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# Health implications of household multidimensional energy poverty for women: A structural equation modeling technique

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ABSTRACT

The twofold novelty of the paper complements the debate about the health impacts of multidimensional energy poverty. First, an adjusted multidimensional energy poverty index (MEPI) is employed to gauge and monitor multidimensional energy poverty. Second, the study targets South and Southeast Asia, the regions previously neglected, to identify the adverse health impacts of multidimensional energy poverty for women using the structural equation modeling technique. With these objectives, the study analyses household survey data of eleven developing countries in Asia: five countries from South Asia and six from Southeast Asia. The results statistically verified the fitness of the study model checking the estimates of good fitness of the structural equation modeling approach. An empirically significant negative causal relationship was found between the indicators of multidimensional energy poverty and health for women including sources and purification of water, types of toilet facility, termination of pregnancy, fertility, contraception or family planning, age at sterilization, mosquito-borne diseases, coverage of health insurance, marital status, literacy, and occupation, subsequently, implying the significant theoretical as well as practical policy implications to mitigate these detrimental health impacts of multidimensional energy poverty in developing countries.



## 1. Introduction

Energy poverty can be defined as the inability to access modern energy services to satisfy basic energy needs. It is a situation when there is a lack of modern energy fuels to prepare food, unavailability of electricity to light the house, and unaffordability to own the assets of entertainment or education, communication, and other household appliances [1]. In this regard, energy plays a vital role in lighting, cooling, preservation of food, regulating indoor temperature, cooking, heating, and washing at the domestic level. Recently, energy poverty has become one of the central global problems risking millions of lives annually. It is posing potential threats to human health and development globally. More than 1 billion people do not have access to electricity, and 2.7 billion people are dependent on solid fuel consumption to prepare a meal [2]. This solid fuel dependency negatively affects mortality [3] and causes fatal and non-fatal cardiovascular and respiratory diseases [4]. The consumption of contaminated kitchen stoves caused 3.8 million premature deaths globally in 2018 and 2 million out of total annual causalities were reported in South and Southeast Asia [5]. Rural households of the regions still lack electrification, clean energy fuels, and modern household appliances [6]. Major cities of the regions including Kabul, Lahore, Karachi, Delhi, Kolkata, Mumbai, Dhaka, Hanoi, Ho Chi Minh City, Phnom Penh, Chiang Mai, Kuching, Kuala Lumpur, and Yangon were reported to have the worst air quality worldwide [7]. Bangladesh, Pakistan, Afghanistan, India, Indonesia, Nepal, and Vietnam with 83.30, 65.81, 58.80, 58.08, 51.71, 44.46, and 34.06 average scores of air quality index respectively were listed among the world's most polluted countries in 2019 [8].

Moreover, South and Southeast Asia are two of the most densely populated regions in the world. The prevalent geostrategic location of the regions offers an attractive consumer market for foreign and domestic companies. It covers approximately 3.717 million square

*Abbreviations:* MEPI, Multidimensional Energy Poverty Index; SEM, Structural Equation Modelling; USAID, United States Agency for International Development; GFI, Goodness-of-Fit Index; AGFI, Adjusted Goodness-of-Fit Index; PGFI, Parsimony Goodness-of-Fit Index; RMSEA, Root Mean Square Error of Approximation; TLI, Tucker Lewis Index; NFI, Normed Fit Index; PRATIO, Parsimony Ratio; DF, Degree of Freedom; AQI, Air Quality Index; AVE, Average Variance Extracted; DHS, Demographic and Health Survey; UNDP, United Nations Development Program; LPG, Liquified Petroleum Gas; CR, Composite Reliability.

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miles area, which accounts for 21.59% of the Asian continent. The total population is 2.60 billion, which accounts for 37.14% of the world's population with one of the fastest-growing regional economies (6.778 Trillion US dollars with a projected growth of 6% in 2020). These characteristics such as household energy consumption, dense population, geostrategic importance, and large attractive consumer market make this area a good context to examine the health consequences of household multidimensional energy poverty in women.

Thus, the ultimate purpose of this study is to investigate the health implications of multidimensional energy poverty for women in developing countries. To examine this statistical relationship, first, it is imperative to calculate multidimensional energy poverty. An adjusted multidimensional energy poverty index (MEPI) is employed to measure multidimensional energy poverty in South and Southeast Asia. After getting the measurement, a statistical relationship between multidimensional energy poverty and indicators of women's health is examined through a structural equation modeling technique. Subsequently, it contributes to the existing debate providing empirical information to comprehend the issue, analyses its impacts on women's health, and proposes some practical and effective policy measures to mitigate detrimental health implications of multidimensional energy poverty for women in developing countries.

## 2. Literature review

Access to affordable and reliable clean energy fuels at the household level is imperative to reduce negative health impacts on the human body due to the consumption of carbonaceous energy fuels/solid fuels such as coal, charcoal, firewood, biomass, crops, straw, and animal waste or dung; widely consumed in developing countries for cooking as compared to other end-use services [5,9]. The widespread cooking practices burning solid fuels and energy deficiency have severe implications for human health [10], economic growth [11], forest/land degradation, and ecology or climate change [1,12]. The particulate matters with a diameter of less than 2.5 μm ($PM_{2.5}$) emitted from indoor/outdoor solid fuel consumption remain suspended in the air. It causes air pollution and envisages severe detrimental impacts on human health and quality of life in developing countries [13–15]. Further, indoor air pollution poses a potential threat to the fertility and mortality of women and girls mostly [16–18]. It causes various lung diseases, stunted growth, child malnutrition, other infectious and parasitic diseases [19].

Naturally, we are not the first to examine the health impacts of energy poverty. The central point of the discussion of some previous studies was the health implications of solid fuel consumption on human illness, asthma [20], lung cancer, and cardiovascular diseases [21]. While other studies examined the statistical relationship of chronic illnesses, stress [22], health index, child age [23], mortality [24], physical and emotional well-being [25], modern latrine services [26], bodily aches and pains, disability, happiness [27], depression, and reduced well-being [28] with energy poverty. Energy-poor dwellings can have serious mental, psychological, and physical repercussions, especially for children [25,29,30]. Living in cold and energy deficient homes results in worse health consequences including increased blood pressure, mood swings, risky health behavior like overheating and smoking [31–34], stroke, chronic bronchitis, allergies, diabetes, and overweight [35]. Thus, energy poverty may not result in deaths or casualties directly, but it increases risks of related health issues and diseases that cannot be avoided easily.

However, our analysis complements and contributes to previous literature by taking into consideration quite different health variables. The study targets South and Southeast Asia, the regions previously neglected, to identify the adverse health implications of energy poverty using a multidimensional approach. Mostly, the previous studies examined the statistical relationship between energy poverty and health risks using unidimensional indicators to measure energy poverty rather than multidimensional indicators such as the multidimensional energy poverty index (MEPI), which uses composite indices to calculate energy poverty unlike a single index of unidimensional indicators[36]. Only a few studies were available that discussed this empirical relationship using the multidimensional approach but focused on a limited area/country [23,26]. Additionally, to the best of our knowledge, health consequences of household multidimensional energy poverty for women specifically such as pregnancy-related complications, sterility, fertility, access to clean water/sources of drinking water, toilet facility, family planning or contraception, health insurance coverage, prevention of mosquito-borne diseases, residence, literacy, occupation, and marital status were overlooked. Thus, this study takes these variables of women's health to analyse its empirical relationship with multidimensional energy poverty.

## 3. Methodology and data

### 3.1. Multidimensional energy poverty index (MEPI)

Single index (expenditure-based/consumption-based) approaches only measure the amount or incidence of energy poverty but ignore the intensity [36], while, the multidimensional energy poverty index (MEPI) utilises a composite-indices simultaneously measuring the incidence (numbers of energy-poor) and intensity (how much are they energy poor) of energy poverty [37]. To examine a statistical relationship between multidimensional energy poverty and indicators of women's health, it is needed to calculate multidimensional energy poverty. This paper uses a multidimensional measure, the multidimensional energy poverty index (MEPI), to gauge multidimensional energy poverty across the targeted countries. The MEPI is proposed by P. Nussbaumer, M. Bazilian, and V. Modi and well explained by S. Alkire and J. Foster [37–40]. The MEPI is a recent model that holistically measures energy poverty and its multiple dimensions related to domestic energy services such as lighting, cooking, telecommunication, education, entertainment, indoor air pollution, and other household appliances to support cooling, heating, and refrigeration.

These variables, dimensions, or indicators of multidimensional energy poverty are specified, fixed, and defined in the MEPI model as per their important roles in daily life activities and necessities [37]. Table 1 explains these dimensions, indicators, weights, and deprivation cut-offs of the MEPI model. The defined variables present the mandatory basic energy services required for a household to live a comfortable and non-deprived life on a daily basis: assets of cooling, heating, washing, communication, entertainment/education, indoor temperature control, and cooking so far. The inability to afford or access them leads to 'multidimensional' energy poverty. The model uses six dimensions and their six respective indicators to measure deprivation in every dimension. The indicator to measure dimensional deprivation for lighting is access to electricity. However, the types of cooking fuel are considered to measure deprivation for cooking. The ownership of assets of communication, cooling, and education is considered to measure deprivation in concerning dimensions.

The MEPI measures the extent and depth of energy poverty in dimensions $d$ across the population $n$ within individuals $i$. We construct, $Y = yij$, a matrix of achievements in a population ($n \times d$) of individual $i$ in variables $j$. Where $yij \geq 0$ denotes the degree of

**Table 1**
Dimension, indicator, and cut-off of multidimensional energy poverty.

| Dimension | Indicator (weighting) | Deprivation threshold |
|---|---|---|
| Cooking | Modern cooking fuel (0.2) | A household is deprived if uses cooking fuel other than electricity, natural gas, kerosene, or biogas. |
| Indoor smoking | Separate room for cooking/kitchen (0.15) | A household is deprived if it has no separate well-ventilated room for cooking. |
| Lighting | Electricity access (0.2) | A household is deprived if it has no access to electricity. |
| Household appliances | Possession of appliances (0.15) | A household is deprived if it has no fridge |
| Entertainment/education | Ownership of assets (0.15) | A household is deprived if it has no television. |
| Communication | Ownership of assets (0.15) | A household is deprived if it has no mobile phone or landline telephone. |

achievements of an individual ($i$ = 1, 2, 3…$n$) across the variables ($j$ = 1, 2, 3…$d$). According to the proponents of the MEPI, the weights $w$ of indicators can be assigned equally that is intuitive [40] or unequally based on desirable judgment because the methodology allows weighting the indicators unevenly [37]. Thus, in this study, although the relative weights are distributed unevenly among the indicators, it embraces the unequal importance of indicators of multidimensional energy poverty in policy formulation and implications for the developing world. The weights of cooking and lighting are comparatively higher than household appliances, telecommunication, and education/entertainment, as access to electricity and clean cooking fuels is far more important than other domestic energy services in developing countries. For instance, if a household does not have access to electricity, the possession of household appliances such as a fridge, television, computer, landline telephone, or washing machine becomes useless. Similarly, access to efficient and clean cooking fuels is also more important in developing nations than other energy services, as it directly impacts the human body due to a direct exposure while cooking. Also, poverty cut-off $k$ is very sensitive to the weights of all dimensions. Thus, the weight vector of all indicators is equal to $\sum_{j=1}^{d} \mathrm{wj} = 1$.

The model also uses dual cut-off parameters including deprivation cut-off $z$ and poverty cut-off $k$ to measure the intensity and headcounts of energy poverty at the same time. The deprivation cut-off $z_j$ denotes the deprivation in a variable $j$ and $g_{ij} = w_j$ presents the matrix achievements of deprivations across the variables and individuals. If the deprivation matrix $g$ of an individual $i$ in a variable $j$ exceeds the deprivation cut-off ($g_{ij} > z_j$), the individual $i$ is deprived of the concerned dimension. In case, this achievement exceeds the deprivation cut-off $z$ for any variable $j$, the assigned weight of that variable (0.15 or 0.20) will be added to the row vector or 0 if it does not exceed. The row vectors present an individual's accumulated achievements across the variables and column vectors present the distribution of achievements of variables across the observations. To sum up an individual's achievement across the variables, we construct another column vector of deprivations counts ($C_i$) that presents an individual's scores across the variables. For example, if an individual is deprived of all dimensions, the deprivation counts ($Ci$) would be equal to 1 and 0 in case of no deprivation in any dimension.

However, poverty cut-off $k$ is an eligibility criterion term to identify multidimensionally energy-poor households. As abovementioned, the choice and selection of poverty off $k$ are quite sensitive, it affects intensity, headcount ratio, and subsequently the MEPI overall. For its selection, we consulted the three different poverty cut-offs proposed by the advocates of the multidimensional approach in UNDP (United Nations Development Program) reports: poverty cut-off to calculate 'vulnerability' is 20% of cross-dimensional deprivations ($k \geq 20\%$), 33% to measure 'acute' energy poverty ($k \geq 33\%$), and 50% to gauge 'severe' energy poverty ($k \geq 50\%$) [41]. In our case, we have set an 'acute' poverty cut-off (33%) which is $k \geq 0.35$. As weights are assigned unequally, $k \geq 0.35$ justifies the percentage of 'acute' poverty cut-off (1/3 or 33%) to identify the multidimensionally energy-poor households. If deprivation counts ($Ci$) exceed poverty cut-off ($C_i \geq k$), the household is identified as a multidimensional energy-poor and opposite otherwise. Finally, a censor column vector $C_ik$ is constructed to truncate the cases/observations of multidimensionally energy-poor households. To censor the vector, $C_ik$ is set to 0, if deprivation counts $C_i$ does not exceed the poverty cut-off ($C_ik < k$).

Now, after explaining all tangible and intangible necessary methodological indices, we can compute equations to measure the headcount ratio Eqn.(1) and intensity Eqn. (2) of multidimensional energy poverty.

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

where $H$ is headcount ratio, $q$ presents the number of multidimensionally energy-poor households (truncated through a censored column vector $Cik$) and $n$ denotes the total population.

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

where $A$ presents the intensity and $C_i(k)$ presents deprivation counts of the multidimensionally energy-poor households

And finally, we calculate multidimensional energy poverty Eqn (3) as a product of headcount ratio and intensity

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

### 3.2. Structural equation modeling (SEM)

The structural equation modeling technique is employed to predict the statistical relationship between the indicators of household multidimensional energy poverty and health risks for women in this study. The structural equation modeling approach integrates a number of different multivariate statistical analytical techniques into one model fitting framework to measure unobserved/latent constructs by multiple indicators and estimates the structural relationship between those factors. Table 2 summarises the exogenous and endogenous latent variables of this study, their respective indicators, and their definitions.

As most social concepts are complex and multifaceted, it cannot be directly measured as manifest variables, named as latent variables. Using a single measure will not adequately cover the full conceptual map of these latent constructs. If we think of happiness, for example, it is quite difficult to come up with a single question/indicator which covers all aspects of an individual's well-being. We probably need to have multiple indicators to get good coverage of the concept. Likewise, we cannot simply or directly measure health by using a single indicator. We need multiple observable indicators to adequately define such a latent construct.

Fig. 1 visualises diagrammatical representation of the theoretical latent variables model of this study using the standardised notation of the SEM. The model presents the structural relationship between latent exogenous construct, multidimensional energy poverty, and health as a latent endogenous variable. Six-factor loadings of domestic energy services present six dimensions of multidimensional energy poverty fixed in the MEPI model (can also

**Table 2**
Explanation of variables of the model.

| Variable | Latent Variable | Observations | Definition |
|---|---|---|---|
| Exogenous Variables | MEPI | HV206 | Has electricity? (No/Yes) |
| | | HV208 | Has television? (No/Yes) |
| | | HV209 | Has refrigerator? (No/Yes) |
| | | HV226 | Is using cooking fuel besides electricity, natural gas, kerosene, or biogas? (No/Yes) |
| | | HV242 | Has a separate room used as the kitchen? (No/Yes) |
| | | HV243A | Has a mobile telephone? (No/Yes) |
| Endogenous Variables | Health | V012 | Respondent's current age |
| | | V025 | Type of place of residence (Rural/Urban) |
| | | V113 | Sources of drinking water |
| | | V116 | Type of toilet facility |
| | | V155 | The literacy level of the respondent |
| | | V201 | Total children ever born |
| | | V228 | Ever had a terminated pregnancy? (No/Yes) |
| | | V312 | Use contraceptive methods? (No/Yes) |
| | | V320 | Age at sterilization (grouped) |
| | | V459 | Has a mosquito bed net for sleeping? (No/Yes) |
| | | V481 | Covered by health insurance? (No/Yes) |
| | | V501 | Current marital status of the respondent |
| | | V717 | Occupation of the respondent (grouped) |
| | | V745 | Ownership status of the house |
| | | HV237 | Anything done to water to make safe to drink |

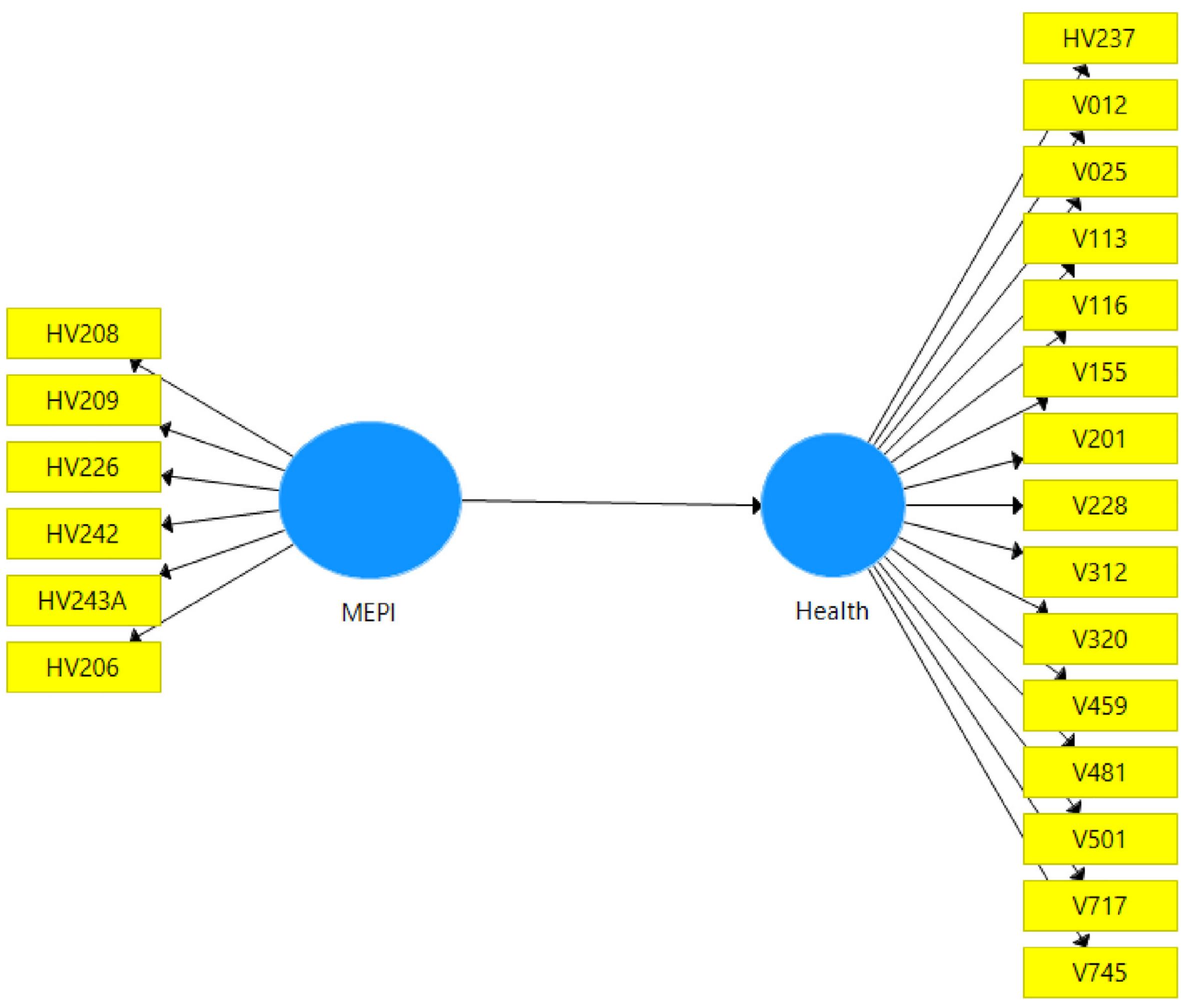


**Fig. 1.** Visualisation of the path diagram of the study model. Note: Table 2 shows the full names of variables.

be presented with MEPI) whereas fifteen factor-loadings give complete coverage of a woman's health profile thus constituting a latent construct. It is also worth noting that this is the first study to analyse a statistical relationship between multidimensional energy poverty and its potential health risks through structural equation modeling, using multidimensional energy poverty as a latent exogenous variable rather than an observed variable that previous studies focused on.

The structural equation modeling commonly uses three matrix equations Eqn. (4), Eqn. (5), and Eqn. (6) to estimate path coefficients, variances, covariances, effects, and errors of exogenous and endogenous observational and latent constructs. Thus, the causal effects of the regression relationship between multidimensional energy poverty and woman's health can be estimated by employing the following matrix equations:

$$Y = \beta X + \varepsilon \tag{4}$$

$$Y = \Delta r_i \beta + \varepsilon_i \tag{5}$$

$$X = \Delta r_i \beta + \varepsilon_i \tag{6}$$

where Y denotes the endogenous latent variable, X presents exogenous latent construct, β is the regression coefficient, ε denotes disturbance/error variance, and $\Delta r$ is the correlation coefficient between latent constructs and their multiple indicators.

### 3.3. Research area and data source

This study uses household survey data from eleven developing countries of Asia: five countries from South Asia and six countries from Southeast Asia. The survey data provides complete information about the demographic and health profile of the households. The type/version of data is Standard DHS-VII and can be acquired after registration and formal request on the website of the DHS database provided by the agency [42]. The data is collected through a household survey by the international development agency, USAID (United States Agency for International Development), with the collaboration of national institutes for a population study of the states involved. Table 3 presents a statistical summary of each explanatory variable including the values of mean, median, minimum, maximum, standard deviation, kurtosis, and skewness for the dataset of the selected countries. The survey gives data about the health characteristics of households and domestic possessions including basic energy services. In this regard, it has vital theoretical and practical policy implications. It is collected by the field workers funded by the involved national institutes of population studies and the USAID.

## 4. Results and discussion

### 4.1. Energy poverty results

This chapter discusses the outcomes of energy poverty and its multifaceted deprivations across the eleven developing countries of Asia after a statistical analysis of the primary data. Fig. 2 presents the results of the occurrences of multidimensional energy poverty for each country. The results show that Myanmar and Cambodia are the most multidimensionally energy-poor countries in the regions with 0.5 and 0.46 MEPI counts, respectively. Bangladesh, Afghanistan, Nepal, Vietnam, and the Philippines are the second most multidimensionally energy-poor countries with relatively low MEPI scores; 0.37, 0.35, 0.31, 0.31, and 0.3 sequentially. Lack of access to efficient and clean cooking stoves (electricity or natural gas) and household's inability to afford modern energy services (means of cooling, refrigeration, heating, or ventilation) and assets of education or entertainment (radio, television, or computer) were the main drivers of multidimensional energy poverty in most countries. Indonesia, Maldives, and Pakistan are the least multidimensionally energy-poor states across the regions with comparatively low rates of the MEPI.

Fig. 3 presents the rates of deprivation regarding cooking fuels in every country. The graph demonstrates that Bangladesh is one of the most deprived countries regarding modern cooking fuels. Over 80% of households do not have access to modern cooking fuels such as electricity, natural gas, biogas, kerosene, and LPG, etc. They still rely on contaminated traditional energy fuels, for example, firewood, coal, charcoal, crops, agricultural straws, and animal dung to prepare a meal. Likely, nearly 70% of the population of Afghanistan and Nepal depend on inefficient kitchen stoves. Over 50% of the households in India and Pakistan also use traditional energy fuels to cook food. The widely used cooking practices on contaminated and inefficient cooking stoves envisage detrimental health impacts with women and girls most affected in the region. The Maldives is the only country with the lowest rate of solid fuel consumption for cooking in the regions.

The burning of solid fuels causes harmful health impacts if the kitchens are poorly ventilated. Even the combustion of traditional energy fuels in open areas contaminates the air [8]. Fig. 4 describes the comprehensive results of solid fuel consumption at the house-

**Table 3**
Statistical summary of each explanatory variable for the aggregate dataset (N = 784,285).

| Variables | Mean | Median | Min | Max | Standard Deviation | Kurtosis | Skewness |
|---|---|---|---|---|---|---|---|
| HV206 | 0.851 | 1 | 0 | 1 | 0.356 | 1.887 | −1.972 |
| HV208 | 0.758 | 1 | 0 | 1 | 0.428 | −0.552 | −1.203 |
| HV209 | 0.391 | 0 | 0 | 1 | 0.488 | −1.802 | 0.445 |
| HV242 | 0.591 | 0.6 | 0 | 1 | 0.432 | −1.526 | −0.427 |
| HV243A | 0.833 | 1 | 0 | 1 | 0.373 | 1.199 | −1.789 |
| HV226 | 0.501 | 1 | 0 | 1 | 0.5 | −2 | −0.006 |
| V012 | 37.525 | 38 | 15 | 49 | 7.856 | −0.516 | −0.496 |
| V025 | 1.579 | 2 | 1 | 2 | 0.494 | −1.898 | −0.319 |
| V113 | 39.103 | 31 | 11 | 99 | 22.568 | −1.059 | 0.585 |
| V116 | 17.545 | 12 | 11 | 99 | 11.551 | 23.775 | 4.159 |
| V155 | 1.516 | 2 | 0 | 9 | 0.8 | 13.726 | 1.231 |
| V201 | 3.573 | 3 | 0 | 18 | 2.049 | 2.376 | 1.329 |
| V228 | 0.208 | 0 | 0 | 9 | 0.357 | 20.999 | 2.439 |
| V312 | 2.242 | 1 | 0 | 20 | 3.647 | 7.196 | 2.525 |
| V320 | 2.269 | 2.23 | 1 | 6 | 0.287 | 54.15 | 6.641 |
| V459 | 0.488 | 0.39 | 0 | 1 | 0.23 | 1.234 | 1.702 |
| V481 | 0.365 | 0.22 | 0 | 9 | 0.424 | 0.291 | 0.813 |
| V501 | 1.195 | 1 | 0 | 5 | 0.732 | 11.032 | 3.189 |
| V717 | 3.065 | 3 | 0 | 98 | 3.715 | 275.872 | 11.197 |
| V745 | 1.249 | 1 | 0 | 9 | 0.981 | −0.689 | 0.132 |
| HV237 | 0.583 | 1 | 0 | 8 | 0.508 | 21.501 | 1.334 |

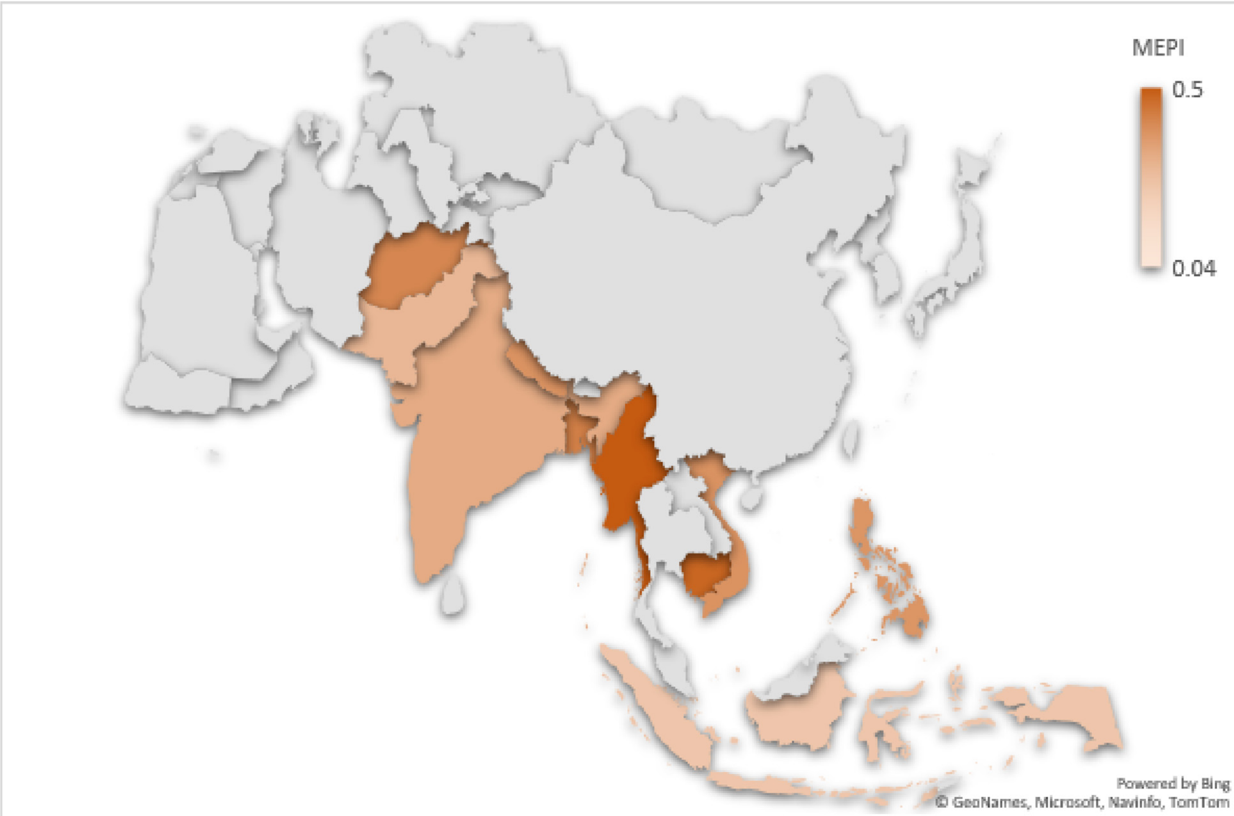


**Fig. 2.** Distribution of multidimensional energy poverty results with the MEPI scores.

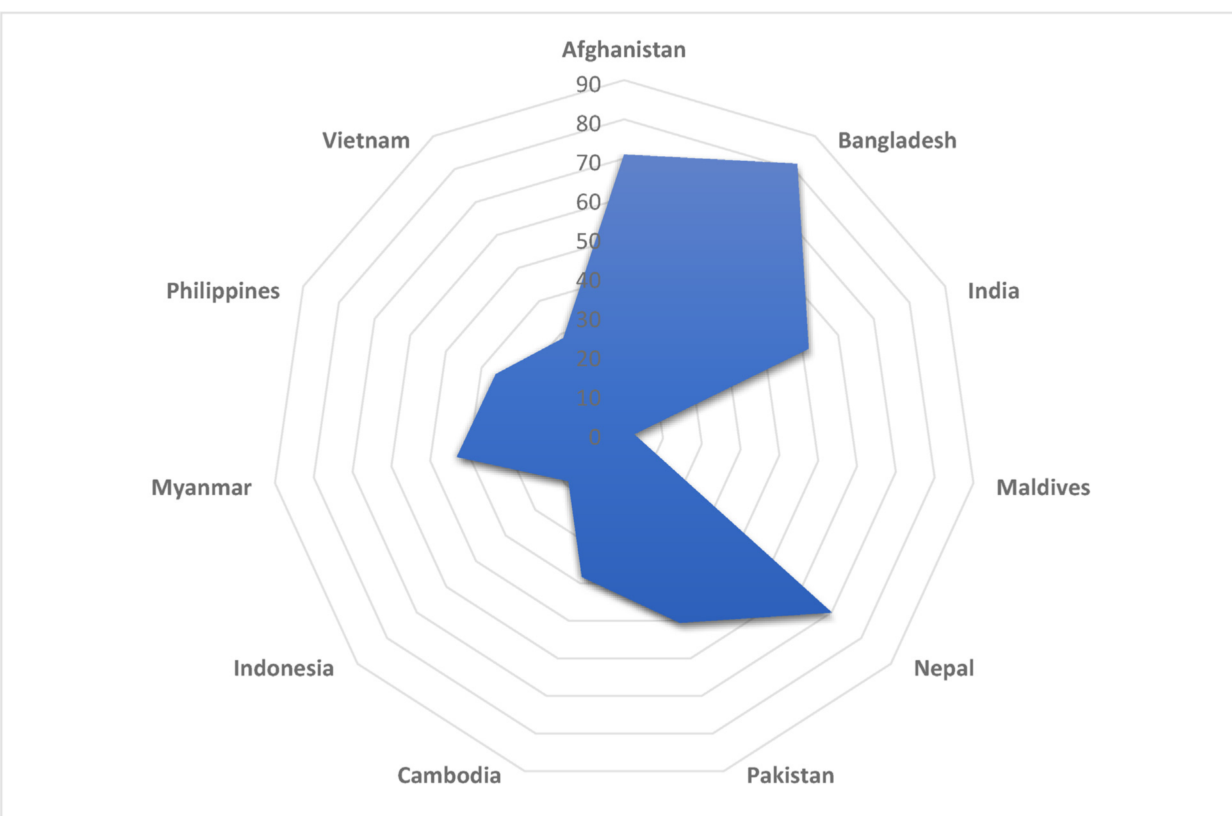


**Fig. 3.** Deprivation details regarding access to clean cooking fuels for each country.

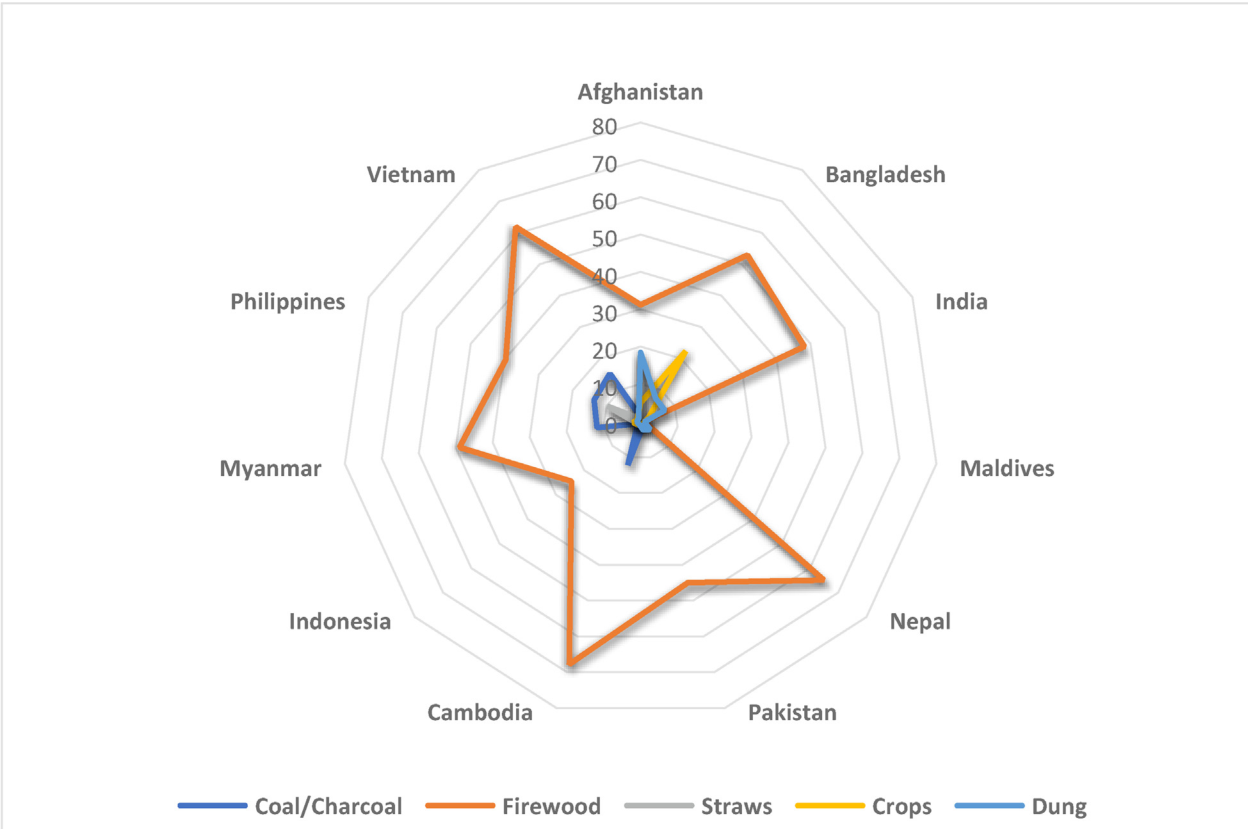


**Fig. 4.** Rates of commonly used solid fuels for every country.

hold level. It is evident that firewood is the most used cooking fuel across the countries with the highest rates of household consumption. More than half of the households in Cambodia, Myanmar, Nepal, Bangladesh, and the Philippines rely on firewood to cook meals daily. The lack of access to modern energy fuels in rural areas leaves no other choice except to rely on woods or animal waste for cooking practices. This consumption of polluted cooking fuels emits poisonous and harmful fine particles ($PM_{2.5}$) in the air [43]. If a house has not a proper ventilation system or a kitchen with no chimney or hood, it causes indoor smoking. Indoor smoking contains a range of health-damaging pollutants, such as small particles and carbon monoxide, and particulates pollution levels higher than the accepted guideline values [44].

Furthermore, Fig. 5 summarises energy poverty results by dimensions for each country. Most countries are deprived of household appliances of cooling or refrigeration such as Afghanistan, Bangladesh, India, Myanmar, Cambodia, and Nepal. Household ownership status of assets of education/entertainment is the second dimension of energy poverty with relatively high rates of deprivation across the regions. Nepal, India, Afghanistan, and the Philippines are the countries with the highest deprivation rates of indoor air pollution indicating poor ventilation kitchen facilities nationwide. Besides, Bangladesh and Cambodia have more numbers of households that lack access to electricity, and it indicates that these countries yet to do more to achieve complete electrification.

The geographical terrain and incapacity of the power generating systems to meet the rampant energy demands of the dense population also leave the rural households susceptible to multidimensional energy poverty in the regions [6]. Almost all countries have shared a similar political, economic, and social characteristic including agrarian societies, more rural population than urban, developing economies, dense population, and not fully industrialised. The rural households of the regions are at large dependent on firewood, straws, dung, and crops to prepare meals. They do not have access to modern cooking fuels because of poor and incomplete electric and gas pipeline networks. They are also unable to afford modern household appliances due to their weak socioeconomic status [45]. Along with these reasons, the developing economies and political instability also prevent the networks of infrastructure, electrification, and gas pipeline. However, rapid economic growth driven by industrial activities can enable the countries to overcome these hazards [46], ameliorate the deprived areas, and provide complete electrification, modern energy services, and clean cooking fuels.

### 4.2. SEM results

It is empirically evident that the socioeconomic status of the household plays a significant role to determine the household multidimensional energy poverty [47]. Socioeconomic and demographic factors including family size, gender, age, employment, housing characteristics, residence, and ownership status of residential property are the significant determinants of multidimensional energy poverty at the household level [45]. Thus, hypothetically, the next step is to examine the impacts of multidimensional energy poverty on health, especially in women. This study aims to examine the health implications of multidimensional energy poverty for women in developing countries using the structural equation modeling technique.

The SEM performs two-staged functions of data analysis: validation of the hypothesised model and fitting the model structurally. Firstly, the models are proposed based on empirical research and then the suitability of the proposed models is verified

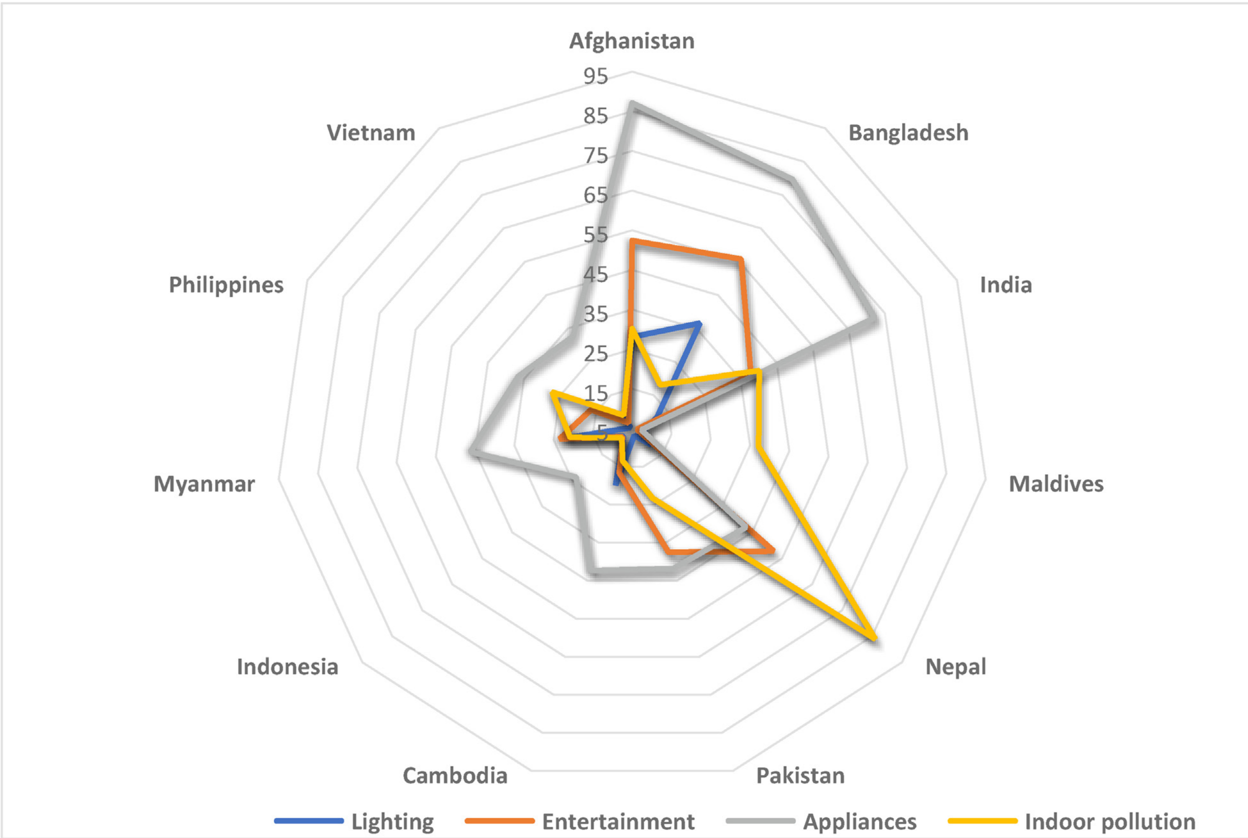


**Fig. 5.** Energy poverty results for each country by dimensions.

based on indicators of good fitness of the SEM model. These parameters include goodness-of-fitness index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), root mean square (RMS/RMSEA), Tucker-Lewis index (TLI), and normed fit index (NFI) [48,49]. The above-mentioned indicators were set by the proponents of the SEM technique to check or verify whether the run SEM model fits and acceptable statistically or not. Secondly, after the model fit verification, the degree of direct, indirect, and total effects between the latent variables and their indicators is checked [50]. At the final stage, if the model passes the fit criterion as per the aforementioned parameters, it is considered an acceptable model. In this study, IBM SPSS Amos 25.0 Graphics, and SmartPLS 3.0 data analysis software [51] was used to run the SEM analysis using a combined dataset of eleven developing countries. The partial least square method was used to estimate the parameters of this recursive model.

The results of construct validity or composite reliability (CR) that is used to test the internal consistency in scale items of the proposed model are shown in Table 4. Most values of standardised factor loadings were less than 0.5, a widely acceptable threshold. Similarly, estimates of average variance extracted (AVE), used to assess the convergent validity of the proposed model, should be equal to or more than 0.5 ($AVE \geq 0.5$) to fulfill convergent validity, in our case, it is 0.31 for the MEPI and 0.11 for health indicators of women. One of the major reasons behind this could be the large dataset (N = 784,285) of the study and too many health indicators. However, discriminant validity and composite reliability (also presented with rho_A reliability coefficient) were fulfilled as their values approached the acceptable thresholds mostly, as CR > 0.7 and the value of discriminant validity 0.56 for latent constructs was close to the value of correlation 0.61.

Fig. 6 depicts the results of path analysis with standardised estimates for latent constructs and each indicator. Path coefficients were estimated to verify the path model of this study. As hypothesised, a significant negative causal relationship was revealed between indicators of multidimensional energy poverty and household health repercussions for women. The statistically significant negative relationship indicates that multidimensionally energy-poor households are susceptible to health diseases.

Table 5 gives a summary of standardised coefficients and Table A presents the correlation estimates of the path model to validate the significance of each indicator. The outcomes of the regression estimates of each component of the path model were significant at the level < 0.01. The causal path between multidimensional energy poverty and women's health was statistically significant with coefficient value −0.613 and the value of t-statistics 170.852. In addition to the path coefficients, direct and total effects were also calculated to examine the cause and effect relati onship between the latent constructs, as shown in Fig. 7, which again shows that the significant negative relationship was evident across the indicators of health in reference to multidimensional energy poverty. The results had verified the negative direct total effects of multidimensional energy poverty on women's health in developing countries.

Lastly, the fitness of the default model was validated in terms of model fit parameters set by the advocates of the structural equation modeling approach. These parameters include chi-square/df, p-value, GFI, AGFI, PGFI, PNFI, NFI, TLI, and RMSEA [48,49]. there were more cases of terminated pregnancies in households with fewer or less modern domestic energy services.

Table 6 presents these model fit parameters, a criterion of accepted values, and model fit estimates of this study. The

**Table 4**
Results of the construct validity of the measurement model of this study.

| Latent Variable | Standard Loadings | AVE | Discriminant Validity | Rho_ A (Composite reliability coefficient) | Cronbach's Alpha |
|---|---|---|---|---|---|
| MEPI | 0.605 | 0.31 | 0.56 | 0.57 | 0.28 |
| | 0.369 | | | | |
| | 0.584 | | | | |
| | 0.589 | | | | |
| | 0.346 | | | | |
| | −0.701 | | | | |
| Health | −0.068 | 0.11 | 0.31 | 0.74 | 0.06 |
| | 0.212 | | | | |
| | −0.328 | | | | |
| | 0.195 | | | | |
| | −0.344 | | | | |
| | 0.188 | | | | |
| | 0.071 | | | | |
| | −0.355 | | | | |
| | 0.103 | | | | |
| | 0.525 | | | | |
| | −0.52 | | | | |
| | 0.025 | | | | |
| | 0.138 | | | | |
| | 0.123 | | | | |
| | 0.112 | | | | |

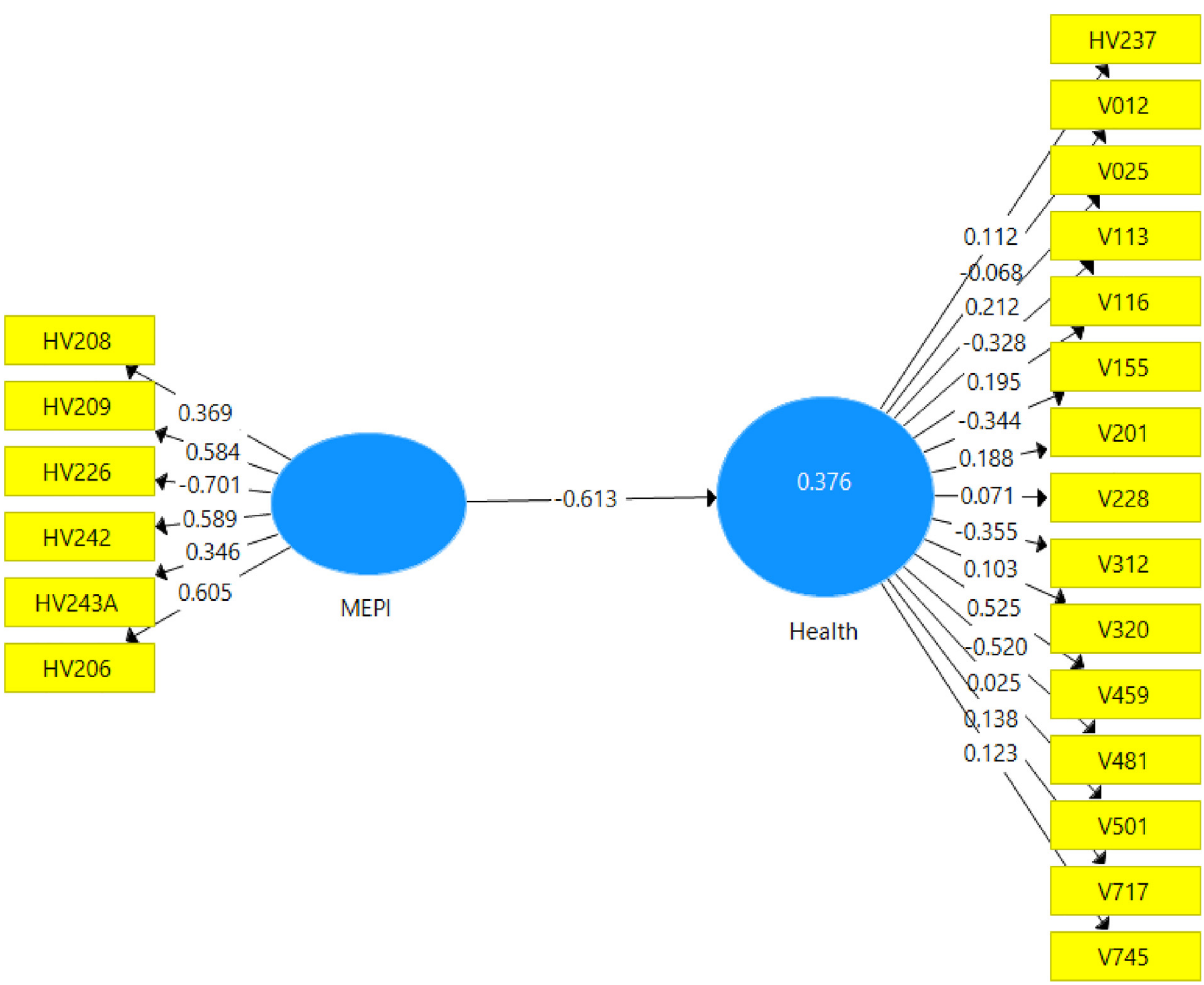


**Fig. 6.** Results of the path model with path coefficients (df = 169 & p < 0.001). Table 2 shows the full names of variables.

**Table 5**
Results of factor loadings with original and sample mean coefficients and t-statistics.

| Path | O. Coefficients | S. Mean | Standard Deviation | T Statistics |
|---|---|---|---|---|
| Health<- MEPI | −0.613 | −0.613 | 0.004 | 170.852*** |
| HV208 <- MEPI | 0.369 | 0.366 | 0.052 | 7.092*** |
| HV209 <- MEPI | 0.584 | 0.579 | 0.083 | 7.062*** |
| HV226 <- MEPI | −0.701 | −0.694 | 0.099 | 7.074*** |
| HV206 <- MEPI | 0.605 | 0.598 | 0.085 | 7.096*** |
| HV242 <- MEPI | 0.589 | 0.583 | 0.083 | 7.062*** |
| HV243A <- MEPI | 0.346 | 0.342 | 0.049 | 7.043*** |
| V012 <- Health | −0.068 | −0.067 | 0.012 | 5.76*** |
| V025 <- Health | 0.212 | 0.21 | 0.03 | 6.955*** |
| V113 <- Health | −0.328 | −0.325 | 0.047 | 7.047*** |
| V116 <- Health | 0.195 | 0.193 | 0.028 | 7.046*** |
| V155 <- Health | −0.344 | −0.34 | 0.049 | 7.026*** |
| V201 <- Health | 0.188 | 0.186 | 0.027 | 6.981*** |
| V228 <- Health | 0.071 | 0.07 | 0.012 | 6.114*** |
| V312 <- Health | −0.355 | −0.351 | 0.05 | 7.045*** |
| V320 <- Health | 0.103 | 0.101 | 0.015 | 6.754*** |
| V459 <- Health | 0.525 | 0.519 | 0.074 | 7.091*** |
| V481 <- Health | −0.52 | −0.515 | 0.073 | 7.09*** |
| V501 <- Health | 0.025 | 0.025 | 0.007 | 3.886*** |
| V717 <- Health | 0.138 | 0.136 | 0.02 | 6.869*** |
| V745 <- Health | 0.123 | 0.122 | 0.018 | 6.773*** |
| HV237 <- Health | 0.112 | 0.111 | 0.017 | 6.689*** |

***Significant at the level < 0.01.

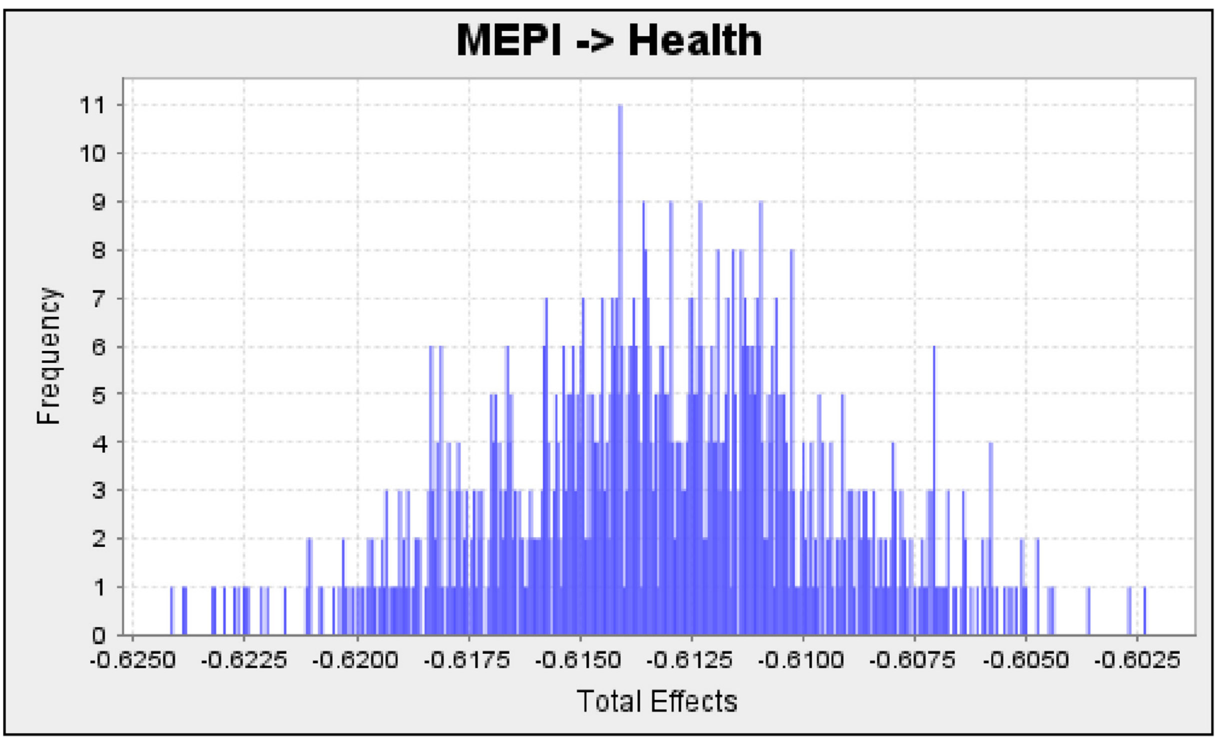


**Fig. 7.** Total effects of the causal relationship between the MEPI and health with histogram.

values of all parameters were above the acceptable estimates for a good fit model and thus met the acceptable criterion. The results confirmed that our model fitted the sample data fairly and was an acceptable model. The fitness of the model demonstrated that the health problems had an empirical cause and effect relationship with multidimensional energy poverty such as the age of sterility, toilet facilities, parasitic/-mosquito bites diseases, fertility, family planning, pregnancy, and health insurance. The negative causal relationship also implies that there were more cases of terminated pregnancies in households with fewer or less modern domestic energy services.

**Table 6**
Model fit criteria, acceptance level, and values of model fit estimates of this study.

| The criterion of model fit | Level of acceptance | Values of model fit |
|---|---|---|
| GFI (Goodness-of-fit index) | Close to 1 (absolute fit) | 0.950 |
| AGFI (Adjusted goodness-of-fit index) | Close to 1 (absolute fit) | 0.937 |
| PGFI (Parsimony goodness-of-fit index) | Close to 1 (absolute fit) | 0.764 |
| NFI (Normed fit index) | Close to 1 (absolute fit) | 0.720 |
| CFI (Comparative fit index) | Close to 1 (absolute fit) | 0.720 |
| IFI (Incremental fit index) | Close to 1 (absolute fit)) | 0.720 |
| TLI (Tucker Lewis index) | Close to 1 (absolute fit) | 0.685 |
| PNFI (Parsimony normed fit index) | Greater than 0.5 (absolute fit) | 0.640 |
| RMSEA (Root mean square error of approximation) | Less than 0.08 (absolute fit) | 0.058 |

## 5. Conclusion and policy implications

The study attempted to construct a comprehensively robust model of the structural relationship between multidimensional energy poverty and its health implications for women in developing countries using the method of structural equation modeling. The fitness of the path model based on proposed estimates had identified the statistically negative relationship between the indicators of multidimensional energy poverty and health for women in South and Southeast Asia and it indicated that there were an empirical cause and effect relationship with indicators of women's health including sources of drinking water, purification of drinking water, types of toilet facility, termination of pregnancy, fertility, contraception or family planning, age at sterilization, mosquito-borne diseases, coverage of health insurance, marital status, literacy, residence, and occupation. The findings also revealed that solid fuel dependency, incomplete electrification, inability to afford household appliances, and lack of access to modern energy services make these developing countries of Asia some of the most susceptible countries to multidimensional energy poverty in the world.

The results provide significant theoretical as well as practical potential policy options to mitigate the detrimental health impacts of household multidimensional energy poverty for women in the developing world. Elevating the socioeconomic status of the households, strengthening their affordability level, and providing efficient cooking fuels can reduce these harmful health impacts of energy poverty. The empirical results also suggest the significant impacts of multidimensional energy poverty on health status is due to indoor air pollution, compounded by households' living conditions such as small space with inhouse kitchen, and the lack of access to modern, efficient, and clean energy fuels. While ensuring access to electricity should be prioritised, it should be accompanied by inclusive development policies to promote rural economy and narrow development gaps.

Therefore, the government should prioritise rural electricity distribution networks, strengthen energy-related agencies' capacity to plan and manage electrification projects, and provide investment opportunities and incentives to potential private investors for rural electrification by developing appropriate policies, legal framework, and regulations such as standard and fiscal incentives. Renewable energy technology should be promoted and encouraged through incentives and subsidies to reduce solid fuel dependency. The harness of renewable energy resources can be helpful to diversify the energy mix and thus enables to reduce energy prices, overcome household air pollution, and reduce potential health risks for women subsequently.

## CRediT authorship contribution statement

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

**Table A**
Correlations of estimates of indicators.

| HV206 | HV208 | HV209 | HV242 | HV243 | HV226 | V012 | V025 | V113 | V116 | V155 | V201 | V228 | V312 | V320 | V459 | V481 | V501 | V717 | V745 | HV237 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | | | | | | | | | | | | |
| 0.48 | 1 | | | | | | | | | | | | | | | | | | | |
| 0.33 | 0.41 | 1 | | | | | | | | | | | | | | | | | | |
| 0.14 | 0.14 | 0.23 | 1 | | | | | | | | | | | | | | | | | |
| 0.22 | 0.32 | 0.30 | 0.18 | 1 | | | | | | | | | | | | | | | | |
| −0.39 | −0.41 | −0.56 | −0.20 | −0.27 | 1 | | | | | | | | | | | | | | | |
| −0.01 | −0.01 | 0.02 | 0.08 | 0.06 | −0.08 | 1 | | | | | | | | | | | | | | |
| −0.09 | −0.06 | −0.07 | −0.07 | −0.02 | 0.10 | −0.02 | 1 | | | | | | | | | | | | | |
| 0.13 | 0.07 | 0.12 | 0.11 | 0.05 | −0.15 | 0.05 | −0.24 | 1 | | | | | | | | | | | | |
| −0.10 | −0.05 | −0.07 | −0.05 | −0.04 | 0.08 | −0.06 | 0.22 | 0.06 | 1 | | | | | | | | | | | |
| 0.13 | 0.10 | 0.12 | 0.13 | −0.04 | −0.19 | −0.01 | −0.22 | 0.10 | −0.12 | 1 | | | | | | | | | | |
| −0.10 | −0.07 | −0.07 | −0.03 | 0.03 | 0.11 | 0.44 | 0.17 | −0.13 | 0.11 | −0.27 | 1 | | | | | | | | | |
| −0.06 | −0.01 | −0.04 | 0.01 | 0.02 | 0.04 | 0.08 | −0.01 | −0.04 | 0.01 | −0.02 | 0.08 | 1 | | | | | | | | |
| 0.14 | 0.08 | 0.13 | 0.12 | 0.07 | −0.15 | −0.04 | −0.13 | 0.14 | −0.11 | 0.12 | −0.08 | −0.03 | 1 | | | | | | | |
| −0.03 | −0.03 | −0.05 | −0.05 | 0.00 | 0.09 | 0.10 | −0.01 | −0.01 | −0.02 | −0.06 | 0.10 | 0.01 | 0.07 | 1 | | | | | | |
| −0.16 | −0.01 | −0.18 | −0.23 | −0.27 | 0.17 | −0.01 | 0.14 | −0.13 | 0.15 | 0.09 | 0.03 | −0.04 | −0.11 | 0.02 | 1 | | | | | |
| 0.18 | 0.11 | 0.18 | 0.22 | 0.08 | −0.23 | 0.06 | −0.18 | 0.18 | −0.08 | 0.20 | −0.08 | −0.01 | 0.19 | −0.07 | −0.29 | 1 | | | | |
| −0.02 | −0.02 | −0.01 | −0.02 | 0.04 | 0.03 | 0.09 | −0.01 | 0.02 | −0.01 | −0.10 | −0.01 | −0.02 | −0.11 | −0.03 | −0.09 | −0.03 | 1 | | | |
| −0.06 | −0.02 | −0.05 | −0.05 | −0.03 | 0.05 | 0.07 | 0.06 | −0.01 | 0.05 | −0.07 | 0.05 | 0.03 | −0.07 | −0.01 | 0.11 | −0.08 | 0.08 | 1 | | |
| −0.09 | −0.03 | −0.05 | 0.01 | 0.01 | 0.06 | 0.11 | 0.18 | −0.11 | 0.07 | −0.08 | 0.19 | 0.06 | −0.05 | 0.02 | 0.01 | −0.06 | −0.15 | 0.04 | 1 | |
| −0.08 | −0.04 | −0.01 | 0.13 | −0.02 | 0.10 | 0.03 | −0.02 | 0.00 | 0.04 | 0.12 | −0.03 | 0.034 | 0.01 | −0.03 | 0.06 | 0.08 | −0.03 | 0.01 | 0.03 | 1 |

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