Examining the state of energy poverty in Rwanda: An inter-indicator analysis

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ABSTRACT

This paper adopted an inter-indicator analytical approach to investigate the state of energy poverty in Rwanda. It used a nationally representative sample of 14,458 households from Rwanda’s Integrated Living Standard Survey conducted between October 2016 and October 2017. The first indicator entailed a multidimensional analysis of energy poverty using eleven pointers of energy deprivation. Each pointer was assigned a weight using principal component analysis to form a household energy poverty index. The paper also employed a ‘modified’ expenditure-based approach that emphasizes affordability and accessibility. This is the approach on which the second indicator of energy poverty was based. This constituted an examination of different levels of household income and energy expenditure patterns as well as the use of biomass for cooking. The results from the multidimensional analysis revealed that the most energy-poor households were concentrated in the southern (30.15%), western (27.69%) and northern (24.86%) provinces of Rwanda. In contrast, the least energy-poor are mostly found in urban areas of the country. A cross-comparison with the second approach showed different magnitudes of energy poverty incidences. Nonetheless, similar trends were observed in terms of areas of concentration of energy poverty. Last, the results from multilevel binary logistic regressions showed that household size, income poverty, education level of the head of the family, rural location and Kigali resident ship were determinants of energy poverty.

1. Introduction

Bridging the energy divide between the poor and the rich through modern energy services provision remains a top priority for most governments and development partners in the developing world. A recent study by Aung et al. (2021) revealed that ultra-poor households experience great depths of energy poverty compared to wealthy households within the same vicinity. However, there is a dichotomy in terms of how energy poverty is defined within a global south context compared to that of the global north. In the global south context, energy poverty means a lack of access to energy services, while in the global north context, it means a failure to cope with high energy costs due to meagre disposable income (Sokolowski et al., 2019; Anderson and White, 2019).

The existing literature presents several energy poverty definitions that largely revolve around two terms, namely, fuel and energy poverty. In some cases, the two terms have been used interchangeably to mean the same thing, and this paper treats these terms as such. However, a closer look at systematic review papers shows that the two terms might mean two different things altogether depending on the context. Gonzalez-E-guino (2015) defined energy poverty as an insufficient level of energy consumption to meet basic household needs. Bouzarovski and Petrova (2015) defined energy poverty as all types of poverty, making it difficult to access and use clean and modern energy services in homes. This leads to a limited choice of options to raise standards of living due to missing fundamentals in areas of education, information and even politics. In most European contexts, energy poverty is synonymous with fuel poverty. Terminology refers to a household’s inability to have adequate energy services for thermal comfort in homes and originates in the United Kingdom (UK), based on the scholarly works of (Boardman, 1993, 2012). Recent review papers on energy poverty definitions show that energy poverty remains a broad concept that encompasses many things (Halkos and Gkampoura, 2021; Faiella and Lavecchia, 2021). The
concepts relate to affordability, accessibility and new technologies regarding domestic energy service provision (Urge-Vorsatz and Herrero, 2012).

Regarding energy poverty measures, different scholars have employed different methodologies to understand and measure the energy poverty phenomenon. These methodologies can be categorized into two main approaches. The first approach involves all those methods that are based on household energy consumption expenditures. On the other hand, the second approach encompasses methods that use composite indicators, which are also termed multidimensional indicators in some review papers (Fizaine and Kahouli, 2018). Under the expenditure-based approach, the most common indicator is the 10% indicator that is used to classify energy-poor households. Under the 10% indicator, a household is deemed energy-poor if it spends more than 10% of its total income on energy services (Boardman, 1991). Some scholars have improved and modified the approach by coming up with measures that take into consideration the differences in energy prices across time and spaces. Others have argued that it was based on an old information base that may not resonate with the modern-day prevailing economic conditions (Lin and Zhao, 2021). One of the most notable modified indicators, aside from the 10% indicator, is the low-income/high-cost (LIHC) dual method, pioneered by Hills in 2011 and 2012. According to Hills, a household is deemed energy-poor if its equalized disposable income is less than 60% of the equalized national median disposable income (Hills, 2011). Again, its equalized fuel expenditure is equal to or greater than the required national median fuel expenditures.

However, Middelmiss (2017) noted that the LIHC indicator does not consider the most vulnerable groups within a society, such as the elderly and those having children, among others. One of the advantages of expenditure-based approaches is that they are measurable and objective, making them easy to compare across different times and spaces (Halkos and Gkampoura, 2021). Disadvantages include the fact that they are very sensitive to threshold levels, thereby passing a challenge to obtain an optimal metric (Fizaine and Kahouli, 2018). In addition, there are consensual social indicators that have been used, mainly in European countries where data are readily available. The consensual social indicators are also based on income poverty and deprivation aspects beyond the usual observation data. Focus is placed on the need to consider social inclusion and material deprivation as prerequisites to lead a dignified life (Fizaine and Kahouli, 2018). There are also those that have been referred to as subjective self-reported indicators that mainly use subjective data from respondents and are associated with subjective bias. In some cases, some scholars have even used what are referred to as restrictive behaviour indicators that usually focus on the indoor temperature (Fizaine and Kahouli, 2018). Some scholars have suggested a need to use composite indicators such as the multidimensional energy poverty index (MEPI), which can use subjective and objective indicators depending on the data available to overcome the shortcomings of expenditure-based approaches (Lin and Zhao, 2021; Gupta et al., 2020; Sadath and Acharaya, 2017; Nussbaumer et al., 2012). The composite indices (multidimensional indicators) help not only account for multidimensional aspects of energy poverty but also generate something that captures the simplicity of expenditure-based approaches. They also help to develop robust measures with condensed information that is easy to interpret (Fizaine and Kahouli, 2018; Thomson and Snell, 2013).

Last, in terms of determinants of energy poverty, previous studies have identified household characteristics such as age, gender, household size, and wealth status as some of the factors that influence household energy poverty (Abbas et al., 2020). In addition, some developing countries encounter geographical challenges about land terrain and remoteness of the areas, which may affect access to modern energy services (Lin and Zhao, 2021). Furthermore, government policies such as cash transfers, which promote social welfare, may also influence household energy poverty. Nawaz and Iqbal (2021) examined the impact of cash transfers on environmental poverty in Pakistan and discovered that cash transfers had a negative and significant impact on environmental poverty.

However, the energy policy activism on the energy deprivation situation in the global south has taken a different tune. In essence, what is referred to as “energy poverty” implies inadequate access to modern energy services to support day-to-day life for cooking, lighting, heating and cooling. This is a result of poor access and affordability challenges regardless of whether one has a national grid connection (Phoumin and Kimura, 2019a,b). The situation is more pronounced in rural areas where a majority of the people are heavily dependent on biomass as their dominant energy source. This development is associated with both adverse health outcomes due to indoor pollution and high opportunity costs for women and children who spend most of their time on fuelwood collection (Day et al., 2016; UNDP 2005; WHO, 2004; Nankhuni and Findeis, 2003). Therefore, this paper carried out an inter-indicator analysis to examine the state of energy poverty in Rwanda. It has used what has been termed as a ‘modified’ expenditure-based approach compared to a multidimensional analysis (Household Energy Poverty Index) approach, as postulated by Phoumin and Kimura (2019a,b) and Gupta et al. (2020), respectively, from a global south country perspective.

As a matter of brief background, Rwanda offers an interesting case study because it is making remarkable progress in terms of the universal provision of electricity to its citizens. However, it seems to lag in terms of access to clean fuels and technologies for cooking. Using microdata from the World Bank, Figures 1 and 2 highlight access to clean fuels and technologies for cooking purposes (percentage of population) as well as in terms of access to electricity (percentage of population) in Rwanda, respectively. This is in comparison to its neighbouring countries, such as Kenya, which registered considerable increases in the past decade, and Burundi, which is lagging. However, the countries’ economic growth trends of GNI per capita in purchasing power parity (PPP) terms appear to be similar, as shown in Figure 3. From Figure 3, a sharp increase in the electricity access rate for Rwanda may partly be attributed to the rolling out of the Rwandan Electricity Access Role-Out Program (EARP), which was intended to boost the electrification rate in the country from six percent in 2009 to 70% in 2017. The national Rwanda Energy Group (REG) was responsible for the implementation of EARP and is also the national entity responsible for the generation of electricity, transmission and distribution, and connection activities to customers. In terms of supply, the country managed to increase the installed electricity generation capacity from 69.5 MW in 2007 to 188 MW in 2016 (REG, 2016; REG, 2019).
A recent review of the literature from the global north on this topic, early on in previous years, focused on affordability challenges that are usually encountered by energy-inefficient low-income households. These are households that experience a cold climate and usually suffer from hospitalizations and excess winter deaths (Pye et al., 2015; O’Sullivan et al., 2012). As such, much policy activism in the global north was initially narrowed down to the offering of relief in the form of direct payments to vulnerable groups such as the elderly and pensioners. Relief was also extended to poor households that lived, mostly, in energy-insufficient homes, based on the “low-incomes/high-costs” definition, mainly for social inclusion purposes (Simcock and Walker, 2015; Hills, 2011; McAvoiy et al., 2007).

Furthermore, the UNAGECC went to an extent of putting a universal threshold of 1200 kilowatt-hours (KWh) per person per year to depict the total amount of energy required by a household to ensure a minimum acceptable level of consumption (UNAGECC, 2010). Modi et al. (2005) also proposed another measure of 9–58.15 KWh, which is equivalent to 50 kg of oil equivalent (Kgoe) per person per year for cooking and lighting, as a benchmark for low-income countries. This is slightly different from the 8140.6 KWh proposed by Mirza and Szirmai (2010), which would be deemed an acceptable threshold to realize a 0.8 level on the Human Development Index (HDI). Sambodo and Novandra (2019) defined energy-poor households as those households that consumed electricity below 32.4 KWh per month. They constituted households that used solar panels with a 20-W peak and four light-emitting diodes. Due to data limitations, this study could not manage to have such extended analysis.

There is a growing body of literature on energy poverty quantification to assess its prevalence and associated determinants. An early study in Guatemala by Forster et al. (2000), a developing country context, employed a survival mode approach that used 2125 Kwh per year as a cut-off point to classify an energy-poor household. Pérez-Fargallo et al. (2018) developed an index that captures an adaptation mechanism towards comfort in utility payments. In his study of energy poverty in Chile, the aim was to gauge the risks associated with fuel poverty in a climate change context. Ogwumike and Ozugah (2016) used a simple multidimensional energy poverty index to study Nigerian energy poverty, and empirical evidence showed that 75% of the population was energy poor. In addition, some of the determining factors were household size, education level, gender and age of household head, general poverty, region of residence and proportion of working members in the household. Nevertheless, in Nigeria, a recent study by Ashagidigbi et al. (2020) showed an average MEPI of 0.38 but still had a high energy poverty
incidence. Additionally, male-headed households, age and rural location were found to be enhancing factors for energy poverty.

In Bangladesh, Barnes et al. (2010) studied energy poverty by computing an energy poverty line (based on household minimum requirements). Evidence showed that 58% of rural households were energy-poor compared to 45% who were found to be poor using monetary poverty indicators. Ye and Koch (2020) also used the Foster-Greer-Thorbecke (FGT) approach and Energy Equivalence scale to study energy poverty in South Africa. This was considered, somehow, an energy advanced context. The findings showed that headcount energy poverty, gap and its severity were quite extreme. Furthermore, decomposition results indicated that energy poverty rates decreased with income.

Nussbaumer et al. (2012) pioneered the multidimensional energy poverty index while utilizing the Alkire-Foster methodology based on household datasets from some African countries. Empirical evidence has shown different levels of energy poverty incidences and intensity levels. For instance, countries such as Angola, Egypt, Morocco, Namibia and Senegal had moderate energy poverty with MEPI less than 0.6, while others [Ethiopia with MEPI greater than 0.9 & Nigeria with MEPI greater than 0.75] had acute energy poverty based on the multidimensional measure.

Sher et al. (2014) studied energy poverty at the province level based on the Alkire-Foster methodology to measure multidimensional energy poverty in Pakistan. The results showed different levels of multidimensional energy poverty incidences that ranged between 47% and 69% across the four studied provinces. The existing literature shows that there is still limited scope and coverage on the estimation of energy poverty in most countries. This is the case because energy poverty has been investigated mainly from an accessibility or affordability perspective while using either a unidimensional or multidimensional approach. Phoumin and Kimura (2019) quantified energy poverty incidence in Cambodia. Their study reported a high incidence of energy poverty of 50% or above throughout the provinces in Cambodia compared to 33% as a nationwide energy poverty incidence.

Last, Castano Rosa and Okushima (2021) developed a new multidimensional approach based on the energy poverty vulnerability framework to examine contextual factors of energy poverty in Japan. The results showed that seasonality and contextual factors (including location, infrastructure availability, area density and household features) played a key role in propagating the risk of energy poverty vulnerability. A brief overview of the energy poverty literature is presented in Table 1.

Different authors have carried out energy poverty studies with clear differences. The differences are in terms of quality as well as scope, coverage and theoretical framework base. As a way of contributing to the body of literature, this study is based on the newly developed conceptual framework for energy poverty vulnerability (Castano-Rosa and Okushima, 2021). This conceptual framework was birthed to address the need to design effective measures for energy poverty in an effective and consistent way. Lessons were drawn from empirical work based on past experiences in Europe and a deep inquiry to the background factors of energy poverty that have been termed “energy poverty vulnerabilities (EP vulnerabilities).” The term “EP vulnerabilities or EP vulnerability factors” has been coined to imply a set of contextual drivers or conditions that may propagate an energy poverty situation (Bouzarovski and Petrova, 2015; Bouzarovski, 2018; Castano-Rosa and Okushima, 2021). It is an extended pioneering work of multiple indicators that focused on six key drivers of energy poverty, namely, access, affordability, flexibility, energy efficiency, needs and practices (Castano-Rosa et al., 2019). The EP vulnerability framework consists of 12 vulnerability factors of energy poverty, originally studied in the Japanese context and is also very pertinent to developing countries such as Rwanda. This framework hinges on 3 pillars of affordability, accessibility and new technologies, which are intricate and interconnected at different levels, as depicted in Figure 4.

Therefore, this paper adopts an inter-indicator approach to examine the incidences of energy poverty. The approach serves to obtain insight

Table 1. A highlight of energy poverty studies in the literature.

| Source | Energy poverty indicator/method | Data and period | Findings |
|--------|---------------------------------|----------------|----------|
| Ye and Koch (2020) | Used the Foster-Greer-Thorbecke (FGT) approach and Energy Equivalence scale | South Africa Living Conditions Survey (LCS) 2014/2015 consisting of 22292 households | Results revealed extensive energy poverty whilst decomposition results showed that energy poverty rates decreased with income |
| Foster et al. (2000) | Used the Foster-Greer-Thorbecke (FGT) approach and Energy Equivalence scale (an energy poverty line equivalent to 2125 kilowatt-hours per year Used the Foster-Greer-Thorbecke (FGT) approach and Energy Equivalence scale (an energy poverty line equivalent to 2125 kilowatt-hours per year | Used Guatemala household dataset | One-fourth of the population with electricity access was fuel poor |
| Owumike and Ougbunu (2016) | Utilized multiple-dimensional multidimensional energy poverty index | Used Nigeria Living Standard Survey data set of 2004 | 75% of the population were energy poor & determinants of energy poverty were household size, education level, gender and age of household head, general poverty, region of residence and proportion of working members in the household |
| Barnes (2010) | Used energy poverty line (based on household minimum requirements) | Cross sectional data set based on a 2004 survey of 2300 households in rural Bangladesh | 58% percent of the rural households were energy poor |
| Nussbaumer et al. (2011,2012) | Pioneered the multi-dimensional energy poverty index by utilizing Alkire-Foster methodology | Datasets Data sets from some African countries (Angola, Morocco, Namibia, Senegal, Ethiopia) | Countries such as Angola, Egypt, Morocco, Namibia and Senegal had moderate energy poverty with MEPI < 0.6 whilst others (Ethiopia with MEPI >0.9 & Nigeria with MEPI >0.75 had acute energy poverty) |
| Sher et al. (2014) | Used the Alkire-Foster methodology to measure multi-dimensional energy poverty in Pakistan provinces | Multi-dimensional energy poverty incidence varied with a minimum of 47% to as high as 69% across the provinces |
| Ashagidigbi et al. (2020) | Utilized multi-dimensional energy poverty index | Nigerian National Demographic Health Survey data | Majority of the households were energy-poor with an average MEPI of 0.38 |
| Phoumin and Kimura (2019) | Used an energy expenditure and modern cooking energy access approach | Latest 2015 Cambodia socioeconomic survey dataset (CSES 2015) | High Energy poverty incidence which was linked to type of fuel used and low consumption of unaffordable clean energy by the household |
| Castano Rosa and Okushima (2021) | used new multi-dimensional approach based on energy poverty vulnerability framework to examine contextual factors of energy poverty | 2013-2017 Family Income and Expenditure Survey dataset | Seasonality and contextual factors (including location, infrastructure availability, area density and household features) influence risk of energy poverty vulnerability |
into EP vulnerabilities in Rwanda and draw empirical lessons to inform the public policy discourse. Ultimately, this will help to design and implement timely effective development interventions that can deal with issues related to energy poverty. In particular, this study investigated some little-known (unexposed) issues in energy poverty within a developing country context. These include regional gaps in terms of access to new modern energy services such as LPG (Chapman and Okushima, 2019). For instance, an exploratory study on cooking fuel choices in urban Rwanda found that fuelwood still dominates in poor households, while charcoal as a transitional fuel remains the most dominant primary cooking fuel not only for the middle class but also for the richest households (Khundi-Mkomba, 2021). Regarding policy implications, the paper also discussed the need to promote an all-inclusive approach. This may involve using welfare policy instruments such as energy access schemes to be implemented under public-private partnerships, especially in the most energy-deprived provinces. Some households may be disadvantaged because they reside in areas where new technologies such as solar or LPG may not be available or not accessible.

Finally, based on the cited literature (Table 1), the exogenous variables that were considered in the multilevel binary logistic regression models in the methodology section came out clear. They comprised household features such as household size; socioeconomic status computed based on income poverty, number of elderly individuals and number of children; rural/urban location; region dummies and others. Analyses were performed using Stata 15 statistical software. The results were interpreted at a 5% level of statistical significance.

3. Data and methodology

The study utilized the household responses of the 2016/2017 EICV5 survey, conducted over 12 months between October 2016 and October 2017 (National Institute of Statistics of Rwanda, 2018). EICV 5 is a nationally representative sample built on previous household living condition surveys that started in 2001, known by its French acronym of “Enquête Integrals Les Conditions de Vie des Ménages (EICV1)” and is done on a regular basis. The EICV5 dataset used in this study was obtained from the National Institute of Statistics of Rwanda web portal, whose use and sharing are released under Creative Commons Attribution 4.0 International (CC BY 4.0) licence. The use of the survey data was authorized electronically by the National Institute of Statistics of Rwanda and World Bank, who are the data custodians.

The National Institute of Statistics of Rwanda used a national master sampling frame that was used for selecting the sample villages in each district. Within each district, the sample villages are selected systematically, with probability proportional to size (PPS), where the measure of size was based on the number of households in each village from the 2012 Census frame and other details are found in the survey report by the National Institute of Statistics of Rwanda (National Statistics Institute of Rwanda, 2018). A sample of 14458 households was used for this study, while others were excluded from the statistical analysis because of missing information. The sample questionnaire covered all of the households’ earnings and expenditures. It also captured dwelling characteristics and housing conditions. Since the focus of this paper is to examine the status of energy poverty in Rwanda using a cross-indicator approach, Table 2 highlights a list of indicators and their definitions based on the current literature to capture the energy status of a household. The next subsection presents detailed procedures in terms of the construction of the household energy poverty index scores.

3.1. Measuring energy poverty using a multidimensional approach

A total of eleven indicators that were categorized based on four dimensions were used to construct a household energy poverty index, following Gupta et al. (2020) and Gupta (2008). This is attributed to the fact that energy poverty is a complex phenomenon that has no universal definition at the moment. As a result, several definitions have been used in the literature to describe this phenomenon. The four broad dimensions consist of the following: (i) ownership of electrical appliances, which depicts the status quo in terms of living standards and possible future electricity demand as previously reported in the literature (Gertler et al., 2016); (ii) communication modes depicted by ownership of mobile phones (Sadath and Acharya, 2017); (iii) indoor pollution indicator, depicted by primary cooking and lighting fuel usage (Lin and Zhao, 2021); and (iv) per capita consumption of electricity and liquefied petroleum gas (LPG), as a measure of the intensity of using clean fuels (Gupta et al., 2020). The eleven indicators were combined to obtain household energy poverty index scores using the weights that were calculated via principal component analysis (PCA). PCA is a statistical analysis tool that deals with the problem of dimensionality within a dataset by transforming it. PCA is increasingly being used to construct multidimensional energy poverty indices in the current literature (Lin and Zhao, 2021; Gupta et al., 2020; Salari and Javid, 2017; Obeng et al., 2008). As part of a requirement to construct the index using the PCA, two indicators, namely, per capita consumption of LPG and per capita consumption of electricity, were normalized to take on a “0” to “1” scale whereby “0” depicts the lowest energy poverty indicator while “1” depicts the highest value of the assigned indicator with the highest energy poverty level. The remaining nine variables were already in a normalized state because there were dummy variables. The normalization formula was expressed as follows (equation 1):

\[ x_{mn} = \frac{\text{MAX}(X_n) - X_{mn}}{\text{MAX}(X_n) - \text{MIN}(X_n)} \]  

where \( m \) = per capita consumption of LPG and per capita consumption of electricity. Thereafter, there was the need to perform a PCA test to determine whether the data used in the study were feasible to carry on with the PCA method. As such, the Kaiser-Meyer-Olkin (KMO) test, used to measure sampling adequacy (MSA) for each variable, and the Bartlett sphericity test, were used to assess whether PCA was feasible. The KMO value was 0.80, indicating that sampling was suitable for PCA. On the other hand, the results from the MSA measure showed that the sampling adequacy for this study was within the acceptable threshold. The probability from the Bartlett test of sphericity was 0.000, which implies that PCA could be used to obtain the weights of the individual indicators in this study.
Table 2. List of indicators used in the HEPIn.

| Indicator                  | Definition                                                                 | Relationship to energy poverty | Source                  |
|----------------------------|---------------------------------------------------------------------------|--------------------------------|-------------------------|
| No Radio                   | A dummy variable (1 – does not have and zero otherwise)                   | Positive                      | Sher et al. (2014)      |
| No Television              | A dummy variable (1 – does not have and zero otherwise)                   | Positive                      | Nussbaumer et al. (2012) |
| No Computer                | A dummy variable (1 – does not have and zero otherwise)                   | Positive                      | Bekele et al. (2015)    |
| No Fan                     | A dummy variable (1 – does not have and zero otherwise)                   | Positive                      | Bekele et al. (2015)    |
| No Laundry machine         | A dummy variable (1 – does not have and zero otherwise)                   | Positive                      | Gupta et al. (2020)     |
| No Refrigerator            | A dummy variable (1 – does not have and zero otherwise)                   | Positive                      | Sher et al. (2014)      |
| No Mobile phone            | A dummy variable (1 – does not have and zero otherwise)                   | Positive                      | Gupta et al. (2020)     |
| No clean cooking fuel      | A dummy variable (1 – uses traditional fuels and zero otherwise)         | Positive                      | Sher et al. (2014)      |
| No clean lighting fuel     | A dummy variable (1 – uses traditional fuels and zero otherwise)         | Positive                      | Nussbaumer et al. (2012) |
| Per capita LPG consumption | Annual Consumption of LPG (RWF) by the household divided by household size| Negative                     | Gupta et al. (2020)     |
| Per capita electricity consumption | Annual Consumption of electricity (RWF) by the household divided by household size | Negative | Gupta et al. (2020)     |

As part of a step-by-step process of the PCA procedure, an 11x11 matrix of correlation between these variables was calculated (has not been presented here for brevity purposes but is available upon request). Thereafter, a determinant equation (equation 2) that was calculated is expressed as

\( (R - \lambda_i F_i) F_i = 0 \)  

(2)

where \( F_i = [f_1 f_2 f_3] \) is an eigenvector corresponding to \( \lambda_i \). This highlighted all the relevant eigenvectors, especially those relevant to each of the three selected eigenvalues since consideration was only to those with roots, which were greater than 1 in this paper.

Regarding the computation of the principal components (equation 3), this was done as follows:

\[ P_{n1} = x_n F_1 \]
\[ P_{n2} = x_n F_2 \]
\[ P_{n3} = x_n F_3 \]

where \( n \) depicts the \( n \)th household and \( x_n \) is the vector of variables for the \( n \)th household. Therefore, \( x_n = [x_{1n} x_{2n} x_{3n} x_{4n} x_{5n} \ldots x_{10n} x_{11n}] \). As such, the Household Energy Poverty Index (HEPIn) for household \( n \)th is just a weighted sum of principle components, whereby the weights are the variance in the successive components, as depicted in equation 4 and equation 5 (Gupta et al., 2020; Gupta, 2008).

\[ HEPIn = \frac{\lambda_1 P_{1n} + \lambda_2 P_{2n} + \lambda_3 P_{3n}}{\lambda_1 + \lambda_2 + \lambda_3} \]  

(4)

3.2. Measuring energy poverty using a “modified” expenditure-based approach

Following Phoumin and Kimura (2019a,b), this study employed a modified expenditure-based approach. It combined two criteria to obtain the probability function for a household to be energy-poor to suit a developing country context. The first approach captured aspects of accessibility and affordability by taking into consideration different levels of household income and energy expenditure patterns that reflect the income quintile category to resource allocation for the basic needs basket. The second approach places more weight on energy use to capture the element of accessibility to modern energy services for cooking. This is a common challenge in developing countries, as the majority of people rely on biomass or, in some cases, they even combine biomass with other clean energy sources such as LPG. Therefore, a household was categorized as energy-poor based on qualifiers, which include the fact that (a) its per capita expenditure was in the bottom quintile; (b) its per capita expenditure was in the third or fourth quintile but had a per capita energy expenditure greater than 10% of the total household expenditure; and (c) it used biomass as the main cooking fuel.

The mathematical expression is as follows (equation 6):

\[ P(Y_i = 1) = f(Y_i = 0_l) + f(Y_i = \{0_2, 0_3, 0_4\} & S > 10\%) + f(Y_i = W_l) \]  

(6)

\[ P(Y_i = 0) \] if the household is non-energy poor.

where \( 0_1, 0_2, 0_3, 0_4 \) represents the per capita household expenditure quintile group; \( S \) is the share of the energy expenditure to total household expenditure; and \( W_l \) captures whether households used biomass as the main cooking fuel. \( f(.) \) is an indicator function that may take a value of 1 if the expression in the brackets holds and a value of 0 if the expression does not hold. It depicts that when \( Q(.) \) takes the value of 1, then that household is energy poor, while the value of zero means otherwise. Therefore, mathematically, the household incidence of energy poverty (EP) is formulated as follows (equation 7):

\[ EP = \frac{1}{N} \sum_{i=1}^{N} \{f(Y_i = 0_l) + f(Y_i = \{0_2, 0_3, 0_4\} & S > 10\%) + f(Y_i = W_l)\} \]  

(7)

3.3. Assessing the determinants of energy poverty among Rwandan households

This study employed a multilevel binary logistic regression to assess factors associated with energy poverty. This type of regression was most preferred because it was meant to ensure correct estimation of the standard errors and to account for the nested structure of the survey data whereby households were nested in districts. In addition, binary regression was also necessary because the dependent variable was dichotomous, taking a value of 1 if a household was falling in a specific energy poverty class and zero if the case was otherwise. Four multilevel binary logistic regression models were estimated since there were four energy poverty groups from the Household Energy Poverty Index scores, namely, the least energy-poor, the less energy-poor, the more energy-poor and the most energy-poor (each group was estimated separately). The fifth model was estimated following the results from the second approach.

3.3.1. A multi-level binary logistic regression model

Following Mulaga et al. (2021), Crowson (2020), and Sommet and Morselli (2017), suppose \( HEP_{ij} \) is the energy poverty status class for the \( i \)th household in district \( f_{ij} \), \( P_{ij} \) is the probability of falling in a particular energy poverty class and \( X_{ij} \) represents household-level characteristics. Now, also that \( HEP_{ij} \) follows a binomial distribution \( (HEP_{ij} \sim Bin(1, P_{ij})) \) based on some of the statistical tests (using qnorm command and symplot
Stata statistical software commands). Hence, the probability of household energy poverty incidence was modeled via a logit link function, and the random intercept model was formulated as follows (equation 8):

$$
\text{logit} \left( P_{ij} \right) = \beta_0 + \beta X_{ij} + \mu_j
$$

where $\beta$ is a vector of fixed effects regression coefficients linked to household-level characteristics ($X_{ij}$); $\mu_j$ is the district-level error term that captures unobserved district-level effects.

4. Results and discussion

4.1. Descriptive analysis

4.1.1. Household energy expenditures situation

Table 3 highlights the disaggregated household expenditures data by location and socioeconomic status (income poverty status). Per capita expenditures for LPG and electricity are high for urban households and for nonpoor households. Both LPG and electricity are considered clean fuels that offer great potential to reduce indoor pollution. Rural households seem to have higher per capita expenditures on kerosene and fuelwood, which are considered dirty fuels, than their urban counterparts. It is also interesting to note that some non-poor households have higher per capita expenditures on kerosene and fuelwood than their poor counterparts. Unfortunately, there seems to be a remarkable difference in terms of access and affordability of clean fuels for both lighting (Figure 5) and cooking (Figure 6) in Rwanda. Per capita total consumption and per capita energy expenditures (Table 3) for rural households are very low as compared to their urban counterparts. Both LPG and electricity are considered clean fuels, whereas kerosene and fuelwood are considered dirty fuels. It is also interesting to note that some non-poor households have higher per capita expenditures on kerosene and fuelwood than their poor counterparts.

4.1.2. Energy poverty incidences under a multidimensional approach

To obtain a thorough understanding of the energy poverty status, the partitioning cluster analysis technique (cluster median) was employed to group the household energy poverty index scores into four different classes: least energy-poor, less energy-poor, more energy-poor, and most energy-poor (Figure 7). Partitioning cluster analysis allows each observation to be assigned to a cluster whose mean, or if using the “cluster mean” or median, if using the cluster median, is closest to the observation value, and new classes are established following this technique. Although this technique is interesting, it fails to capture the presence of neutrality, as is the case with other common Likert scales. Despite this shortcoming, this method is still being applied to energy poverty studies (Gupta et al., 2020). The results from this multidimensional analysis show that the most energy-poor households are concentrated in southern (30.15%), western (27.69%) and northern (24.86%) provinces.

4.1.3. Energy poverty incidences under a “modified” expenditure-based approach

Using the modified expenditure-based approach, the data show that energy poverty is highly concentrated in rural areas, with high incidences in the southern (51.13%), western (41.61%) and northern (40.7%) provinces, based on the first energy poverty measure, as highlighted in Figure 8.

4.1.4. Selection of the independent variables for assessing determinants of energy poverty

The inclusion of some of the independent variables was based on the existing literature (Table 4) regarding determinants of energy poverty (Castano-Rosa and Okushima, 2021; Ashagidigbi et al., 2020; Phoumin and Kimura, 2019a,b; Bouzarovski, 2018; Ogwumike and Ozughalu, 2016; Bouzarovski and Petrova, 2015). These variables comprised household demographics such as age, gender, household size, income poverty status, presence of elderly members, presence of children, rural-urban residence and the region in which the household lives. Data analysis was performed using the Stata 15 statistical software package. The results were interpreted at a 5% level of statistical significance.

4.2. Determining factors associated with energy poverty under an expenditure-based approach

Table 5 and Table 6 show the results from multilevel binary logistic regression models to investigate factors that determine energy poverty status. For brevity purposes, the discussion focuses only on the significant variables at a 5% level of statistical significance across all five models. The district-level random effects from model 1 were significant, suggesting some variations in the incidences of energy poverty across districts. District-level random effects in model 1 explained 16% of the variation with an indication of substantial clustering with an intraclass correlation coefficient of 0.05. This is the same as the conventional threshold of 0.05, which indicates substantial evidence of clustering (Heck et al., 2014). However, district-level random effects explained 7% of the variation in Model 2, 2% of the variation in Model 3, 3% of the

Table 3. Disaggregated energy consumption (mean values) situation in Rwanda 2016/2017.

| Urban vs Rural | Consumption non-poor vs poor |
|---------------|-----------------------------|
| Urban | Rural | Non-poor | Poor |
| LPG expenditure/capita (RWF) | 1644.06 | 67.02 | 502.06 | 0.00 |
| Electricity expenditure/capita (RWF) | 7914.04 | 695.99 | 2805.30 | 153.64 |
| Kerosene expenditure/capita (RWF) | 189.50 | 253.35 | 289.45 | 148.96 |
| Charcoal expenditure/capita (RWF) | 21227.87 | 2180.91 | 7918.70 | 407.25 |
| Wood expenditure/capita (RWF) | 1266.83 | 1782.85 | 2277.51 | 534.61 |
| Candles expenditure/capita (RWF) | 722.79 | 301.78 | 465.99 | 188.03 |
| Energy expenditure/capita (RWF) | 32679.21 | 5228.39 | 14125.41 | 1420.68 |
| Total consumption/capita (RWF) | 846479.40 | 264672.30 | 483586.60 | 123459.50 |

Source: Author’s computations using EICVS.

Figure 5. Main lighting fuel sources (%).
variation in Model 4 and 9% of the variation in Model 5 without substantial clustering.

Some factors were associated with the status of energy poverty. From Model 1, the results showed that household sizes increased the odds of incidences of energy poverty (OR = 0.95, CI = 0.93–0.97); (OR = 1.10, CI = 1.07–1.13) under Model 2; (OR = 0.89, CI = 0.87–0.91) under Model 3; (OR = 0.94, CI = 0.92–0.97) and (OR = 0.97, CI = 0.91–1.03) under Model 4.

Furthermore, households that were rural-based had 5.32 times more odds of energy poverty incidences (OR = 5.32, CI = 4.39–6.44) than their urban counterparts under Model 1. The other models showed varying odds ratios as follows: Model 2 (OR = 0.29, CI = 0.25–0.34); Model 3 (OR = 2.58, CI = 2.22–3.01); Model 4 (OR = 2.98, CI = 2.51–3.54) and Model 5 (OR = 2.30, CI = 1.56–3.40). Several reasons explain this result. For instance, Roberts et al. (2015) noted that the strong linkage of rural locations and energy poverty is a result of limited consumption of clean energy fuels due to low populations, low densities and demand levels, and the possibility of high line losses.

Likewise, being income poor (OR = 2.03, CI = 1.86–2.22 under Model 1; (OR = 0.34, CI = 0.30–0.40) under Model 2; (OR = 2.14–2.59) under Model 3; (OR = 1.25, CI = 1.12–1.39) under Model 4; (OR = 1.48, CI = 1.19–1.84) increased the odds of energy poverty incidences. This result resonates well with that of Ashagidigbi et al. (2020), who, in a Nigerian study, found that low-income households depended much on biomass fuels, partly because, sometimes, it is accessed free of charge. A previous study by Anker and Anker (2017) also found a similar result in Kenya. Additional empirical evidence from Poland by Sokolowski et al. (2020) and Rutkowski et al. (2018) showed similar results whereby disparities were established between income and energy
poverty. For instance, Sokolowski et al. (2020) found that households affected by multidimensional poverty were, potentially, in the worst situation in terms of satisfying their energy needs. Specifically, the overlap between income and multidimensional energy poverty was the largest among farmers who form a large part of the rural population in developing countries. Similar explanations also apply to the asset variable, which was found to be significant across all the models.

Last, being in Kigali, as a place of residence, has both advantages and disadvantages. This is the case because the results showed varying odds ratios of energy poverty incidences. Likely, the urban poor find it difficult to afford clean fuels, while the affluent find it easy to access all types of modern energy services.

Table 4. Descriptive statistics of the variables.

| Variables        | Definition                                                                 | Mean  | SD   |
|------------------|----------------------------------------------------------------------------|-------|------|
| Education        | Education of household (1 = has formal education)                          | 0.77  | 0.42 |
| Household size   | Household size (total number of persons)                                   | 4.43  | 2.11 |
| Age              | Age of household head (years)                                              | 45.24 | 15.62|
| Poor             | Income poverty status (1 = yes)                                            | 0.33  | 0.47 |
| Gender           | Gender of household head (1 = male head)                                   | 0.74  | 0.43 |
| Rural            | Rural location (1 = yes)                                                   | 0.83  | 0.37 |
| Marital status   | Household head is married (1 = yes)                                        | 0.64  | 0.48 |
| Debt             | Presence of any household member who has debts (1 = yes)                  | 0.66  | 0.47 |
| Land ownership   | Land ownership by any household member (1 = yes)                          | 0.82  | 0.38 |
| Education        | Off-farm participation by any household member (1 = yes)                  | 0.38  | 0.49 |
| Enpoclass1       | Household classified as least energy-poor                                  | 0.27  | 0.45 |
| Enpoclass2       | Household classified as less energy-poor                                   | 0.27  | 0.44 |
| Enpoclass3       | Household classified as more energy-poor                                   | 0.26  | 0.40 |
| Enpoclass4       | Household classified as most energy-poor                                   | 0.24  | 0.43 |
| Enpo (2nd approach) | Household classified as energy-poor                                      | 0.39  | 0.49 |
| Province         | Household located in Kigali – 1, southern – 2, Western – 3, Northern – 4, Eastern – 5 | 3.15   | 1.33 |

Table 5. Multilevel binary logistic regression for energy poverty status under the expenditure approach.

| Independent variables | Model 1 (Energy poor) | Model 2 (Least energy poor) | Model 3 (Less energy poor) | Model 4 (More energy poor) | Model 5 (Most energy poor) |
|-----------------------|-----------------------|-----------------------------|-----------------------------|----------------------------|-----------------------------|
| Odds ratio            | (95% CI)              | Odds ratio                  | (95% CI)                    | Odds ratio                 | (95% CI)                    |
| Land ownership        | 1.67 (1.46-1.92)      | 1.12 (0.99-1.28)            | 1.47 (1.26-1.71)            | 1.10 (0.81-1.50)           | 1.71 (1.46-2.00)            |
| Education             | 0.80 (0.72-0.88)      | 0.78 (0.71-0.86)            | 0.95 (0.85-1.07)            | 0.79 (0.63-0.99)           | 0.99 (0.91-1.07)            |
| Age                   | 1.01 (1.00-1.01)      | 1.11 (1.02-1.21)            | 1.30 (1.27-1.32)            | 1.48 (1.19-1.84)           | 1.29 (1.10-1.51)            |
| Income poverty        | 2.03 (1.86-2.22)      | 1.17 (1.15-1.18)            | 1.30 (1.27-1.32)            | 0.84 (0.69-1.05)           | 1.20 (1.01-1.41)            |
| Asset value (logarithms) | 0.90 (0.89-0.91)   | 0.99 (0.97-0.99)            | 0.94 (0.92-0.97)            | 0.91 (0.91-1.03)           | 0.97 (0.91-1.03)            |
| Debt                  | 0.88 (0.80-0.96)      | 0.73 (0.63-0.84)            | 0.95 (0.86-1.05)            | 0.85 (0.69-1.05)           | 1.05 (0.77-1.43)            |
| Rural                 | 5.32 (4.39-6.44)      | 1.52 (1.29-1.80)            | 2.98 (2.51-3.54)            | 2.30 (1.56-3.40)           | 0.99 (0.81-1.10)            |
| Household size        | 0.95 (0.93-0.97)      | 1.08 (0.94-1.23)            | 0.95 (0.81-1.10)            | 0.86 (0.64-1.17)           | 0.99 (0.85-1.15)            |
| Kigali                | 1.20 (0.10-0.37)      | 1.06 (0.86-1.29)            | 1.08 (0.87-1.34)            | 0.65 (0.41-0.99)           | 0.90 (0.73-1.10)            |
| Western               | 0.95 (0.62-1.46)      | 0.73 (0.63-0.84)            | 0.96 (0.86-1.05)            | 0.85 (0.69-1.05)           | 0.95 (0.73-1.21)            |
| Southern              | 1.56 (1.03-2.36)      | 1.09 (0.90-1.33)            | 1.20 (0.97-1.48)            | 0.63 (0.42-0.96)           | 0.88 (0.80-0.96)            |
| Northern              | 0.97 (0.60-1.54)      | 0.96 (0.77-1.20)            | 1.05 (0.80-1.34)            | 0.67 (0.41-1.07)           | 1.00 (0.86-1.17)            |
| Constant              | 0.11 (0.08-0.17)      | 0.10 (0.07-0.13)            | 0.01 (0.00-0.01)            | 11.05 (5.71-21.39)         | 0.07 (0.04-0.13)            |
| District level random effects | 0.07 (0.04-0.13)       | 0.02 (0.01-0.05)          | 0.03 (0.01-0.06)          | 0.09 (0.04-0.23)          | 0.16 (0.08-0.28)          |

Note: * shows statistical significance at 95% confidence interval and confidence intervals are presented in the brackets.

5. Conclusion and policy lessons

This paper has examined the status of energy poverty in Rwanda by adopting an ‘inter-indicator analytical approach’. The first approach involves the multidimensional measure of energy poverty using eleven indicators of energy deprivation. Each indicator was assigned a weight using principal component analysis to form a household energy poverty index. On the other hand, the second approach employed a ‘modified’ expenditure-based approach that emphasizes affordability and accessibility by taking into consideration different levels of household income and energy expenditure patterns. These two household characteristics reflect the income quintile category of resource allocation for basic needs baskets and the use of biomass as cooking fuel. These energy poverty measures were applied to Rwandan Integrated Household Living Conditions Survey (EICVS) data for 2016–2017.

The results from the multidimensional analysis show that the most energy-poor households are concentrated in southern (30.15%), western (27.69%) and northern (24.86%) provinces, while the least energy-poor households are mostly found in urban areas. A cross-
comparison with the results from the ‘modified’ expenditure-based approach (2nd approach in this paper) showed a high magnitude of energy poverty incidences but a similar trend in terms of the concentration of energy poverty. Specifically, under the second approach, energy poverty was highly concentrated in rural areas and had high incidences in the southern (51.13%), western (41.61%) and northern (40.7%) provinces. Furthermore, a multilevel binary logistic regression model was used to investigate factors that determine the incidence of energy poverty. The district-level random effects of the multilevel binary logistic regression models were all significant, indicating that there were some differences regarding energy poverty status across districts. District-level random effects accounted for 16% of the variation in the incidences of energy poverty, with substantial clustering in the districts under the modified expenditure approach (Model 1), while the rest of the models showed a minimal variation of less than 10% and did not show substantial clustering. In addition, other factors, such as household size, income poverty, education level of the household head, rural location and being a Kigali resident, also determine energy poverty.

Drawing policy lessons, the study findings suggest the need to focus on the heterogeneity of energy poverty groups by adopting welfare state policy instruments. For instance, the government, in collaboration with nongovernmental organizations and other private stakeholders, may introduce energy local funds for implementing energy access schemes. These schemes may be accessed within groups under the umbrella of community financial group savings and loans revolving funds. This may address the challenges of affordability and accessibility for vulnerable groups that cannot afford the individual ‘pay as you go’ schemes in the country. In addition, the government should consider prioritizing and intensifying decentralized energy projects (i.e., through mini-grids depending on the local resources) in the three provinces that have high energy poverty incidences.

Further research needs to be carried out to examine the role of energy efficiency and energy prices and other subjective measures that also influence energy poverty while using consensual approaches. The consensual approach is based on self-reported assessments and is useful to address the limitation of using the PCA tool in this study. This current investigation was limited by the unavailability of relevant information in the dataset. As such, future research in this field would be of great help in addressing these limitations.

Declarations

Author contribution statement

Fydess Khundi-Mkomba: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Akshay Kumar Saha & Umaru Garba Walli: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

The authors do not have permission to share data. The data can be accessed upon special request from the National Institute of Statistics of Rwanda (http://www.statistics.gov.rw).

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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