ability of household members to pursue education, acquire adequate skills, and undertake employment and other income-generating activities, subsequently making them more susceptible to poverty (31). At the household level, as the task of collecting, processing, and using traditional energy is mainly vested with the female members, thus this type of activity reduces the time available for the female members to undertake education, rest, and other income-generating activities (31, 32), and afterward intensifies the gender gaps in health, education, and economic front. Heavy dependence on traditional energy also serves as a major hindrance for the household members in maintaining a decent living standard by availing improved housing conditions filled with modern amenities such as induction cooker, TV, refrigerator, air-conditioner, computer, mobile phone, etc., for lighting, heating, cooling, cooking, entertainment purposes that further worsen the educational and economic standard of the household members and subsequently, the household became more vulnerable to multidimensional poverty.

Households' ability to meet basic energy needs for lighting, refrigeration, communication, and health services is also highly disrupted due to power outages resulting from the regular occurrence of calamities such as cyclones, storms, and floods, which is more noticeable in Indian states like West Bengal, Odisha, and Andhra Pradesh. More than 96 percent of power outages in India are driven by severe weather conditions, and the most affected were poorer households having no power backup systems like batteries or solar panels (33). The negative impact of prolonged power outage on health outcomes spikes hospitalization and mortality, especially in communities lacking robust health care infrastructure (34). In this situation, low-cost distributed solar solutions offer a promising pathway to address energy poverty and foster local economic development in rural communities.

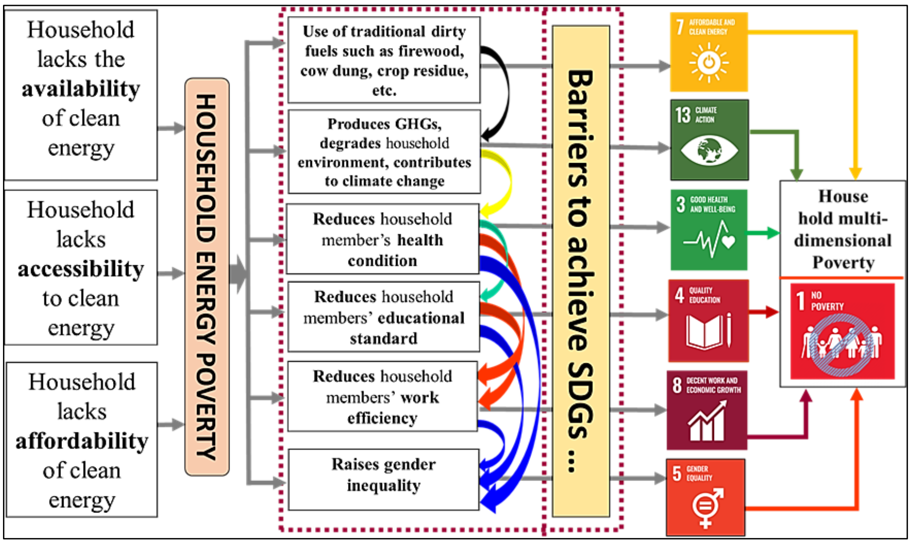

Figure 1: Household Energy Poverty - Causes and Consequences

From the above discussion, it can be stated that household energy poverty has multifaceted impacts on the overall well-being of the household members and serves as a significant barrier in attaining sustainable development goals (SDGs) on affordable and clean energy (SDG7), good health and well-being (SDG3), education (SDG4), gender equality (SDG5), decent work and economic growth (SDG8), and climate action (SDG13) and serves as a major contributor to multidimensional poverty (SDG1) shown in Figure 1.

Energy poverty study also identifies different socio-economic factors, such as education of the household head (15, 19, 35-37), household income (13, 38), household size (37), and occupation of the household head (15, 19, 39) that are critical to influencing household energy poverty. The increased educational level of the household head enhances his earning potential, increases the household's capacity to own modern and improved energy sources, and thereby supports in reducing energy poverty (37). The educated household head also creates awareness among other household members to use clean and modern energy instead of traditional energy that emits harmful gases and subsequently helps reduce energy poverty (35). Studies also divulge that household income and energy poverty are inversely related, i.e., households with lower income experience higher energy poverty (19), and households with high income are associated with lower energy poverty (13, 38). Low household income compels rural people to depend mainly on traditional energy, which is cheaper and even costless in certain circumstances, and is accountable for making the household more susceptible to energy poverty (6). Households' primary occupation also influences energy poverty. Farm-based households tend to use more traditional cooking sources, such as firewood and charcoal, due to their easier access, which makes the household more prone to energy poverty (15), while households engaged in off-farm activities are less prone to energy poverty (19). Household size also plays an important role in determining multidimensional energy poverty. Larger family size not only leads to the availability of more people for the collection of traditional fuel easily but also leads to higher energy demands, which may serve as an important barrier to transitioning from traditional to modern forms of energy, and subsequently, the household is more exposed to energy poverty (37).

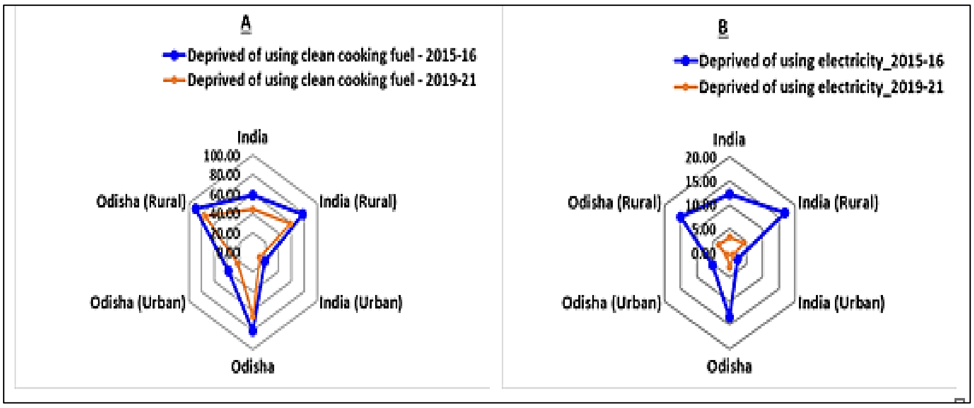

Figure 2: (A) Persons Deprived of Using Clean Cooking Fuel (In Percent), (B) Persons Deprived of using Electricity (In Percent)

Global statistics reveal that although there has been a steady rise in access to electricity around the globe from 75 percent in 2000 to 90 percent in 2020 still, around 1.18 billion people were living in the dark without electricity, which might be due to the lack of electricity provision available with the people or their inability to afford electricity expenses (40). Additionally, with the rapid increase in the use of electricity, around 2.1 billion people globally still use traditional sources of energy, i.e., coal, kerosene, animal dung, crop waste, and fire-wood for household cooking, which pollutes the air and are accountable for around 3.2 million premature deaths every year (41). India, a high-populous, lower-middle-income Asian country, witnessed 43.90 percent of people deprived of using clean cooking fuel in 2019-21, as against 58.47 percent in 2015-16 (42). The picture of rural India using clean cooking fuel for the same period is more acute than in urban India. A 48 percent deprivation gap persists between rural and urban India during 2019-21, as shown in

Figure 2. In using electricity, although the position of India is satisfactory, which was evidenced by around 97 percent of people's access to electricity and the rural-urban gap in using electricity is very minimal, i.e., about 3 percent during 2019-21 (42); still, more than 65 lakhs of rural people in the country live in the dark without electricity.

Odisha, an eastern coastal Indian state, also witnessed about 66 percent of people deprived of using clean cooking fuel and 3 percent using electricity in 2019-21 against around 81 percent and 13 percent, respectively, for the same indicator during 2015-16 (42). It is observed from Figure 2 that in electricity use, although Odisha's position is satisfactory, with around 97 percent of people having access to electricity during 2019-21 (42), still a rural-urban gap of around 2.5 percent persists in the state. Jagatsinghpur, an agrarian coastal district of Odisha, although recognized as a second non-poor district with only 12 percent of the population falling under multidimensional poverty against 30 percent in the state and 25 percent in the country, still about 87 percent of the population of the state were deprived of using clean cooking fuel and 7 percent of using electricity (43). There is enough potential to install wind energy and solar energy in Jagatsinghpur district. ONGC Tripura Power Company Ltd. has received approval for an onshore wind farm in Jagatsinghpur district, a part of a wider 148.5 MW package across the state approved in October, 2024 by the Odisha Single Window Committee (44). The district also gets the benefit of solar energy under state and central schemes, viz., Odisha Renewable Energy Policy 2022, PM Surya Ghar: Muft Bijli Yojana and Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyan.

Rural electrification initiatives in Odisha have been a cornerstone of energy poverty reduction strategies, especially in the context of socio-economic upliftment and climate resilience. The Saubhagya Scheme, or Pradhan Mantri Sahaj Bijli Har Ghar Yojana, is being implemented in the State to provide energy access to all by providing last-mile connectivity and electricity connections to all un-electrified households in the rural and urban areas of the country to attain universal electrification. As a result, 100 per cent of villages have been electrified in the state as of March 31, 2019 (45). The electrification in Odisha is correlated with increased household incomes, education levels, and productivity, though the opportunity costs—like land use and subsidy reliance—are nontrivial (46). The Government of Odisha has also implemented several renewable energy policies and schemes, viz., the Odisha Renewable Energy Policy 2022 (a state government initiative), PM Surya Ghar: Muft Bijli Yojana, and Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyan, both central government initiatives, to boost sustainable energy infrastructure and its production. Various incentives have been provided under these schemes to increase the installed capacity of renewable energy. These schemes resulted in around six- fold increase in the installed capacity of renewable energy between 2014 and 2024 - from 115.13 MW as on March 31, 2014 to 670.48 MW as on March 31, 2024 (47, 48). This increased access to clean energy, particularly in remote and tribal regions, has shown measurable impacts on health, education, and local economic activities by extending energy services beyond lighting to small-scale enterprises and irrigation (49). An empirical study on the use of clean energy for sustainable livelihood in rural areas of southern Odisha advocates for clean energy adoption—such as solar microgrids and biomass cookstoves—as a sustainable livelihood strategy in South Odisha, which reduces dependence on unreliable grids and supports local economic resilience (50).

As conferred, the use of clean energy firstly mitigates the health risks associated with use of traditional fuels, secondly creates a conducive environment for children's education, thirdly enhances the overall security of women and girls, fourthly promotes gender equality by increasing educational opportunities and financial security for women, fifthly reduces deforestation and the hazards of climate change, and lastly improves the quality of life, and therefore, addressing energy poverty is highly significant not only for the socio-economic development of the household but also for the society. Against this backdrop, this study aims to measure the magnitude of multidimensional energy poverty among rural households in the Jagatsinghpur district of Odisha and examine the influence of different socio-economic variables on multidimensional energy poverty at the household level. The study's novelty lies in the household-level analysis of multidimensional energy poverty in the rural

Jagatsinghpur district of Odisha. The rest of the article is structured as follows: Section 2 discusses the materials and methods, Section 3 discusses the results, and Section 4 concludes.

Methodology

This study uses a multi-stage random sampling technique to collect information from the selected households between December 2023 and March 2024. The first, second, third, and fourth stages constitute the district, blocks, villages, and households, respectively. With 11.83 percent of the population coming under multidimensional poverty, the Jagatsinghpur district is documented as the second non-poor district of Odisha (43); still, it occupies the 19th position from the top among 30 districts of the State in terms of using clean cooking fuel. Therefore, this district is purposefully selected for our study to examine the status and factors affecting energy poverty in a multidimensional framework. The second stage constitutes all eight blocks of the sample district. In the third stage, 24 villages were randomly selected for the study, i.e., three villages from each block. The fourth stage captures sample households where 384 sample households are selected out of 2, 33,626 households of the district using the Rao-soft online sample size calculator. 5.46 percent of the households are selected from each sample village, using a simple random sampling technique in Table 1. The position of the sample district, along with its eight blocks, is presented in Figure 3 (51).

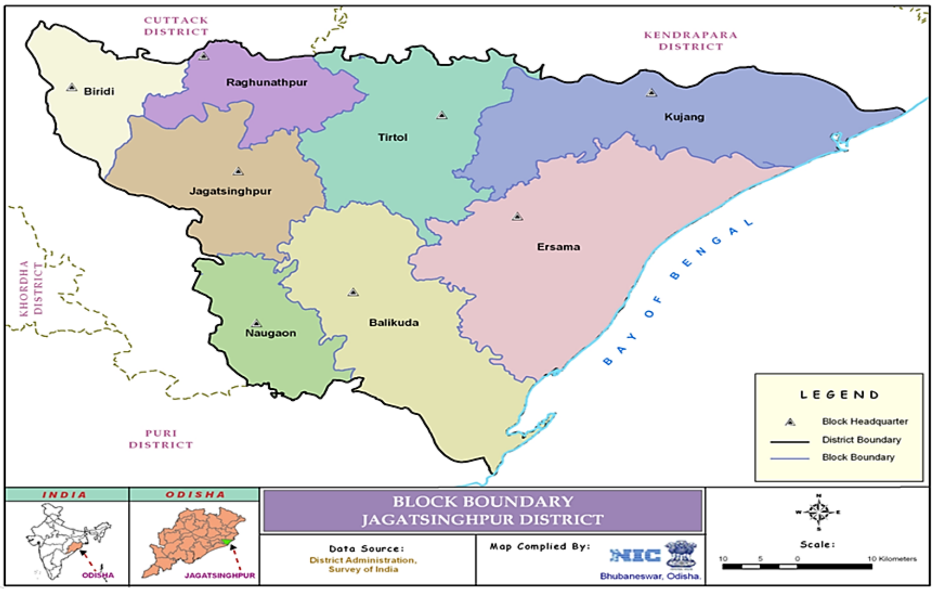

Figure 3: Block Map of Jagatsinghpur District of Odisha

The Alkire-Foster approach has been used to construct a multidimensional energy poverty index with suitable modifications to determine the status of a household and a block in terms of multidimensional energy poverty (52). For this purpose, five dimensions and five indicators with equal-weighting structures were used, which are presented in Table 2. In the field of multidimensional energy poverty study, other researchers also include similar types of dimensions and indicators to construct the MEPI, i.e., access to clean fuel such as electricity and LPG, and traditional fuel such as fire-wood, dung, and crop-residue under the household cooking dimension (12, 15, 28, 36-39, 53), access to electricity under the household lighting dimension (12, 15, 28, 36-38, 53), access to fan and refrigerator under the household appliances dimension (12, 15, 28, 36, 38, 53), access to TV under the household entertainment dimension (28), and access to mobile phone with internet facility under the household communication and education dimension (12, 28, 37, 39, 53).

Table 1: Sampling Frame

District	Total Household (no)	Sample Household size (no)	Block	Village	Total Household (no)	Sample Household size(no)
Jagatsinghpur (Odisha)	2,33,626	384	Balikuda	Bhoda	220	12
				Kalio	346	19
				Khaleri	136	7
			Biridi	Alando	329	18
				Balia	321	18
				Batimira	436	24
			Ersama	Arada	94	5
				Bartol	112	6
				Kothi	200	11
			Jagatsinghapur	Mahakaleswar	115	6
				Palli	131	7
				Punanga	537	29
			Kujang	Arakhia	303	17
				Hasina	509	28
				Zillanasi	323	18
			Naugaon	Erada	335	18
				Ghodanasa	351	19
				Tentoi	472	26
			Raghunathpur	Barti	161	9
				Jaisol	227	12
				Patenigan	162	9
			Tirtol	Bisunpur	573	31
				Ibirisingh	348	19
				Manapur	290	16
		Total			7031	384

Note: (1) Total number of households in each sample village, block, and district are acquired using Census 2011 (GoI) information; (2) From each sample village, 5.46 percent [(384/7031) *100] households were selected

The energy deprivation score (Di) is calculated at the household level by constructing an index using Equation [1].

$$Di = \sum_{i=1}^{5} w_i c_i = w_1c_1 + w_2c_2 + \ldots + w_5c_5 \quad [1]$$

where 'ci' indicates the component indicator – assigned with '1' for deprived household and '0' for non-deprived household in the i^{th} indicator, 'wi' is the weight assigned to the i^{th} indicator, and 'Di' lies between values '0' or '1', where '0' indicates that a household is not deprived in all the indicators of energy poverty under study, and '1' indicates the deprivation of household in all the indicators.

Incidence (H) and intensity (A) of energy poverty are computed to estimate the MEPI for all eight blocks and the sample district. The incidence of poverty (H) is estimated by dividing the total number of individuals in sample households whose overall energy deprivation score (Di) is equal to and above 0.3333 (q) with the total number of individuals in sample households (n), i.e., q/n. The intensity of poverty (A) is the average deprivation score of multidimensional energy-poor individuals in a specific group. The multiplication of the incidence of poverty with intensity of poverty, i.e., 'H x A', gives the value of MEPI.

Different energy poverty threshold levels such as less than 0.20, between 0.20 and 0.3333, between 0.3333 and 0.50, and 0.50 or above, are used to identify whether one household or one block is coming under the category of multidimensional energy non-poor (MDENP), vulnerable to multidimensional energy poor (VMDEP), multidimensional energy poor (MDEP), or severely multidimensional energy poor (SMDEP) respectively.

Table 2: MEPI (Dimensions, Indicators, and Weights with Deprivation Conditions)

Dimension	Weight	Indicator	Weight	The household is deprived if it…
Cooking	0.2	Access to clean cooking fuel	0.2	Is using solid and dirty fuel, i.e., coal, firewood, cow dung, and crop residue for cooking.
Lighting	0.2	Access to electricity	0.2	Has no access to electricity.
Electrical appliances	0.2	Access to electric fan and refrigerator	0.2	Has no access to an electric fan, refrigerator, or both.
Entertainment	0.2	Access to TV	0.2	has no access to TV
Education and communication	0.2	Access to mobile phone with internet facility	0.2	Has no access to a mobile phone with an internet facility.

The impact of different socio-economic and demographic variables on multidimensional energy poverty has been assessed using the binomial logistic regression model (54). MEPI, the dependent variable taken in this study, assigned a value of '1' if the household is energy poor and '0' if non-poor, with an energy poverty threshold of 0.3333. Independent variables taken in this study constitute both continuous variables, viz., number of household members (HHSIZE) and completed years of education of the head of household (EDNHH), and categorical variables, viz., household income level (HHINCOME), main occupation of the household (HHOCC), and poverty status of the household (HHPOVSTAT) as determined by the government, i.e., above poverty line (APL) and below poverty line (BPL). The logistic regression model adopted in this study is as follows.

$$Logit(P) = In(\frac{Pi}{1-Pi}) = \alpha_1 + \alpha_2 \text{ EDNHH} + \alpha_3 \text{ HHSIZE} + \alpha_4 \text{ DHHINCOME1} + \alpha_5 \text{ DHHINCOME2} + \alpha_6 \text{ DHHINCOME3} + \alpha_7 \text{ DHHINCOME4} + \alpha_8 \text{ DHHINCOME5} + \alpha_9 \text{ DAPL} + \alpha_{10} \text{ DFARM} + \alpha_{11} \text{ DDAIRY} + \alpha_{12} \text{ DBUS} + \alpha_{13} \text{ DPVTSER} + \alpha_{14} \text{ DGOVTSER} + ui \qquad [2]$$

where,

$Logit(P) = In\left(\frac{Pi}{1-Pi}\right)$ is the dependent variable, {Pi = E[Yi = 1(MEPI ≥ 0.3333)|X_i]};

EDNHH: Highest educational qualification of the household head, HHSIZE: Total number of family members in the household, DHHINCOME1: Dummy variable for the income group 1 ('1' if household's annual income is greater than one lakh and less than two lakhs, '0' otherwise); (reference category is the income group 0, where the household's income is less than or equal to 1 lakh), DHHINCOME2: Dummy variable for the income group 2 ('1' if the household's annual income is greater than two lakhs and less than three lakhs, '0' otherwise), DHHINCOME3: Dummy variable for the income group 3 ('1' if the household's annual income is greater than three lakhs and less than four lakhs, '0' otherwise);

DHHINCOME4: Dummy variable for the income group 4 ('1' if the household's annual income is greater than four lakhs and less than five lakhs, '0' otherwise);

DHHINCOME5: Dummy variable for the income group 5 ('1' if the household's annual income is equal to or greater than five lakhs, '0' otherwise);

DAPL: Dummy variable for the poverty status of household ('1' if the household belongs to APL category, '0' otherwise); (reference category household belonging to BPL category);

DFARM: Dummy variable for crop farming as the main occupation of household ('1' if the main occupation of household is crop farming, '0' otherwise);

DDAIRY: Dummy variable for dairy farming as the main occupation of household ('1' if the main occupation of household is dairy farming, '0' otherwise);

DBUS: Dummy variable for business activity as the main occupation of household ('1' if the main occupation of household is business, '0' otherwise);

DPVTSER: Dummy variable for private sector service as the main occupation of household ('1' if the main occupation of household is private sector service, '0' otherwise);

DGOVTSER: Dummy variable for government service as the main occupation of household ('1' if the main occupation of household is government service, '0' otherwise); (reference category daily wage earner).

Results and Discussion

The sample profile, important for understanding the research context and its findings' applicability, typically describes the characteristics of the subjects involved in this study, presented in Table 3. Analysis of the main occupation of sample households reveals that one in every three households has a daily wage earner. About one-fourth of households have private service or business as the main occupation. Only around four percent of households have government service as the main occupation of the household. About 90 percent of households have an income below three lakhs per annum and about 81 percent of households coming under BPL category. Illiterate heads of households constitute only 3.65 percent, and about half of heads of households have a secondary level of education.

The estimated multidimensional energy poverty index (MEPI) at the household level for the study district using the indicators and methodology discussed in the materials and methods section is presented in Table 4. The study divulges that about one-third of sample households are multidimensionally energy non-poor, and the rest, 68.75 per cent, are categorised as multidimensionally energy-poor.

Multidimensional energy poverty status across household characteristics indicates that most sample households with livestock and daily labour as the households' main occupation are multidimensionally energy poor. Households with service (government or private) and business as the main occupation are less susceptible to multidimensional energy poverty. A statistically significant Pearson Chi-Square coefficient indicates the existence of a relationship between the main occupation of the household and multidimensional energy poverty. Similarly, the poverty status of the household and its annual income level are observed to be significantly associated with multidimensional energy poverty. Households belonging to the BPL category and with income levels less than two lakhs per annum are more multidimensional energy-poor than other categories. The educational level of the household head also has a significant relationship with multidimensional energy poverty. More than 70 per cent of sample households are observed to be multidimensional energy poor, where the highest educational qualification of the head of household is at the secondary level or less.

Table 3: Characteristics of Sample Households

		Sample HH (No)	Percent
Main Occupation of Household	Daily Labour	124	32.29
	Farming	57	14.84
	Livestock	5	1.30
	Business	90	23.44
	Pvt. Service	93	24.22
	Govt. Service	15	3.91
Poverty Status	BPL	312	81.25
	APL	72	18.75
Household Income Level (Rs.)	Below 1 lakh	153	39.84
	1 - 2 Lakhs	117	30.47
	2 - 3 Lakhs	73	19.01
	3 - 4 Lakhs	22	5.73
	4 - 5 Lakhs	7	1.82
	Above 5 Lakhs	12	3.13
Educational Level of Household Head	Illiterate	14	3.65
	Lower Primary	56	14.58
	Upper Primary	46	11.98
	Secondary	187	48.70
	Higher Secondary	40	10.42
	Graduation	34	8.85
	Other	7	1.82

Figure 4 and Table 5 illustrate the indicator-wise energy poverty across eight blocks of the study district. All the sample households have access to electricity. The Government of Odisha's commitment to connect every state village with electricity and its effective implementation in this district results in zero deprivation of households in their access to electricity. The highest deprivation is observed in access to clean cooking fuel (81 per cent of the district), followed by access to electric fans and refrigerators (68 per cent of the district). The study observed that 213 households (55.47 per cent) do not have access to clean cooking fuel and are still using wood and cow dung. Only 73 households (19.01 per cent) use LPG and /or induction cookers. Although 98 households (25.52 per cent) possess LPG, they do not use clean cooking fuel. Affordability is observed to be a major factor for less use of clean cooking fuel. Rural households in the district using dirty fuel have easy access to firewood collected from the trees grown on their land, and also prepare cow-dung cakes by themselves. Hence, the opportunity cost of using dirty fuel (wood and cow-dung cake) in terms of clean fuel is very high. Also, about 97 per cent of households using dirty fuel belong to the BPL category and are not in a position to afford LPG and/or electric induction cookers. This demonstrates that the objective of the Government of India to make clean cooking fuel available to rural and deprived households and to reduce the detrimental impacts of traditional cooking fuel on the health of rural women as well as on the environment under "Pradhan Mantri Ujjwala Yojana" (PMUY) and "Pratyaksh Hanstantrit Labh Scheme" (PAHAL) has not been achieved satisfactorily.

Table 4: Multidimensionally Energy Poverty Status across Household Characteristics

		Multidimensionally energy non-poor household		**Multidimensionally energy poor household**		**Pearson Chi-Square (Asymptotic Significance)**
		No.	**Percent**	**No.**	**Percent**	
Main Occupation of Household	Daily Labour	4	3.23	120	96.77	90.877 (0.000)
	Farming	13	22.81	44	77.19	
	Livestock	0	0.00	5	100.00	
	Business	46	51.11	44	48.89	
	Pvt. Service	47	50.54	46	49.46	
	Govt. Service	10	66.67	5	33.33	
Poverty Status	BPL	70	22.44	242	77.56	60.171 (0.000)
	APL	50	69.44	22	30.56	
Household Income Level (in annual Rs.)	Below 1 lakh	10	6.54	143	93.46	137.263 (0.000)
	1 - 2 Lakhs	28	23.93	89	76.07	
	2 - 3 Lakhs	51	69.86	22	30.14	
	3 - 4 Lakhs	16	72.73	6	27.27	
	4 - 5 Lakhs	4	57.14	3	42.86	
	Above 5 Lakhs	11	91.67	1	8.33	
Educational Level of Head of Household	Illiterate	0	0.00	14	100.00	85.857 (0.000)
	Lower Primary	4	7.14	52	92.86	
	Upper Primary	8	17.39	38	81.61	
	Secondary	52	27.81	135	72.19	
	Higher Secondary	23	57.50	17	42.50	
	Graduation	27	79.41	7	20.59	
	Other	6	85.71	1	14.31	
Total Household		120	31.25	264	68.75	

Further, almost all households (98.95 per cent) own electric fans, 32.29 per cent own refrigerators, and only 122 households (31.77 per cent) own both electric fans and refrigerators. Therefore, 68.23 per cent of households were poor in the household appliance dimension. About 95 per cent of households that have no access to household appliances belong to the BPL category. Lack of purchasing power to own refrigerators, power failure for a longer period of time, and low voltage in rural areas are the major factors for the low possession of refrigerators.

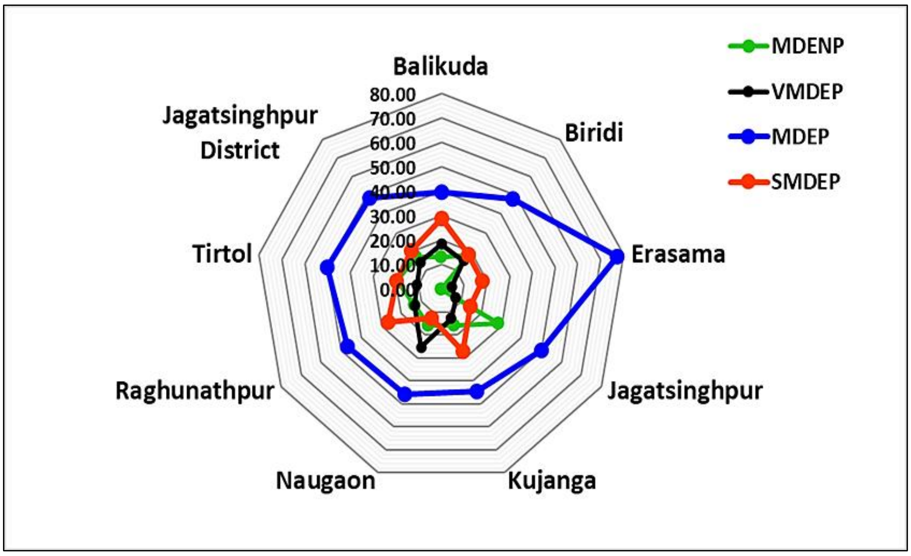

Figure 4: Household Multidimensional Energy Poverty Status across Different Blocks

Table 5: Indicator-Wise Household Deprivation Status across Different Blocks

Block/ District	Cooking Access to clean cooking fuel		Lighting Access to electricity		Electric Appliances Access to electric fan and refrigerator		Entertainment Access to TV		Education and communication Access to mobile phone with internet facility	
	No	Percent	No	Percent	No	Percent	No	Percent	No	Percent
Balikuda	31	51.58	0	0.00	27	71.05	4	10.53	12	31.58
Biridi	47	78.33	0	0.00	42	70.00	0	0.00	11	18.33
Erasama	22	100.00	0	0.00	20	90.91	3	13.64	3	13.64
Jagatsinghpur	30	71.43	0	0.00	27	64.19	1	2.38	6	14.29
Kujanga	52	82.54	0	0.00	45	71.43	1	1.59	18	28.57
Naugaon	51	80.95	0	0.00	34	53.97	1	3.33	13	20.63
Raghunathpur	26	86.67	0	0.00	22	73.33	1	0.00	8	26.67
Tirtol	52	78.79	0	0.00	45	68.18	0	0.00	15	22.73
District	311	80.99	0	0.00	262	68.23	11	2.86	86	22.40

The study observed the existence of regional inequity in multidimensional energy poverty in the Jagatsinghpur district. All the sample households of Ersama block and more than 80 per cent of households of Raghunathpur, Kujanga, and Naugaon have been observed to be deprived of clean cooking fuel. Ersama block has the highest deprivation amongst all eight blocks in access to clean cooking fuel (100 per cent), household appliances (90.91 per cent), and TV (13.64 per cent). About 90 per cent of households belong to the BPL category, reflecting their low purchasing power and limited access to household assets, including clean cooking fuel. About 81 per cent of households have wage labour and farming as the main occupation. Frequent visits of natural disasters (floods and cyclones) are mainly responsible for the low economic status of households, particularly households with farming, dairy, and daily wages as primary occupations. The energy poverty status of households across eight blocks in Table 6 indicates that none of the sample households of the Ersama block come under the MDENP category, and about 95 per cent of households are categorised as either MDEP or SMDEP. Raghunathpur, Kujanga, and Tirtol blocks, along with Ersama, have multidimensionally energy-poor households above the district average.

Incidence (proportion of the population deprived) and intensity (severity of the deprivation) of multidimensional energy poverty provide a fuller picture of energy poverty and help policymakers design targeted interventions. The block-wise incidence and intensity of multidimensional energy poverty are shown in Table 7. The incidence of multidimensional energy poverty depends on the breadth or extent of multidimensional energy poverty in a given population and is typically represented as the percentage of persons who experience energy deprivation based on certain thresholds or criteria. The study reveals that 68.5 per cent of the total rural population of the district is under multidimensional energy poverty. Ersama block witnessed the highest incidence of multidimensional energy poverty (0.9605), and Naugaon block was the lowest (0. 5614), as shown in Figure 5.

The intensity of multidimensional energy poverty, measured through the average percentage of deprivations suffered by the poor population, indicates the depth of deprivation for those living in multidimensional energy poverty. It reflects how far the individuals are from the energy poverty threshold.

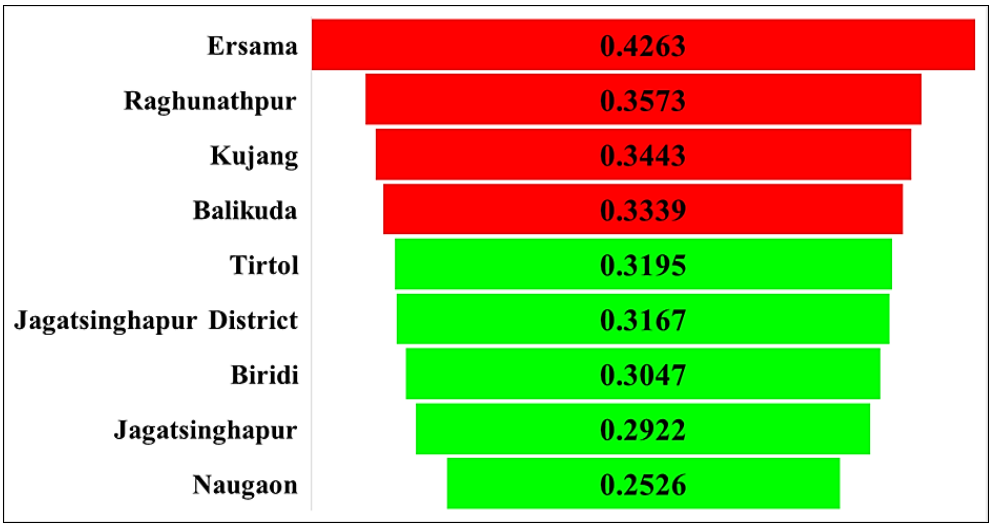

Figure 5: Block-Wise Energy Poverty Status in Jagatsinghpur District of Odisha

NB: The red bar indicates a multidimensional energy-poor block, and the green bar indicates energy non-poor with an energy poverty threshold of 0.3333.

Table 6: Household Multidimensional Energy Poverty Status across Different Blocks

Block/District	MDENP		VMDEP		MDEP		SMDEP		NON-POOR		POOR	
	No.	Percent	No.	Percent	No.	Percent	No.	Percent	No.	Percent	No.	Percent
Balikuda	5	13.16	7	18.42	15	39.47	11	28.95	12	31.58	26	68.42
Biridi	11	18.33	9	15.00	29	48.33	11	18.33	20	33.33	40	66.67
Erasama	0	0.00	1	4.55	17	77.27	4	18.18	1	4.55	21	95.45
Jagatsinghpur	12	28.57	3	7.14	21	50.00	6	14.29	15	35.71	27	64.29
Kujanga	10	15.87	8	12.70	28	44.44	17	26.98	18	28.57	45	71.43
Naugaon	10	15.87	16	25.40	29	46.03	8	12.70	26	41.27	37	58.73
Raghunathpur	4	13.33	4	13.33	14	4.7	8	26.67	8	26.67	22	73.33
Tirtol	13	19.70	7	10.61	33	50.00	13	19.70	20	30.30	46	69.70
District	65	16.93	55	14.32	186	48.44	78	20.31	120	31.25	264	68.75

NB: (i) To identify multidimensional energy-poor and non-poor households, the poverty threshold level is considered as 0.3333; (ii) MDENP: Multidimensional energy non-poor (poverty threshold - less than 0.20); VMDEP: Vulnerable to multidimensional energy poor (poverty threshold - between 0.20 and 0.3333); MDEP: Multidimensional energy poor (poverty threshold - between 0.3333 and 0.50); SMDEP: Severely multidimensional energy poor (poverty threshold - 0.50 or above)

As observed from Table 7, there are no major differences in the intensity of energy poverty for all eight blocks under study and also for the district as a whole, and the intensity of energy poverty revolves around 46 percent, indicating that on average, poor people are deprived in 46 percent of the weighted indicators.

Table 7: Block-Wise Multidimensional Energy Poverty Status

Block / District	Total Population	*Number of Persons Deprived	Incidence of Poverty (H)	Intensity of Poverty (A)	MEPI = H x A	Poverty Status
Balikuda	127	86	0.6772	0.4930	0.3339	Poor
Biridi	212	141	0.6651	0.4582	0.3047	Non-poor
Ersama	76	73	0.9605	0.4438	0.4263	Poor
Jagatsinghpur	154	99	0.6429	0.4545	0.2922	Non-poor
Kujang	201	144	0.7164	0.4806	0.3443	Poor
Naugaon	228	128	0.5614	0.4500	0.2526	Non-poor
Raghunathpur	103	77	0.7476	0.4779	0.3573	Poor
Tirtol	246	175	0.7114	0.4491	0.3195	Non-poor
District	1347	923	0.6852	0.4622	0.3167	Non-poor

NB: *Number of persons deprived with energy poverty threshold 0.3333

In order to check the robustness of the multidimensional energy poverty result, a sensitivity analysis was conducted by constructing the block-wise Cumulative Distribution Function (CDF) using different energy poverty threshold levels between 0 and 100 per cent, which is presented in Figure 6. It is observed from the Figure 6 that any poverty threshold level between 0 and 40 percent, Ersama block witnessed the highest incidence of multidimensional energy poverty, i.e., highest percentage of the total population deemed energy poor, whereas any poverty threshold level between 20 and 80 percent, Naugaon block has the lowest incidence of multidimensional energy poverty. Zero incidence of multidimensional energy poverty across all the blocks and the Jagatsinghpur district as a whole is observed when the poverty threshold level is taken between 80 and 100 per cent. Block-wise MEPI in Jagatsinghpur district of Odisha at different poverty threshold levels between 1 per cent and 90 per cent is also computed and presented in Figure 7. It is observed from Figure 7 that for any poverty threshold level between 0 and 40 per cent, the Ersama block witnessed the highest MEPI score, whereas for any poverty threshold level between 20 and 80 per cent, the Naugaon block has the lowest MEPI score.

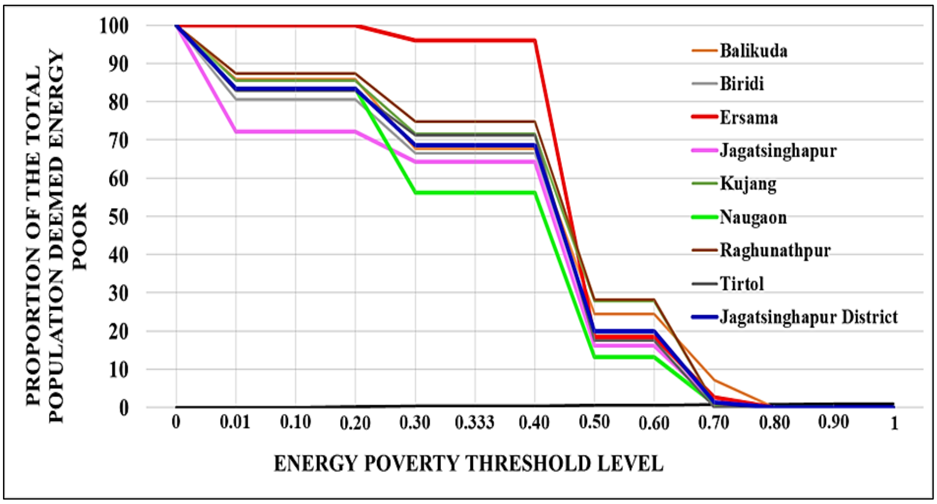

Figure 6: Block-Wise Energy Poverty Status in Jagatsinghpur District of Odisha at Different Poverty Threshold Levels

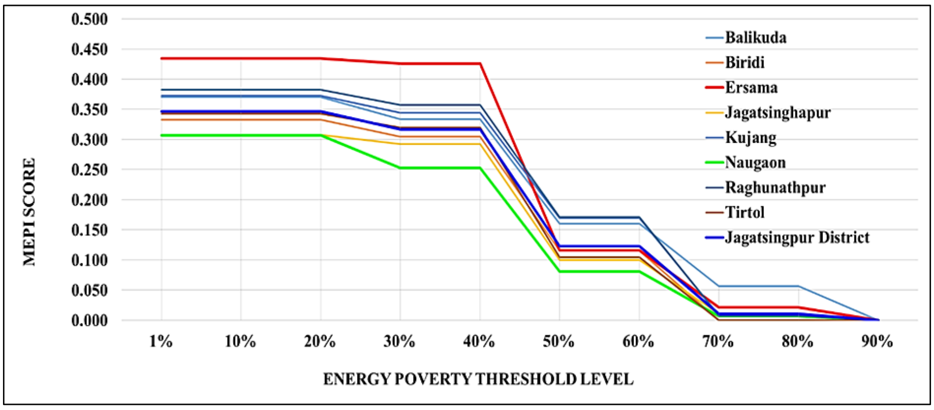

Figure 7: Block-Wise MEPI in Jagatsinghpur District of Odisha at Different Poverty Threshold Levels

Table 8 shows the model evaluation of the binary logistic regression adopted in the study to evaluate the effect of independent variables on multidimensional energy poverty. The Omnibus test evaluates the overall significance of the logistic regression model and assesses whether the independent variables as a whole significantly improve the model compared to a baseline (intercept-only) model. The goodness of fit tests show that there is no indication of gross deficiencies with the model. It is also observed from Table 8 that the p-value of 0.000 of the chi-squared statistic is less than the typical significance threshold level of 0.05, which implies that one or more of the five predictors of the model is important for predicting the probability of multidimensional energy poverty. Hence, the model with the five predictors is statistically significant and performs better than a model with no predictors (intercept-only model). The p-value of the Hosmer-Lemeshow test is 0.384, which is greater than 0.05, indicating that the observed frequencies match the expected frequencies across the groups and that the model fits well. Cox and Snell R Square (0.428) and Nagelkerke R Square (0.602) also indicate the overall model fit. The model strength is assessed through correct and incorrect predictions, i.e., 85.7 percent of cases have been correctly classified.

Table 8: Model Evaluation of Binary Logistic Regression

			Chi-square	df	Sig.
Omnibus Tests of Model Coefficients	Step 1	Step	214.832	13	0.000
		Block	214.832	13	0.000
		Model	214.832	13	0.000
Model Summary				Cox and Snell R Square	Nagelkerke R Square
			Step 1	0.428	0.602
Hosmer and Lemeshow Test			Chi-square	df	Sig.
		Step 1	8.529	8	0.384
				Predicted	
			MEPI		
Classification Table	Step 1	Observed	Non-poor	Poor	Percentage Correct
		Non-poor	83	37	69.2
		Poor	18	246	93.2
		Overall Percentage			85.7

The effect of socio-economic determinants on multidimensional energy poverty undertaken in the study has been presented in Table 9. The p-value for each regression effect, except for dairy farming, private service, and government service as the main household occupation, is smaller than 0.05, so each regression coefficient is significantly different from zero, and each odd-ratio is significantly different from 1. The p-value for regression effects of the variables, viz., number of household members, completed years of education of the head of household, and poverty status of the household, is smaller than 0.05, so each regression coefficient is significantly different from zero, and each odd-ratio is significantly different from 1. Similarly, the p-value for regression effects of two dummy variables, i.e., household income level and main occupation of the household, as a whole, is significantly different from zero. However, the coefficients of dairy farming and government service as the main occupation of the household are not statistically significant even at a 10 percent level of significance, indicating these two categories of the main occupation of the household are not influencing the household multidimensional energy poverty level.

Table 9: Socio-Economic Determinants of Multidimensional Energy Poverty

	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	5.027	1.031	23.759	1	0.000	152.547
Educational Level of Household Head	-0.232	0.057	16.553	1	0.000	0.793
Number of Household Members	0.413	0.174	5.610	1	0.018	1.511
Household Income (Reference category: less than one lakh)			30.951	5	0.000	
DHHINCOME1	-2.104	0.747	7.923	1	0.005	0.122
DHHINCOME2	-3.809	0.818	21.696	1	0.000	0.022
DHHINCOME3	-3.750	0.978	14.696	1	0.000	0.024
DHHINCOME4	-2.951	1.280	5.318	1	0.021	0.052
DHHINCOME5	-5.039	1.542	10.683	1	0.001	0.006
DAPL	-1.126	0.449	6.276	1	0.012	0.324
Main Occupation of HH (Reference category - Daily Labour)			14.514	5	.013	
DFarm	-2.334	.765	9.305	1	0.002	0.097
DDairy	16.602	17134.659	0.000	1	0.999	16229548.209
DBus	-1.338	0.655	4.176	1	0.041	0.262
DPvtSer	-1.259	0.678	3.445	1	0.063	0.284
DGovtSer	0.496	1.043	0.226	1	0.634	1.643

Logistic regression results presented in Table 9 indicate that an increase in the education level of the household head decreases the likelihood of the household becoming multidimensionally energy-poor. This finding of the study corroborates the findings of earlier studies (11, 14, 15, 19, 28, 35, 38). The present study shows that a one-year increase in the educational level of the head of the household decreases the odds of falling into the multidimensional energy poverty category by about 21 percent. The study further observed a positive impact of household size on multidimensional energy poverty, which supports the earlier studies (14, 15, 35, 37, 39). An increase in one household member increases the odds of becoming multidimensionally energy-poor by about 51 percent. The income and poverty level of the household negatively influence multidimensional energy poverty. As the income level of the household increases, the odds of falling into a multidimensional energy poverty level continuously decrease. This finding of the study also supports the findings of the earlier studies (13, 14, 19, 35). An increase in household income from one lakh to two lakhs decreases the odds of becoming multidimensionally energy-poor by 88 percent. But as the income level increases to five lakhs, the odds of falling into an energy poverty level decrease by 99 percent in comparison to the income level of one lakh. Similarly, if the household is elevated into the APL category, the odds of being energy-poor decrease by 68 percent compared to a BPL-category family.

The study also observed a decreasing influence of farming, business, and private service as the main occupation of the household on energy poverty in comparison to daily wage labour. Households with businesses and private sector services witnessed a decrease in odds of becoming energy-poor to the extent of around 72 percent. If a household shifts its main occupation from a daily wage earner to farming, the odds of falling into the multidimensional energy-poor category are reduced by about 90 percent, substantiating the earlier study (55).

Conclusion

This study is undertaken to analyze multidimensional energy poverty in the rural areas of the Jagatsinghpur district of Odisha. This study is the first of its kind in analyzing multidimensional energy poverty for all blocks of the study district, which justifies the novelty of this study. 384 households randomly selected from all eight blocks of the district constitute the sample units for this study. This study assesses the extent of multidimensional energy poverty measured through five indicators across five dimensions using the methodology developed in past study (52). Further, to examine the factors influencing multidimensional energy poverty among rural households, binomial logistic regression analysis has been applied.

Access to electricity by all sample households is one major finding of the study, which portrays the positive role played by the state government in this regard. About 55 percent of households have no access to clean cooking fuel, which is another major finding of the study. Most of these households belong to the BPL category. The easy availability of wood and cow-dung cake at a very low cost is considered a factor for the low use of LPG. Further, it is observed that about 25.52 percent of households, although possessing LPG, do not use clean cooking fuel. This necessitates covering eligible BPL households without LPG connection under PMUY and PAHAL. In addition, households possessing LPG and using traditional cooking fuel need to be aware of the detrimental impacts of traditional cooking fuel on the health conditions of household members and the environment. The creation of awareness among family members, particularly women, on a continuous basis regarding the health hazards of traditional cooking fuel can help rural households increase their dependence on clean cooking fuel and curb energy poverty.

The study observed the positive role played by education in reducing multidimensional energy poverty, suggesting that education can be a key driver in mitigating energy poverty in rural areas. Education of the head of household improves energy literacy and creates awareness among family members about the hazards of traditional cooking fuel and the benefits of accessing clean energy. Schemes like Pradhan Mantri Poshan Shakti Nirman (PM POSHAN) for Classes I to VIII to arrest the dropouts at primary school level through nutritious meals to students, National Talent Search Examination (NTSE) for economically disadvantaged children, the New India Literacy Programme (NILP) to improve literacy among women, SC, ST, minorities, and disadvantaged groups are in operation to improve the educational status of the household members. Implementing the National Education Policy 2020 in the State of Odisha is expected to help reduce dropouts, especially among marginalized groups, in elementary, high school, and higher secondary education in the district. The existence of regional disparity in multidimensional energy poverty, as observed in this study, calls for the attention of policy planners. Special attention needs to be given to the Ersama block while designing policies for providing clean cooking fuel and reducing multidimensional energy poverty.

Abbreviations

APL: Above Poverty Line, BPL: Below Poverty Line, CO_2: Carbon Dioxide, CO: Carbon Monoxide, GoI: Govt. of India, MDENP: Multidimensionally Energy Non-poor, MDEP: Multidimensionally Energy Poor, MEP: Multidimensional Energy Poverty, MEPI: Multidimensional Energy Poverty Index, NILP: New India Literacy Programme, NTS: National Talent Search Examination, PM POSHAN: Pradhan Mantri Poshan Shakti Nirman, PMUY: Pradhan Mantri Ujjwala Yojana, PAHAL: Pratyaksh Hanstantrit Labh Scheme, SC: Scheduled Caste, SDG: Sustainable Development Goal, SMDEP: Severely Multidimensionally Energy Poor, ST: Scheduled Tribe, UNDESA: United Nations Department of Economic and Social Affairs, UNDP: United Nations Development Programme, VMDEP: Vulnerable to Multidimensionally Energy Poor, WHO: World Health Organization.

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Author Contributions

Snehashis Samantaray: literature review, methodology, data analysis, interpretation, conclusion, references, Minaketan Sarangi: literature review, problem formulation, discussion, conclusion, Santosh Kumar Mishra: literature review, discussion, conclusion.

Conflict of Interest

There is no conflict of interest.

Ethics Approval

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