Energy 251 (2022) 123977

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Measurements and determinants of extreme multidimensional energy poverty using machine learning

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ARTICLE INFO

Article history:
Received 12 October 2021
Received in revised form
7 April 2022
Accepted 9 April 2022
Available online 12 April 2022

Keywords:
Severe energy poverty
Multidimensional approach
Socioeconomic determinants
Machine learning
Developing world

ABSTRACT

The contribution of this study is twofold. First, it calculates the depth, intensity, and degrees of energy poverty in developing countries using a multidimensional approach. The data analysis of 59 developing countries of Asia and Africa confirmed a widespread ‘severe’ energy poverty across multiple dimensions. The results revealed that Afghanistan, Yemen, Nepal, India, Bangladesh, and the Philippines in Asia and DR Congo, Chad, Madagascar, Niger, Sierre Leone, Tanzania, and Burundi in Africa were the most susceptible countries to extreme multidimensional energy poverty. Second, the study employed supervised machine learning algorithms to identify the most pertinent socioeconomic determinants of extreme multidimensional energy poverty in the developing world. The results of machine learning identified the accumulated wealth of a household, size and ownership status of a house, marital status of the main breadwinner, and place of residence of the main breadwinner to be the five most influential socioeconomic determinants of extreme multidimensional energy poverty. Therefore, the robust findings of an accurate assessment of extreme energy poverty and its socioeconomic determinants have policy significance to eradicate severe energy poverty by announcing additional incentives, allocating resources, and providing special assistance to those who are at the bottom.

1. Introduction

Policy efforts and incentives to eradicate energy poverty may leave extreme energy-poor households behind because that requires some additional incentives and effective support programs. The inability to identify those who are at the bottom does not provide additional incentives and financial support to ameliorate their conditions, who may have different characteristics as compared to moderate energy-poor [1,2] and their deprivations may be more chronic deprivations comparatively [3,4]. Thus, it is an important question to ask whether energy poverty reduction has actually taken place among the extreme energy-poor households or not, and what are the prominent determinants of that extreme energy poverty? For that, the identification of those who are exposed to chronic forms of energy poverty and its driving socioeconomic factors is imperative. But such identification requires setting different parameters and indices to distinguish between the poor from the poorest or energy poverty (acute) from destitution (extreme), which is also one of the pivotal steps to be taken for the measurement of energy poverty [5,6].

Bearing it in mind, this research contributes in two ways. First, it calculates extreme energy poverty in multiple dimensions across the developing countries of Asia and Africa using the multidimensional energy poverty index (MEPI). It has policy significance in the investigation of severe energy poverty with a robust approach leading to its reduction ultimately. Second, the identification of socioeconomic determinants of multidimensional energy poverty (extreme or moderate) is also of utmost priority to formulate reduction-oriented policies in various parts of the world. Therefore, this study uses advanced supervised machine learning approaches, such as Feature Selection and Multilayer Perceptron Artificial Neural Network, to identify the socioeconomic determinants of

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https://doi.org/10.1016/j.energy.2022.123977
0360-5442/

household extreme multidimensional energy poverty by analyzing the dataset of 59 developing countries. These supervised machine learning techniques are advanced and powerful for classification or regression tasks, better in precision, accuracy, and predictions in contrast to classical statistics, and can process a large and complicated dataset in a short time [7–12]. The major difference between traditional statistics and machine learning is inference and prediction. Classical statistics infer a relationship using a sample whereas machine learning makes generalizable predictive patterns [13,14]. Subsequently, the identification of severe multidimensional energy poverty paves the way to its eradication by announcing different additional incentives, allocating resources, and providing special assistance to those who are at the bottom.

2. Literature review

2.1. Calculation of energy poverty

As energy poverty is a complex and multi-faceted concept [15], different indicators were employed by the researchers to gauge, understand, and monitor it. The multidimensionality of the concept led to the capture of its social, economic, and technical aspects adequately through a set of indicators [16]. These indicators, with their shortcomings and benefits, differ from each other based on measuring approaches and ultimate targets. Unidimensional indicators only measure the occurrence of energy poverty (headcount ratio) focusing on one aspect of deprivation such as 10%, MIS (minimum income standard), HEP (hidden energy poverty), AFCP (after fuel cost poverty), and LIHC (low-income high cost) indicators that take income or consumption against energy expenditures a standard parameter to distinguish deprived from non-deprived [16–18].

The multidimensional indicators superseded unidimensional indicators because of their inability to measure the intensity (how much poor) of energy poverty along with the headcount ratio: prominently MEPI, a worldly recognized indicator to measure deprivations across the multiple dimensions of domestic energy services [19]. The unidimensional indicators only used a single index to measure energy poverty whereas the MEPI employs composite indices to understand, gauge, and monitor the multidimensionality of the concept and its potential implications [20]. Therefore, this study consults a ‘severe’ poverty cut-off as a hidden parameter to enable the MEPI for the identification of households susceptible to severe multidimensional energy poverty overlooked previously [21]. Such identification based on robust methodology leads to the reduction of extreme energy poverty in developing countries. It also paves the way to formulate reduction-oriented policies by allocating special funds and resources to uplift households susceptible to it. This reduction of extreme multidimensional energy poverty can further avoid its adverse impacts for overall physical and mental health [22–25], woman's health (pregnancy, fertility, sterility, birth weight, mortality) [26–29], children [30], gender disparity [31,32], biodiversity and environment [33,34], education [35,36], standard of living [37], and socioeconomic development [38,39].

2.2. Determinants of energy poverty

After the measurements of the index, the next important step is to find out factors, whether social, demographic, geographical, ecological, or economic, that determine energy poverty in various dimensions because this identification also leads to its reduction ultimately. There is a consensus on a point that no single socioeconomic factor determines household energy poverty or leads to its severity but the combination of multiple factors, such as housing and family characteristics, nature of the occupation, accumulated wealth of a household, residence, and diversity in ecology and other dynamic properties, drives a household to this undesirable situation [40–46]. Although, various studies have discussed the identification of socioeconomic and other dynamic determinants of energy poverty in various countries (South Asia countries, Germany, France, India, West Africa, and Ghana) employing different conventional statistical techniques [32,47–51].

However, this study aims to use powerful supervised machine learning approaches (Feature Selection and Multilayer Perceptron Artificial Neural Network) to review the impacts of socioeconomic factors in determining household energy poverty. All pertinent socioeconomic factors are taken into consideration to shortlist the most influential determinants of household multidimensional energy poverty in the developing world. These innovative and powerful machine learning approaches can process a large and complicated dataset in a short time and make predictions between input and target variables more accurately [52,53]. Instead of complex mathematical rules and procedures, artificial neural networks can learn key information patterns in the multidimensional information domain. In addition, neural networks are robust, fault-tolerant, reliable, and noise-resistant [54–56]. Since they are inherently noisy, data from energy systems are good candidates for solving problems that can be solved with neural networks [57].

Therefore, it is necessary to employ powerful and advanced techniques that can minimize prediction inaccuracy and manage data abnormalities and missing values to train the model and eventually estimate an empirical association between the predictor and target variables. Thus, supervised machine learning techniques are employed and trained to test an empirical association between the socioeconomic profile of a household and extreme energy poverty in various dimensions and finally, predict which are the most imperative socioeconomic determinants of extreme multidimensional energy poverty in developing countries.

3. Material and methods

3.1. Measurements of severe energy poverty with the MEPI

This study employs MEPI to calculate the depth and degrees of energy poverty across multiple dimensions of household energy services. Multidimensional Energy Poverty Index (MEPI) was developed by Ref. [19] in 2012 and improved by Ref. [58] to measure energy poverty within its six pertinent dimensions: lighting, cooking, indoor smoking, telecommunication, education/entertainment, and household appliances, shown in Table 1. The MEPI calculates energy poverty using a composite index that makes it a valuable technique to understand the concept, its dimensionalities, complexity, measurements, significance, and its policy implications [25,27,35,59].

The MEPI measures energy poverty in terms of its intensity (denoted with A) and headcounts ratio (denoted with H) in the dimensions d for the population n. A matrix of achievement ($n \times d$) of population n in dimensions d of the MEPI can be constituted with $\mathrm{Y} = \mathrm{y_{ij}}$. Where $\mathrm{y_{ij}} \leq 0$ describes the achievement of an individual $i = 1, 2, 3.._{\mathrm{n}}$ in column vectors across the variables $j = 1, 2, 3.._{\mathrm{d}}$ in row vectors. The weight w to each variable j is equally distributed and the total weight of all variables j is $\sum_{j=1}^{d} wj = 1$. Additionally, the multidimensional index employs two cut-offs: deprivation cut-off denoted with z and poverty cut-off denoted with k. Both hidden cut-off parameters are vitally important because it measures the headcount ratio and intensity of energy poverty.

The deprivation cut-off z is established to differentiate between deprivation and non-deprivation for any variable j in the

Table 1
Dimensions, indicators, and deprivation thresholds of measuring energy poverty.

Dimension	Indicator (Weight)	**Deprivation threshold** *Deprived if ….*
Cooking	Type of cooking fuel (1/6)	A household uses cooking fuel besides electricity, natural gas, biogas, and kerosene.
	Indoor smoke (1/6)	A household has not a separate room (kitchen) for cooking (with no chimney or hood).
Lighting	Electricity access (1/6)	A household has no electricity access.
Telecommunication	Asset's ownership (1/6)	A household does not possess more than a mobile phone or landline telephone.
Entertainment/Education	Possession of the concerned means (1/6)	A household does not own a radio, TV, or computer.
Household appliances	Ownership of assets (1/6)	A household does not have a fridge.

dimensions of energy poverty. $Z_j \leq 0$ presents the achievement degree of any variable *j* and for individual *i*, the matrix achievement is $g_{ij} \leq Z_j$. If a household is deprived of a particular dimension, the assigned weight will be $z_j = 1/6$, and $z_j = 0$ in case of no deprivation. For example, if a household does not have access to electricity, the weighted achievement will be 1/6 and 0 otherwise in a row vector. In other words, 1/6 is for deprivation and 0 for no deprivation in a dimension.

The selection of poverty cut-off *k* is a sensitive matter in the methodology as it affects the overall calculation of headcount ratio and intensity of the MEPI and identification of a household to be multidimensionally energy poor (moderate or extreme) as well. A poverty cut-off *k* establishes an eligibility criterion to identify the multidimensional energy-poor household. The reports of the Oxford Poverty and Human Development Initiative (OPHI) proposed three cross-dimensional poverty cut-offs to examine the degrees of energy poverty from 'vulnerability' to 'severity'. Energy '*vulnerability*' can be simply measured by setting the poverty cut-off *k* to 1/5 or 20% ($k \geq 20\%$). For example, if a household is deprived of more than one of the five dimensions of multidimensional energy poverty fixed and specified in the MEPI, that household will be considered '*vulnerable*' regarding access to household energy services. Likewise, '*acute*' energy poverty can be measured with 1/3 or 33% of cross-dimensional deprivations ($k \geq 33\%$) identifying simultaneous deprivation in two or more two of the total dimensions. The third proposed poverty cut-off is '*severe*' and the most stringent poverty cut-off. It identifies extreme energy poverty when poverty cut-off *k* is set to 50% (1/2) indicating the presence of deprivations in half of the total dimensions at the same time [60–63]. Therefore, this study uses the '*severe*' cross-dimensional poverty cut-off ($k \geq 50\%$ that is 0.48 as per weight vector of the variables) to measure the extreme form of multidimensional energy poverty in the study areas.

Lastly, a column vector, denoted with C*i*, to accumulate the total deprivation scores achieved by any individual *i* in all variables *j* is constructed. $Ci \geq k'$ is set to censor the observations of the extremely multidimensional energy-poor households and $Ci \leq k$ otherwise. 1 presents the cases of extremely energy-poor in a newly censored vector and 0 for not being energy poor. Now, after defining all hidden and tangible parameters of the index, the headcount ratio (H), intensity (A), and finally, extreme multidimensional energy poverty can be calculated using Eqs. (1)–(3), respectively.

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

q presents the number of multidimensionally energy-poor households filtered through a censored column vector $Ci \geq k$, and *n* presents the total population of the sample size.

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

Ci(k) denotes the total scores achieved by the multidimensionally energy-poor households (*q*).

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

The MEPI is a product of headcount ratio (*H*) and intensity (*A*).

3.2. Identification of socioeconomic determinants of the MEPI

The impacts of a household's socioeconomic profile on multidimensional energy poverty can be investigated considering various demographic and geographic factors, such as wealth, conditionalities of the residential property (location, age, ownership, size, and type or nature), gender, education level, employment, and marital status of the main breadwinner, family size, gender disparity within a family, heating systems, and geographic and environmental diversity. Due to such diversity, variation, and interdependence in socioeconomic factors, there can be single or different multiple socioeconomic factors that lead to multidimensional energy poverty in any area. Therefore, a statistical analysis of the effects of these factors on household multidimensional energy poverty will determine policy direction and its formulation. Thus, this study aims to empirically examine a range of demographic factors and consequently, their statistical association with household multidimensional energy poverty. This will help to understand the significant influence of socioeconomic determinants on energy poverty that, based on robust findings, will ultimately pave the way to its reduction.

3.2.1. Model and data preprocessing

Data preprocessing is one of the essential and foremost statistical steps for developing an accurate machine learning model. The input data of the constructed model may vary in terms of unit, magnitude, and nature. This model has a combination of different types of socioeconomic variables, which are categorical, binary, and continuous, as shown in Table 2. It is also very important to preprocess and transform data to prevent the predomination of large numeric values over small values [64]. The ultimate objective of data preprocessing is to remove the biases, noise, anomalies, outliers, or skewness that otherwise can trigger inaccuracy [65]. Therefore, it becomes critical to scale down data to achieve good performance of the model. Various researchers have endorsed the vital importance of data normalization for examining the predictive accuracy and performance of machine learning models, for example, Support Vector Machine [66], k-Nearest Neighbor [67], and Artificial Neural Network [68] in medicine [65,69], genomics [70], biometric system [71], motor fault detection [72], leaf classification [73], and stock exchange market [74].

There are several proposed techniques to normalize data before any machine learning algorithm by detecting outliers and noise, managing missing values or incomplete data, and transforming the input variables [67,75]. Two robust techniques, normalization, and standardization are widely used to preprocess the input data. Normalization, by definition, helps to scale down a feature (X) between 0 (min) to 1 (max) whereas standardization transforms the features (x) based on standard normal distribution-mean (μ) is

Table 2
Variables of the predictive model and its definitions.

Variable		Definition
Input	House	Number of rooms used for sleeping
	Wealth	Wealth index (grouped)
	Education	The educational level of the main breadwinner
	Family size	Number of total family members
	Marriage	Current marital status of the main breadwinner
	Occupation	Occupation (grouped)
	Status	Ownership status of a house
	Residence	Type of place of residence
	Sex	Sex of head of household
	Age	Age of head of household
Output	MEPI	A binary censored vector of extreme multidimensional energy poverty; 1) extremely energy-poor and 0) not energy-poor

0 and the standard deviation (σ) is 1. This study uses z-score normalization (standardization) algorithms, which is estimated employing Eq. (4) importing StandardScaler from sklearn preprocessing library.

$$Z = \frac{X-\mu}{\sigma} \tag{4}$$

It is worthful to keep in mind that deep learning algorithms, such as k-Nearest Neighbor, k-Means Clustering, Artificial Neural Network, Convolution Neural Network, and regression, require scaling and normalization of the input data [68]. Whereas, other machine learning algorithms, for instance, Decision Trees, Random Forest, XGBoost, or Feature Selection can be performed without standardization of data. Because in the end, the target is to build trees based on the features devoid of low or high values-it will not affect the outputs and performance of boosting algorithms [64].

3.2.2. Feature selection

The feature selection or feature weighting process is used to shortlist the number of predictors in the development of a predictive model: primarily redundant input variables are removed based on their weak strength of correlation with the output variable [76]. The presence of irrelevant input variables in the predictive model causes noise and inefficiencies and subsequently, slows down the process of training, validation, and testing by occupying the system memory in a large amount [77]. Therefore, it is preferable to reduce features to enhance the overall performance and effectiveness of the model and also save its computational cost subsequently [11,78]. The adoption of a supervised or unsupervised feature selection method depends upon the type of data and target variables. This study uses a supervised approach because the study model has a target variable; however, in the case of no response variable, an unsupervised method could be adopted [79].

For the supervised method, the Pearson correlation coefficient is commonly used if the output variable is continuous and the Mutual Information Ranking method is preferred when the response variable is categorical or binary [80,81]. As per the mixed nature of input and output variables (continuous, binary, and categorical) of survey data, this study employs both methods to select the most pertinent features to establish an ultimate predictive model. Pearson's correlation coefficient is the most common statistical measure employed to remove the uncorrelated predictors in developing the model [82,83]. Eqs. (5) and (6) explain the Pearson correlation coefficient method to predict highly correlated features for a target variable.

$$R_i = \frac{cov(X_i\ ,Y)}{\sqrt{var(X_{i,}\ \mathrm{var(Y)}}} \tag{5}$$

$$R_i = \frac{\sum_i (x_i-\overline{x}_i)(\ y_i-\overline{y}_i)}{\sqrt{\sum_i (x_i-\overline{x}_i)^2 \sum_i (y_k-\overline{y}_i)^2}} \tag{6}$$

In Eq. (5), *cov* denotes the covariance and *var* designates the variance. In Eq. (6), $\overline{x}_i$ and $\overline{y}_i$ refer to the mean of X and Y, respectively and R_i represents the correlation value of linear relationship between X and Y that could be between -1 and 1. Therefore, R_i sets or enforces a ranking criteria for the fitness of good linear association between the variables [83]. Whereas, Eqs. (7) and (8) define the ranking criteria based on the Mutual Information method. The MI is a feature selection method of information theory that applies information gain (typically in form of decision trees) to filter the number of input features by retaining the most relevant ones based on class discriminatory information in predicting output and redundancy with other variables as well [84]. It measures information between random input variables in a symmetric and non-negative way (*importing scikit-learn mutual_info_classif()function*): the gain value is zero if the variables are independent (uncorrelated) of each other [85]. This method was proposed, reviewed, and improved by Refs. [81,86,87] and it relied on statistical estimation of mutual information between each predictor and response variable [88].

$$I(i) = \iint_{x_i y} P(x_i,\ y) log\ \frac{p(x_i,y)}{p(x_i)p(y)} dxdy \tag{7}$$

$$I(i) = \sum_{x_i}\sum_{y} P(X=x_i,\ \ Y=y) log \frac{P(X=x_i, Y=y)}{P(X=x_i)P(Y=y)} \tag{8}$$

In Eq. (7), $P(x_i)$ is the probability density of x_i and p(y) of y, and $P(x_i,\ y)$ is mutual density. $I(i)$ measures the dependence of density d between the nominal input variable x_i and nominal or binary output variable y. The probabilities between the variables are then calculated using Eq. (8) from the frequencies where $P(Y = y)$ designates frequency counts of class probabilities, $P(X = x_i)$ designates the distribution of frequency counts of predictors, and $P(X=x_i, Y=y)$ presents the frequency counts of probabilities of combined observations. Let suppose, the class probabilities $P(Y = y)$ are 3 and the distribution of frequency counts of predictors $P(X = x_i)$ is 4: thus, frequency counts of joint probabilities $P(X=x_i, Y=y)$ will be 12 that is much larger like constructing a decision tree.

3.2.3. Artificial neural network

Once the highly relevant input features were selected, a supervised artificial neural network (ANN) equipped with the multilayer perceptron approach (MLP) was developed and trained to classify and predict the socioeconomic determinants of multidimensional energy poverty and finally, assessed the prediction accuracy of the constructed model as per the parameters of good fit. The MLP had superseded the feed-forward neural network [89]. A multilayer architecture of ANN has multiple interconnected neurons (the key processing units) and input, hidden, and output layers connected through neurons. The neurons store the information in form of weights. The input layer signals the information for processing, the hidden layer(s) performs the task of computation, and the output layer makes predictions and classification [57], as explained in Eq. (9).

$$y_{li} = f_{li}(z_{li}); z_{li} = \sum_{j=1}^{n_{l-1}} w(l-1)_j,\ liY(l-1)_j + b_{li} \tag{9}$$

where lth are layers, ith are neurons, y_{li} denotes output, f_{li} refers activation function, w is weight, and b_{li} are the biases. The activation function connects the nodes of a layer by signaling information (weighted sum of a node) to the nodes of the next layer. The neural computations in hidden and output layers can be explained through Eqs. (10) and (11), sequentially. Where b1 and b2 are the biases, W1 and W2 are the weight vectors, G and s are the activation functions. $\varnothing = \{W(1),\ b(1),\ W(2),\ b(2)\}$ is set for the parameters to learn [57].

$$o(\mathrm{x}) = \mathrm{G}(\mathrm{b}(2) + \mathrm{W}(2)\mathrm{h}(\mathrm{x})) \tag{10}$$

$$h(x) = \varnothing(x) = s(b(1) + W(1)x) \tag{11}$$

The training process is a collection of predictors and output patterns that are computed to train the ANN model. The dependent variables are the outputs that a neural network produces corresponding to input variables. When every pattern is read, the network generates an output from the input data which is then compared to an accurate output. If the training process encounters any difference or error (occasionally not regularly), the connection weights automatically change their directions in a way that the error gets minimized. If the error still exists and is greater than the accepted threshold even after running through all input patterns, the ANN continues to repeat this process of input patterns until the error falls within the desired tolerance. Once it reaches the desirable tolerance level, the network stops training, makes connection weights constant, and instead starts using new input information to define associations [90,91].

One of the practical advantages of the MLP is the back-propagation learning algorithm that trains the neurons in a way that it can adapt weights (input signals to a neuron) and coefficients [92]. A multilayer ANN is capable of handling large and complex systems with many interconnected parameters ignoring any extra items that are minimal and focusing instead on the more important ones. The MLP is developed to maximize continuous function to solve non-linear and differential problems through approximation, classification, and prediction [93,94].

3.3. Data source

This study uses primary household survey data from 20 Asian and 39 Sub-Saharan African countries. Standard DHS-VII data type was acquired from an independent agency named the United States Agency for International Development (USAID). The agency gathers, analyzes, and disseminates accurate and representative data from more than 90 countries on population, health, HIV, and nutrition under the Demographic and Health Survey (DHS) Program in association with the national institutes of involved countries. This household survey data is collected through questionnaires by joint field staff of the agency and the concerned country. Therefore, data provides a complete demographic, social, economic, and health profile of the households and household possessions. In this regard, data have all the necessary variables needed for all indicators of household multidimensional energy poverty and have theoretical as well as practical policy implications aimed to reduce energy poverty nationally, regionally, and globally. The survey data can be obtained from the agency after registering to its portal and making a formal request with a research proposal [95].

4. Results and discussion

4.1. Results of severe multidimensional energy poverty

Fig. 1 gives the results of the most affected countries with extreme multidimensional energy poverty in Asia and Africa whose data was provided by USAID. The results showed that Myanmar and Cambodia had the highest numbers of '*destitute*' households in Asia concerning access to modern household energy amenities with 0.41 and 0.36 MEPI scores, respectively. Afghanistan, Yemen, Nepal, India, Bangladesh, and the Philippines were the countries with the second highest rates of extreme energy poverty with 0.29, 0.29, 0.27, 0.27, 0.25, and 0.23 counts, sequentially. Ironically, these are the countries located in South and Southeast Asia except for Yemen and have an immensely dense population, developing economies, predominantly agrarian societies rather than industrialized, and underdeveloped gas and electricity infrastructure as compared to other regions or countries of Asia [26].

The DHS data on Yemen was collected in 2013–14, pre-civil war years. After the breakout of the continued civil war (2015 to present), it is quite pragmatic to say that multidimensional energy poverty would have risen drastically and exacerbated the situation in recent years. Afghanistan, another volatile country in Asia, has been under the shadows of wars for the last four decades. It has resulted in political instability, economic fallout, food insecurity, clean water scarcity, and destruction of roads, gas, electricity, and communication networks that aggravate the energy poverty scenario. Central Asian countries (Kazakhstan, Uzbekistan, Kyrgyzstan, and Tajikistan) and West Asian states (Turkey, Armenia, and Azerbaijan) experienced the least rates of severe energy poverty across the basic energy services.

In the case of Africa, the Democratic Republic of Congo and Chad were found to be the most affected countries where more than 70% of the households were susceptible to the extreme form of multidimensional energy poverty. Likewise, Madagascar, Niger, Sierre Leone, Tanzania, and Burundi can be listed in the second tier of the most affected states because of their energy poverty rates of 0.63, 0.63, 0.62, 0.61, and 0.60, respectively. Rwanda, Burkina Faso, Ethiopia, the Republic of Congo, and Zambia were reported to be in the third most precarious position where almost 50% of the households experienced severe energy poverty. Besides, the results also reported that Benin, Ivory Coast, Gambia, Guinea, Kenya, Mali, Mozambique, Nigeria, Togo, and Zimbabwe had more than 40% of the household facing problems regarding access to clean energy fuels, electricity, and modern household energy facilities. Lastly, South Africa, Liberia, and Malawi had the least rates of energy destitution 0.11, 0.16, 0.16, in sequence.

Lastly, Table 3 gives a summary of the whole discussion regarding the situation of extreme energy poverty in multiple dimensions in the developing countries of Asia and Africa. The households of most countries have access to electricity except for Afghanistan and Yemen in Asia. In the Asian continent, the

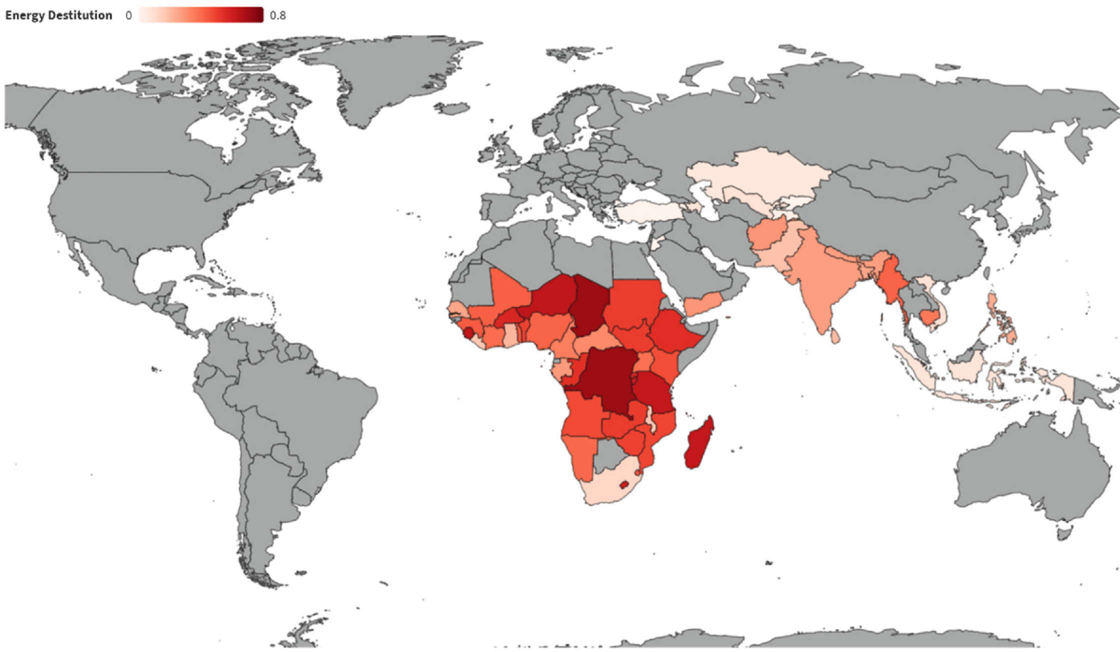

Fig. 1. Results of extreme multidimensional energy poverty across the developing countries of Asia and Africa.

Table 3
Detailed results of access to electricity and clean cooking fuels, intensity (A), headcount ratio (H), and extreme multidimensional energy poverty (MEPI) in the study areas.

Country	Year	Lighting (%)	Clean fuels (%)	H (%)	A (%)	MEPI (%)
Asia						
Afghanistan	2015–16	71.9	27.7	48	61	29.2
Armenia	2015–16	63.4	93	1	5	0.5
Azerbaijan	2006–07	88.1	85	13	51	6.6
Bangladesh	2015–16	98	16.1	40	64	25.6
India	2017–18	88.7	37.8	43	62	26.6
Indonesia	2016–17	93.2	54.7	13	55	7.1
Jordan	2017–18	80.1	99	3	47	1.4
Cambodia	2014–15	97.9	19	52	67	34.8
Kazakhstan	2000–01	77.8	84.2	10	56	5.6
Kyrgyzstan	2012–13	94.5	74.3	51	2	1.02
Myanmar	2015–16	98.2	20.5	57	71	40.4
Maldives	2016–17	99	94.9	1	48	0.5
Nepal	2016–17	99	26.8	43	62	26.6
Philippines	2017–18	99	37.3	37	62	22.9
Pakistan	2017–18	97.5	48.3	30	61	18.3
Tajikistan	2017–18	99	88.9	56	2	1.12
Turkey	2013–14	98.3	–	2	45	0.9
Uzbekistan	2002–03	99	84.2%	34	51	17.3
Vietnam	2005–06	99	36.8%	15	49	7.3
Yemen	2013–14	77	61.6%	42	68	28.5
Africa						
Angola	2015–16	33.8	41	68	68	47
Benin	2017–18	36.3	34	69	71	49
Burkina Faso	2017–18	15	13.4	67	85	56
Burundi	2016–17	12	16.6	67	89	60
Cameron	2018	52	28.5	67	52	35
Cent. African Rep.	1995	3	53	59	55	32
Chad	2014–15	8	8.3	76	93	71
Comoros	2012	70.7	26.3	68	48	32
Congo	2012	22.9	13.9	71	75	53
Congo D. Republic	2017–18	11	2	80	88	71
Ivory Coast	2012	46.5	11	68	58	39
Eswatini	2006–7	62	37.6	71	63	44
Ethiopia	2016	36.1	10.6	77	71	54
Gabon	2012	70.3	62.1	67	42	28
Gambia	2013	41.1	2.3	65	63	41
Ghana	2019	78.2	21.2	62	34	21
Guinea	2018	43.5	2.1	65	65	43
Kenya	2015	34.6	5	64	71	46

Table 3 (*continued*)

Country	Year	Lighting (%)	Clean fuels (%)	H (%)	A (%)	MEPI (%)
Lesotho	2014	25.9	38.1	73	81	59
Liberia	2016	13.3	1	75	21	16
Madagascar	2016	22.1	1	76	82	63
Malawi	2017	25.3	4	62	25	16
Mali	2018	47.1	2	65	64	42
Mozambique	2018	35.9	8	72	67	48
Namibia	2013	48.7	43	71	55	39
Niger	2012	22.9	2.2	75	83	63
Nigeria	2018	44.7	25.3	68	61	41
Rwanda	2017	35.2	2.3	71	79	56
S. Tome & Principe	2008–9	51.1	17	63	53	33
Senegal	2019	55.8	17.3	55	44	25
Sierra Leone	2016	13.8	1	72	87	62
South Africa	2016	90	83	58	20	11
Tanzania	2017	23.1	4	74	83	61
Togo	2017	44.6	6.9	67	63	43
Uganda	2018–19	37.6	1.6	63	61	38
Zambia	2018	28.8	8.3	70	72	50
Zimbabwe	2015	39.9	37.9	73	67	49

countries of South and Southeast Asia were found to have more deprived households mainly, which did not have access to clean and efficient energy fuels including Bangladesh, Cambodia, Myanmar, Nepal, and Afghanistan: Almost 40% of households in Myanmar, 35% in Cambodia, 30% in Afghanistan, 29% in Yemen, 27% in India and Nepal, 26% in Bangladesh, and 23% of households in the Philippines are susceptible to extreme energy poverty. Whereas this percentage rises to 52%, 48%, 44%, 35%, 35.5%, 40%, 44%, and 33% in terms of moderate household multidimensional energy poverty in the countries respectively. Likewise, these are the countries with lower rates of household access to clean energy fuels for cooking and electricity.

In contrast to the situation of energy poverty in Asian countries, the African states face considerable precariousness in the affordability and accessibility of basic energy services. Hardly a few nations have successfully provided electricity access to more than 50% of the households nationwide such as Cameron, Comoros, Eswatini, Gabon, Ghana, S. Tome & Principe, Senegal, and South Africa. The situation to access modern energy fuels for household consumption is even worse, exposing most of the population to the adverse health impacts of using inefficient and contaminated energy fuels. In addition, more than 50% of the households of most African countries are rated as multidimensionally energy poor. Only South Africa is an African country with the lowest cases of multidimensional energy poverty is less than 15% of the total population.

4.2. Results of socioeconomic determinants

4.2.1. Data normalization

Table 4 presents a summary of descriptive statistics of raw input data. The results of standard deviation and skewness show that the original data of five input variables (house, marriage, occupation, status, and sex) is skewed. This abnormal distribution can prevent good performance and accuracy of our predictive model. Therefore, standard scaling is used to preprocess and rescale the input data. Fig. 2 visualizes the results of the z-score normalization of original input data. Fig. 2(a) showed the abnormally distributed raw input data, whereas Fig. 2(b) confirmed that the StandardScaler successfully transformed the data between 0 and 1, and observational distributions of each feature between both values. The ANN model accepts the standardized inputs between 0 and 1 which helps to learn the weights more quickly and efficiently and ultimately results in better performance and predictive accuracy as compared to un-standardized data [64].

Table 4
Statistical summary of the input variables.

Variable	Minimum	Maximum	Mean	Std. Deviation	Skewness
House	0	25	1.95	1.126	3.595
Wealth	1	5	2.89	1.402	.108
Education	0	3	1.44	1.021	-.274
Family size	1	48	5.83	.1885	-.121
Marriage	0	5	1.61	.571	−1.238
Occupation	0	8	2.50	2.088	1.401
Status	0	3	2.40	1.284	−1.015
Residence	1	2	1.70	.459	-.866
Sex	1	2	1.15	.353	2.012
Age	10	98	48.20	13.965	.300

4.2.2. Selection of features

After successfully rescaling the input data, feature selection algorithms were employed to measure the impacts of each input feature on the response variable to finally build an ANN predictive model of the study. Fig. 3 illustrates the outcomes of feature selection methods based on their importance to the output (MEPI). The Pearson correlation coefficients and mutual information techniques were used to reduce the number of redundant predictors in the final multilayer perceptron classification model. Fig. 3 (a) shows that wealth, residence, house, marriage, and status are the most important features of input data based on their strong correlation with the extreme multidimensional energy poverty (MEPI) according to the Pearson correlation coefficient method. Mutual information (MI) algorithm as an additional method, which is very useful for building a classification model, was also used to have a picture of robust selection. The outcomes of full features are ranked in Fig. 3(b) which endorsed the shortlist of correlation coefficient method that wealth index, marital status, types of residence, and size and status of the house are statistically the most related predictors. It had been confirmed by both algorithms that age, occupation, sex, and education level of the main breadwinner and family size were the least correlated features. Therefore, the study reduces the number of overall ten predictors to the five most relevant features to build a final neural network model by removing the five least correlated input features.

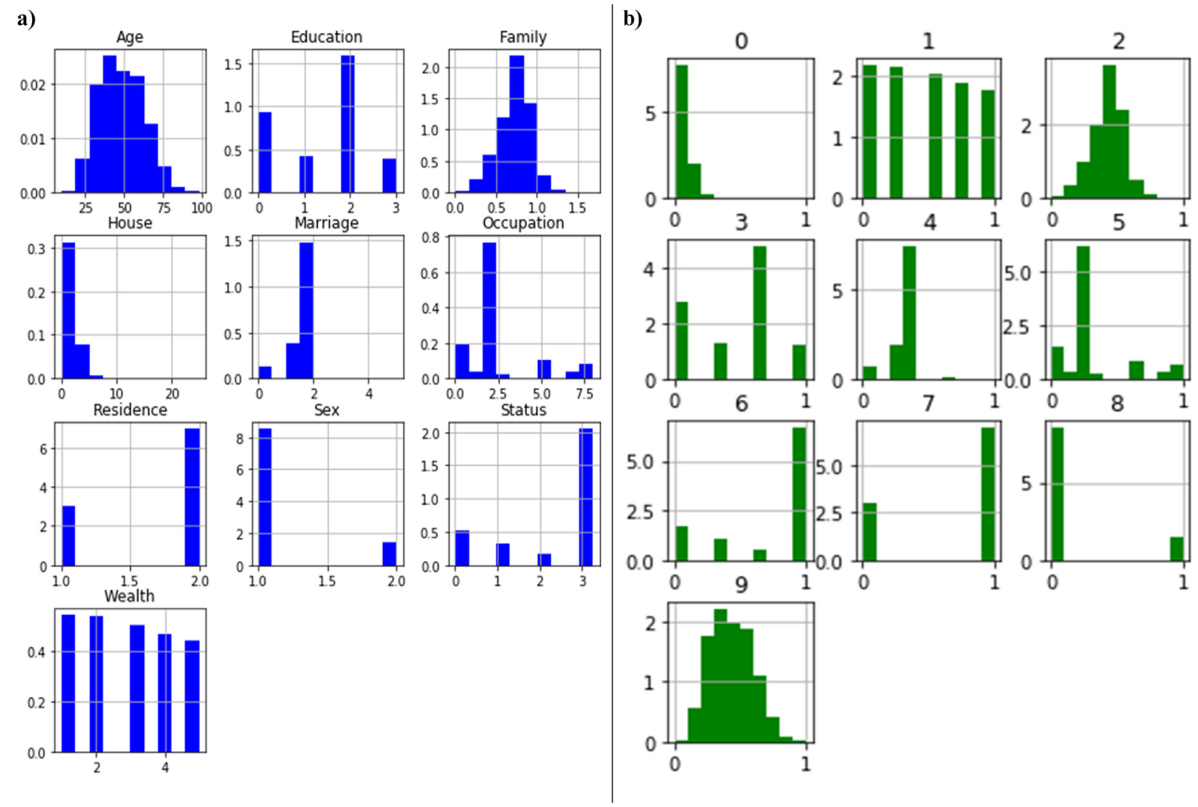

Fig. 2. Results of normalization of the raw input data.

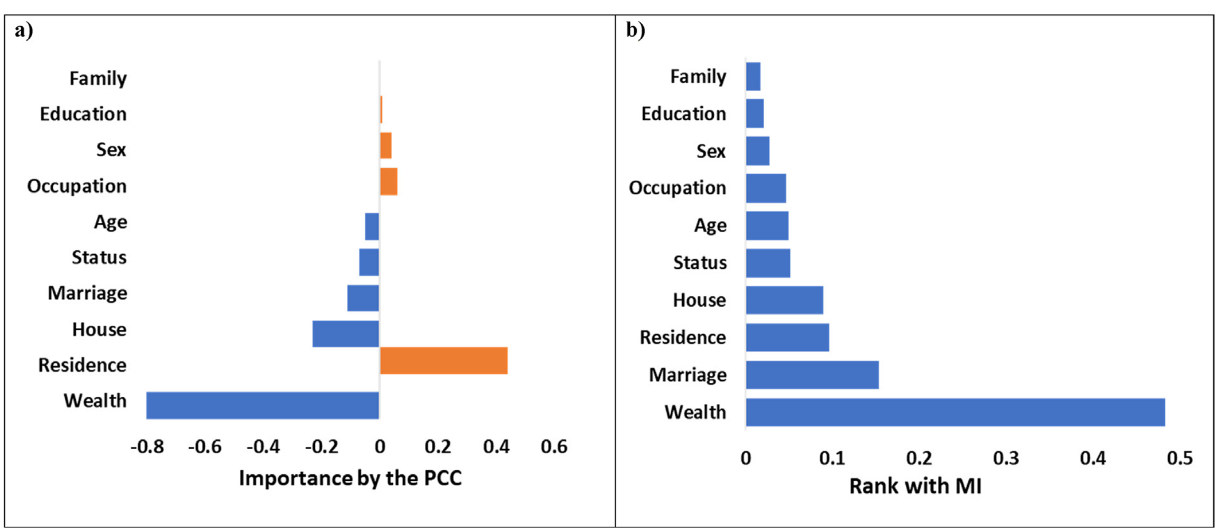

Fig. 3. Results of feature selection using Pearson correlation coefficient (a) and mutual information algorithms (b).

4.2.3. Artificial neural network

Fig. 4 represents the architecture of the neural network model for regression tasks using a multilayer perceptron algorithm. The MLP consists of two hidden layers that are interconnected with nodes. The model was built to predict the most influential socio-economic factors of extreme multidimensional energy poverty in developing countries. The dependent variable is a continuous variable that presents the accumulated scores of each household across the six dimensions of the index ranging from 0 to 1. Table 5 provides information regarding the case processing summary of the network. Following the typical partition ratio, the network used 70.1% cases of sample data to train the model and the rest of 29.1% for testing, achieving typical 100% validation of case processing.

Table 6 summarizes the network information of the model. The input layers consist of a total of 18 nodes of factorial and covariate predictors shortlisted from the feature selection process and one

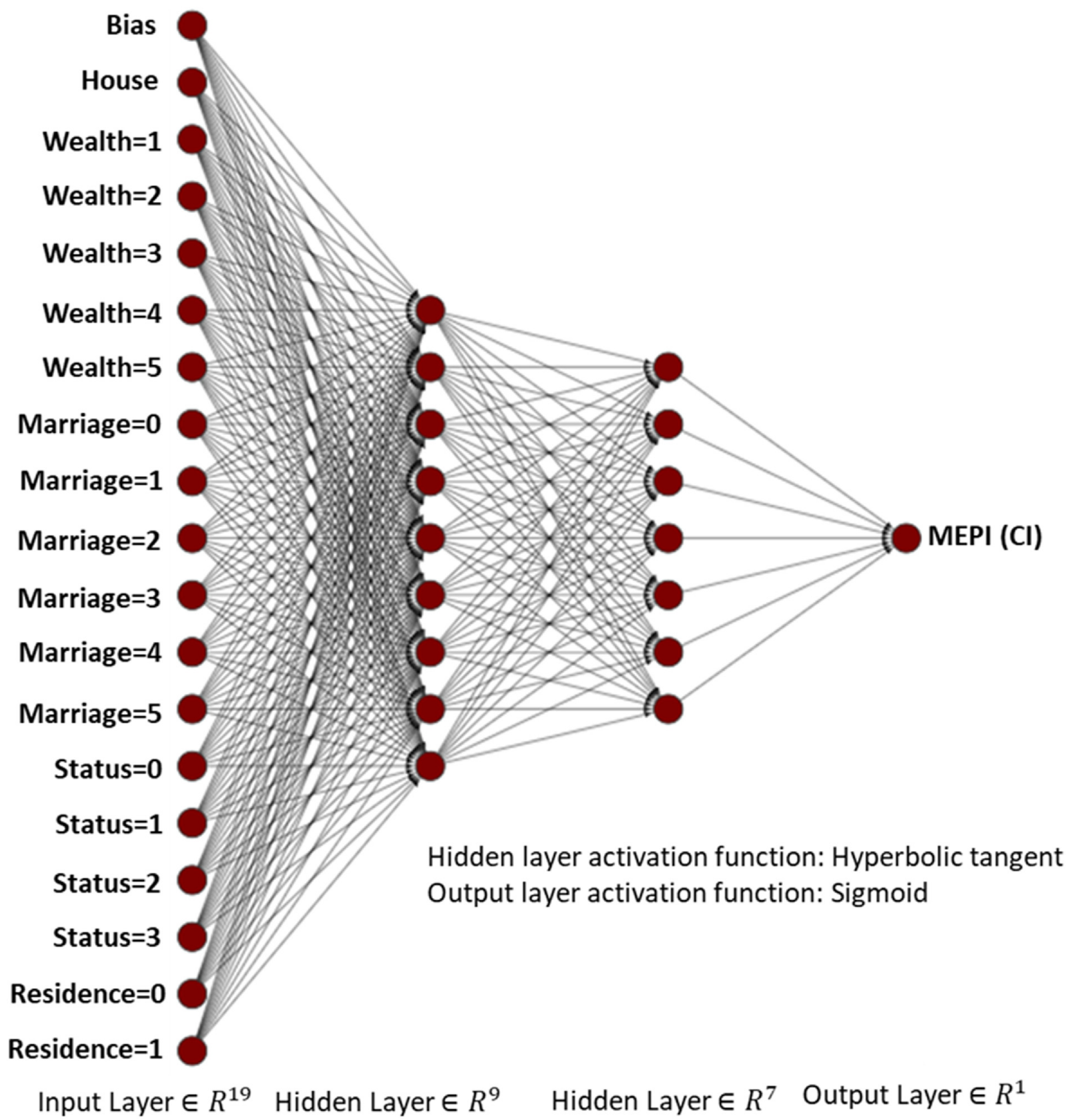

Fig. 4. Architecture of artificial neural network for deprivation counts (continuous outcome) of MEPI.

Table 5
Results of case processing summary.

		N	Percent
Sample	Training	472,459	70.1%
	Testing	201,836	29.9%
Valid		674,295	100.0%
Excluded		0	
Total		674,295	

bias. There are 8 units in hidden layer 1 and 6 in hidden layer 2 excluding the bias units. One neuron of continuous output is in the output layer. For initializing synaptic weights (connections) to each neuron in multiple layers, Hyperbolic tangent, $\tanh(a) = (e^a - e^{-a})/(e^a + e^{-a})$, as an activation function was used in the hidden layer. Hyperbolic tangent activation function (tanh) optimizes and tunes hyperparameters, such as the amount of hidden layer(s), units, and learning rate, to construct and train a robust model [55,96]. The benefits of using tanh activation function are that it maps negative predictors purely negative and zero predictors strongly alongside zero in the chart. Also, it is preferred to be a monotonic and differentiable function [97,98].

Whereas, the Sigmoid activation function $S(x) = \frac{1}{1+e^{-x}}$ was used to estimate the relative probability distribution for continuous

Table 6
Results of network information.

Network Information				
Input Layer	Covariates	1		Number of rooms in a house
	Factors	1		Wealth index
		2		Current marital status
		3		Type of place of residence
		4		Status of house
	Number of Units[a]			18
	Rescaling Method			Normalized
Hidden Layer(s)	Number of Hidden Layers			2
	Number of Units in Hidden Layer 1[a]			8
	Number of Units in Hidden Layer 2[a]			6
	Activation Function			Hyperbolic tangent
Output Layer	Dependent Variable		1	Deprivation scores of MEPI
	Number of Units			1
	Activation Function			Sigmoid
	Error Function			Sum of Squares

[a] Excluding the bias unit.

Table 7
Model summary of artificial neural network.

Training	Sum of Squares Error	4191.836
	Relative Error	.290
	Stopping Rule Used	Relative change in training error criterion (.0001) achieved
	Training Time	0:00:20.08
Testing	Sum of Squares Error	1791.320
	Relative Error	.289

Dependent Variable: Deprivation scores of MEPI.

Table 8
Results of normalized importance of input features to the outcomes.

Independent variable importance	Importance	Normalized importance
Wealth index	.505	100.0%
Current marital status	.104	20.5%
Owns a house alone or jointly	.230	45.4%
Type of place of residence	.030	6.0%
Number of rooms used for sleeping	.131	26.0%

output between 0 and 1 [96,99]. The sum of squares error function was used to validate the model, as shown in Table 7. The sum of the squares error function was 4191.836 in training and 1791.320 in testing indicating 2.9% incorrect predictions of the model. The stopping rule was also implemented to achieve error criterion (0.0001) in terms of relative change and prevent over-fitting in model training as well.

Lastly, Table 8 summarizes the rates of assessed importance of the filtered socioeconomic factors about severe multidimensional energy poverty in the developing world. The analysis presents that the accumulated wealth index of the households (grouped into the poorest, poor, middle, rich, and the richest) among all socioeconomic predictors has the highest (100%) indication of normalized importance with the dependent variable in the constructed MLP neural network. Ownership status of the residential property (45.4%) is found to be the second most important socioeconomic determinant of multidimensional energy poverty. Besides, the results revealed that the overall size of the house (26%) and the current marital status of the main breadwinner (20.5%) were the third most influential demographic determinants of energy poverty in developing countries.

The result analysis provides concrete empirical evidence that the socioeconomic profile of the households plays an important role in determining their susceptibility level to severe multidimensional energy poverty. Although, this study is in line with the findings of the previous studies on the size of the house [49], income/wealth, and place of residence [47,50] to be the driving socioeconomic factors of energy poverty. However, it supersedes them by providing additional concrete evidence that the marital status of the breadwinner and ownership status of the house are also influential predictors of multidimensional energy poverty in the developing world. The findings reveal that poor households with a lower wealth index are deprived because their income cannot cover energy costs. Without increasing incomes, they will no longer have access to modern energy services and poverty will continue. Therefore, these households must raise their income levels to a level that can provide energy convenience. This is especially true in the private sector, where wages are low and household energy costs are generally not covered.

Previous studies claimed that the marital status and ownership status of the residence of the breadwinner had no statistical link with household multidimensional energy poverty [47]; however, the outcomes of this study disclose that both factors are also important determinants. Multidimensional energy poverty is more prevalent in accommodation that is not owned by the household but rented. Therefore, it is highly recommended that governments should come up with financial schemes that can help deprived families to have their residential property so that household income that would have been used to pay rent could instead be spent on energy services. Housing schemes based on public-private partnerships can be helpful to provide an opportunity to build affordable houses and to enable energy-poor households to buy their homes in manageable installments.

Regarding the marital status of the household, single-parent families (especially having widowed or divorced female breadwinners) are considered more susceptible to energy poverty comparatively, where a single person is responsible to accommodate all expenses of the family. Though the wealth quartile is one of the most important socioeconomic determinants, the findings imply that no single independent variable leads to an extreme form of multidimensional energy poverty but an amalgamation of some socioeconomic factors leads to this precariousness. Therefore, policies should be directed to develop local economies (microeconomy) and lift the overall socioeconomic status of the households in developing countries to achieve desirable energy poverty reduction goals.

5. Conclusion

The study focused on the measurement of the extent and depth of extreme multidimensional energy poverty in developing countries employing MEPI based on the proposed ‘severe’ poverty cutoff and identification of its socioeconomic determinants using supervised machine learning. The results of the MEPI confirmed a widespread presence of severe energy poverty in multiple dimensions across Asian and African countries. Afghanistan, Yemen, Nepal, India, Bangladesh, and the Philippines in Asia and DR Congo, Chad, Madagascar, Niger, Sierre Leone, Tanzania, and Burundi in Africa were the most susceptible countries to chronic multidimensional energy poverty.

Similarly, results of machine learning algorithms identified and shortlisted the five most influential socioeconomic factors of multidimensional energy poverty; the accumulated wealth of a household, size and ownership status of a house, marital status of the main breadwinner, and place of residence of the main breadwinner. The results provide concrete evidence that socioeconomic factors significantly determine levels of household multidimensional energy poverty. 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 the 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 multidimensional energy poverty.

The empirical findings imply significant policy implications directed to energy poverty reduction. The governments must formulate policies particularly focused on the provision of basic energy services, especially universal electrification and clean cooking fuels [27]. Further, policy measures should be taken to elevate the overall socioeconomic status of the households that will considerably be helpful to reduce any type of energy poverty [47], moderate or severe and unidimensional or multidimensional. Policy measures should be taken to strengthen the microeconomy by incentivizing small and medium industries that generate more business activities and create more jobs for the local communities. This will ultimately trigger an elevation in socioeconomic status and standard of living of the households.

Lastly, the robust findings disclosed that high energy poverty occurred due to household inaccessibility to electricity and clean cookstoves primarily. The results suggest that the fundamental focus of the stakeholders should be providing universal access to lighting by building and expanding transmission lines and electric infrastructure and connecting the far and remote areas of the country. Also, the networks of gas pipelines must be established and extended to rural households as well. Achieving success of implementation in these policy directions will substantially and considerably lead to the reduction of multidimensional energy poverty nationally, regionally, and globally.

Credit author statement

Khizar Abbas: Conceptualization, Writing – original draft, Methodology, Software, Visualization, Formal analysis, Investigation, Deyi Xu: Resources, Data curation, Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Khalid Manzoor Butt: Formal analysis, Investigation, Validation, Supervision, Muhammad Ali, Khan Baz, Shanwal Hussain Kharl, Mansoor Ahmad: Writing – review & editing, Software, Visualization, Validation.

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.

Acknowledgment

This research was funded by the Natural Science Foundation of China (No. 72074197, 71991482, 72164002 & 71991480), Major Project of National Social Science Foundation of China (No. 21&ZD106) the Open Fund Project of Hubei Provincial Research Base for Regional Innovation Capacity Monitoring and Analysis Soft Science (No. HBQY2020z11), and the Major Research Projects of Guangxi Department of Natural Resources in 2019 (Sub-bid C) (No. GXZC2019-G3-25122-GXGL-C).

Appendix A

Table 9
Estimated parameters of the input, hidden, and output layers of the neural network

Parameter Estimates																
Predictor		Predicted														
		Hidden Layer 1								Hidden Layer 2						Output Layer
		H (1:1)	H (1:2)	H (1:3)	H (1:4)	H (1:5)	H (1:6)	H (1:7)	H (1:8)	H (2:1)	H (2:2)	H (2:3)	H (2:4)	H (2:5)	H (2:6)	Ci
Input Layer	(Bias)	-.345	-.334	-.197	-.140	.371	-.259	-.157	.489							
	[Wealth = 1]	.010	.974	-.081	.442	.150	.075	.841	-.588							
	[Wealth = 2]	.064	-.169	.011	.419	.084	.693	.132	-.293							
	[Wealth = 3]	.275	.367	.525	-.065	-.213	-.483	.244	-.033							
	[Wealth = 4]	.173	.183	.260	-.008	.498	-.132	-.839	.449							
	[Wealth = 5]	-.968	-.493	-.137	-.592	-.395	-.555	-.205	.892							
	[Marriage = 0]	-.050	-.261	-.349	.411	-.122	.104	-.280	.074							
	[Marriage = 1]	.232	-.101	-.376	.367	-.205	-.093	.123	.433							
	[Marriage = 2]	.203	-.411	.140	-.278	.429	.003	-.232	-.282							
	[Marriage = 3]	.337	.051	.500	-.433	-.394	.173	.052	-.228							
	[Marriage = 4]	-.483	-.265	-.309	.233	-.461	.065	.053	-.231							
	[Marriage = 5]	-.139	.274	-.046	.285	.111	.321	-.159	-.327							
	[Status = 0]	.021	.578	.164	.313	.167	-.363	.216	-.220							
	[Status = 1]	-.450	-.233	.084	-.367	.171	-.307	-.468	.377							
	[Status = 2]	-.198	.330	.017	.239	.068	.277	.245	-.310							
	[Status = 3]	.576	.424	.060	-.139	.480	-.050	.411	.106							
	[Residence = 1]	-.317	-.151	.556	.323	.196	-.086	-.312	-.265							
	[Residence = 2]	.439	.151	.325	-.195	-.270	.105	.031	.209							
	House	-.035	.198	.507	.040	.003	-.178	.115	.220							
Hidden Layer 1	(Bias)									-.503	-.149	-.310	.332	.400	-.506	
	H (1:1)									.040	-.389	.129	-.605	.125	.134	
	H (1:2)									-.170	-.033	.335	-.010	.531	.165	
	H (1:3)									-.353	.094	.112	.024	.084	-.003	
	H (1:4)									-.067	-.180	.232	-.365	.319	.249	
	H (1:5)									-.345	-.035	.080	-.244	-.071	.329	
	H (1:6)									.430	-.439	-.109	-.008	.207	.048	
	H (1:7)									.439	-.474	-.071	-.170	.488	-.319	
	H (1:8)									-.137	.206	-.502	.067	-.432	-.220	
Hidden Layer 2	(Bias)															-.271
	H (2:1)															.327
	H (2:2)															-.689
	H (2:3)															.566
	H (2:4)															-.705
	H (2:5)															.711
	H (2:6)															.419

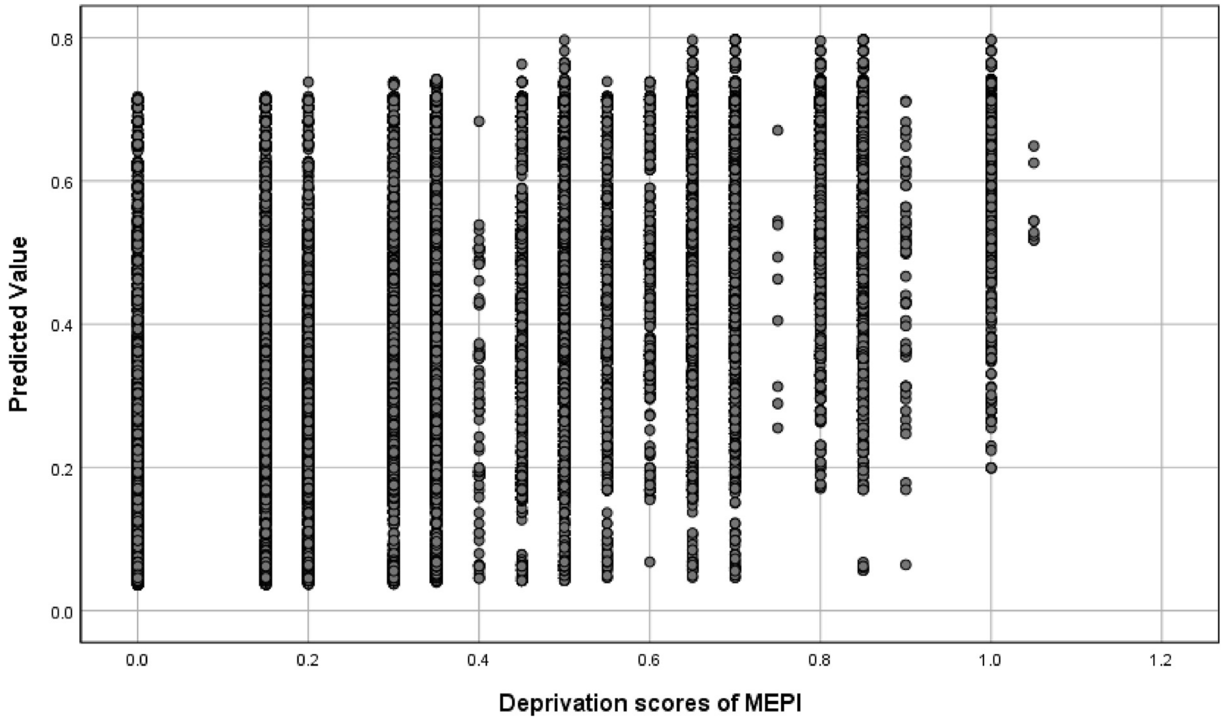

Fig. 5. Predicted by observed graph.

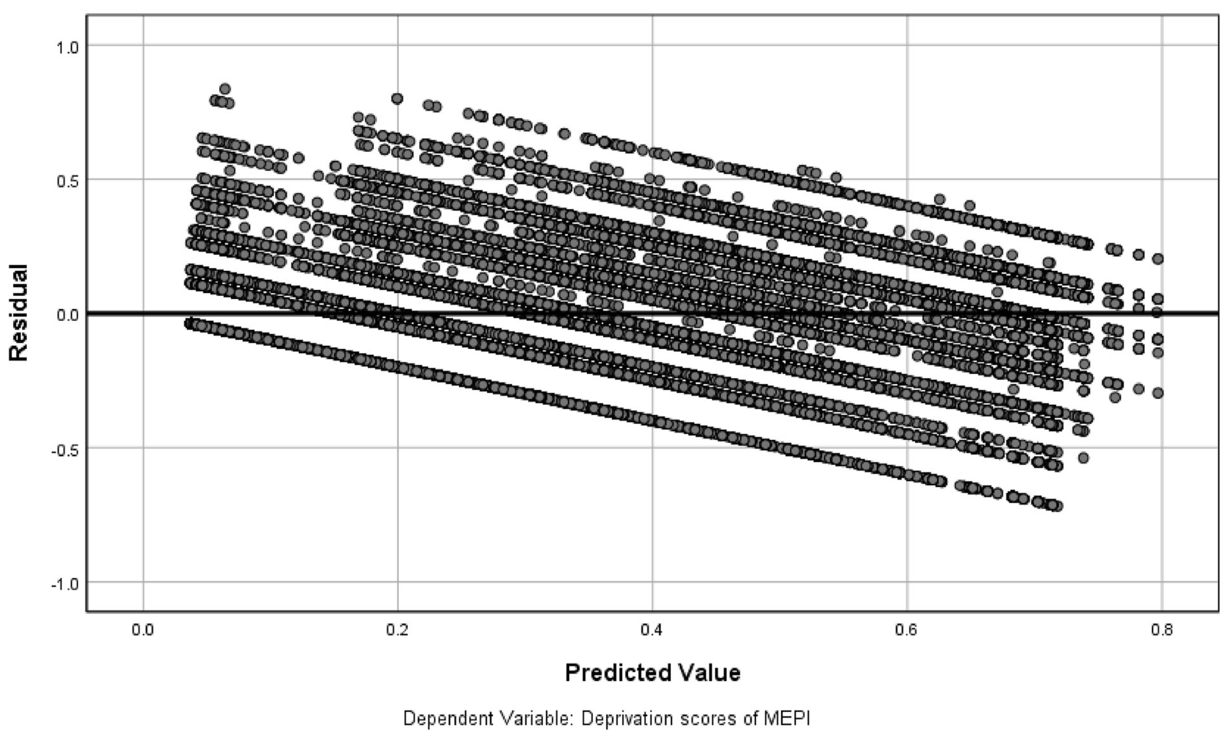

Fig. 6. Residual by the predicted chart.

Appendix BSupplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2022.123977.

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