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Research article

Multidimensional energy poverty: A study of its measurement, decomposition, and determinants in Indonesia

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A R T I C L E I N F O

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A B S T R A C T

This study estimated Indonesian households' Multidimensional Energy Poverty Index (MEPI) using Alkire-Foster's multidimensional poverty concept to capture the incidence, intensity, decomposition, and changes over time. The study used monetary and non-monetary variables to identify the availability, accessibility, affordability, consumption, and deprivation of modern energy services; and compared existing affordability indicators. Redundancy, robustness, and sensitivity tests were conducted with three weighting schemes and deprivation cut-offs. The study decomposed and determined household-head (HH) socio-economic, demographic, and geographic factors for MEP using the Logit, Probit, Tobit, and Heckman Selection models. The results show that the low-income and high cost (LIHC) was the most robust affordability indicator, followed by the ten percent rule (TPR). The complement-frequency weighting scheme gave the smallest and most robust MEPI compared to equal and principal component analysis (PCA) weighting. Three alternative deprivation cut-offs can show households as "vulnerable," "moderately," or "severely" energy poor. The MEP incidence decreased, but its intensity remained high and increased. Energy-poor households were averagely deprived of 55–60 % of all weighted indicators. The lack of modern cooking services was the primary cause. MEPI differed by geographical location and HH gender, education, business field, and employment status. Policies that boost education levels, raise household income, and increase the availability, accessibility, and affordability of modern cooking technology in the rural, hinterland, or non-coastal forested locations in the eastern islands of Indonesia may minimize the number of households experiencing MEP.

1. Introduction

Modern energy services underpin various capacities for human well-being and socio-economic development, including the Sustainable Development Goals (SDGs) [1–7]. Household access to clean, affordable and efficient energy has interactions with other SDGs in different contexts [6,8–10]. Fig. 1 shows the association between energy consumption per capita, Gross Domestic Product (GDP) per

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capita, and the Human Development Index [11–13]. Due to the inability to achieve the socially and materially necessary level of domestic energy services, some households experience a daily energy consumption problem known as "energy poverty" (EP) [14,15]. EP can affect health, education, and productivity, all of which in turn affect human well-being [14,16–20].

There are differences in EP measurements between developed and developing countries [14,15,21–24]. Developed countries measure EP in affordability terms using objective and subjective monetary indicators [25–27], and several affordability indicators exist [27–30]. Developing countries measure EP in accessibility term using non-monetary binary indicators [23,31]. However, binary metrics are insufficient to explain the impact of EP on socio-economic development. There are still challenges to mixing monetary and non-monetary indicators to ensure everything is covered, reduce bias, and create a consistent measurement framework that broadens the evaluation scope [31–39]. Recent research has shown that EP is complex and multifaceted [15,40,41]; as well as that socio-economic and geographical factors also determine household EP status [42–52].

Indonesia as a developing country faces the energy poverty problem [53–56]. Increasing energy demand and decreasing oil and gas production have given rise to energy security conflicts, energy poverty, and climate change [53,57–59]. Previous studies on EP used only one or a few indicators separately to identify EP for LPG [54], or electricity [60], or both [55,56] in certain regions or nationally in Indonesia. Utami and Hartono [61] measured multidimensional energy poverty (MEP) through accessibility and affordability dimensions and its impact on health. However, Indonesia's MEP decomposition and determinants are not yet known. In addition to socio-economic factors, we suspect that geographic factors may hinder efforts to provide clean energy universally. Providing electricity and clean cooking technologies to all remote and disadvantaged regions by 2030 is challenging [59]; rural and low-income households are vulnerable to EP [56,62].

Therefore, first, this study measured Indonesian households' Multidimensional Energy Poverty Index (MEPI) using Alkire-Foster's multidimensional poverty concept [32,33,63,64] to capture the incidence and intensity through five dimensions of availability, accessibility, affordability, consumption, and various uses of modern energy. It was necessary to make an identification comprehensively using monetary and non-monetary indicators, both objectively and subjectively. The study compared affordability indicators such as the proportion of energy expenditure (TPR [65]), median energy expenditure (double median – 2M [66]; half median – M/2 [67]), and LIHC [68]). However, the study did not use subjective indicators because they were not routinely available. Second, the study decomposed MEPI by households' socio-economic, demographic, and geographic factors to show how their interactions create different patterns. Changes over time in MEP were also systematically analysed [69]. Finally, the study examined how socio-economic, demographic, and geographic factors influenced the likelihood of Indonesian households experiencing MEP between 2014 and 2018.

This study is essential because Indonesia – the largest tropical archipelagic country with the fourth largest population – has many energy sources. Households' socioeconomic, demographic, and geographic conditions affect modern energy availability, accessibility, and affordability [10,70,71]. The geographic factors were found to be significant contributors to the decomposition component and the probability of a household being multidimensionally energy-poor between 2014 and 2018 in Indonesia. The study used matched data from the National Socio-Economic Survey (SUSENAS) and the National Village Potential census or Potensi Desa (PODES) in 2014 and 2018.

This multidimensional study advances the 2030 SDG-1 agenda by directly addressing SDG-7.1. The study fills some gaps in knowledge of the decomposition and determinants of EP in Indonesia. Policymakers need EP measures that account for households' socio-economic, demographic, and geographical characteristics. They help in improving data collection and making it more targeted, thereby making the analysis faster, more accurate, and more informative to reduce MEP.

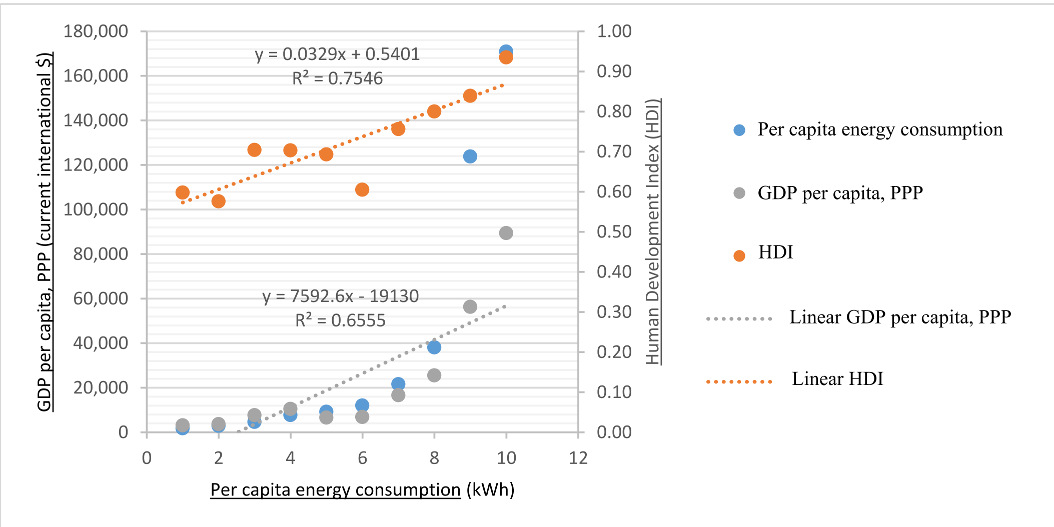


Fig. 1. Scatterplot between energy consumption per capita, GDP per capita, and the Human Development Index of Southeast Asian countries, 2016. Sources: https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD?view=chart; https://hdr.undp.org/data-center/human-development-index#/indicies/HDI;https://ourworldindata.org/energy-access

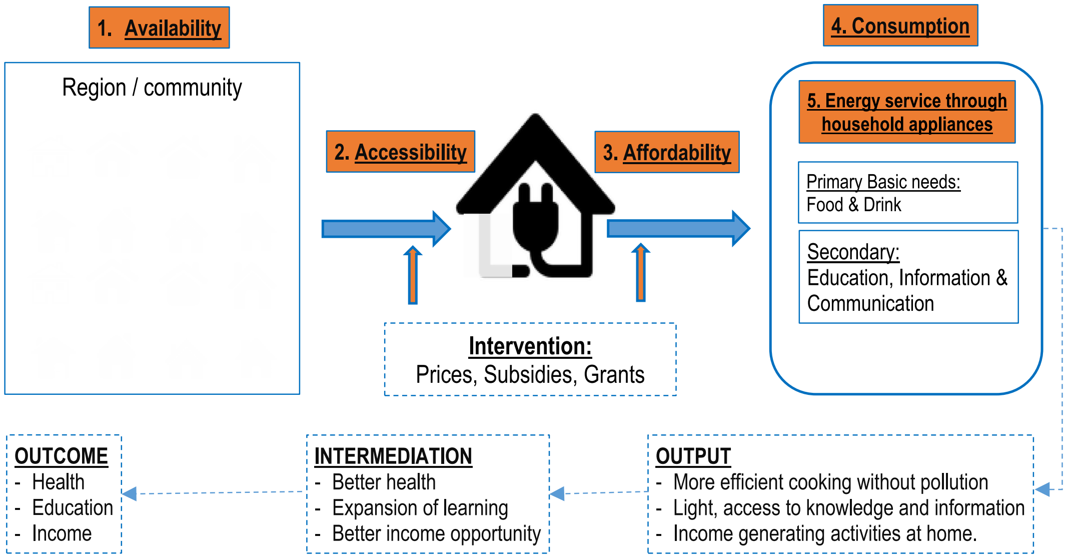


Fig. 2. Household multidimensional energy poverty measurement framework.
Source: Authors' own construction based on some literature

This study conducted redundancy, robustness, and sensitivity tests [72–76]. In conducting the robustness test, we evaluated results using the Logit [49,51], Probit [20,38,77,78], Tobit [42,48], and Heckman Selection models [79]. The results show that the LIHC was the most robust affordability indicator, followed by the TPR. The complement-frequency weighting scheme had the smallest and most robust MEPI. Meanwhile, the PCA weighting method yielded the highest MEPI and was not robust. Three alternative deprivation cut-offs could identify vulnerable, moderately, and severely energy-poor households. The results show that household MEP incidence decreased, with high intensity, where the energy-poor household experienced an average deprivation of 55–60 % from all dimensions and the MEPI was 0.399–0.850. The MEPI differed depending on the HH's socio-economic and geographical characteristics. Economically, MEP affected households with low income and low education, large families, and renters.

The following section discusses some different definitions, measurements, and conceptual frameworks of EP used in earlier research. The third section describes the data and method, determining indicators, weights, and thresholds. The fourth and fifth sections discuss the results and conclusion.

2. Literature review

2.1. *Definition and measurement of 'energy poverty'*

Global literature defines 'household EP' as a disability to obtain energy services needed materially and socially at home [5,15,80]. Access to reliable, safe, and affordable energy services, directly or indirectly, helps people attain vital functions like good health, education, a job, and social life [5]. Global household EP is connected to modern energy accessibility and affordability for basic needs, decent living standard deprivation, household income, energy expenditure, and efficiency.

Various single indicators and composite indices derived from quantitative-objective and qualitative-subjective data with various measurement methods have been used to analyse and evaluate household EP in developed and developing nations [36,81]. This study considered the results of ranking EP measures [29,30] according to the Bellagio Sustainability Assessment and Measurement Principles (Bellagio STAMP) [82], adapting to data availability and analysis objectives.

2.1.1. *A single indicator of energy poverty: objective and subjective*

Developing countries use a single binary indicator to stand for EP because not all households have modern access and because it is easy to measure and communicate. Developed countries mostly use a single affordability indicator, reflecting the energy cost burden. These indicators use the energy expenditure share to total expenditure (e.g., TPR), median energy expenditure (e.g., 2M; M/2), and minimum income (e.g., After Fuel Cost Poverty – AFCP, Minimal Standard Income – MIS, LIHC) [29,30,81].

The TPR indicator [65] identifies energy poor households when their expenditure portion exceeds 10 % of income, but an incorrect use of this indicator can result in some high-income households becoming energy poor. The median energy expenditure indicators identify energy poor households with high [66] and low [67] absolute expenditures due to economic constraints, but both do not determine a minimum income [27]. High-income households tend to have high or low absolute energy costs due to lifestyle or more efficient equipment. The LIHC [68] identifies energy poor households by energy expenditure and net income, but it has been criticized because the use of energy expenditure modeling would eliminate the effect of household energy efficiency [37].

Scientific debates on affordability indicators based on energy expenditure or minimum income involve actual or needed energy spending, the equivalence of minimum family earnings or housing costs, and the EP line [25]. Specific affordability indicators are easy to calculate, use, and interpret according to national or international norms.

Subjective indicators are based on direct or third-party household assessments, including energy purchasing power [83,84]; modern energy awareness, behaviour, and preferences [35]; and house conditions, electricity bill payment, and home comfort [36]. For identifying energy-poor households, objective and subjective indicators are best since subjective indicators yield diverse findings [36,37,85].

However, single indicators sometimes present a narrow picture, unsuitable for complex problems like EP, which are multidimensional and require a framework for using multiple indicators. Several indicators can capture multiple dimensions, but tracking progress and gaining meaningful insights are impractical. Due to method and data source limitations, EP measures require multiple indicators to pinpoint household energy deprivation from various aspects through a multidimensional approach.

2.1.2. Composite indicators of energy poverty

Composite indicators attempt to overcome the simplicity of a single indicator and some complexity in capturing multidimensional aspects by gathering information on a single measure, making analysis and interpretation easier. However, methodological problems, the assumptions needed, and value simplification may require more work to understand these indicators. Composite indicators can mislead policies when data interpretation is oversimplified or when indicators are poorly created. Table 1 lists Bellagio STAMP-compliant composite indicators. This study used MEPI, one of the most popular indices, for further analysis.

2.2. Conceptual framework

Access to modern energy, directly and indirectly, can change energy use behaviour and household welfare. After accessing modern energy services, households usually increase their daily energy use. For instance, electric lamps expand activity into the night and cost less per lumen than kerosene lamps [100]. Cheaper energy can boost utility for similar-income households. The utility framework helps us understand the relationship between household energy consumption—through income levels, availability, and prices of various energy sources—and household welfare caused by (one or more) changes in the energy mix's relative prices, as occurs in the energy sector [100–102].

As real income rises, households buy more energy service equipment and use more energy, which means an increase in utility. This equipment, in turn, produces outputs such as quality lighting, more efficient cooking, better food preservation, access to knowledge and information, and a comfortable home—all things that would not be possible without modern energy. These outputs can lead to intermediate outcomes like study time, better health, productive activities, and income opportunities. Access to modern energy can affect outputs and outcomes, like education, health, and productivity, raising household incomes. Thus, the availability, accessibility, affordability, and consumption of modern energy services can help with this (see Fig. 2).

3. Data and methodology

This study employed 2014 and 2018 matched SUSENAS and PODES datasets from the Central Statistics Agency (BPS) to obtain household socio-economic demographic information supported by regional potentials [103]. SUSENAS is an annual cross-sectional household socio-economic and demographic survey that collects household and individual data covering all 34 provinces and 514 districts in Indonesia and can form a district panel for tracking changes over time. The pooled sample was 604,312 households, namely 309,157 in 2014 and 295,155 in 2018 spread across 23,736 villages/sub-districts. PODES collects information on administrative, infrastructure, facilities, and regional topography, covering all 83,926 villages/sub-districts in 34 provinces and 514 districts. The study did not include subjective indicators due to a lack of related data. The study limited household MEP identification to the availability, accessibility, affordability, consumption, and use of modern energy services. The decomposition of MEP was based on households' socio-economic, demographic, and geographical characteristics.

3.1. Multidimensional Energy Poverty Index (MEPI)

MEPI quantifies MEP incidence and intensity [32,33], and it is flexible, robust, well-established, and adaptable to national contexts and policy-oriented goals. MEPI allows group disaggregation for a more in-depth study and joint deprivation. MEPI correctly targets and ensures policies by determining each dimension and indicator contribution.

3.1.1. Dimensions and indicators

MEPI first lists important indicators and dimensions from the SUSENAS and PODES data contents through normative determination. Theoretical, empirical, and policy issues can inform normative determination. It can also follow the goals of national or international development plans. This study proposed MEPI with objective monetary and non-monetary variables. The study divided potential indicators into five dimensions representing the availability, accessibility, affordability, and consumption of modern energy services through household appliances for the sub-dimensions of food and drink processing, education, entertainment, information, and communication (Table 2).

Availability refers to the physical presence of modern energy services at a suitable distance in the same geographic location. Accessibility is critical in identifying households without access to modern energy services, whether due to unavailability or unaffordability. Even though the Indonesian Government has zoned energy supply, many households still lack access to it due to financial

Table 1
Composite indicators of energy poverty conforming to the Bellagio STAMP.

Composite indicators	References
1. Structural EP Vulnerability Index (SEPVI)	[86]
2. Fuel Poverty Index (FPI)	[87]
3. Energy Vulnerability Composite Index (EVCI)	[88]
4. Energy Poverty Index (EPI)	[89]
5. Multidimensional Energy Poverty Index (MEPI)	[33,34,36,90–96]
6. Energy Development Index (EDI)	[97]
7. Total Energy Access (TEA)	[98]
8. Multi-Tier Framework (MTF)	[99]

Sources [29,30]:

Table 2
Dimensions and potential indicators of the MEPI.

Dimension	Indicators	Description	Variable type	Reference
1. Availability	- Percentage of households with or without access to electricity and/or clean cooking fuels.	- modern energy facilities in the same geographic location (or at the community level).	- non-monetary objective	- Kaygusuz (2011) [105]
2. Accessibility	- Electricity access - LPG access	- main light source - main cooking fuel	- non-monetary objective - non-monetary objective	- Nussbaumer et al. (2012, 2013) [32, 33]
3. Affordability	- TPR - 2 M - M/2 - LIHC - LI-L/HC	- Energy expenditure - A portion of energy expenditure - A portion of energy expenditure - Disposable income - Relative or absolute energy expenditure - Disposable income	- objective monetary - objective monetary - objective monetary - objective monetary - objective monetary	- Boardman (1991) [65]; - Liddell et al. (2012) [66]; - Rademaekers et al. (2014) [67]; - Hills (2012) [68] - Author
4. Energy Consumption	- per capita electricity consumption - per capita cooking fuel consumption	- Electricity consumption - Cooking fuel consumption	- non-monetary objective - non-monetary objective	- Martínez & Ebenhack (2008) [1]; AGECC (2010) [108]; Ouedraogo (2013) [2]; IEA (2020) [109]; Hartono et al. (2020) [56].
5. Energy services through household appliances, for:				
5. a. Processing food and beverages (Primary)	- ≥ 5.5 kg gas cylinders ownership - Refrigerator ownership	- Household appliance ownership - Household appliance ownership	- non-monetary objective - non-monetary objective	- Aguilar et al. (2019) [106]; Khanna et al. (2019) [107]; Nussbaumer et al. (2012, 2013) [32,33]; A. R. Qurat-ul-Ann & Mirza (2020) [31]
5. b. Education, Entertainment, Information & Communications (Secondary)	- ≥ 30-inch flat television ownership - Computer ownership (PC/Laptop) - HP ownership	- Household appliance ownership - Household appliance ownership - Household appliance ownership	- non-monetary objective - non-monetary objective - non-monetary objective-	

Source: authors' own construction based on some literature

issues [104]. Financial difficulties prevent households from using modern energy and having energy-related appliances. Even though the government has launched an energy subsidy program for low-income families, energy tariff regulations can make households energy-poor when social safety nets cannot keep up with rising energy prices. The modification and combination of objective monetary indicators used in developed countries define a household's energy affordability. Energy consumption determines a good life's energy needs. This study identified energy-poor households as: i) without access and unable to reach minimum consumption of modern energy services; ii) without access but capable of doing so; and iii) having access but unable to afford it. The study also examined modern energy services' input to household needs through appliance ownership.

The first adjustment was to alter the limit of median approach energy expenditure (2M, M/2) to a relative threshold of "q%" or "$q \bullet median$" with $q \in R_+$ and $q \leq 1$, such as a 50 % median, to meet the basic requirements of the "Position Invariant Burdening" requirement, i.e., changes in poverty levels when income changes [81]. Since SUSENAS did not offer income data, LIHC metrics were adjusted to the poverty line (ibid.). Using the affordability indicator, the limits were adjusted into three. Thus, an energy-poor household is one where the disposable income is below the poverty line (low income) and where the total energy expenditure is less than 50 % of the median (low cost) or the energy expenditure share is 10 % or more (excessive cost).

Modern energy consumption indicators use a minimum approach to electricity and cooking fuel to meet basic human needs with standard equipment. It is 50–100 kWh per person per year [108] or 500 kWh per household per year [109], and 50–100 kgoe[a]or 1200 kWh per capita per year [108], respectively. Household appliances for lighting, cooking, food processing, entertainment, education, and communication are indicators of modern energy services [31–33,90,106,107,110].

This study recorded the observed variable's achievement (x) for the i-th household from all n population samples, on the j-th variable from m observed variables, where $x_{ij} > 0$. So:

$X = [x_{ij}]_{n \times m}$ is a $n \times m$ status achievement matrix, where:

$x_{i\bullet}$ = is a row vector representing the i-th household achievement on the j-th variable, and

$x_{\bullet j}$ = is a column vector representing the j-th variable achievement among households-i.

This study performed a redundancy test to analyse the relationship between potential indicators [72]. A redundancy test allows the inclusion or exclusion of indicators, combines redundant variables, adjusts weights, or categorises indicators into dimensions. The test is informative, and normative decisions should clarify the MEPI structure's rationale. Appendix 1 shows Cramer's V correlation coefficients for redundancy between two indicators. Household appliances had high energy redundancy. This study kept these indicators for comparison and normative sequencing. Appendix 2 supplies summary statistics for deprivation indicators and HH socio-economic, demographic, and geographical characteristics.

3.1.2. Weights and cut-off point

Some relevant literature debates the appropriate weighting method. Decancq & Lugo [111] compare data-driven, normative, and hybrid weighting, while Seth & Mcgillivray [112] suggests a normative but intuitive approach. Endogenous weighting violates monotonicity and subgroup consistency, and exogenous weights are arbitrary [113]. This study used three weighting schemes: equal weight for each indicator, empirical data's complementary distribution, and multivariate statistical techniques [72,73,111].

Complementary distribution-based weighting gives the mildly deprived more weight because families focus on the component where most do not have deficiencies. Bandwagon effects have been observed in accessing electricity [114] and LPG usage [115]. Statistical methods create a new ordered-uncorrelated component in the eigenvector and eigenvalues to weight indicators based on achievement distribution. This study used a weighted normalization of one.

W_j: j-th variable weight and $\sum_{j=1}^{d} W_j = 1$.

MEPI uses double-cut-off and sets a threshold "t" for each indicator's minimal achievement. It classifies households as "deprived" or "non-deprived" in each indicator. A normative determination of the eligibility threshold can follow international or national standards and literature, participatory or consultative processes. Table 3 presents deprivation thresholds and weights based on equal and data-driven weights.

t_j: Deprivation threshold on j-th variable

The sixth step compares all households' achievements to each indicator's deprivation threshold. A household is multidimensionally energy-poor if its weighted deprivation score exceeds the cross-dimensional threshold.

$D = [d_{ij}]_{n \times m}$: represents the i-th household's multidimensional weighted-deprivation matrix in the j-th variable.

If $x_{ij} \leq t_j$ then $d_{ij} = w_j$, and if $x_{ij} > t_j$ then $d_{ij} = 0$.

Setting it:

$t_i = \sum_{j=1}^{m} d_{ij}$: is a multidimensional weighted deprivation column vector for the ith household.

The next step is identifying households with multidimensional weighted-deprivation in the column vector-t_i by defining cut-offs ($k > 0$) and assuming energy-poor households when the weighted deprivation exceeds k: $t_i(k) = 0$ if $t_i \leq k$ and $t_i(k) = t_i$ if $t_i > k$.

Thus, $t(k)$ represents the censored multidimensional energy deprivation average weighted vector. Three cross-dimensional depletion cut-offs (k = 0.20, 0.33, and 0.70) are for "vulnerable," "moderately," and "severely" energy-poor [72–76].

Next, the incidence, or headcount ratio (H, Eq. (3.1)), determines how many households are multidimensionally energy poor.

$$H = q/n \tag{3.1}$$

Where q is the energy-poor people from n sample households.

Next, it calculates the MEP intensity (A, Eq. (3.2)), representing the weighted censored multidimensional energy deprivation average:

$$A = \sum_{i=1}^{n} t_i(k) \Big/ q \tag{3.2}$$

[a] 1 kgoe = 11.63 Kwh.

Table 3
Indicators of deprivation cut-off and weights by dimensions and sub-dimensions.

Dimensions/Sub-Dimensions/Indicators	Deprivation Cut-off	Weights				
		Equal in indic.	Compl. freq. distribution (Avg)		PCA (Avg)	
			2014	2018	2014	2018
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Availability		**0.167**	**0.251**	**0.228**	**0.161**	**0.104**
a. Electricity	The community has no electricity.	0.083	0.158	0.133	0.052	0.049
b. Clean cooking fuel	The cooking fuel is used by most households.	0.083	0.094	0.095	0.109	0.055
2. Accessibility		**0.167**	**0.231**	**0.225**	**0.265**	**0.255**
a. Electricity	Households have no access to electricity (On-grid or Off-Grid).	0.083	0.154	0.131	0.073	0.062
b. Clean cooking fuel	Households cook with traditional biomass (firewood, cow dung, wood, charcoal).	0.083	0.077	0.094	0.192	0.193
3. Affordability (Average)						
a. TPR	If the share of energy expenditure >10 % of the expenditure.	0.083	0.151	0.130	0.015	0.001
b. 2M	Household energy expenditure > twice the median level of national household energy expenditure.		0.142	0.116	0.000	0.037
c. M/2	Household energy expenditure < half the median level of national household energy expenditure.		0.142	0.123	0.024	0.047
d. LIHC	1. Households require high energy costs (above the national median level); and 2. Low-income households, when: a. income below the 30th percentile of equivalent income [Belaid, 2018; Okushima, 2017] or b. below 60 % of the median population of equivalent income less housing costs.		0.158	0.133	0.012	0.001
e. LI-L/HC	1. Energy expenditure proportion is more than 10 % (after considering the house-size and household members); or 2. Energy expenditure <50 % median (after considering the size of residence and the number of household members); and 3. Residual income after energy expenditure, below the monetary poverty line (adjusting LIHC or MIS indicators).		0.149	0.131	0.023	0.017
4. Energy Consumption		**0.167**	**0.108**	**0.200**	**0.195**	**0.282**
a. Electricity (KWh)	Electricity consumption for basic human needs with standard equipment is around 50 to 100 kWh/person/year (AGECC, 2010) or around 500 kWh/household/year (IEA, 2020).	0.083	0.068	0.110	0.057	0.095
b. Gas (1 kgoe = 11,63 Kwh)	The minimum consumption of modern cooking fuel is around 50–100 kgoe (kilogram oil equivalent) or equivalent to 1200 kWh/capita/year.	0.083	0.040	0.090	0.137	0.187
5. Services provided through household appliances		**0.417**	**0.262**	**0.221**	**0.364**	**0.339**
5. a. Food & beverage processor (Primary)		**0.167**	**0.086**	**0.090**	**0.205**	**0.176**
1) Gas cylinder ownership	Households using LPG gas do not have gas cylinders ≥5.5 kg; they have only 3 kg LPG gas cylinders (subsidized LPG).	0.083	0.020	0.015	0.071	0.050
2) Ownership of refrigerator	Households do not have refrigerators or freezers.	0.083	0.066	0.075	0.134	0.126
5. b. Education, Information & Communication (Secondary)		**0.250**	**0.176**	**0.131**	**0.159**	**0.163**
1) TV	The household does not have a 30 Inch flat-screen television.	0.083	0.014	0.018	0.014	0.056
2) Telephone/HP	The household does not have a cellphone/phone.	0.083	0.138	0.085	0.076	0.039
3) PC	The household does not have a computer/laptop.	0.083	0.024	0.028	0.069	0.068
	TOTAL WEIGHT	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Source: authors' own construction based on some literature

Finally, the MEPI (Eq. (3.3)) is defined:

$$M = H \times A \tag{3.3}$$

The MEPI is estimated using ***mpi*** [116] and ***mpitb*** [117] STATA commands to robustness test the results.

3.2. Decomposition and changes over time

The following empirical strategy involves calculating the contribution of decomposition, changes over time, and sub-group populations to the incidence (H), intensity (A), and MEPI (M, Eq. (3.4)) [69]. This formula divides the population into subgroups (h):

$$\boldsymbol{M} = \sum_{h=1}^{l} v_h M_h \quad ; v_h = \frac{n_h}{n} \tag{3.4}$$

As for $\boldsymbol{H}$ and $\boldsymbol{A}$.

MEP change rate over time (Eq. (3.5)) is calculated using:

$$\Delta \boldsymbol{M} = M^1 - M^0 \tag{3.5}$$

Also determined are the relative change rate (Eq. (3.6)) and MEP percentage difference between periods 0 and 1:

$$\boldsymbol{\delta M} = \frac{M^1 - M^0}{M^0} \times 100 \tag{3.6}$$

Two steps are taken to calculate the annual absolute change rate ($\overline{\Delta}$, Eq. 3.7) and the annual relative change ($\overline{\delta}$, Eq. 3.8):

$$\overline{\Delta}\boldsymbol{M} = \frac{M^1 - M^0}{p^1 - p^0} \tag{3.7}$$

$\boldsymbol{p^0}$ = initial period; $\boldsymbol{p^1}$ = end period.

$$\overline{\delta}M = \left[\left(\frac{M^1}{M^0}\right)^{\frac{1}{p^1 - p^0}} - \mathbf{1}\right] \times 100 \tag{3.8}$$

Finally, population subgroups' contribution to EP reduction is calculated (Eq. (3.9)):

$$\Delta\boldsymbol{M} = \sum_{h=1}^{l}\left[v_h^1 M_h^1 - v_h^0 M_h^0\right] \tag{3.9}$$

3.3. Determinants of multidimensional energy poverty

This study examined geographic factors and household socio-economic characteristics as control variables, using the Logit [49,51], Probit [20,38,77,78], Tobit [42,48], and Heckman Selection models [79] (see Eq. (3.10)). The Logit and Probit models were used as the binary dependent variable, $\boldsymbol{EPov_i} = \mathbf{1}$ when energy poverty and 0 otherwise. In the Tobit and Heckman Selection models, we used the deprivation score $t_i(k)$ as the dependent variable, which ranges from 0, meaning no deprivation in any dimension, to 1, meaning deprivation in all dimensions and censored below the threshold k. In this situation, the Tobit model considered censored data by modeling the probability that a household is above the threshold (energy poor, left censoring) and, at the same time, addressed the endogeneity problem between the dependent variable and several independent variables. Tobit models provide more efficient parameter estimates than OLS and can be interpreted similarly to OLS when dealing with censored data. The Heckman Selection model is used to control self-selection and follows a two-step procedure: first, estimating the probability of being in the sample, and second, estimating the relationship between independent variables and deprivation score using the selected sample.

Table 4 presents MEP determinants [42,49,118–120]. Targeted policy interventions, especially those that help energy-poor and vulnerable households, require profiles for empirical evaluation:

$$\boldsymbol{EPov_i} = \boldsymbol{\alpha_0} + \sum_{i=1}^{p}\boldsymbol{\alpha_i x_i} + \sum_{l=1}^{k_j-1}\boldsymbol{\alpha_{jl} D_{jl}} + \boldsymbol{\epsilon_i} \tag{3.10}$$

x_i is the explanatory variable, D_{jl} is a jth dummy variable with l category and ϵ_i as the error term.

Table 4
Research variables related to the determinants of multidimensional energy poverty.

Independent variable		Description
1. Place of residence	D_1	Location of residence (rural or urban).
2. Coastal area	D_2	Geographical characteristic of the residence
3. Forest area	D_3	Geographical characteristic of the residence
4. Topography	D_4	Geographical characteristic of the residence
5. Island	D_5	Island of residence
6. HH Gender	D_6	Gender of the household head
7. HH Marital status	D_7	Marital status of the household head
8. HH Age cohort	D_8	The grouping is based on the age of the household head.
9. HH Education	D_9	The main breadwinner achieves the highest level of education (no school, primary, secondary, or higher).
10. HH Business Field	D_{10}	The business field of the household head (income recipients, primary, secondary, or tertiary sectors)
11. HH Occupation	D_{11}	Job-status of the household head (income recipient, self-employed/assisted, employee/worker, unpaid)
12. Poverty Status	D_{12}	Economically poor status (code 1)
Dependent variable	$\boldsymbol{EPov}$	Binary variable for Logit and Probit models, 1 for the i-th household whose multidimensional weighted deprivation score (t_i) exceeds the k-multidimensional cut-off and 0 otherwise. The deprivation score $t(k)$ ranges from 0, with no deprivation in any dimension, to 1, which implies deprivation in all dimensions, for the Tobit and Heckman Selection models.

Source: authors' own construction based on some literature

4. Results and discussion

This section examines the incidence and intensity of Indonesian households' Multidimensional Energy Poverty, deprivation and contribution of MEPI indicators, and MEPI in 2014 and 2018. The results reflect an objective integration between monetary and non-monetary indicators of modern energy availability, accessibility, affordability, consumption, and utilisation. This study compared TPR, 2M, M/2, and LIHC, proposed affordability indicators with "low income" and "high share energy expenditure" or "low total energy expenditure," and decomposed and determined MEP by socio-economic and geographical characteristics of the household head.

4.1. Indonesia's household Multidimensional Energy Poverty Index

4.1.1. Deprivation and contribution of MEPI indicators

Table 5 and Fig. 3 display MEPI indicators' deprivation and contribution. Households deprived of electricity and clean cooking fuel declined. This was in line with the LPG conversion programme [121] and 90 % electrification aim by 2020 [122]. Lack of electric availability and accessibility contributed almost 1 % to vulnerable and moderately EP households, but 6 % to severely EP households. Lack of clean cooking fuel contributed 5–15 % to Indonesia's MEPI. Despite increasing access to modern energy, access to clean cooking fuels still needed improvement [56].

Affordability deprivation was measured differently. Indicators 2M and M/2 had the highest deprivation (13.62 %), then LI-L/HC at 8.85 %, TPR at 6.80 %, and LIHC at 2.76 %. On average, it contributed about 2–3% to Indonesia's MEPI. The deprivation of modern energy consumption was high, but it had reduced. This shows that the availability of and access to electricity and LPG increased consumption, which was still affordable. However, the government's LPG conversion programme must be made more balanced, especially among rural and low-income households [54,56,62].

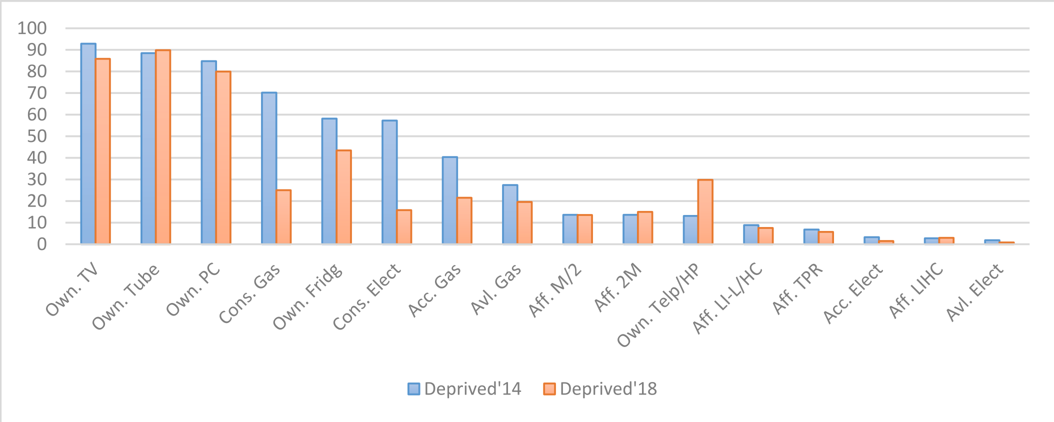
Household appliance deprivation had mixed results (see Table 5 or Fig. 3, panel a.). Ninety percent of households used subsidized 3 kg LPG, which was rising. More households needed refrigerators to keep processed foods fresh. Household appliance ownership - related deprivation of education, information, and communication services was decreasing, except for the one related to fixed-line phones. Energy-service appliances deprivation contributed 5–15 % to MEPI (see Table 5 or Fig. 3, panel b.). Deprivation of access, consumption, and ownership of modern cooking technology is the biggest cause of MEPI. Thus, reducing Indonesia's MEP requires a policy to increase household accessibility, minimal usage, and affordability of modern cooking fuel.

4.1.2. The incidence and intensity of Indonesia's household MEP and the Country's household MEPI

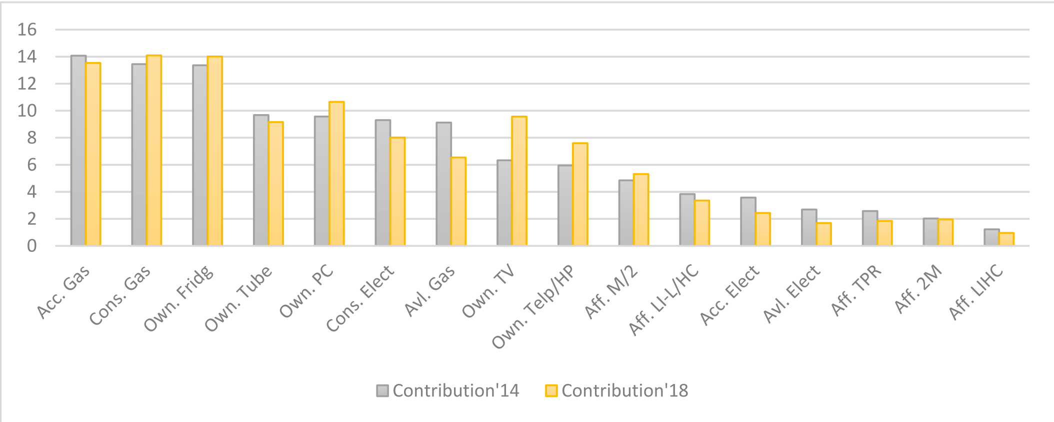
Appendix 3–4 summarise the comparison of the incidence and intensity of Indonesia's household MEP and the country's MEP Index with five affordability indicators and three weighting schemes at each cut-off and specific cut-offs in 2014 and 2018. The results of several robustness tests and sensitivity analyses (Appendix 7–10) show that the complementary frequency weighting gave a low and robust MEPI, and the equal weighting scheme gave a moderate and robust MEPI. In contrast, the PCA weighting gave a high but not

Table 5
Deprivation and contribution of indicators to Indonesian household MEPI, 2014 and 2018 (%).

Dimensions/Sub-Dimensions/Indicators	2014				2018			
	Deprived (%)	Contribution (%)			Deprived (%)	Contribution (%)		
		0.2	0.33	0.7		0.2	0.33	0.7
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Availability								
a. Electricity	1.86	0.69	0.96	6.42	0.83	0.41	0.59	4.07
b. Clean cooking fuel	27.41	7.83	9.00	10.54	19.58	5.71	6.01	7.90
2. Accessibility								
a. Electricity	3.27	1.19	1.73	7.80	1.49	0.67	0.96	5.67
b. Clean cooking fuel	40.36	13.26	14.27	14.69	21.52	11.22	13.92	15.46
3. Affordability								
a. 2M	13.62	2.97	2.00	1.10	14.98	2.67	1.87	1.33
b. M/2	13.62	4.07	5.07	5.40	13.54	4.87	5.47	5.60
c. LI-L/HC	8.85	2.90	3.90	4.70	7.53	2.80	3.40	3.87
d. TPR	6.80	2.13	2.60	3.00	5.71	1.63	1.77	2.13
e. LIHC	2.76	0.93	1.27	1.47	2.96	0.97	1.03	0.87
4. Energy Consumption								
a. Electricity	57.27	10.48	9.57	7.86	15.79	6.62	7.47	9.96
b. Clean cooking fuel	70.20	14.95	14.52	10.87	25.03	12.37	14.86	15.05
5. Energy services through household appliances								
5. a. Food & beverage processor								
i. ≥ 5.5 Kg gas cylinder/tube ownership	88.49	11.32	10.43	7.29	89.85	11.51	9.75	6.22
ii. Refrigerator ownership	58.17	14.62	13.72	11.75	43.45	15.52	14.73	11.79
5. b. Education, Information & Communication								
i. ≥ 30 inch flat TV ownership	92.86	7.53	6.85	4.61	85.85	11.99	10.14	6.57
ii. Telephone/HP ownership	13.11	4.43	5.75	7.67	29.81	8.05	7.67	7.07
iii. PC ownership	84.78	11.09	10.27	7.35	79.95	13.31	11.21	7.45



a. Deprivation of MEP indicators, 2014 and 2018 (%)



b. Average Contribution of MEP indicators, 2014 and 2018 (%)

Fig. 3. Deprivation and average contribution of MEP indicators, 2014 and 2018 (%).
Source: authors' calculation

robust MEPI. Dutta [113] demonstrates that data-driven weights violate key properties of poverty indices. LIHC estimates yielded a robust, low-deprivation score, followed by TPR. The analysis also used the LIHC indicator.

LIHC estimates were all significant (Table 6). According to the weighting, EP incidence decreased from 2014 to 2018. Vulnerable EP decreased from 56-92 % to 40–80 % and moderate EP from 27-80 % to 18–58 %. Meanwhile, severe EP ranged from 1–21 % to 1–8%. The weighting affected the intensity. The deprivation intensity of vulnerable EP was around 35–53 % of all weighted indicators, and moderate EP was around 45–60 %. Severe EP deprived 80–85 %. Indonesia's MEPI was low to moderate until 2018, but the intensity was high.

Fig. 4 shows the incidence, intensity, and MEPI based on the LIHC indicator for different weights and cut-offs. Overall, the parameters decreased. However, the intensity of moderate and severe EP did not change. Based on the weighting scheme, the complementary distribution, equal weight, and PCA produced the parameters' lowest, medium, and highest levels. Therefore, the data-driven weighting scheme can be an alternative to the lower and upper bounds of MEPI estimates besides normative weighting.

4.1.3. Changes over time in multidimensional energy poverty

Table 7 shows the LIHC affordability indicators' absolute, relative, and yearly change rates in MEPI parameters based on weighting and specific cut-offs. In general, the incidence of vulnerable, moderate, and severe EP decreased, although the intensity of moderate and severe EP increased.

4.2. MEPI subgroup decomposition in Indonesia

This study compared subgroup decomposition, contribution, and changes over time according to HH socio-economic, demographic, and geographical characteristics for the incidence, intensity, and MEPI using the LIHC affordability indicator (Table 8). MEPI decomposition analysis helps prioritise strategies and design policies.

Males headed most households at 84 %. Female HH had slightly higher parameters. MEP affected single HH more. Single women

Table 6
Statistical Inference of H, A, and M by LIHC affordability indicator at specific cut-offs and weighting scheme, 2014 and 2018.

Cut-off	Index	Weighting	2014 (n = 309,157 HH)				2018 (n = 295,155 HH)			
			Coef.	St. Err.	95 % Conf. Interval		Coef.	St. Err.	95 % Conf. Interval	
(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	
0.20	H	Freq	**0.558**	0.001	0.556	0.561	**0.397**	0.001	0.395	0.400
		Equal	**0.917**	0.001	0.916	0.918	**0.802**	0.001	0.800	0.804
		PCA	**0.831**	0.001	0.829	0.833	**0.605**	0.001	0.603	0.608
	A	Freq	**0.346**	0.000	0.346	0.347	**0.358**	0.000	0.357	0.359
		Equal	**0.480**	0.000	0.479	0.480	**0.404**	0.000	0.403	0.404
		PCA	**0.534**	0.001	0.533	0.535	**0.471**	0.001	0.470	0.473
	M	Freq	**0.193**	0.000	0.193	0.194	**0.142**	0.000	0.141	0.143
		Equal	**0.440**	0.000	0.439	0.441	**0.324**	0.001	0.323	0.325
		PCA	**0.444**	0.001	0.443	0.445	**0.285**	0.001	0.284	0.287
0.33	H	Freq	**0.266**	0.001	0.264	0.268	**0.181**	0.001	0.179	0.183
		Equal	**0.794**	0.001	0.792	0.796	**0.588**	0.001	0.585	0.590
		PCA	**0.661**	0.001	0.659	0.663	**0.222**	0.001	0.222	0.224
	A	Freq	**0.446**	0.000	0.445	0.447	**0.476**	0.000	0.475	0.477
		Equal	**0.515**	0.000	0.515	0.516	**0.459**	0.000	0.459	0.460
		PCA	**0.602**	0.000	0.601	0.603	**0.739**	0.000	0.738	0.740
	M	Freq	**0.118**	0.000	0.118	0.119	**0.086**	0.000	0.085	0.087
		Equal	**0.409**	0.001	0.408	0.410	**0.270**	0.001	0.269	0.271
		PCA	**0.398**	0.001	0.397	0.400	**0.164**	0.001	0.163	0.165
0.70	H	Freq	**0.013**	0.000	0.013	0.014	**0.010**	0.000	0.010	0.011
		Equal	**0.061**	0.000	0.060	0.062	**0.029**	0.000	0.028	0.029
		PCA	**0.213**	0.001	0.212	0.215	**0.088**	0.000	0.087	0.089
	A	Freq	**0.806**	0.001	0.805	0.808	**0.798**	0.001	0.796	0.799
		Equal	**0.794**	0.000	0.793	0.794	**0.792**	0.001	0.791	0.793
		PCA	**0.798**	0.000	0.797	0.798	**0.845**	0.000	0.844	0.846
	M	Freq	**0.011**	0.000	0.011	0.011	**0.008**	0.000	0.008	0.008
		Equal	**0.048**	0.000	0.048	0.049	**0.023**	0.000	0.022	0.023
		PCA	**0.170**	0.001	0.169	0.171	**0.074**	0.000	0.073	0.075

Source: authors' calculation

HH suffered more than HH couples in all absolute and relative change rate parameters. Age group decomposition shows that the middle-aged (35–44 years) and pre-retirement HH (44–54 years) had the lowest parameters with the most significant contribution (23–25 %). In contrast, Young (15–24 years) and elderly (65+ years) HH suffered more. All parameters for all age groups decreased, with pre-retirement HH having the highest decrease and young HH having the lowest.

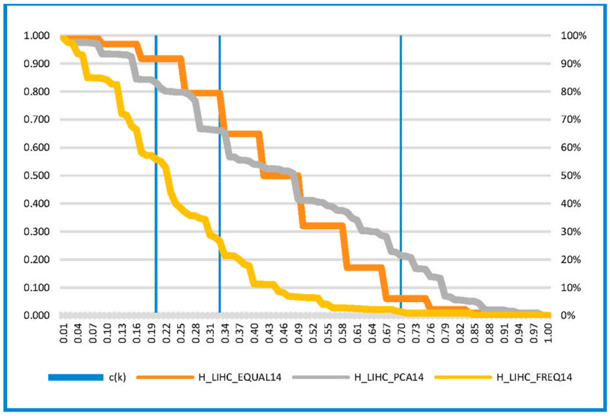
HH education level inversely affected related parameters. Education could lead to high-income jobs, reducing the likelihood of EP. Non-schoolers and primary-schoolers HH had the highest parameters. HH's primary sector was still vulnerable to MEP due to its high contribution (40–50 %) and intensity (53–59 %), with the lowest annual decline (−9%). Income recipients, unpaid workers, and self-employed or assisted HH workers had higher parameters than HH employees. Self- or assisted workers HH had the most prominent parameters with a low decline.

During this period, low-income energy-poor families decreased by 4 % annually, from 96 % to 81 %, contributing 10 %. EP decreased by 12 % annually for non-poor families, contributing 90 %. 81–96 % of low-income families were energy-poor, but less than non-poor families.

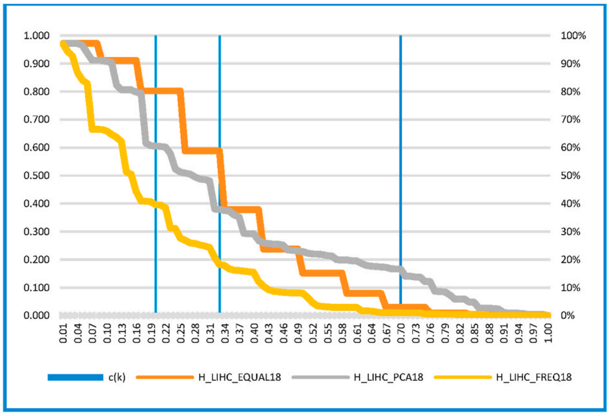
In 2014, 90 % of rural families experienced MEP, compared to 68 % of urban families, with an intensity of 58 % and a MEPI of 0.519. Until 2018, the incidence, intensity, and MEPI declined by 8 %, 3 %, and 10 %, respectively. There was a rise in modern energy services. Nevertheless, the rural-urban EP differences reflected spatial inequalities in modern energy services, and their adoption and equipment.

The geographic decomposition shows that MEPI parameters were higher among households in non-coastal areas (H = 87 %, A = 60 %, and M = 0.510), forested areas (H = 96 %, A = 73 %, and M = 0.704), highlands and hillside areas (H = 93 %, A = 61 %, and M = 0.569), and Maluku-Papua islands (H = 100 %, A = 76 %, and M = 0.753). Fig. 5 shows results at the provincial level. Papua, East Nusa Tenggara, and Maluku had high parameters. Meanwhile, DKI Jakarta, North Kalimantan, and East Kalimantan had the lowest scores.

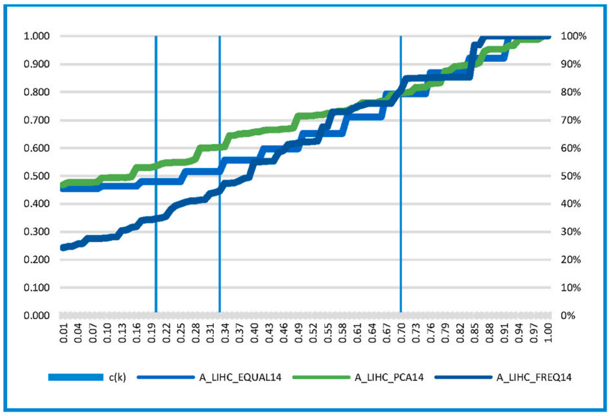
MEPI decomposition displays population share-based subgroup contributions to MEPI. To reduce MEP, the household heads—a single female, young or elderly, with low education, working in the primary sector as an unpaid or self-employed or assisted worker, living in rural, hinterland, non-coastal, forested, and highland areas in Maluku-Papua islands—need attention.



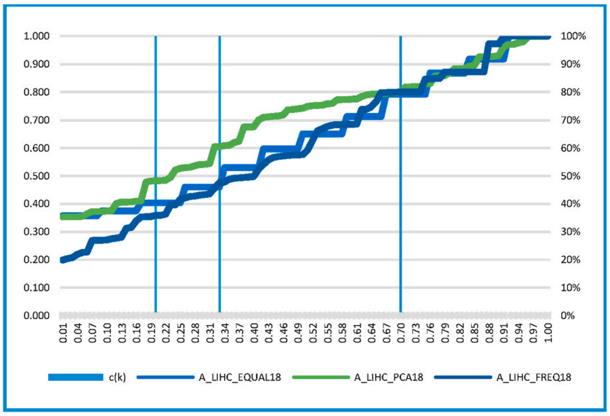
a. Incidence (H) by LIHC with Compl-Freq., Equal, & PCA weighting, 2014



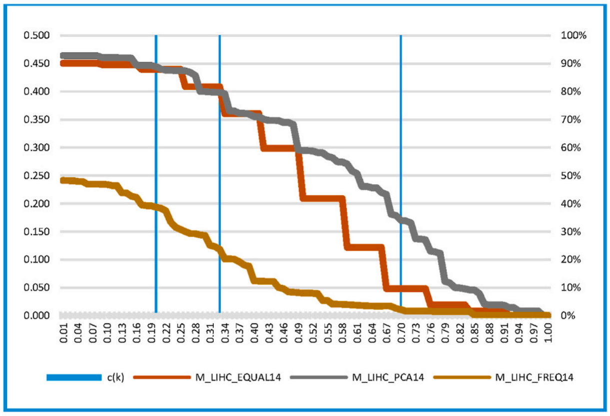
b. Incidence (H) by LIHC with Compl-Freq., Equal, & PCA weighting, 2018



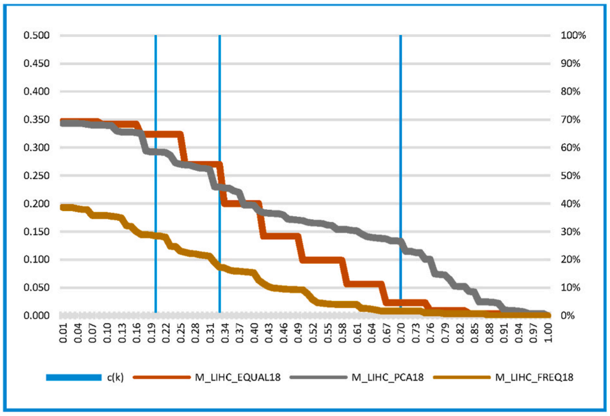
c. Intensity (A) by LIHC with Compl-Freq., Equal, & PCA weighting, 2014



d. Intensity (A) by LIHC with Compl-Freq., Equal, & PCA weighting, 2018



e. MEPI (M) by LIHC with Compl-Freq., Equal, & PCA weighting, 2014



f. MEPI (M) by LIHC with Compl-Freq., Equal, & PCA weighting, 2018

Fig. 4. Incidence (H), Intensity (A) and MEP Index (M) by LIHC affordability indicator for different weighting and poverty cut-offs (k), 2014 and 2018.
Source: authors' calculation

Table 7
Changes over time in MEPI by LIHC affordability indicator at specific cut-offs and weighting scheme, 2014 to 2018.

Cut-off	Index	Weighting	2014	2018	Absolute change rate (Δ)	Relative change rate (δ %)	Annual absolute change rate ($\overline{\Delta}$)	Annual relative change rate ($\overline{\delta}$ %)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
0.20	H	Freq	**0.558**	**0.397**	−0.16	−0.29	−0.04	−8.16
		Equal	**0.917**	**0.802**	−0.12	−0.13	−0.03	−3.29
		PCA	**0.831**	**0.605**	−0.23	−0.27	−0.06	−7.63
	A	Freq	**0.346**	**0.358**	0.01	0.03	0.00	0.86
		Equal	**0.480**	**0.404**	−0.08	−0.16	−0.02	−4.22
		PCA	**0.534**	**0.471**	−0.06	−0.12	−0.02	−3.09
	M	Freq	**0.193**	**0.142**	−0.05	−0.26	−0.01	−7.38
		Equal	**0.440**	**0.324**	−0.12	−0.26	−0.03	−7.37
		PCA	**0.444**	**0.285**	−0.16	−0.36	−0.04	−10.49
0.33	H	Freq	**0.266**	**0.181**	−0.09	−0.32	−0.02	−9.18
		Equal	**0.794**	**0.588**	−0.21	−0.26	−0.05	−7.23
		PCA	**0.661**	**0.222**	−0.44	−0.66	−0.11	−23.87
	A	Freq	**0.446**	**0.476**	0.03	0.07	0.01	1.64
		Equal	**0.515**	**0.459**	−0.06	−0.11	−0.01	−2.84
		PCA	**0.602**	**0.739**	0.14	0.23	0.03	5.26
	M	Freq	**0.118**	**0.086**	−0.03	−0.27	−0.01	−7.60
		Equal	**0.409**	**0.270**	−0.14	−0.34	−0.03	−9.86
		PCA	**0.398**	**0.164**	−0.23	−0.59	−0.06	−19.88
0.70	H	Freq	**0.013**	**0.010**	0.00	−0.23	0.00	−6.35
		Equal	**0.061**	**0.029**	−0.03	−0.52	−0.01	−16.96
		PCA	**0.213**	**0.088**	−0.13	−0.59	−0.03	−19.83
	A	Freq	**0.806**	**0.798**	−0.01	−0.01	0.00	−0.25
		Equal	**0.794**	**0.792**	0.00	0.00	0.00	−0.06
		PCA	**0.798**	**0.845**	0.05	0.06	0.01	1.44
	M	Freq	**0.011**	**0.008**	0.00	−0.27	0.00	−7.65
		Equal	**0.048**	**0.023**	−0.03	−0.52	−0.01	−16.80
		PCA	**0.170**	**0.074**	−0.10	−0.56	−0.02	−18.77

Source: authors' calculation

4.3. The determinants of multidimensional energy poverty in Indonesia

The Ordinary Least Square (OLS) regression, Logit, Probit, Tobit, and Heckman Selection (HS) models were compared to check the consistency of results. The dependent variable in the Logit and Probit models is the binary status classified from the censored weighted multidimensional deprivation score ($\boldsymbol{t_i(k)}$) —whether it exceeds the multidimensional cut-off k (code 1 = MEP) or not (code 0 = not MEP). In the Tobit and Heckman Selection models, $\boldsymbol{t_i(k)}$ is used.

All models are valid and explain 22–47 % of MEP variation. All household heads' characteristics were statistically associated with MEP (Table 9). The marginal effect shows a change likelihood when only one HH characteristic changes by one unit and all others stay the same. Households living in rural, non-coastal, forested and highland areas; on eastern Indonesian islands; or in disadvantaged, frontier and outermost areas had an increased likelihood of MEP.

Males and couples HH had a lower risk of MEP. The HH pre-retirement age, middle age, and retirement age groups had the negative and lowest probability of entering MEP. In contrast, HH children, young and elderly age groups were vulnerable to entering MEP. The chance of MEP occurring was less often and increased with the HH education level. Agricultural HH were more vulnerable to MEP. Employee HH and 'self-employed or assisted HH' had a negative chance of experiencing MEP. Low-income HH was more likely to be in MEP.

5. Conclusion and policy implications

This study used matched SUSENAS and PODES data for 2014 and 2018 to identify the incidence and intensity of Indonesia's MEP, the country's MEP Index, and MEP decomposition and determinants under Indonesia's HH socio-economic and geographical characteristics. The study identified the availability, accessibility, affordability, consumption, and deprivation of modern energy services. Affordability indicators were compared within three weighting and deprivation cut-off schemes. The results show that the LIHC was the most robust affordability indicator. The complementary-frequency weighting gave the smallest and most robust MEPI, compared to the equal and PCA weightings, and those who were vulnerable, moderately or severely energy poor could be identified.

Table 8
MEPI subgroup decomposition[b], contribution, and changes over time by HH socio economic, demographic, and geographical characteristics.

	2014					2018																	
	H		A	M		H		A	M		H				A				M				
	Coef.	Contrib.	Coef.	Coef.	Contrib.	Coef.	Contrib.	Coef.	Coef.	Contrib.	Δ	δ %	$\overline{\Delta}$	$\overline{\delta}$ %	Δ	δ %	$\overline{\Delta}$	$\overline{\delta}$ %	Δ	δ %	$\overline{\Delta}$	$\overline{\delta}$ %
(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)	(12)	(14)	(15)	(16)	(17)	(19)	(20)	(21)	(22)	(24)	(25)	(26)	(27)
Aggregate	0.795		0.514	0.408		0.497		0.480	0.238		−0.30	−0.37	−0.07	−11.08	−0.03	−0.07	−0.01	−1.70	−0.17	−0.42	−0.04	−12.61
HH Gender																						
Female	0.838	0.157	0.553	0.463	0.169	0.597	0.182	0.511	0.305	0.194	−0.24	−0.29	−0.06	−8.13	−0.04	−0.08	−0.01	−1.94	−0.16	−0.34	−0.04	−9.91
Male	0.787	0.843	0.507	0.399	0.831	0.479	0.818	0.472	0.226	0.806	−0.31	−0.39	−0.08	−11.67	−0.04	−0.07	−0.01	−1.78	−0.17	−0.43	−0.04	−13.25
HH Marital Status																						
Single	0.852	0.200	0.552	0.470	0.215	0.635	0.249	0.513	0.326	0.267	−0.22	−0.25	−0.05	−7.09	−0.04	−0.07	−0.01	−1.78	−0.14	−0.31	−0.04	−8.74
Couple/Married	0.781	0.800	0.504	0.394	0.785	0.463	0.751	0.469	0.217	0.733	−0.32	−0.41	−0.08	−12.25	−0.04	−0.07	−0.01	−1.82	−0.18	−0.45	−0.04	−13.85
HH Cohort (year)																						
Young (15–24)	0.914	0.029	0.537	0.491	0.030	0.783	0.043	0.496	0.388	0.045	−0.13	−0.14	−0.03	−3.79	−0.04	−0.08	−0.01	−2.00	−0.10	−0.21	−0.03	−5.72
Early worker (25–34)	0.823	0.179	0.502	0.413	0.175	0.515	0.156	0.441	0.227	0.144	−0.31	−0.37	−0.08	−11.06	−0.06	−0.12	−0.02	−3.19	−0.19	−0.45	−0.05	−13.90
Middle-aged (35–44)	0.772	0.264	0.494	0.381	0.253	0.437	0.221	0.453	0.198	0.209	−0.34	−0.43	−0.08	−13.26	−0.04	−0.08	−0.01	−2.11	−0.18	−0.48	−0.05	−15.09
Pre-retirement (45–54)	0.761	0.236	0.502	0.382	0.230	0.438	0.222	0.473	0.207	0.219	−0.32	−0.42	−0.08	−12.90	−0.03	−0.06	−0.01	−1.50	−0.18	−0.46	−0.04	−14.20
Pension (55–64)	0.787	0.168	0.524	0.412	0.171	0.505	0.190	0.495	0.250	0.197	−0.28	−0.36	−0.07	−10.50	−0.03	−0.05	−0.01	−1.39	−0.16	−0.39	−0.04	−11.74
Elderly (65+)	0.863	0.124	0.578	0.499	0.140	0.631	0.167	0.534	0.337	0.186	−0.23	−0.27	−0.06	−7.53	−0.04	−0.08	−0.01	−1.97	−0.16	−0.32	−0.04	−9.35
HH Education																						
No school	0.923	0.289	0.589	0.544	0.332	0.724	0.317	0.523	0.379	0.360	−0.20	−0.22	−0.05	−5.89	−0.07	−0.11	−0.02	−2.92	−0.17	−0.30	−0.04	−8.64
Primary school	0.848	0.479	0.508	0.431	0.474	0.585	0.492	0.439	0.257	0.469	−0.26	−0.31	−0.07	−8.86	−0.07	−0.14	−0.02	−3.58	−0.17	−0.40	−0.04	−12.13
Secondary school	0.664	0.191	0.437	0.290	0.162	0.350	0.164	0.406	0.142	0.144	−0.31	−0.47	−0.08	−14.79	−0.03	−0.07	−0.01	−1.83	−0.15	−0.51	−0.04	−16.35
High School	0.442	0.041	0.407	0.180	0.033	0.172	0.027	0.442	0.076	0.026	−0.27	−0.61	−0.07	−21.02	0.03	0.09	0.01	2.06	−0.10	−0.58	−0.03	−19.39
HH Business Field[c]																						
Primary Sector	0.910	0.396	0.590	0.537	0.455	0.693	0.437	0.528	0.366	0.482	−0.22	−0.24	−0.05	−6.58	−0.06	−0.11	−0.02	−2.74	−0.17	−0.32	−0.04	−9.14
Secondary Sector	0.784	0.178	0.467	0.366	0.161	0.456	0.167	0.419	0.191	0.146	−0.33	−0.42	−0.08	−12.67	−0.05	−0.10	−0.01	−2.67	−0.18	−0.48	−0.04	−15.01
Tertiary Sector	0.690	0.312	0.442	0.305	0.268	0.341	0.256	0.425	0.145	0.228	−0.35	−0.51	−0.09	−16.16	−0.02	−0.04	0.00	−0.96	−0.16	−0.52	−0.04	−16.96
Income Recipient	0.789	0.115	0.520	0.410	0.116	0.525	0.139	0.499	0.262	0.145	−0.26	−0.33	−0.07	−9.68	−0.02	−0.04	−0.01	−1.01	−0.15	−0.36	−0.04	−10.59
HH Occupation																						
Self/assisted employee	0.830	0.475	0.546	0.453	0.504	0.535	0.458	0.510	0.273	0.488	−0.30	−0.36	−0.07	−10.40	−0.04	−0.07	−0.01	−1.67	−0.18	−0.40	−0.05	−11.89
Employee	0.758	0.402	0.475	0.360	0.372	0.450	0.393	0.436	0.196	0.357	−0.31	−0.41	−0.08	−12.22	−0.04	−0.08	−0.01	−2.14	−0.16	−0.46	−0.04	−14.10
Unpaid employee	0.806	0.008	0.526	0.424	0.008	0.520	0.009	0.533	0.277	0.010	−0.29	−0.35	−0.07	−10.38	0.01	0.01	0.00	0.31	−0.15	−0.35	−0.04	−10.10
Income Recipient	0.789	0.115	0.520	0.410	0.116	0.525	0.139	0.499	0.262	0.145	−0.26	−0.33	−0.07	−9.68	−0.02	−0.04	−0.01	−1.01	−0.15	−0.36	−0.04	−10.59
HH Poverty Status																						
Not poor	0.781	0.905	0.506	0.395	0.890	0.475	0.893	0.472	0.224	0.878	−0.31	−0.39	−0.08	−11.69	−0.03	−0.07	−0.01	−1.73	−0.17	−0.43	−0.04	−13.22
Poor	0.955	0.095	0.595	0.568	0.110	0.805	0.107	0.547	0.440	0.122	−0.15	−0.16	−0.04	−4.18	−0.05	−0.08	−0.01	−2.09	−0.13	−0.23	−0.03	−6.18
Residence area																						
Rural	0.901	0.586	0.576	0.519	0.657	0.656	0.598	0.520	0.341	0.649	−0.25	−0.27	−0.06	−7.63	−0.06	−0.10	−0.01	−2.53	−0.18	−0.34	−0.04	−9.97
Urban	0.681	0.414	0.426	0.290	0.343	0.365	0.402	0.419	0.153	0.351	−0.32	−0.46	−0.08	−14.44	−0.01	−0.02	0.00	−0.39	−0.14	−0.47	−0.03	−14.77
Coastal area																						
Coast	0.784	0.857	0.501	0.393	0.836	0.484	0.872	0.471	0.228	0.856	−0.30	−0.38	−0.08	−11.36	−0.03	−0.06	−0.01	−1.54	−0.17	−0.42	−0.04	−12.73

(*continued on next page*)

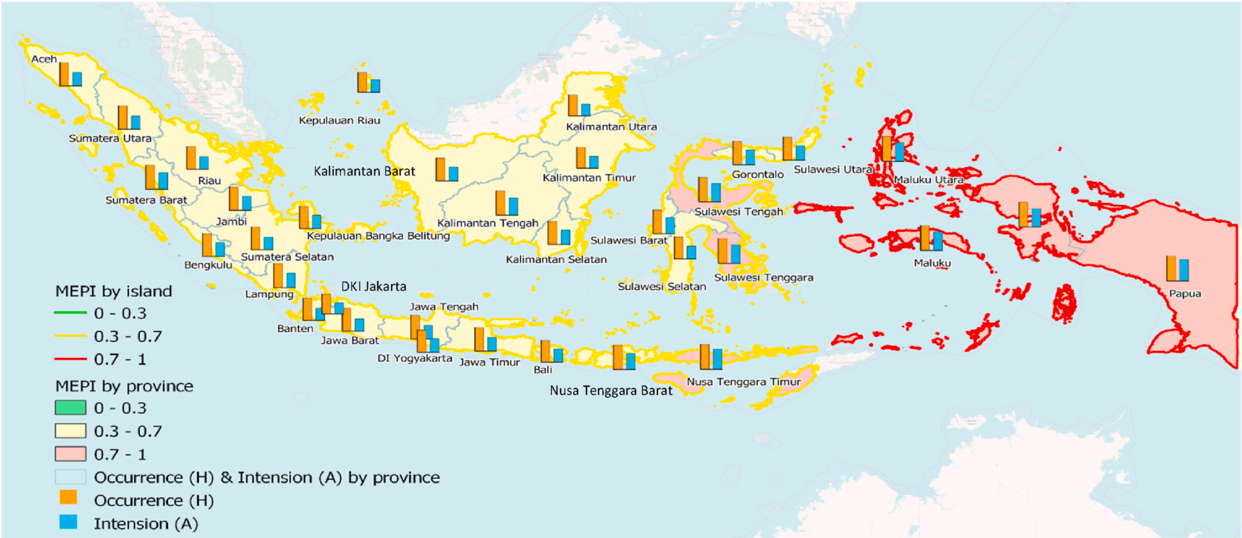
Table 8 (*continued*)

	2014					2018																
	H		A	M		H		A	M		H				A				M			
	Coef.	Contrib.	Coef.	Coef.	Contrib.	Coef.	Contrib.	Coef.	Coef.	Contrib.	Δ	δ %	$\overline{\Delta}$	$\overline{\delta}$ %	Δ	δ %	$\overline{\Delta}$	$\overline{\delta}$ %	Δ	δ %	$\overline{\Delta}$	$\overline{\delta}$ %
(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)	(12)	(14)	(15)	(16)	(17)	(19)	(20)	(21)	(22)	(24)	(25)	(26)	(27)
Not Coastal	0.866	0.143	0.589	0.510	0.164	0.602	0.128	0.538	0.324	0.144	−0.26	−0.30	−0.07	−8.69	−0.05	−0.09	−0.01	−2.23	−0.19	−0.36	−0.05	−10.72
Forestry area																						
Outside forest	0.794	0.994	0.513	0.407	0.991	0.494	0.988	0.478	0.236	0.984	−0.30	−0.38	−0.08	−11.19	−0.03	−0.07	−0.01	−1.75	−0.17	−0.42	−0.04	−12.74
Inside forest	0.964	0.006	0.730	0.704	0.009	0.807	0.012	0.643	0.519	0.016	−0.16	−0.16	−0.04	−4.35	−0.09	−0.12	−0.02	−3.13	−0.19	−0.26	−0.05	−7.34
Topography area																						
Highlands/hillside	0.928	0.149	0.613	0.569	0.178	0.751	0.149	0.581	0.436	0.180	−0.18	−0.19	−0.04	−5.15	−0.03	−0.05	−0.01	−1.36	−0.13	−0.23	−0.03	−6.44
Valley	0.900	0.024	0.614	0.553	0.029	0.754	0.021	0.593	0.447	0.027	−0.15	−0.16	−0.04	−4.33	−0.02	−0.04	−0.01	−0.89	−0.11	−0.19	−0.03	−5.18
Lowland	0.772	0.826	0.492	0.380	0.793	0.464	0.830	0.459	0.213	0.793	−0.31	−0.40	−0.08	−11.95	−0.03	−0.07	−0.01	−1.73	−0.17	−0.44	−0.04	−13.47
Island																						
Sumatra	0.775	0.191	0.501	0.388	0.186	0.476	0.198	0.452	0.215	0.186	−0.30	−0.39	−0.07	−11.47	−0.05	−0.10	−0.01	−2.54	−0.17	−0.45	−0.04	−13.72
Java	0.775	0.552	0.472	0.366	0.507	0.464	0.550	0.446	0.207	0.511	−0.31	−0.40	−0.08	−12.04	−0.03	−0.06	−0.01	−1.41	−0.16	−0.43	−0.04	−13.28
Bali-Nusra	0.885	0.057	0.616	0.545	0.069	0.749	0.081	0.617	0.462	0.104	−0.14	−0.15	−0.03	−4.09	0.00	0.00	0.00	0.04	−0.08	−0.15	−0.02	−4.05
Kalimantan	0.756	0.054	0.529	0.400	0.055	0.435	0.052	0.460	0.200	0.050	−0.32	−0.42	−0.08	−12.91	−0.07	−0.13	−0.02	−3.45	−0.20	−0.50	−0.05	−15.91
Sulawesi	0.865	0.117	0.614	0.531	0.140	0.526	0.071	0.508	0.267	0.075	−0.34	−0.39	−0.08	−11.69	−0.11	−0.17	−0.03	−4.64	−0.26	−0.50	−0.07	−15.79
Maluku-Papua	0.997	0.029	0.755	0.753	0.043	0.988	0.048	0.732	0.723	0.074	−0.01	−0.01	0.00	−0.23	−0.02	−0.03	−0.01	−0.79	−0.03	−0.04	−0.01	−1.01

[b] Using a weighted PCA that produces the greatest results.

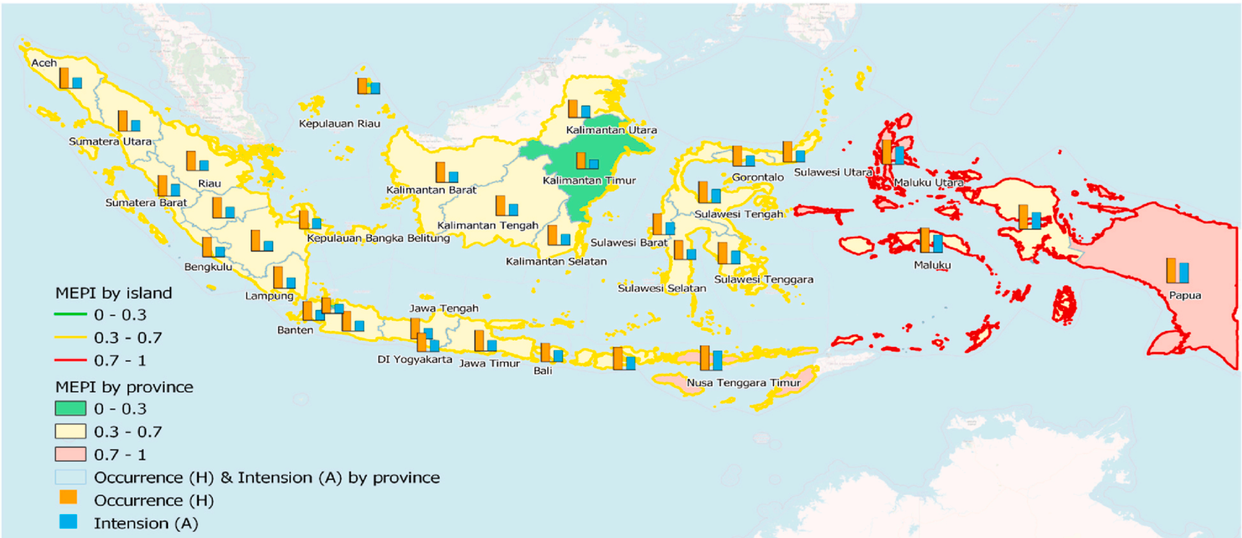
[c] Primary Sector: agriculture, plantation, fishery, livestock, forestry, mining, and quarrying; Secondary Sector: industry, construction; Tertiary Sector: services.

Source: authors' calculation



Source: authors' calculation

a. MEPI parameters across islands and provinces in Indonesia, 2014



Source: authors' calculation

b. MEPI parameters across islands and provinces in Indonesia, 2018

Fig. 5. Spatial distribution of MEPI parameters across islands and provinces in Indonesia, 2014 and 2018.
Source: authors' calculation

From 2014 to 2018, the MEP incidence among the vulnerable household ranged from 56–92 % to 39–80 %, with a low MEPI of 0.142–0.264. However, the MEP intensity was high, and energy-poor households deprived themselves of 60–79 % of weighted indicators. MEP differed by geography and HH subgroups, like gender, education, business field, and employment status.

The results prove that geographic factors significantly determined Indonesia's household MEP level. Indonesia's non-coastal, forested eastern islands were more vulnerable to MEP. In contrast, all HH socio-economic characteristics reduced MEP, except for poor status.

This study on MEPI measurement, decomposition, and determinants has various MEP reduction policy implications. Clean and modern cooking fuel must be made more accessible, especially in rural, non-coastal, forested areas and on Indonesia's eastern islands. Apart from that, it is also necessary to maintain the affordability of modern energy by increasing household income or reducing energy expenditure. Combining these variables can increase modern energy consumption, especially for the basic needs of lighting and cooking. Policies to improve the economy of low-income families and increase education levels will reduce the number of households falling into MEP.

Table 9
The regression coefficient estimate using the OLS, Logit, Probit, Tobit, and Heckman Selection models.

	OLS		Logit		Probit		Tobit		Heckman	
	Base	Control	Base	Control	Base	Control	Base	Control	Base	Control
	(1)	(2)	(3)	(3)	(3)	(4)	(4)	(4)	(3)	(4)
_cons	0.176***	0.360***	−1.669***	−0.332***	−0.985***	−0.233***	0.330***	0.446***	−0.906***	−0.171***
	(0.000)	(0.020)	(0.000)	(0.001)	(0.011)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)
<u>Geographic characteristic</u>										
Place of Residence	−0.146***	−0.091***	−1.383***	−0.996***	−0.732***	−0.535***	−0.098***	−0.061***	−0.757***	−0.533***
(Urban = 1)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.005)
Coastal area	0.059***	0.054***	0.472***	0.501***	0.256***	0.274***	0.031***	0.027***	0.270***	0.289***
(Coastal = 1)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.005)
Forest area	0.126***	0.105***	0.766***	0.692***	0.445***	0.392***	0.060***	0.044***	0.434***	0.377***
(Forest = 1)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.000)	(0.000)	(0.017)	(0.018)
Topography (Plain = 1)										
Height	0.150***	0.135***	0.944***	0.954***	0.539***	0.540***	0.085***	0.074***	0.498***	0.472***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.006)
Valley	0.125***	0.116***	0.786***	0.823***	0.451***	0.464***	0.075***	0.067***	0.409***	0.403***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.011)	(0.012)
Island (Java = 1)										
Sumatera	−0.012***	−0.005***	−0.066***	0.027***	−0.045***	0.023***	−0.010***	−0.005***	0.013**	0.079***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)
Bali_Nusra	0.171***	0.167***	1.128***	1.289***	0.638***	0.735***	0.089***	0.088***	0.733***	0.838***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.008)	(0.008)
Kalimantan	0.012***	0.022***	0.163***	0.297***	0.080***	0.177***	0.001***	0.006***	0.108***	0.196***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.008)	(0.008)
Sulawesi	0.133***	0.133***	0.855***	1.002***	0.483***	0.583***	0.058***	0.061***	0.442***	0.537***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.007)
Maluku_Papua	0.301***	0.315***	1.687***	2.133***	0.980***	1.221***	0.190***	0.200***	0.973***	1.171***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.009)	(0.009)
Disadvantaged,Frontier & Outermost Areas	0.191***	0.166***	0.861***	0.817***	0.527***	0.483***	0.087***	0.073***	0.524***	0.483***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.007)	(0.007)
<u>Socioeconomic characteristic</u>										
HH Gender		−0.025***		−0.153***		−0.077***		0.002***		−0.078***
(Male = 1)		(0.000)		(0.001)		(0.001)		(0.000)		(0.008)
HH Marital status		−0.076***		−0.697***		−0.403***		−0.058***		−0.345***
(Couple = 1)		(0.000)		(0.001)		(0.001)		(0.000)		(0.008)
<u>HH Age cohort</u>:										
(Early Worker = 1)										
(25–34 yr)										
1. Children		0.184***		0.891***		0.535***		0.101***		0.815***
(–14 yr)		(0.004)		(0.019)		(0.011)		(0.001)		(0.145)
2. Young		0.019***		0.345***		0.196***		0.054***		0.212***
(15–24 yr)		(0.000)		(0.002)		(0.001)		(0.000)		(0.015)
3. Middle-age		−0.025***		−0.287***		−0.156***		−0.023***		−0.149***
(35–44 yr)		(0.000)		(0.001)		(0.000)		(0.000)		(0.007)
4. Pre-retirement		−0.035***		−0.389***		−0.209***		−0.032***		−0.201***
(45–54 yr)		(0.000)		(0.001)		(0.001)		(0.000)		(0.007)
5. Pension		−0.023***		−0.241***		−0.128***		−0.031***		−0.160***
(55–64 yr)		(0.000)		(0.001)		(0.001)		(0.000)		(0.008)
6. Elderly		0.072***		0.403***		0.238***		0.008***		0.126***

(*continued on next page*)

Table 9 (*continued*)

	OLS		Logit		Probit		Tobit		Heckman	
	Base	Control	Base	Control	Base	Control	Base	Control	Base	Control
	(1)	(2)	(3)	(3)	(3)	(4)	(4)	(4)	(3)	(4)
(_> 65 yr)		(0.000)		(0.001)		(0.001)		(0.000)		(0.009)
HH Edu: (no sch. = 1)										
1. Primary sch.		−0.090***		−0.581***		−0.333***		−0.047***		−0.339***
		(0.000)		(0.001)		(0.000)		(0.000)		(0.005)
2. Secondary sch.		−0.114***		−1.159***		−0.636***		−0.083***		−0.616***
		(0.000)		(0.001)		(0.001)		(0.000)		(0.007)
3. High sch.		−0.120***		−1.513***		−0.812***		−0.121***		−0.758***
		(0.000)		(0.002)		(0.001)		(0.000)		(0.011)
HH Business Field:										
(Primary = 1)										
1. Secondary		−0.068***		−0.597***		−0.331***		−0.037***		−0.290***
		(0.000)		(0.001)		(0.000)		(0.000)		(0.007)
2. Tertiary		−0.082***		−0.750***		−0.410***		−0.047***		−0.374***
		(0.000)		(0.001)		(0.000)		(0.000)		(0.006)
3. Income recipients		−0.069***		−0.414***		−0.243***		−0.039***		−0.248***
		(0.000)		(0.001)		(0.001)		(0.000)		(0.008)
HH Job status										
(self/assisted worker = 1)										
1. employee/worker		−0.007***		−0.048***		−0.022***		0.000***		−0.058***
		(0.000)		(0.001)		(0.000)		(0.000)		(0.005)
2. unpaid worker		−0.013***		−0.116***		−0.061***		−0.006***		−0.058**
		(0.000)		(0.000		(0.002)		(0.000)		(0.022)
Poor = 1		0.167***		1.108***		0.637***		0.094***		0.007***
		(0.000)		(0.001)		(0.000)		(0.000)		(0.010)
Household	604,312	604,312	604,312	604,312	604,312	604,312	604,312	604,312	604,312	604,312
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2/Pseudo R^2	0.173	0.249	0.176	0.272	0.175	0.274	0.483	0.773	0.320	0.469

Source: authors' calculation

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Rofiq Nur Rizal: Writing – original draft. **Djoni Hartono:** Supervision, Formal analysis. **Teguh Dartanto:** Supervision, Conceptualization. **Yohanna M.L. Gultom:** Writing – review & editing, Supervision.

Declaration of competing interest

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

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Appendix A. Supplementary data

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