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Do socioeconomic factors determine household multidimensional energy poverty? Empirical evidence from South Asia

Khizar Abbas [a], Shixiang Li [b,*], Deyi Xu [c], Khan Baz [c], Aigerim Rakhmetova [a]

[a] School of Public Administration, China University of Geosciences, Lumo Road 388, Wuhan, 430074, PR China

[b] Ph.D./ Professor/Director of Public Administration Department, School of Public Administration, Mineral Resources Strategy and Policy Research Center, China University of Geosciences, Lumo Road 388, Wuhan, 430074, PR China

[c] School of Economics and Management, China University of Geosciences, Lumo Road 388, Wuhan, 430074, PR China

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ABSTRACT

This paper examines the socioeconomic factors of energy poverty at the household level using a dataset of 674,834 households from six South Asian countries. An adjusted multidimensional energy poverty index (MEPI) is used to measure the extent and depth of energy poverty, and a Tobit model is employed to examine the significance of socioeconomic status for multidimensional energy poverty. An ordinary least squares (OLS) regression model is compared with the results of the Tobit model, using the combined dataset and the datasets for each country separately. House size, household wealth, education, occupation (clerical, sales, or agricultural), and gender of the head of the households are significant negative socioeconomic determinants of household multidimensional energy poverty. Place of residence, house ownership status, family size, and the age of the primary breadwinner play a significant positive role in multidimensional energy poverty. These results suggest that effective policy measures for improving the socioeconomic status of households will mitigate multidimensional energy poverty. With implications for the design and implementation of policy, the evidence-based results of this study will contribute to reducing the detrimental impacts of multidimensional energy poverty nationally, regionally, and globally.

1. Introduction

Multidimensional energy poverty is one of the most critical challenges in the contemporary world. Increases in global energy demands and the rampant population growth have left many households hardly able to afford basic energy services (IEA, 2019). Worldwide, almost 1.1 billion people have faced energy precariousness in recent years, and 1 billion do not have access to clean energy. Nearly 2.8 billion people still rely on traditional energy sources such as coal, charcoal, biomass, firewood, crops, straw, and animal dung. Dependence on contaminated cooking fuels for indoor use has severe detrimental consequences for health, with women and children most affected. Indoor air pollution causes 2.8 million premature deaths per annum globally, of which about 44% are children and 33.6% are women (IEA, 2017). Even in the developed world, energy poverty is a major challenge with economic, environmental, social, political, and health implications (Besagni and Borgarello, 2019; Boardman, 1991; Heindl and Schuessler, 2015; Marchand et al., 2019; Middlemiss and Gillard, 2015; Papada and Kaliampakos, 2018; Robinson et al., 2018). Alongside this challenge, developing countries also face air pollution, food shortages, shelter poverty, climate change, and water scarcity, each of which aggravates energy poverty.

As a region of developing countries, South Asia is particularly affected by these problems. Highly unreliable access to energy services makes it one of the areas in the world most susceptible to multidimensional energy poverty. Its limited capacity to meet growing energy demands creates problems at the national level (Alalouch et al., 2017), and the consumption of solid fuels for cooking purposes is a common issue throughout the region. The inability to access clean energy has severe health implications, including respiratory disease, lung cancer, diabetes, cardiovascular problems, malnutrition, high blood pressure, and premature death (HEI, 2019). In some rural areas, women and children spend most of the day searching for cooking fuel and drawing and transporting water; this also drives poverty through lost opportunities

* Corresponding author.
E-mail addresses: khizarabbass971@cug.edu.cn (K. Abbas), lishixiang@cug.edu.cn (S. Li), xdy@cug.edu.cn (D. Xu), khanbaz114@yahoo.com (K. Baz), vip.orazovna@mail.ru (A. Rakhmetova).

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for educational and human development.

Many studies have discussed the affordability, reliability, and sustainability of clean energy and domestic energy services. However, to the best of our knowledge, there have been few attempts to identify the socioeconomic determinants of multidimensional energy poverty in South Asia, where disparities in the socioeconomic status of households prevent efforts to achieve universal access to clean energy. Studies examining the influence of household wealth, property ownership status, structural, socioeconomic, and geographic factors on energy poverty are also lacking (Marchand et al., 2019). The existing studies (Legendre and Ricci, 2014; Primc et al., 2019; Romero et al., 2018) have focused on energy-poor households using a consumption- or expenditure-based approach. For example, Romero et al. (2018) used expenditure-based indicators to calculate energy poverty, establishing an empirical relationship between those indicators and housing characteristics; Legendre and Ricci (2014) used an income-based approach to identify vulnerable energy households. In contrast, the present study uses composite indices, rather than a single index, to measure multidimensional energy poverty, taking into consideration both housing and socioeconomic factors. A Tobit regression model is used to analyse the determinants of multidimensional energy poverty statistically.

The objective of this study is to contribute to the debate about the socioeconomic determinants of multidimensional energy poverty. First, it describes the occurrences and intensity of multidimensional energy poverty in South Asia. Second, it analyses a range of socioeconomic factors to identify the determinants of household multidimensional energy poverty in that region. Third, and on the basis of the empirical findings, it identifies effective policy implications for reducing multidimensional energy poverty. The comparative primary data provides indepth analytical information that can be used in designing policies to alleviate multidimensional energy poverty and improve the socioeconomic status of households.

The structure of the paper is as follows. Section 2 provides a brief critical review of the relevant literature on energy poverty and its implications. The data source, research methods, measurements of energy poverty and its determinants are then explained in Section 3. Section 4 analyses the data and discusses the results. Section 5 concludes the argument of the paper and proposes policy implications based on the empirical findings.

2. Literature review

Many researchers have explained the concept of energy poverty, its relativity, and its multidimensionality (Boardman, 1991; Bouzarovski and Petrova, 2015; Grevisse and Brynart, 2011; Li et al., 2014; Thomson and Bouzarovski, 2018). Energy poverty can be defined as a lack of access to energy services that are sufficient, reliable, and modern. It includes all types of poverty that make it difficult or impossible to obtain clean energy and modern energy services at the household level (Bouzarovski and Petrova, 2015). Households in energy poverty are unable to avail themselves of energy facilities that are sufficient, reliable, affordable, environment-friendly, safe or healthily.

Beyond the household, reliable clean energy supply and affordable basic energy services play a significant positive role in the health sector, information industry, education sector, political participation, and indicators of economic prosperity such as industrial production, per capita income, and GDP growth (Narula et al., 2017). Access to clean energy sources also brings environmental sustainability, increasing energy efficiency by reducing deforestation and minimising reliance on solid fuels (Nadimi and Tokimatsu, 2018; Nadimi et al., 2017; Park et al., 2015). Conversely, Nadimi and Tokimatsu (2018) and Nadimi et al. (2017) proved the relationship between energy vulnerability and quality of life, with energy poverty having negative impacts on health, education, the environment, and economic growth. In connection with these detrimental implications of energy poverty, Day et al. (2016) suggested harnessing renewable energy sources and abandoning traditional contaminated fuels. Similarly, in their discussion of the relationship between energy poverty and development, González-Eguino (2015) highlighted the negative impacts of energy poverty on health, agriculture, economy, and the environment.

Papada et al. (2016) proposed a distinctive strategy for fighting against the energy deprivation: constructing underground houses in mountainous areas. These underground dwellings consume 28–40% less energy than dwellings on the surface. Bazilian et al. (2014) discussed energy governance involving global, regional, and national institutions as a way to manage the energy poverty. For a better understanding of energy deprivation, Bouzarovski and Simcock (2017) coined the term 'energy injustice', a specific type of injustice that marginalises the distribution of energy services, whereas 'spatial justice' focuses on the role of geography and demography in the creation of energy inequity and social inequality. Therefore, three kinds of justice, namely distributive, procedural, and recognition justice, should be taken into account to alleviate energy poverty. Stakeholders should not undermine the importance of 'spatial justice' in the policy-making process and for the alleviation of energy poverty, and there have been calls to put the impacts of energy poverty on productivity, climate, human well-being and health, standards of living, and gender equality at the centre of global efforts (Healy and Clinch, 2002; Scarpellini et al., 2019). From this perspective, it is imperative to facilitate household access to basic energy services, and the empirical information base makes it possible to trace the determinants of energy poverty and strengthen potential affordability.

3. Methodology and data

3.1. Measurements of energy poverty

As energy poverty is a complex and multifaceted concept, researchers use different indicators to gauge, understand, and monitor it. Because of the multidimensionality of the concept, a set of indicators must be carefully selected to capture its social, economic, and technical aspects adequately. The present study uses an adjusted multidimensional energy poverty index (MEPI) to measure the multidimensional energy poverty in South Asia. The MEPI approach was defined and applied in the context of energy poverty in African countries by Nussbaumer et al. (2012) with the collaboration of the Oxford Poverty and Human Development Initiative and the Oxford Department of International Development, and subsequently developed and improved in the work of Alkire and Foster (2011a), Alkire et al. (2017), and Datt (2013). The MEPI measures energy poverty using a composite index, an approach that not only measures the numbers of energy-poor households but also quantifies the intensity of their energy deprivation.

The MEPI focuses on the basic household energy needs of cooking, lighting, heating/cooling, household appliances, entertainment/education, and telecommunication. The different dimensions of these basic energy needs are captured with various variables, chosen carefully for their relevance to quantifiability. For example, cooking is measured by the type of fuel used for preparing a meal, and lighting is measured by electricity access/connection. The other dimensions are measured by ownership/possession of assets such as a refrigerator, a television, and a mobile phone. This study measures deprivation in terms of these basic elements of daily life. Table 1 summarizes the dimensions and indicators used here to measure multidimensional energy poverty, including cutoff points at which a household is considered to be deprived.

The MEPI measures the extent and severity of energy poverty on dimensions d of the population n in individuals. So, $Y = y_{ij}$ denotes the achievement matrix $n \times d$ of an individual i across variables j, and $y_{ij} \geq 0$ presents the degree of an individual's achievements $i = 1,2,3 \ldots. n$ on variables $j = 1,2,3 \ldots d$. Every row vector represents achievements of individual i in various variables j, whereas the column vector represents the distributive achievements in variables j among individuals.

The relative weights are distributed arbitrarily among the indicators;

Table 1
Deprivation dimensions, indicators, and cut-offs.

Dimension	Indicator (weighting)	Household deprivation cut-off
Cooking	Modern cooking fuel (0.2)	Deprived if using cooking fuel other than electricity, natural gas, kerosene, or biogas.
Indoor air-pollution	Separate room for cooking (0.15)	Deprived if no separate room for cooking with a chimney or hood.
Lighting	Electricity access (0.2)	Deprived if no electricity connection.
Household appliances	Possession of appliances (0.15)	Deprived if no fridge.
Entertainment /education	Ownership of assets (0.15)	Deprived if no television.
Communication	Ownership of assets (0.15)	Deprived if no mobile telephone or landline telephone.

however, the MEPI recognises the unequal importance of energy poverty indicators (Nussbaumer et al., 2012). The vector of weight w of variables j is equal to $\sum_{j=1}^{d} wj = 1$. The MEPI utilises dual cut-off parameters to measure headcounts and intensity of energy poverty, deprivation cut-off z, and poverty cut-off k. The deprivation cut-off z_j denotes the level of deprivation for any variable j. As with the matrix of achievements $n \times d$, we also take a deprivation matrix g_{ij} with a typical entry $g_{ij} = wj$. Therefore, $g_{ij} \geq z_j$ for an individual i who is deprived in any variable j of energy services, and $g_{ij} < z_j$ otherwise.

The deprivation cut-off z is not enough to detect which households are multidimensionally energy-poor, as it captures deprivation in a specific dimension only. An additional, less tangible cut-off is required, poverty cutoff k, which sets a minimum eligibility criterion in terms of multidimensional energy poverty. The choice of poverty cut-off overall affects the measurements of MEPI, intensity (A), and headcount ratio (H); the choice is therefore a sensitive one that should take into account policy targets and priorities. For instance, some dimensions appear to be important than others, and this can be reflected in appropriate choices of w and k. In this study, the weights assigned to cooking and lighting are higher than for other dimensions, reflecting their relative importance in the study area. The choice of k can be a normative one. The MEPI in the United Nations Human Development (UNDP) reports proposed three different poverty cut-offs: severe (1/2), acute (1/3), and vulnerability (1/5) (Alkire and Foster, 2011b; Nussbaumer et al., 2012). This study utilises the 'acute' poverty cut-off (1/3) to identify households that are multidimensionally energy-poor. Thus, the poverty cut-off is set to $k \geq 0.35$ as per unequal assigned weights. We construct a column vector c_i to accumulate deprivation scores. By definition, $c_i \geq k$ for a household that is multidimensionally energy-poor (that is, the sum of the weighted deprivation scores exceeds the poverty cutoff), and $c_i < k$ otherwise.

Thus, a household is identified as multidimensionally energy-poor if (1) deprivation occurs in three of the four dimensions of indoor air pollution, education/entertainment, household appliances, and telecommunications, (2) there is also deprivation in cooking and lighting, and (3) a household is deprived in one of the two dimensions of lighting and cooking plus one of the other dimensions. Therefore, a household is multidimensionally energy-poor, if $c_i \geq k$. The column vector c_i is set to 1 to censor observations of multidimensionally energy-poor households and 0 otherwise. The column vector C_ik denotes a censored vector.

The measure of multidimensional energy poverty is therefore obtained by means of the equations below. The MEPI measures the incidence H and intensity A of energy poverty. Headcount ratio H is extracted when the total numbers of the multidimensionally energy-poor q are divided by the total population n. The intensity delineates the average of the deprivation values for the multidimensionally energy-poor. Thus,

$$H = q/n \tag{1}$$

where H = headcount ratio, q = number of multidimensionally energy-poor, and n = total population

$$A = \sum_{i=1}^{n} Ci(k) \Big/ q \tag{2}$$

where A = intensity, $C_i(k)$ = deprivation count of the multidimensionally energy-poor, and q = number of multidimensionally energy-poor.

Finally, we calculate multidimensional energy poverty as a product of headcount ratio and intensity of energy poverty:

$$M = H \times A \tag{3}$$

3.2. Determinants and Tobit model

The effects of the socioeconomic profile of households on energy poverty can be analysed in terms of various demographic and geographic variables. These socioeconomic factors include income, nature or type of house, size of the house, age of the residential property, employment, education, location of the residential area, central heating system, geographical and ecological diversity (Atsalis et al., 2016; Crentsil et al., 2019; Legendre and Ricci, 2014; Marchand et al., 2019; Primc et al., 2019; Romero et al., 2018). Because of this diversity and variation in factors, different factors lead to multidimensional energy poverty, and statistical analysis of the impacts of socioeconomic factors on household multidimensional energy poverty will shape policy formulation. Table 2 summarizes some of these socioeconomic variables and their definitions.

STATA^{MP} 15.0 was used to run a Tobit model to estimate the statistical significance of parameters of socioeconomic variables using the maximum likelihood method. The Tobit model is used to detect the relationship between the non-negative dependent and independent variable(s) for truncated data. The dependent variable in this study is the deprivation score C_i for multidimensional energy poverty, which is truncated in our regression. Values of C_i range from 0, the lowest deprivation score (left-censored), which indicates no deprivation in any dimension, to 1, the highest deprivation score (right-censored), which indicates deprivation in all dimensions. Thus, to generate more accurate regression results, a two limit Tobit model was used:

$$y_i^* = x_i\beta + \varepsilon_i \tag{4}$$

Table 2
Independent and dependent variables.

Independent Variable	Description/Definition
Wealth Index	An ordinal variable based on a household's living standard, divided into five groups: poorest, poor, middle, rich, and richest.
House size	The total number of rooms in a house.
House ownership status	Whether the residential property is owned or rented.
Occupation	Type of employment of the head of the household (e.g., unemployed, professional/managerial, sales, services, agriculture, skilled).
Family Size	The total number of members of the household.
Marital Status	Current marital status of the head of the household
Education	The highest level of education attained by the main breadwinner (primary, secondary, higher, none).
Residence	Type of place of residence (rural or urban).
Sex	Gender of the head of the household.
Age	Age of the head of the household.
Dependent Variable	**Description**
MEPI	Deprivation count (*Ci*) for a household on the MEPI: the sum of allocated weight to the basic energy services of cooking fuel, electricity, household appliances, means of communication, and assets of entertainment/education.

$$y_i = \begin{cases} 0, & \text{if } y_i^* \leq 0 \\ y_i^*, & \text{if } 0 < y_i^* < 1 \\ 1, & \text{if } y_i^* \geq 1 \end{cases} \tag{5}$$

where y_i* is a latent dependent variable dual-censored at lower limit 0 and upper limit 1, ε_i is a distributive error term, and i represents the number of observations. y_i is the distributed dependent variable, and x_i is the vector of independent variables for the ith observation. β is a vector coefficient parameter. Any truncated observation can be presented by $C = \{i: y^* \leq 0 \cap y^* \geq 1\}$.

3.3. Study area and data

South Asia is one of the most densely populated regions in the world. Its geostrategic importance also offers an attractive consumer market for foreign and domestic companies. It covers an area of approximately 2 million square miles, which accounts for 3.5% of the world's surface and 11.7% of the Asian continent, (see Fig. 1). It is home to 1.92 billion people (24.8% of the world's population), and it has one of the fastest-growing regional economies (worth 3.5 trillion US dollars in 2019, with projected growth of 7.1% in 2020–21).

South Asia is also one of the most energy-precarious regions in the world. The three most populated countries of the region, India, Bangladesh, and Pakistan, have relatively high rates of death attributable to indoor air pollution. Annually, almost 481,700 people in India, 59,100 in Pakistan, 70,300 in Bangladesh, 19,400 in Afghanistan, 11,200 in Nepal, and 5480 in Sri Lanka die prematurely from household air pollution. More than half of the population of the region is exposed to outdoor air pollution: 71% of the population in Afghanistan, 52% in Pakistan, 60% in India, 79% in Bangladesh, 65% in Nepal, and 45% in Sri Lanka (HEI, 2019). These characteristics of household energy use, geostrategic prevalence, large consumer markets, and dense population make South Asia a particularly good context in which to investigate the relationship between the socioeconomic profile of households and multidimensional energy poverty.

This study used household survey collected by an international organisation, United States Agency for International Development (USAID), with the collaboration of national institutes of population studies of the countries involved. USAID collects and disseminates data worldwide on a wide range of health issues including maternal health care, family planning, domestic violence, disability, malaria, women and children's nutrition, child health, sexual activity, HIV/AIDS, and fertility. As well as socioeconomic profiles of households, the survey provides comprehensive information about housing characteristics, household possessions, and household members, and it includes various indicators of multidimensional energy poverty. An additional advantage of this data is the insight it provides into the development of policy measures.

The sample of the dataset used in this study consists of 674,834 households from six South Asian countries. Table 3 gives a statistical summary of various socioeconomic variables across these countries and the mean and standard deviation of each explanatory variable. The data is available on the official website of the Demographic and Health Survey (DHS, 2019), this study used Standard DHS-VII 2017-18 data obtained from a formal request made after registering on the website. Sri Lanka was excluded because of the lack of recent data, and Bhutan was excluded because of the non-availability of data. Thus, the socioeconomic and energy poverty variables were taken from a comprehensive dataset for the purposes of empirical analysis.

4. Results and discussion

4.1. Multidimensional energy poverty

Fig. 2 shows the distribution of multidimensional energy poverty at the national level. The Maldives and Pakistan are the least multidimensionally energy-poor countries in the region; Afghanistan and Bangladesh are the most multidimensionally energy-poor countries, with MEPI values of 0.37 and 0.36, respectively. In Afghanistan, the ongoing counterterrorism operations and forced human displacement

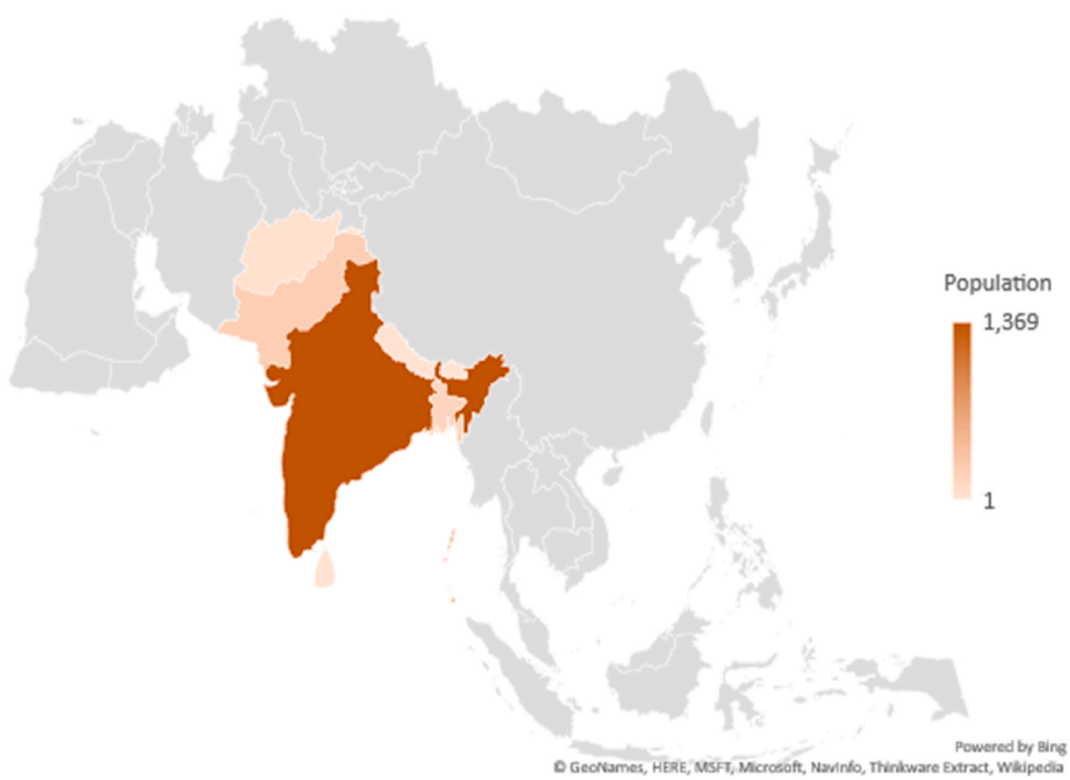

Fig. 1. South Asia on the map of the Asian continent: illustrated according to the population in millions.

Table 3
Statistical summary of each explanatory variable across the countries and combined dataset.

Variable	Afghanistan	Bangladesh	India	Maldives	Nepal	Pakistan	Combined	Mean	St.D
House size	24,395	17,299	601,509	6050	11,040	14,540	674,833	1.95	1.12
Wealth Index	24,395	17,300	601,509	6050	11,040	14,540	674,834	2.89	1.40
Education								1.74	2.03
Uneducated	5516	4206	141,991	140	4423	869	187,858		
Primary	15,376	5226	75,964	2718	2561	12,005	85,513		
Secondary	2717	6722	306,800	2570	2846	1323	320,539		
Higher	786	1709	76,754	622	1210	871	80,385		
Family size	24,395	17,863	601,509	4342	4063	14,540	666,149	6.01	2.99
Residence	24,395	17,300	601,509	6050	11,040	14,540	674,834	1.71	0.45
Marital Status	24,395	17,863	112,122	4342	4063	14,540	177,325	1.89	3.83
Occupation								4.34	8.41
Not working	364	11,818	85,327	723	400	119	98,035		
Professional	1465	430	9112	1242	624	587	18,413		
Clerical	13,995	–	404,237	449	1320	121	413,738		
Sales	3380	474	11,305	214	2190	594	12,748		
Agricultural	1732	2654	47,028	2164	3023	578	50,543		
Services	1799	979	10,871	346	51	11,377	19,172		
Skilled and unskilled	1660	1508	33,629	912	3432	1692	40,084		
House ownership status	24,395	–	216,165	4342	4063	15,068	277,732	1.67	3.26
Sex	24,395	17,300	601,509	6050	11,040	14,540	674,834	1.15	0.35
Age	24,392	17,299	601,509	6050	11,040	14,540	674830	47.78	14.16
Share%	**3.61**	**2.56**	**89.13**	**0.92**	**1.63**	**2.15**	**100**		

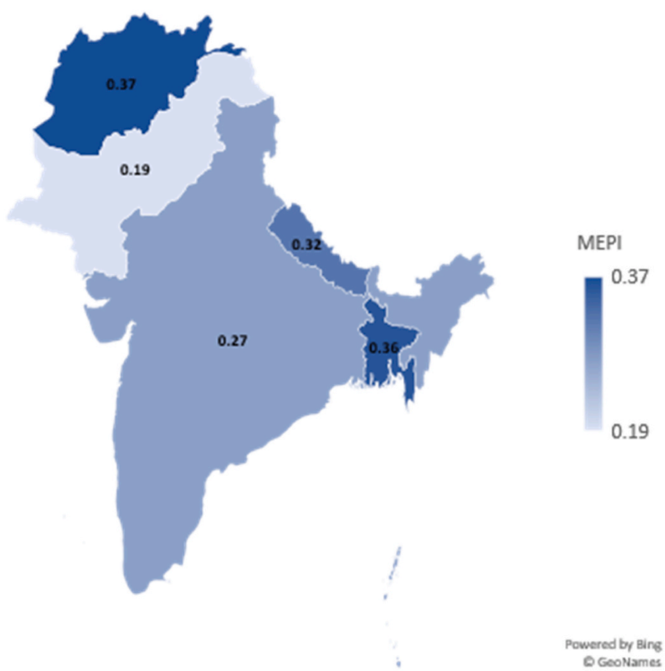

Fig. 2. Results of multidimensional energy poverty for South Asian countries.

have prevented infrastructural and socioeconomic development for the last two decades. Moreover, the mountainous geographic terrain makes it hard to provide infrastructure, gas pipeline networks, electrification, and modern cooking fuels (natural gas) nationally. The urban population accounts for only 23% of the whole population and is concentrated in a small number of metropolitan areas, such as Kabul, Jalalabad, Kunduz, and Kandahar. This leaves the rest of the territory sparsely populated and vulnerable to multidimensional energy poverty.

These geographical, infrastructural, economic, and political factors have prevented efforts to elevate the socioeconomic status of households and to improve access to essential energy services such as electricity, household appliances, and assets of education/entertainment. Most rural households still burn wood, straw, crops, or animal dung for cooking, which causes indoor air pollution and has negative health implications, particularly for women and girls. The situation is similar in the border areas of Pakistan (previously known as Federal Administered Tribal Areas). However, the Pakistan government has taken many developmental steps to uplift these areas by introducing socioeconomic and legal reforms and implementing special financial support schemes.

In Bangladesh, the other South Asian country with a comparatively high MEPI, lacks electrification and access to modern cooking fuel. Household appliances are the main drivers of multidimensional energy poverty in rural areas (accounting for 65%), which are also disadvantaged by the physical geography of the country, low income, and population density.

Wood, liquefied petroleum gas (LPG), and animal dung are the most commonly used cooking fuels across the entire region (see Fig. 3). However, the Maldives is the only country where LPG is widely used to prepare food (92.3% of cases). Approximately 35% of people in Pakistan and 36% in India also burn LPG to prepare food. Firewood is the most common cooking fuel in terms of the usage spectrum. Most of the population resides in rural areas and is heavily dependent on agriculture; wood, seasonal crops, and straw are cheap and easily accessible. Women are generally responsible for gathering wood or straw, and they sometimes make *dung bread* by collecting animal dung and drying it in the sun. When used for cooking, dung bread causes significant amounts of indoor air pollution, triggering health issues, with women usually most affected.

Additionally, the lack of gas pipeline networks leaves the rural population dependent on traditional fuels. Unfortunately, electricity, the safest and most eco-friendly cooking fuel, is the least commonly used in the entire region. The Maldives is the country with the highest rate of use of electricity for cooking, at only 2.7%.

Fig. 4 shows the energy poverty in the region by dimension. Most households are deprived of household appliances. Afghanistan, Nepal, and Bangladesh have relatively high levels of deprivation in all dimension. For instance, in Afghanistan, almost 87% of households do not have a fridge, 52% do not own any entertainment/education assets, and 71% are unable to access modern cooking fuel. Similarly, deprivation rates for appliances, cooking fuels, and entertainment assets are relatively high in Nepal and Bangladesh. The lowest levels of deprivation are found for lighting and telecommunication, as very large number of people own a mobile phone in this globalised world. Nevertheless, 35% of people in Bangladesh and 28% in Afghanistan are deprived of electricity.

Finally, Table 4 gives the MEPI, headcount ratio, and deprivation intensity values for the South Asian states included in this study. The

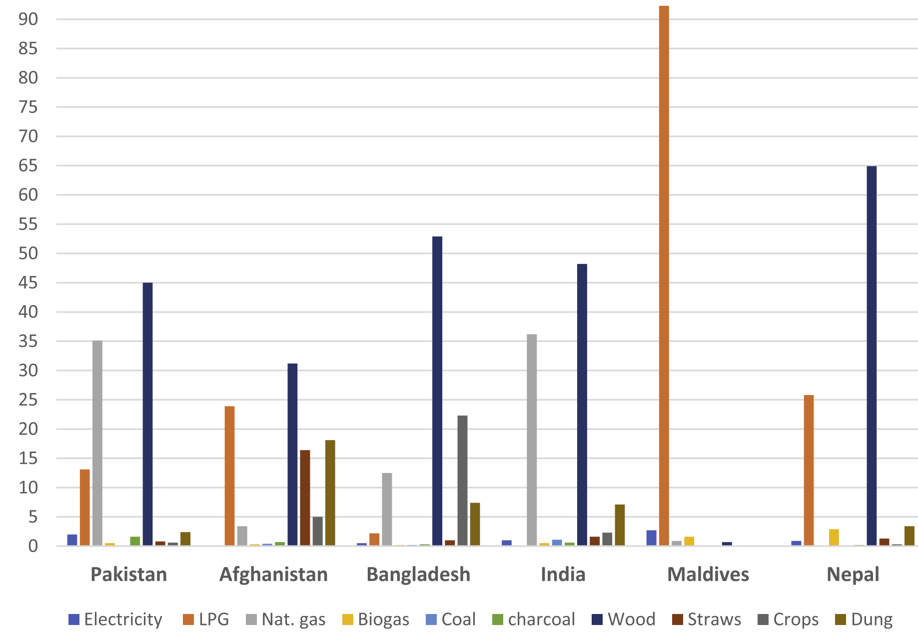

Fig. 3. Commonly used cooking fuels in South Asia.

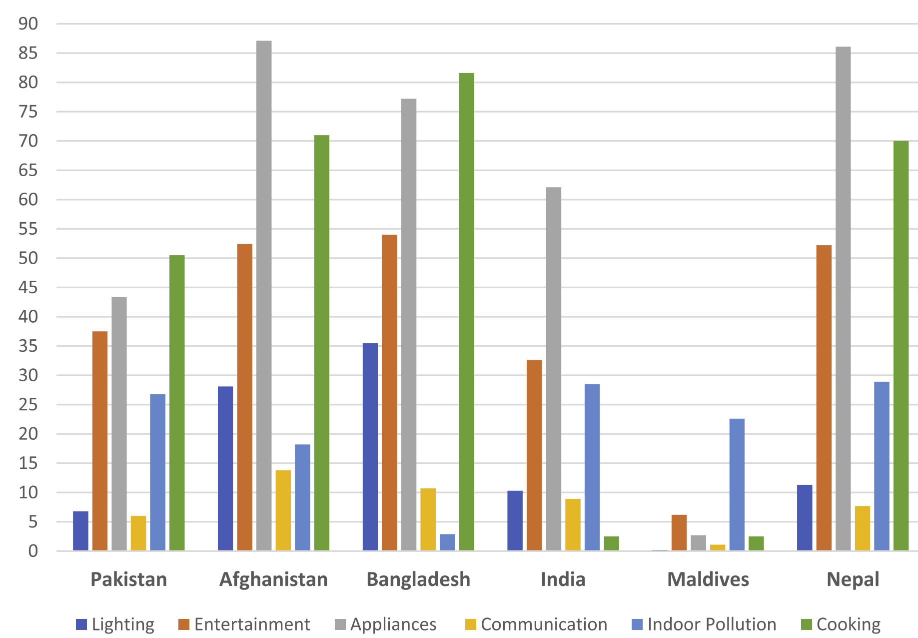

Fig. 4. Deprivations for basic energy services in the region.

Maldives and Pakistan are the only states with low rates of multidimensional energy poverty (0.01 and 0.31, respectively).

Table 4
Detailed results of multidimensional energy poverty, headcount ratio, and intensity at the national and regional level.

Country	Headcount ratio	Intensity	MEPI
Afghanistan	0.58	0.64	0.37
Bangladesh	0.55	0.65	0.36
India	0.37	0.64	0.27
Maldives	0.01	0.54	0.01
Nepal	0.53	0.60	0.26
Pakistan	0.31	0.61	0.19
South Asia	**0.38**	**0.64**	**0.24**

4.2. Socioeconomic determinants of multidimensional energy poverty

This section explains the roles played by a number of socioeconomic factors in determining the extent of multidimensional energy poverty at the household level. This study used ten socioeconomic variables and the MEPI as a dependent variable to analyse cross-sectional data from the six South Asian countries. Fixed-effects models were employed, and country was used as dummy variable for the regression results of the combined dataset. To check the consistency of the results, the ordinary least squares (OLS) regression model for the combined dataset and the datasets for each country were compared separately with the Tobit model results. The outcomes of the regressions were consistent with our discussion above. The statistically significant effects were evident in the regression results regardless of which proxy we used (the OLS regression model or the Tobit model) to detect socioeconomic determinants of multidimensional energy poverty.

Table 5 gives the regression results for multidimensional energy poverty and socioeconomic factors for each country using the OLS model. The results show that house size, household wealth, place of residence, gender and age of the main breadwinner have a statistically significant relationship with multidimensional energy poverty in most countries. The wealth index of the household is consistently a significant negative factor in multidimensional energy poverty. However, the coefficients of residence, sex, and age of the main breadwinner are significantly positive in most countries, which suggests that these socioeconomic factors play a broadly positive role in determining the level of household multidimensional energy poverty.

Furthermore, the size of a family has a positive significant relationship with MEPI in Afghanistan and Bangladesh whereas this empirical relationship with MEPI is negative in India. The current marital status of the head of the household plays an empirically significant role in both India and the Maldives. However, house ownership status is significant (negatively so) in India only, which is the most populous country in South Asia, accounting for 89% of the cases in the dataset. The effects of most of the education and occupation variables were not significant in the model.

Similarly, Table 6 shows the results of the Tobit regression estimation for each country. The findings are similar overall with few variations. In most countries, house size, household wealth, family size, place of residence, age and sex of the head of the household have a significant empirical relationship with multidimensional energy poverty.

Table 7 summarizes the outputs of the Tobit regression estimation and the OLS model for the whole region using combined dataset. The results are consistent across the region and are compatible by large with the discussion. House size, household wealth, marital status and gender of the head of the household are the significant negative socioeconomic determinants of household multidimensional energy poverty. Family size has a significant positive relationship with the MEPI, according to the Tobit likelihood estimation. However, place of residence, ownership status, and age of the primary breadwinner are the main significant positive factors in determining the level of multidimensional energy poverty throughout the region. Education and occupation have a negative link with the MEPI, except for the occupational categories of skilled, unskilled, services, and professional.

It is worth noting that household wealth has a significant reverse effect on multidimensional energy poverty in all the regression results: as the accumulative wealth of households increases, levels of multidimensional energy poverty decrease. Similarly, the results indicate that households in rented accommodation are more susceptible to multidimensional energy poverty than those that own the house they live in. When a significant portion of a family's income is used to pay rent, little money is left for domestic energy facilities, and energy precariousness is the likely result. It is also statistically evident that families with bigger houses are less vulnerable to multidimensional energy poverty. This may be because rich families can afford bigger houses.

5. Conclusion and policy implications

This study has empirically examined a range of socioeconomic variables and their significant statistical relationships with multidimensional energy poverty at the household level. The outcomes of the regressions were consistent with our discussion, regardless of which proxy we used (the OLS regression model or the Tobit model).

The results provide concrete evidence that socioeconomic factors significantly determine levels of household multidimensional energy poverty in South Asia. House size, household wealth, gender, education, occupation (clerical, sales, or agricultural), and marital status of the head of the household are significant negative socioeconomic determinants of household multidimensional energy poverty. Place of residence, house ownership status, family size, and age of the primary breadwinner play a significant positive role. In most cases, these socioeconomic characteristics overlap and are interdependent. For example, it is observed that the spectrum of accumulated wealth or salaries is determined by the nature of employment, which in turn is determined by level of education. Thus, no single socioeconomic variable causes or defines multidimensional energy poverty; it is a combination of a number of these variables that leads to the outcome.

The results of this study have a number of critical policy implications for policymakers attempting to mitigate multidimensional energy poverty. As improvements in household socioeconomic status facilitate universal access to clean energy and affordability of domestic energy amenities, the following recommendations are offered.

(1) Poor households with a lower wealth index are more deprived because their income cannot satisfy their energy expenditure. Unless their earnings increase, they will remain unable to spend

Table 5
Regressions results with OLS for each South Asian country.

Variables	Afghanistan	Bangladesh	India	Maldives	Nepal	Pakistan
	MEPI	MEPI	MEPI	MEPI	MEPI	MEPI
House size	0.0002** (2.08)	0.001 (1.60)	−0.004*** (−24.47)	−0.011*** (−12.75)	−0.021*** (−11.59)	−0.000 (−0.19)
Wealth index	−0.067*** (−58.29)	−0.139*** (−172.39)	−0.16 *** (−1048.91)	−0.011*** (−14.52)	−0.116*** (−65.80)	−0.14*** (−147.59)
Education						
Primary	−0.002 (−0.38)	0.008*** (2.94)	0.001*** (3.13)	−0.006 (−0.80)	−0.037*** (−6.40)	0.010 (1.42)
Secondary	0.000 (0.19)	0.003 (1.31)	0.000 (0.43)	−0.002 (−0.28)	−0.052*** (−8.90)	0.004 (0.73)
Higher	0.007 (0.89)	0.001 (0.46)	0.000 (1.24)	−0.002 (−0.25)	−0.059*** (−7.63)	0.007 (0.96)
Family size	0.003*** (9.12)	0.001*** (2.64)	−0.008*** (−12.94)	0.0001 (0.38)	0.0001 (0.16)	−0.000 (−1.16)
Marital status	−0.000 (−0.16)	0.0001 (0.11)	−0.002*** (−11.19)	0.002* (1.74)	0.004 (1.26)	−0.001 (−0.57)
Occupation						
Professional/Managerial	0.0003 (0.03)	−0.005 (−0.75)	0.002 (1.44)	0.003 (0.90)	−0.015 (−1.20)	0.001 (0.10)
Clerical	−0.016 (−1.14)	–	0.002*** (3.36)	0.006 (1.21)	−0.002 (−0.25)	0.002 (0.12)
Sales	−0.001 (−0.14)	−0.001 (−0.28)	0.002* (1.85)	0.010 (1.55)	−0.003 (−0.30)	−0.004 (−0.32)
Agricultural	0.003 (0.28)	0.002 (0.98)	0.001** (1.95)	0.005 (1.24)	0.012 (1.15)	−0.013 (−0.93)
Services	0.013 (1.14)	0.006 (1.41)	−0.001 (−0.74)	0.002 (0.43)	0.007 (0.25)	0.001 (0.09)
Skilled & Unskilled	0.009 (0.81)	0.001 (0.50)	0.000 (0.01)	0.008* (1.87)	0.002 (0.22)	0.000 (0.02)
House ownership status	−0.000 (−0.03)	–	−0.002*** (−8.02)	−0.004 (−1.60)	−0.003 (−0.72)	0.0001 (0.06)
Residence	0.168*** (47.09)	0.058*** (24.96)	0.026*** (59.11)	−0.078*** (−22.28)	0.191*** (40.90)	0.068*** (25.77)
Sex	0.023** (2.33)	0.021*** (7.30)	0.008*** (16.59)	−0.003 (−1.44)	−0.027*** (−5.43)	0.004 (1.02)
Age	−0.0008*** (−9.77)	0.0002*** (3.90)	0.0004*** (35.92)	0.0003*** (4.56)	−0.003*** (−2.32)	0.0001** (1.98)
N	24,395	17,300	601,509	6050	11,040	14,540
R^2	0.361	0.730	0.746	0.168	0.679	0.722

***Significant at the level 0.01, **Significant at the level 0.05, *Significant at the level 0.1.

Table 6
Tobit regression estimation results for each country in South Asia.

Variable	Afghanistan	Bangladesh	India	Maldives	Nepal	Pakistan
	MEPI	MEPI	MEPI	MEPI	MEPI	MEPI
House size	0.0002** (2.17)	0.001 (1.26)	−0.006*** (−28.86)	−0.035*** (−11.55)	−0.025*** (−11.64)	−0.000 (−0.42)
Wealth index	−0.074*** (−59.02)	−0.144*** (−163.19)	−0.182*** (−955.94)	−0.030*** (−12.05)	−0.12*** (−62.37)	−0.186*** (−131.41)
Education						
Primary	−0.003 (−0.55)	0.009*** (3.02)	0.001 (1.54)	−0.010 (−0.43)	−0.040*** (−6.13)	0.013 (1.41)
Secondary	−0.0007 (0.13)	0.004 (1.49)	−0.000 (−1.19)	−0.001 (−0.06)	−0.060*** (−8.99)	0.002 (0.32)
Higher	0.008*** (90.84)	0.002 (0.61)	−0.000 (−0.09)	0.002 (0.09)	−0.077*** (−8.67)	0.006 (0.62)
Family size	0.003*** (8.89)	0.001*** (2.40)	−0.008*** (−10.36)	0.0004 (0.37)	0.0001 (0.26)	0.0005 (1.26)
Marital status	−0.0006 (−0.23)	−0.0001 (−0.06)	−0.002*** (−8.57)	.006 (1.41)	0.005 (1.31)	-.003 (−1.12)
Occupation						
Professional/Managerial	−0.001 (−0.09)	−0.006 (−0.89)	0.002 (1.44)	0.014 (1.11)	−0.017 (−1.17)	0.003 (0.21)
Clerical	−0.018 (−1.13)	–	0.002*** (2.57)	0.017 (1.11)	−0.003 (−0.28)	−0.015 (−0.64)
Sales	0.014 (1.15)	0.0001 (0.02)	0.003* (1.83)	0.025 (1.26)	−0.007 (−0.55)	−0.008 (−0.44)
Agricultural	0.004 (0.40)	0.003 (1.26)	0.001* (1.92)	0.017 (1.23)	0.014 (1.17)	−0.019 (−1.01)
Services	−0.002 (−0.19)	0.007 (1.42)	−0.001 (−0.76)	0.001 (0.10)	0.012 (0.35)	−0.016 (−0.83)
Skilled & Unskilled	0.008 (0.71)	0.001 (0.46)	−0.000 (−0.22)	0.025* (1.82)	0.002 (0.20)	−0.0009 (−0.05)
House ownership status	−0.0001 (−0.05)	–	−0.002*** (−6.81)	−0.011 (−1.37)	−0.004 (−0.84)	0.002 (0.63)
Residence	0.187*** (47.61)	0.068*** (26.58)	0.043*** (79.89)	−0.20*** (−20.97)	0.210*** (39.47)	0.085*** (23.90)
Sex	0.027*** (2.50)	0.023*** (7.17)	0.010*** (17.11)	−0.005 (−0.87)	−0.032*** (−5.73)	0.011** (2.12)
Age	−0.0009*** (−10.02)	0.0002*** (3.40)	0.0004*** (26.23)	0.0005** (2.29)	−0.001*** (−3.89)	0.00002 (0.24)
Observations	24,395	17,300	601,509	6050	4063	14,538
Pseudo R^2	1.00	2.83	1.40	0.244	2.28	1.09
Uncensored	22,036	15,710	481,202	1858	3494	9835
Left-censored	2037	1512	108,066	4192	521	4617
Right-censored	322	78	12,241	0	48	86

*** Significant at the level 0.01, ** Significant at the level 0.05, * Significant at the level 0.1.

Table 7
Regression results in South Asia (combined dataset) with the Tobit model and OLS.

Variables	Tobit Regression		OLS regression	
	MEPI		MEPI	
House size	−0.007*** (−33.53)		−0.005*** (−29.17)	
Wealth index	−0.176*** (−901.80)		−0.154*** (−981.30)	
Education				
Primary	−0.003*** (−4.94)		−0.002*** (−3.56)	
Secondary	−0.011*** (−20.39)		−0.008*** (−18.56)	
Higher	−0.010*** (−13.53)		−0.007*** (−11.91)	
Family size	0.0001** (2.12)		−0.000 (−0.70)	
Marital status	−0.008*** (−17.36)		−0.007*** (−18.38)	
Occupation				
Professional/Managerial	0.001 (1.28)		0.000 (0.32)	
Clerical	−0.026*** (−30.10)		−0.023*** (−31.36)	
Sales	−0.006*** (−3.60)		−0.005*** (−3.86)	
Agricultural	−0.010*** (−10.94)		−0.008*** (−10.60)	
Services	0.019*** (13.68)		0.015*** (13.58)	
Skilled & Unskilled	−0.001 (−1.43)		−0.000 (−0.83)	
House ownership status	0.004*** (17.69)		0.004*** (18.84)	
Residence	0.049*** (86.98)		0.031*** (68.34)	
Sex	−0.001*** (−3.14)		−0.002*** (−4.33)	
Age	0.0002*** (14.42)		0.0003*** (23.78)	
Number of Obs.		652,733	N	674,834
Pseudo R^2		1.26	R^2	0.703
Uncensored		523,760		
Left-censored		116,293		
Right-censored		12,680		

*** Significant at the level 0.01, ** Significant at the level 0.05, * Significant at the level 0.1. The country as dummy variables are constant.

more on access to energy services, and their deprivation will continue. Income levels should therefore be increased to a level that will enable these households to afford energy amenities. This applies particularly to the private sector, where wages are lower and typically do not cover household energy expenditures.

In addition to low income, expensive energy services cause multidimensional energy poverty. The spending on electricity and cooking fuels accounts for a significant portion of household income, leaving less to spend on other domestic energy services. There are two ways to deal with this situation. First, as mentioned above, governments should either increase salary levels to match energy expenditures or reduce and control the prices of energy services (primarily electricity and natural gas). Second, support programmes should be set up to help cover energy expenditures. For example, the government of Pakistan has subsidised electricity and cooking fuel prices in order to prevent deprivation, and similar policies could be implemented in other states.

(2) The results reveal that family size and housing characteristics are also important factors. Larger families are more susceptible to energy poverty than smaller ones, and multidimensional energy poverty is more prevalent in rented accommodation than in accommodation that is owned by the household. Therefore, governments should develop financial schemes that help impoverished families to buy their own houses so that household income that would have been used to pay rent could instead be spent on energy services. For example, governments could initiate public–private partnership housing schemes to build affordable houses and to enable energy-poor households to buy their homes in manageable instalments. One such national housing scheme was recently launched in Pakistan to help the homeless and the extremely poor (Khan, 2018).

(3) Reliance on traditional cooking fuels is a major problem in rural areas. As well as poverty and low income, the nature of the geographical terrain is an obstacle to comprehensive electrification and reliable access to clean cooking methods. A network of gas pipelines and electricity lines should therefore be established to link remote areas.

(4) The age and gender of the primary breadwinner are also important socioeconomic determinants of multidimensional energy poverty. Households with a female primary breadwinner are more vulnerable to multidimensional energy poverty, and increased age also aggravates energy vulnerability. In South Asia, gender disparity affects job opportunities and salary levels, with female workers generally paid less than male workers in the private sector. In rural areas, where wages depend on the poorly

managed agriculture sector, the situation is even worse for female workers. Governments must therefore formulate effective policies to promote gender parity and financial equality.

It should be noted that this study has targeted a limited geographical area and its findings may therefore not be generalisable. However, it provides a baseline from which further studies can examine the socio-economic determinants of energy poverty in a wider range of areas and households. The evidence-based information provided here will inform the design and implementation of measures to reduce the detrimental impacts of multidimensional energy poverty nationally, regionally, and globally.

CRediT authorship contribution statement

Khizar Abbas: Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing, Supervision. **Shixiang Li:** Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Deyi Xu:** Formal analysis, Writing - review & editing. **Khan Baz:** Software, Resources, Writing - review & editing. **Aigerim Rakhmetova:** Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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