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Identifying and assessing the global causality among energy poverty, educational development, and public health from a novel perspective of natural resource policy optimization

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ABSTRACT

With the gradual depletion of natural resources and the rapid development of renewable energy, reducing energy poverty will inevitably have a crucial impact on public health and educational development. However, the long-term cointegration link and the two-way causality among them at the global level, especially in developing countries, remain a black box, which was the initial incentive for this study. Based on annual panel data from 50 developing countries between 2000 and 2017, this study initially adopted second-generation unit root and cointegration tests to eliminate pseudo-regression. It then utilized impulse response function and Granger causality test to clearly demonstrate causality and its direction. In emerging economies and nations with high energy poverty rates, public health is positively influenced by educational development. In contrast, in non-emerging economies and countries with lower energy poverty rates, public health is negatively influenced by educational development. Thus, it is important to optimise natural resource policies to suit the local conditions. In summary, our empirical findings have implications for decreasing energy poverty, promoting educational development, and improving public health in developing countries; and for their natural resource policy formulation, especially in the post COVID-19 pandemic era.

1. Introduction

Energy availability is at the core of numerous pressing issues in the current global development context, including poverty and inequality, climate change and food insecurity, as well as health and education. Although energy is the lifeblood of civilisation, there is rampant inequality in the access to sufficient and inexpensive sources. The International Energy Agency reports that hundreds of millions of people worldwide lack access to and do not use modern energy sources. There are concerns about mitigation because of the rapidity of resource depletion and reliance on fossil fuels. The utilisation of renewable energy sources, improvements in energy efficiency, clean development mechanisms, and other similar initiatives are considered viable solutions to this issue (Irfan et al., 2023). The most widely recognized definition of energy poverty is the 'inability to cook with modern cooking fuels and the lack of a bare minimum of electric lighting to read or for other household and productive activities at sunset'. It is also defined as the inability to obtain affordable, reliable, and modern forms of energy. It is a major barrier to achieving the Millennium Development Goals (MDGs).

Achieving environmental sustainability while combating climate change and its effects has emerged as a global initiative (Bekun, 2022). The 2015 Sustainable Development Goals aim to eliminate global poverty in all forms, including energy poverty, by 2030. Energy poverty has, to some extent, threatened people's physical and mental health as well as several countries' ability to advance economically and socially. The traditional extensive growing pattern mainly relies on fossil energy consumption and is expected to lose momentum for the foreseeable future, which has naturally captured the attention of policymakers worldwide. In addition, the outbreak of the novel coronavirus disease 2019 (COVID-19) in 2020, along with the subsequent economic downturn, has intensified the pre-existing energy poverty and introduced novel experiences thereof. Coupled with the depletion of fossil resources over time, the impact of the COVID-19 pandemic, especially the

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lockdown, and the instability of the international oil market caused by the outbreak of the Russian–Ukrainian conflict, have resulted in a slowdown in world trade and changes in the use of natural resources. It was reported that the COVID-19 lockdown and the profound changes in working styles after the pandemic led to significant socioeconomic changes, which consequently affected natural resource use. Some empirical studies also show that the COVID-19 pandemic shock has made the energy, oil futures, stocks, precious metal markets, and gold prices more volatile (Atri et al., 2021; Ha, 2022; Tuna and Tuna, 2022; Hu and Jiang, 2023). Simultaneously, with the ensuing economic blockade and increased restrictions and constraints, people worldwide are struggling to meet their basic survival needs, including electricity and other forms of energy (Banerjee et al., 2021). During the initial stages of the COVID-19 pandemic, a significant number of households in the United States, approximately 2.4 million, were unable to fulfil their energy bill payments, while 1.7 million households were issued energy disconnection notices (Memmott et al., 2021). Against this backdrop, it is necessary to adopt policies that address education and energy poverty in order to advance public health.

Concerning the nexus among energy poverty, educational development, and public health, several studies have been conducted based on empirical analyses, which serve as a reference for this study. For instance, a higher rate of poor health (both physical and mental) is observed among energy-deprived populations than among non-energy-deprived households in most nations (Thomson et al., 2017a). Additionally, a decrease in general health is associated with increased energy poverty (Churchill and Smyth, 2021). In the face of increasingly serious public health issues, we need to find ways to alleviate energy poverty through global cooperation and contribute to the realisation of sustainable development. Therefore, studying the connections among energy poverty, educational development, and public health under such circumstances is urgent and practical.

Our research sheds light on the interplay between energy poverty, public health, and educational development and identifies the long-term effects of energy poverty and educational development on public health. Long-term interdependence among energy poverty, public health, and educational development in emerging nations exists as shown by several factors, the primary being that energy poverty is associated with poor health and increased medical care and pharmaceutical intake, as shown by Oliveras et al. (2020). Secondly, Apergis et al.'s (2022) empirical research provides new insights into the interaction between education and energy poverty, demonstrating a negative and statistically significant correlation there. Finally, health and education are two of the most critical factors in ensuring a prosperous future for individuals and communities, and people who obtain more education enjoy a healthier and longer life than their less-educated counterparts (Zajacova and Lawrence, 2018). Thus, we infer that energy poverty and educational development are essential for determining health outcomes.

This study also focuses on alleviating energy poverty, arguing that the fundamental problem behind energy poverty is the misallocation of natural resources, which is determined by natural resource policies. Energy poverty may worsen owing to ineffective resource policies (Li et al., 2021). The top 10 countries that consume the most renewable energy also use the most natural resources (Yu et al., 2023), thus it is necessary to identify the impact of energy poverty from the perspective of natural resource allocation. The trend of energy structure transformation is resulting in fossil energy substitution, renewable energy development, and the construction of new energy storage facilities. The investment in, design of, and management of natural resource allocation will affect the process of alleviating energy poverty. Therefore, the importance of a natural resource policy created with government support and with market mechanism at its core has been highlighted. However, in the current policy formulation process of most developing countries, there is a tendency to copy the experiences of other countries, which has caused counterproductive effects, such as overcapacity and waste of resources. Therefore, it is imperative to optimise natural resource policies to alleviate energy poverty.

To achieve the goal of optimal allocation of natural resources, this study considers natural resources, especially petroleum energy, as the starting point and integrates energy poverty, educational development, and public health in developing countries into a framework. This study is closely related to that of Banerjee et al. (2021), which analyses how energy poverty has affected the health and education outcomes in 50 developing nations between 1990 and 2017. It submits that low energy poverty is associated with improved education and health outcomes and has a significant impact on health outcomes for nations with a high rate of poverty. In contrast to Banerjee et al. (2021), we differentiate our sample and discuss the relationships among energy poverty, public health, and educational development in emerging and non-emerging economies. Compared to non-emerging economies, we believe that emerging economies have clear international advantages such as large populations, abundant resources, and massive markets. Therefore, differentiating the subsamples is important for this discussion. Another distinction between our study and that of Banerjee et al. (2021) is that we examine the long-term cointegration link and the two-way causal relationship among energy poverty, health, and education. Banerjee et al. (2021) study the one-way causal relationship of energy poverty on health and education. Various approaches have been used to examine the effects of energy poverty on health and education. However, additional research is needed to fully understand the two-way causal connections among them in developing nations, as well as their long-term cointegration link. We believe that establishing a cointegration link and a two-way causal relationship among the three is essential for optimizing natural resource policies, especially in developing countries.

The possible marginal contributions of our study are reflected in the following five aspects: first, unlike previous research that discusses the one-way causal relationship between energy poverty and public health or the unidirectional effect of energy poverty on educational development, this study examines the cointegration links among energy poverty, education development, and public health using annual panel data for 50 countries between 2000 and 2017 through the Westerlund and Edgerton (2007) cointegration test, which considers cross-sectional dependence (CSD) (Wang et al., 2021). Second, multiple econometric models are applied, such as the second-generation unit root test, Westerlund and Edgerton's (2007) cointegration test, pooled mean group (PMG) estimation, and two-way causality analysis, thereby providing a new perspective for the quantitative study of causality. Third, we discuss the long-term influence of energy poverty and educational development on public health in the entire sample and in two subsamples of emerging and non-emerging countries. Additionally, the impact of energy poverty and educational development on public health can differ among countries with different levels of energy poverty, educational development, and public health. Additionally, we build six sub-samples (High-EU and Low-EU samples, High-AYS and Low-AYS samples, and High-LE and Low-LE samples) to investigate whether the links among energy poverty, educational development, and public health differ. Finally, we explore the concept of energy poverty alleviation from the perspective of natural policy optimization, which provides policy guidance for developing countries to alleviate energy poverty. In summary, the results of our empirical research have significant implications for reducing energy poverty, facilitating educational progress, and enhancing public health in developing nations. These findings can provide guidance for the development of natural resource policies in developing countries, particularly during the post COVID-19 pandemic era.

The remainder of this paper is organized as follows: section 2 presents the content of relevant literature. Section 3 introduces the methodology and explains how it is employed in this study in a scientific way. Section 4 presents the outcomes of the empirical analysis, which examines the relationship between the variables, formulates conclusions, compares them with prior conclusions, and identifies the differences. Finally, section 5 concludes the paper, provides research inferences, and suggests countermeasures and policies.

2. Literature review

The existing literature can be divided into three broad categories: energy poverty and educational development, energy poverty and public health, and educational development and public health. However, the cointegration link and two-way causality among energy poverty, public health, and educational development have received little attention despite evidence suggesting that different types of energy poverty significantly affect the other two variables at the individual, regional, and international levels (Banerjee et al., 2021; Grimm et al., 2015; Bonan et al., 2017; Ahmad et al., 2014).

2.1. Energy poverty and educational development

In recent years, research on energy poverty has mainly focused on its one-way causal relationship with education, with the popularized point being that reduced energy shortages contribute to improved living standards, economic development, and increased literacy rates. According to the Energy, Poverty, and Development hypothesis (Karekezi et al., 2012), students' ability to access electricity is directly correlated with their likelihood of enrolling in and attending school regularly. Moreover, classrooms with adequate lighting and improved working conditions for teachers are another benefit of increased access to modern energy services because an increase in education costs, such as those associated with heating and cooling, allows for a greater number of students to continue their education. Access to clean energy and advances in energy-efficient building technology are two factors contributing to the reduction of energy shortages. For example, in colder climates, schools require access to electricity and heating systems. Additionally, evidence reveals that the access to an energy grid provides families with better education because children can learn more easily after dark using the grid network (Cabraal et al., 2005).

Furthermore, numerous empirical studies at the microscopic level have discovered an association between reduced energy poverty and increased scholastic achievement. According to Oum (2019), the prevalence of energy poverty decreased as the number of people living in Laos' rural areas with access to electricity increased. Additionally, Oum (2019) studies how energy poverty impacts education and health in Laos and finds that it decreases the average number of years spent in schools for children from homes with limited access to energy. Acharya and Sadath (2019), who utilise a multidimensional energy poverty index and data from a survey of Indian homes, conclude that education is essential in preventing the further spread of energy poverty. According to Apergis et al.'s (2022) empirical research, higher educational levels lead to a decrease in the prevalence of energy poverty. Zhang et al. (2021) conduct a study that reveals how students in China are impacted by energy poverty and how their performance in Chinese and mathematics classes can reflect this influence. Therefore, we hypothesize that energy poverty and educational development have a cointegration link and that greater energy poverty is inversely linked to better educational development in developing nations in the long run.

2.2. Energy poverty and public health

Previous research on energy poverty has primarily approached the issue from the viewpoint of fuel poverty by examining how inadequate access to energy affects a family's material and mental well-being, thereby shedding light on the nexus between energy poverty and public health (Hills, 2012; Thomson et al., 2017a, 2017b; Churchill and Smyth, 2020, 2021). Access to electricity, in both urban and rural areas, is a primary indicator of energy poverty (Nkoa et al., 2023), and the geometric mean of energy use is a better index of energy poverty (Banerjee et al., 2021). Moreover, a significant amount of research has demonstrated that greater energy poverty is associated with poor public health. For instance, indoor air pollution, accidents from gathering fuelwood, a lack of access to cold food and inaccessible medical care are just a few of the many ways in which communities living in energy poverty endanger their health (Sovacool, 2012). Furthermore, increases in fuel poverty have been linked to increases in respiratory infections and general illnesses in children (Liddell and Morris, 2010). Pan et al. (2021) use annual data from a large panel of 175 nations from 2000 to 2018 to investigate the negative impact of energy poverty on public health. Additionally, Llorca et al. (2020) report that people living in fuel poverty tend to have poorer health; in other words, objective fuel poverty and other poverty-related characteristics have a more pronounced effect on health. A correlation exists between a household's incapacity to fulfil fundamental energy requirements and the manifestation of unfavourable health outcomes. Memmott et al. (2021) indicate that the COVID-19 outbreak has resulted in an increase in the incidence of energy insecurity and potentially exacerbated pre-existing racial inequalities in the probability of experiencing energy insecurity. In addition, it is necessary to note that the COVID-19 pandemic has had a massive impact on energy. For instance, using an artificial neural network model, Q. Zhang et al. (2021) found that the pandemic could have profound implications for the renewable energy sector, climate, and energy policy. Kang et al. (2021) find that owing to the negative impact of the outbreak on energy consumption, new energy systems are needed in the post COVID-19 pandemic era to effectively manage energy demand at the community level.

Even in industrialized countries, the lack of access to affordable energy is a significant contributor to poor health (Wilkinson et al., 2007). Using cross-sectional data from European countries, Thomson et al. (2017a) conclude that energy-poor households have significantly worse physical and mental health than non-energy-poor households. This trend is more common in societies with relatively less income inequality and higher overall incomes. Welsch and Biermann (2017) demonstrate that an increase in the price of energy is associated with a decline in personal well-being across a sample of 21 European countries. Using cross-sectional data from Australia and a multidimensional health measure, Churchill and Smyth (2020) conclude that fuel poverty significantly reduces well-being; that is, energy poverty reduces the overall public health of Australia's energy-poor adult population.

In less-developed countries, the public health issues caused by a lack of access to affordable energy are much worse, as corroborated by the findings of the limited number of studies that have been carried out on this subject in developing countries. For instance, Oum (2019) uses data from the Lao People's Democratic Republic Economic Consumption Survey to illustrate that the lack of access to affordable electricity negatively affects the health of individuals and households. Additionally, Zhang et al.'s (2019), econometric study conducted in China, which utilizes extensive household-level survey data collected between 2012 and 2016, establishes that energy poverty has a negative impact on health. Therefore, we hypothesize that energy poverty, which arises from social, economic, and environmental problems, has significant implications for public health in developing nations, although the evidence presented thus far is mainly related to a single country or a small group of countries.

2.3. Educational development and public health

At the macro-level, the correlation between educational development and public health suggests that the two may affect one another. Highly educated individuals are shown to enjoy better health, live longer, and be less likely to experience negative emotional states (Zajacova and Lawrence, 2018). Zajacova and Lawrence also claim that people with higher levels of education have a lower risk of disease and longer life expectancy. This may be attributable to health-behavioural, economic, medical care accessibility, and socio-psychological factors. Similarly, health literacy has been proposed as a mechanism to explain the well-documented link between education and health. Health literacy plays a role in explaining the underlying mechanism that determines the link between poor health and low levels of education (van der Heide et al., 2013). According to the fundamental cause assumption, socioeconomic factors, such as level of education, are among the most important contributors to health and illness because they determine access to a wide range of protective factors (Link and Phelan, 1995). In addition, Mubarak et al. (2021) suggest that health education can reduce the fear of being infected with COVID-19 because it enables individuals to improve their knowledge and attitude towards a disease.

By contrast, adults with lower educational levels had poorer health. According to cumulative advantage theory, the health gap between education levels widens during most or all of adulthood due to differences in the rate of health deterioration. For decades, the rising significance hypothesis has predicted that education will widen the gap in the rate of health decline (Mirowsky and Ross, 2008). In contrast to those with a bachelor's degree or higher, those with lower educational levels are more likely to suffer from chronic health problems (Johnson-Lawrence et al., 2017). Additionally, those with lower educational levels tend to have more significant difficulties in daily life and are more likely to be disabled (Tsai, 2017). Nonetheless, we have been unable to locate any worldwide empirical work that uses data from developing countries to analyse the health-education nexus. Therefore, we infer that if a country's education system is of a better quality, it will have a beneficial effect on the health of its citizens, and the positive feedback effect will also be supported.

2.4. Review comments

Based on the literature review, contemporary scholars generally believe that energy poverty constitutes a critical pathway towards public health and educational development. However, few studies have examined whether there are bidirectional cointegration relationships among energy poverty, public health, and educational development or whether energy poverty and educational development affect public health bidirectionally. Discovering the cointegration link and two-way causality among energy poverty, public health, and educational development can help governments understand how these are related. This study utilized annual panel data from 50 developing countries from 2000 to 2017, employed second-generation unit root and cointegration tests to eliminate pseudo-regression, and adopted the impulse response function and Granger causality test to clearly demonstrate causality and its direction.

3. Data and theoretical strategy

3.1. Variables and data source

This study investigated the links between energy poverty, educational development, and public health from the novel perspective of natural resource policy optimization, using country-level panel data from 50 developing countries from three regions (Asia, Latin America, and Africa) between 2000 and 2017. Hence, our sample consists of a balanced panel of 900 annual observations from 50 countries over 18 years (see the list of countries in Appendix 1). Following the work of Banerjee et al. (2021), energy poverty was captured using the geometric mean of energy use (EU) and the data on energy use for the sample countries were obtained from the World Development Indicators (WDI). Additionally, Energy Development Index (EDI) is used as a substitution variable for energy poverty in the robustness test. Similarly, following Acharya and Sadath (2019), we used various countries' average years of schooling (AYS) obtained from the Barro-Lee Database to measure educational development. Moreover, progression to secondary school (PR) was used as a substitution variable for educational development in the robustness test. Several studies have used infant mortality rate and life expectancy to measure public health, especially when analysing energy poverty at the country level. For example, Wang (2002) finds that life expectancy and infant mortality rate are regarded as essential health indicators from a country-level development policy perspective, which is similar to Wilkinson et al. (2007), who note that the effect of providing global energy services can be cached by higher life expectancy and infant birth rates in the context of achieving the United Nations MDGs on health. Therefore, we chose life expectancy rate to capture public health in our study. Data on life expectancy rate (LE) were obtained from the WDI. Furthermore, it is worth noting that we performed logarithmic processing on the data for these three variables. The definitions and sources of the variables are presented in Table 1.

3.2. Description of the data

The scattergrams of LE, EU, LE, and AYS are presented in Figs. 1 and 2. Fig. 1, shows that EU ranges from 5.0 to 8.0 in most countries, while LE ranges from 3.8 to 4.4 in most countries, with a small percentage of observations of less than 3.8. Additionally, the fitting lines for LE and EU indicate a positive correlation between EU and LE; higher energy use is often linked to higher public health. Similarly, we found that the AYS distribution was predominantly between 0 and 2.5, and that a higher level of educational development was often associated with higher public health. However, whether EU and AYS positively affect LE remained a black box, which deserved further investigation. Thus, we decided to systematically verify this by employing the long-term cointegration link and two-way causality among these three variables, which may provide new inspiration for academia.

Next, the fundamental statistical distributions of the three variables are presented in Table 2. The mean LE for the entire sample was 4.175, with a standard error of 0.140. The maximum and minimum values were 4.381 and 3.763, respectively. The EU standard error, mean, maximum, and minimum values were 0.693, 6.554, 8.140, and 4.728, respectively. For AYS, the standard error and mean values were 0.474 and 1.770, respectively, indicating relatively low educational levels in these countries. For the descriptive statistical analysis of both subsamples, we found that the EU average for the emerging market subsample was 6.949, whereas for the non-emerging market subsample it was 6.443. Similarly, the average LE of the emerging market subsample was 4.258, whereas the average LE for the non-emerging market subsample was 4.151, indicating that the former had higher public health and lower energy poverty levels than the latter. For educational development, the average AYS value for the emerging market subsample is 2.033, whereas the average AYS value for the non-emerging market subsample is 1.696, suggesting that the former has higher educational development than the latter at the mean level.

3.3. Estimation strategy

This study used a balanced panel dataset of 50 developing countries from 2000 to 2017 to empirically examine the links among energy poverty, educational development, and public health. Panel data, especially global panel data, have the property of inbuilt CSD among random errors. For instance, because some of the developing countries selected in this study are regional neighbors connected through multiple modes of globalization, a macroeconomic shock in one could affect the other selected developing countries. Therefore, after fully considering potential CSD, this study adopted a series of empirical methods that allowed for CSD. The structure of the empirical modelling consisted of four stages: (1) estimation of cross-sectional independence and slope homogeneity, (2) estimation of the unit root and cointegration between the selected variables, (3) estimation of long-term relationships, and (4) estimation of two-way causality. The stages of the research methodology are illustrated in Fig. 3.

3.3.1. Panel cross-sectional dependence estimate

The first-generation panel unit root test assumes that countries are independent of cross-sections, but this hypothesis has limitations (Munir et al., 2020). Notably, CSD is a general problem with panel data that can invalidate traditional panel estimations (Baltagi and Hashem Pesaran,

Table 1
Definitions and sources of variables.

Variables		Descriptions	Sources
Energy poverty	Geometric mean of Energy use	It is measured in kilograms of oil equivalent per capita	WDI
	Energy Development Index	Geometric mean of Energy use (kilo of oil equivalent per capita), renewable energy consumption (% of total final energy consumption), access to electricity (% of population) and electric power consumption (kWh per capita)	WDI
Education development	Average (mean) years of schooling	Average number of completed years of education of a country's population aged 15 years and older, excluding years spent repeating individual grades.	Barro-Lee Database
	Progression to secondary school (%)	Progression to secondary school refers to the number of new entrants to the first grade of secondary school in a given year as a percentage of the number of students enrolled in the final grade of primary school in the previous year (minus the number of repeaters from the last grade of primary education in the given year).	WDI
Public health	Life expectancy at birth, total (years)	It indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.	WDI

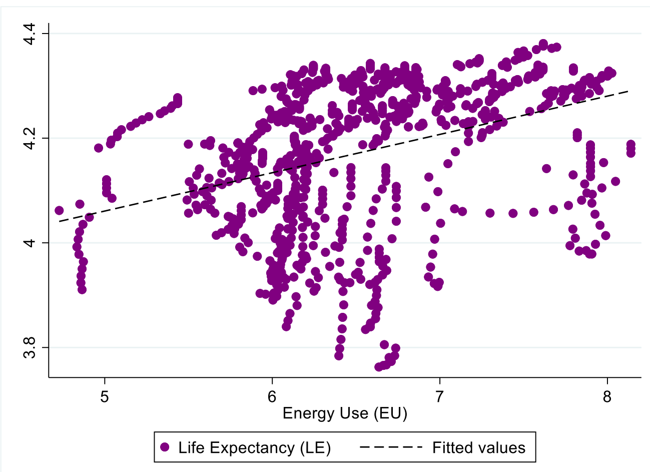

Fig. 1. Scatter plot of life expectancy and energy use.

Fig. 2. Scatter plot of life expectancy and average years of schooling.

2007; Gengenbach et al., 2009). Accordingly, we referred to Wang et al. (2022) and used the Pesaran (2004) and Pesaran (2015) CSD tests to check for the presence of CSD. Furthermore, we explicitly tested the model as follows:

$$y_{it} = \alpha_i + \beta_{it} x_{it} + \mu_{it} \tag{1}$$

Here, i represents country; t represents the time factor; α_i indicates the constant parameter; β_{it} is the coefficient vector for such variables; x_{it} is

Table 2
Summary of descriptive statistics.

	Variable	N	Mean	SD	Min	Median	Max
Full	LE	900	4.175	0.140	3.763	4.220	4.381
	EU	900	6.554	0.693	4.728	6.476	8.140
	AYS	900	1.770	0.474	0.095	1.872	2.407
Emerging	LE	198	4.258	0 .085	3.979	4.270	4.381
	EU	198	6.949	0.627	6.024	6.780	8.008
	AYS	198	2.033	0.206	1.482	2.041	2.407
Non-emerging	LE	702	4.151	0.143	3.763	4.173	4.352
	EU	702	6.443	0.670	4.728	6.330	8.140
	AYS	702	1.696	0.501	0.095	1.808	2.398

the variable; μ_{it} represents the regression residual. CSD is calculated as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \tag{2}$$

Here, ρ_{ij} implies the correlation errors of countries i and j.

Given the heterogeneous slope of small samples, Pesaran (2015) additionally applies a CSD test called a weak CSD test, and the ρ_{ij} is given by

$$\rho_{ij} = \rho_{ji} = \frac{\sum_{t=1}^{T} \mu_{it}\mu_{jt}}{\left(\sum_{t=1}^{T} \mu_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} \mu_{jt}^2\right)^{1/2}} \tag{3}$$

Here, μ stands for the estimation residual.

3.3.2. Second-generation unit root estimate

If CSD exists, a unit-root test method that considers CSD should be utilized. Therefore, we applied Pesaran's (2007) second-generation covariate-augmented Dickey–Fuller (CADF) unit root test to examine the stability of all the variables, mainly because it incorporates CSD. The CADF model is expressed as follows:

$$\Delta y_{it} = \partial_i + \theta_i y_{it-1} + \vartheta_i \bar{y}_{it-1} + \sum_{j=1}^{\rho} \tau_{ij} \Delta y_{it-1} + \sum_{j=0}^{\rho} \omega_{ij} \Delta \bar{y}_{t-j} + d_{it} + \varepsilon_{it} \tag{4}$$

Here, $\bar{y}_t = \frac{1}{N} \sum_{i=1}^{N} y_{it}$, θ is the coefficient of the first lag term; ω_{ij}, τ_{ij}, and ϑ_i represent the standard time effects, linear trends, and individual specific effects, respectively. Furthermore, a stationarity test was performed using the t-statistic of θ based on the CADF model.

3.3.3. Westerlund cointegration estimate

Next, we tested for cointegration. According to Westerlund and Edgerton (2007), the panel cointegration method has the advantage of a large sample size and can solve the problems of heterogeneity and common factor restrictions. Therefore, this study uses a panel cointegration test to examine the long-term links among *LE*, *EU*, and *AYS*. Westerlund and Edgerton (2007) performed four-panel cointegration

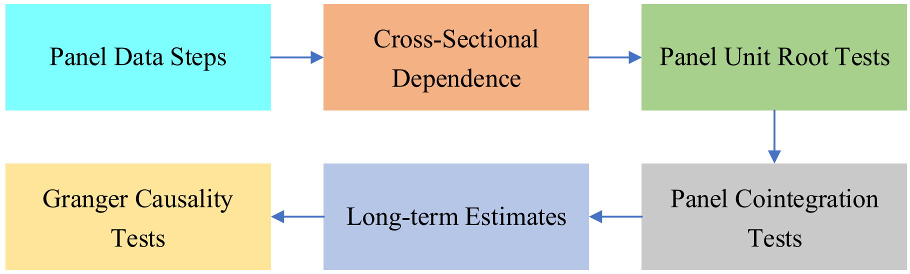

Fig. 3. Methodology steps.

tests, Gτ, Gα, Pτ, and Pα, using an error correction model (ECM). The two-panel tests (Pτ and Pα) are designed to test the alternative assumption that the entire panel is cointegrated. In contrast, the other two tests (Gτ and Gα) aim to test the alternative hypothesis that at least one cross-section is cointegrated. In these tests, the null assumption is not cointegration. The cointegration model is expressed as follows:

$$y_{it} = \theta_{0i} + \theta_{1it} + n_i D_{it} + \vartheta_i \bar{y}_{it-1} + x_{it}\beta_i + (D_{it}x_{it})\varepsilon_i + Z_{it} \tag{5}$$

Here, D_{it} stands for the potential structural break; $x_{it} = x_{it,t-1} + \varphi_{it}$ is I (1) progress; if $t > T_i^b$, then $D_{it} = 1$; otherwise, $D_{it} = 0$, and D_{it} denotes the breakpoint location for country *i*.

3.3.4. PMG estimation

According to Ma (2015) and Balcilar et al. (2019), the estimation of PMG is an efficient and robust method for solving CSD and non-stationarity, which are universal problems that cannot be addressed by traditional methods. Additionally, the PMG method can identify the influence of energy poverty and educational development on public health from long- and short-term perspectives using a single equation. Therefore, to handle non-stationarity, CSD, and heterogeneity, we applied PMG estimation to identify the short- and long-term effects of *EU* and *AYS* on *LE*. The PMG estimation model is presented as follows:

$$\Delta LE_{it} = \varphi_0 + \varphi_1 \Delta EU_{it} + \varphi_1 \Delta AYS_{it} + d_1(v_t) + \mu_{it} \tag{6}$$

Here, v_t is subtracted from the explanatory variable; this is a general procedure applied to each set of unit coefficients. v_t is also any potentially ruled-out trait process that may evolve.

3.3.5. Panel granger non-causality estimate

The second-generation unit root test, cointegration test, and PMG estimation techniques reveal the long-run relationships among these three variables but cannot be used to analyse causation. Determining the direction of causation among the three selected variables is vital for comprehensive policymaking. Causality outcomes can also be used to support the regression results. Therefore, after estimating the long- and short-term coefficients using the PMG method, we examine the causal relationships among the three selected variables using a panel causality test, following Dumitrescu and Hurlin (2012). In contrast to those causality methods that do not consider the problems of heterogeneous slope coefficient in their analysis, the Dumitrescu and Hurlin (2012) methods consider the problem of slope heterogeneity and control for the problem of slope heterogeneity, which significantly improves the accuracy of estimating causation by considering alternative assumptions about causation between at least one variable in several cross-sectional elements. The cause-and-effect process emphasises the following linear specification:

$$y_{it} = \alpha_i + \sum\nolimits_{i=1}^{K} \gamma_i^k y_{i,t-k} + \sum\nolimits_{i=1}^{K} \beta_i^k x_{i,t-k} + \varepsilon_{it} \tag{7}$$

Here, *t*, *K*, β_i^k, and α_i represent the time period, lag length, slope coefficients, and cross-sectional units, respectively (Çetin et al., 2023). The null assumption implies that no causality exists in the panel, whereas the alternative assumption indicates that causality exists in at least one cross-sectional unit. In this process, Z- and W-bar statistics are used to test the null hypothesis. The statistics are given as follows:

$$W = \frac{1}{N}\sum\nolimits_{i=1}^{N} W_i \tag{8}$$

$$Z = \sqrt{\frac{N}{2K}}(W - K) \tag{9}$$

4. Empirical findings

4.1. CSD results

As CSD is a general problem for panel data, if we do not consider it, it can invalidate our results (Nepal et al., 2022), therefore, we apply the Pesaran (2004) and Pesaran (2015) tests to execute the CSD tests. Table 3 presents an analysis of CSD. Moreover, the results of Pesaran's (2004) test confirmed the CSD for all the three selected variables: LE, EU, and AYS. Consequently, we apply Pesaran's (2015) test, and the results show that all three variables reject the null hypothesis of a weak CSD. Furthermore, the emerging and non-emerging subsample results show similar evidence that all the three selected variables exhibit CSD.

Given that all the three selected variables in our panel data have problems with CSD, the traditional panel unit root and panel cointegration tests may report bias (Wang et al., 2022). Therefore, we employ Westerlund and Edgerton (2007) second-generation unit root and cointegration tests to obtain reliable results for the relationships among the three selected variables.

4.2. CADF unit root estimation results

Table 4 presents the results of the second-generation CADF unit root test for the entire sample and two subsamples, assuming that none of the three selected variables are stationary. In Table 4, the LE statistic of the total sample is −1.640, which implies that the significance test does not pass the 10% level, indicating that the LE level is not stationary. More importantly, the ΔLE, with a statistic of −3.362, passed the significance test at the 1% level, confirming that the first difference in LE was stationary. Similarly, we find that both the EU and AYS follow Progression I (1) of earlier analyses. This conclusion is supported by the results of the two subsamples.

4.3. Cointegration test results

Finding that all three selected variables feature CSD and I (1) progress, we applied the Westerlund and Edgerton (2007) cointegration test, which takes CSD among these three selected variables into consideration. Table 5 presents the results of the cointegration tests for the three selected variables. The explained variable was*LE*, whereas the explanatory variables were *EU*, *AYS,* and *EU-AYS*. Table 5 shows that almost all the statistics for the total sample are significant, at least at the 5% level, suggesting the long-term development of *LE* and *EU*. Similar results were obtained with the *LE-AYS* models and *LE-EU-AYS* models. Furthermore,

Table 3
Cross-section dependence tests.

	Variable	Pesaran (2004)				Pesaran (2015)	
		CSD-test	*p*-value	Corr	abs(corr)	CSD	p
Full	LE	126.950***	0.000	0.855	0.922	148.482***	0.000
	EU	63.770***	0.000	0.429	0.605	148.373***	0.000
	AYS	120.400***	0.000	0.811	0.837	147.411***	0.000
Emerging	LE	30.710***	0.000	0.976	0.976	31.464***	0.000
	EU	18.920***	0.000	0.601	0.710	31.459***	0.000
	AYS	25.300***	0.860	0.804	0.804	31.446***	0.000
Non-emerging	LE	94.860***	0.000	0.821	0.907	115.481***	0.000
	EU	43.710***	0.000	0.379	0.578	115.376***	0.000
	AYS	93.710***	0.000	0.811	0.844	114.460***	0.000

Note: t statistics in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Results from the CADF panel unit root test.

LE	ΔLE	EU	ΔEU	AYS	ΔAYS
Full					
−1.640	−3.362***	−1.309	−2.590***	−1.394	−2.246***
(0.622)	(-11.310)	(2.916)	(-5.958)	(2.331)	(-3.576)
Emerging					
−1.886	−2.468***	−1.855	−2.574***	−1.477	−2.881***
(-0.442)	(-2.333)	(-0.341)	(-2.678)	(0.887)	(-3.678)
Non-emerging					
−1.712	−3.468***	−1.179	−2.668***	−1.475	−2.195***
(0.111)	(-10.638)	(3.374)	(-5.745)	(1.564)	(-2.848)

Note: The statistic of CADF is t-bar, and Z[t-bar]is in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the results of the two subsamples support this conclusion, except for the *LE-EU-AYS* models in the emerging subsamples.

Our results show that energy poverty, public health, and educational development have evolved over time. Unlike studies that point to only a one-way causal relationship between public health and energy poverty or educational development, this study confirms a two-way relationship among these three variables. Based on our findings, governments should consider the consequences of these relationships among energy poverty, public health, and education development and the complex interactions among them when formulating natural resource policies. This means that current public health and education development should be a priority if policymakers want to reduce energy poverty because any possible negligence or ill consideration could render the policy ineffective.

4.4. PMG estimation results

We examine the long- and short-term impacts of *EU* and *AYS* on *LE* using the PMG method, which considers CSD (Pesaran et al., 1999). Table 6 summarizes the PMG results. The emerging sample, with an *EU* coefficient of 0.521, passes the 5% significance test, offering strong evidence that energy use has a significant long-term positive impact on public health. Similarly, the non-emerging sample with an *EU* coefficient of 1.828 passes a significance test of 1%, thus confirming that energy use has a significant long-term positive impact on public health.

As shown in Table 6, the total sample with an *AYS* coefficient of −0.022 passes the 1% significance test. This result shows that educational development exerts a long-term negative influence on public health, which is in line with the results of the non-emerging samples. In contrast, the emerging samples show an entirely different influence between educational development and public health, in that educational development exerts a long-run positive influence on public health. Potential reasons for this discrepancy are as follows: emerging economies experience faster economic growth and higher social inclusion than non-emerging economies; therefore, rapid educational development, due to the global advocacy to strengthen the education of their residents, can help emerging economies achieve higher levels of public health. However, in non-emerging economies, religious beliefs, energy poverty, and gender discrimination, constrain the positive impact of education on health. It is reasonable to believe that educational outcomes can benefit public health only in the long term when non-emerging economies reach a certain level of economic development. Until then, educational development will not significantly impact public health, and it may even harm public health. Studies have shown that women are the most vulnerable in countries where energy is scarce. Women and children

Table 5
Panel cointegration test.

	Model	G_τ- value	G_α- value	P_τ- value	P_α- value
Full	LE V.S. EU	−4.668***	−4.545	−40.263***	−8.120***
		(-22.752)	(3.374)	(-30.201)	(-6.195)
	LE V.S. AYS	−5.857***	−8.583**	−33.122***	−12.998***
		(-32.105)	(-1.871)	(-23.018)	(-13.965)
	LE V.S. EU& AYS	−4.113***	−4.276	−36.641***	−8.798***
		(-15.959)	(5.467)	(-23.753)	(-3.709)
Emerging	LE V.S. EU	−2.103	−2.531	−19.118***	−7.466***
		(-1.203)	(2.809)	(-14.400)	(-2.417)
	LE V.S. AYS	−4.479***	−5.553	−24.677***	−9.768***
		(-9.972)	(0.968)	(-19.991)	(-4.137)
	LE V.S. EU& AYS	−1.669	−2.978	−2.806	−1.696
		(1.319)	(3.250)	(2.785)	(2.473)
Non-emerging	LE V.S. EU	−5.392***	−5.113	−35.532***	−8.199***
		(-25.123)	(2.328)	(-26.645)	(-5.583)
	LE V.S. AYS	−6.245***	−9.438***	−27.952***	−14.539***
		(-31.056)	(-2.633)	(-19.021)	(-14.501)
	LE V.S. EU& AYS	−4.803***	−4.642	−33.212***	−8.983***
		(-18.771)	(4.463)	(-21.803)	(-3.483)

Note: t statistics in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6
Result of the PMG estimation.

Dependent variable: LE			
Independent variable: EU & AYS			
	Full	Emerging	Non-emerging
Long-run			
EU	0.004	0.521**	1.828***
	(0.987)	(2.029)	(11.734)
AYS	−0.022***	2.216***	−0.983***
	(-4.189)	(3.182)	(-7.922)
CONS	0.080**	−0.024	−0.014
	(2.161)	(-0.770)	(-0.329)
Short-run			
ECM	−0.017*	−0.005	−0.003
	(-1.903)	(-0.851)	(-0.483)
ΔEU	0.002	−0.003	−0.002
	(0.273)	(-0.513)	(-0.160)
ΔAYS	−0.009	−0.007	0.002
	(-1.209)	(-1.085)	(0.227)

Note: t statistics in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

usually collect fuel; the time taken to collect fuel in fuel-scarce areas can range from one to 5 h per day, with women often having an infant strapped to their back (Asia et al., 2007). Moreover, collecting solid fuels is time-consuming, hence discouraging women's participation in other social work and wasting time that children could have spent on educational activities (Sovacool, 2013). Table 6 presents a short-term estimation of the PMG results. The *ECM* coefficient of the total sample is −0.017, which passes the significance test at the 10% level, indicating that the *EU*, *AYS*, and *LE* move together. However, the coefficients of *ΔEU* and *ΔAYS*do not pass the significance test at the 10% level, suggesting that energy poverty and educational development do not significantly affect public health. This leads us to infer that to improving public health involves long-term activities that can take more than 3–5 years to achieve. Therefore, when assessing the impact of energy poverty and educational development, governments should focus on long-term rather than short-term effects. The impulse response function, shown in Fig. 4, suggests an intercausal relationship among the selected variables.

4.5. *Causality analysis*

After completing the CSD, second-generation unit root, panel cointegration, and panel PMG tests to assess the coefficients of the variables, the causal relationships between the variables were analyzed. To this end, a causality test of the Dumitrescu-Hurlin panel was applied. The results shown in Table 7 suggest a two-way causal relationship among explanatory variables, namely energy poverty, educational development, and public health. These findings confirm that public health is determined by long-term energy poverty and educational development. Fig. 5 summarizes the directional relationships of the Granger causality expressions.

4.6. *Robustness test*

4.6.1. *Subsamples*

To demonstrate the reliability of our previous results, we further examined the empirical tests based on several subsamples of *LE*, *EU*, and *AYS* levels. Specifically, we referred to Wang et al. (2022). If a country's average *LE* is larger than the median *LE* for the entire sample, we placed it in a subsample with High-LE. Otherwise, we placed it in the Low-LE

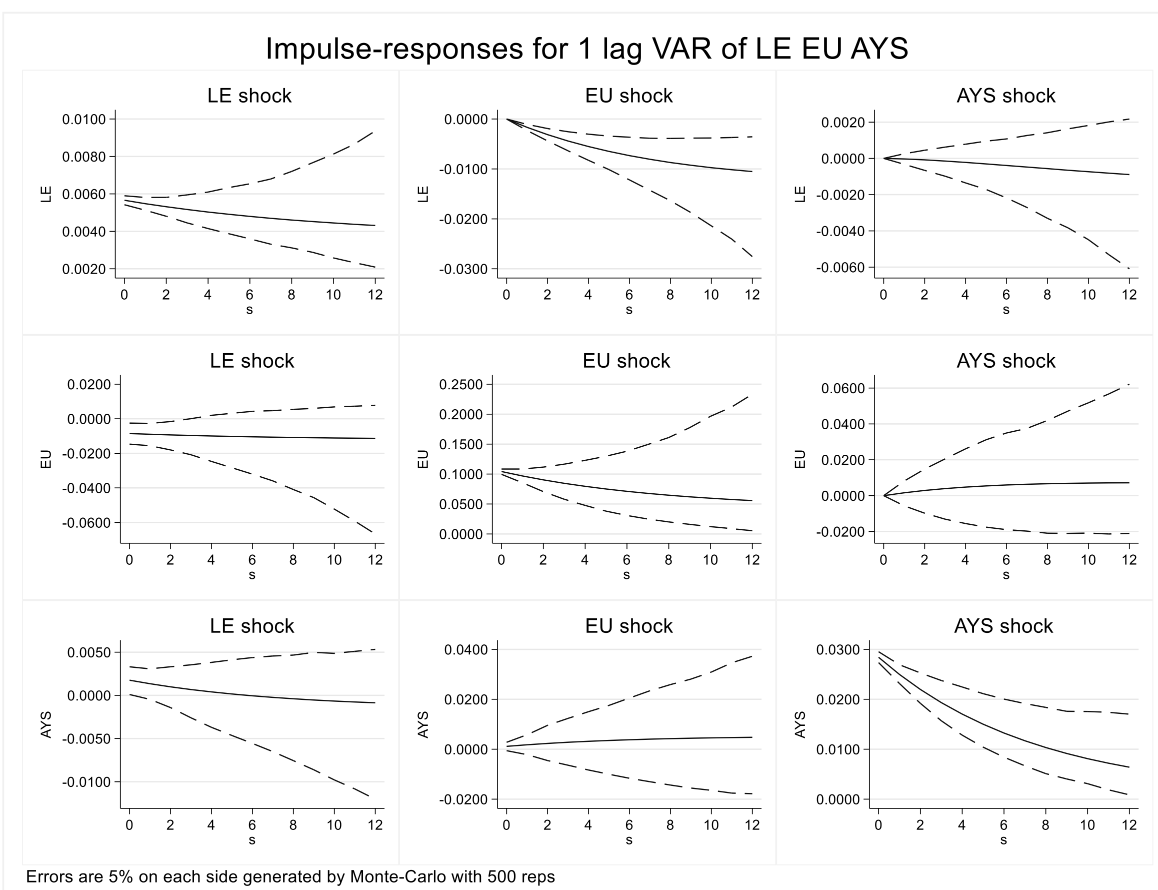

Fig. 4. Impulse response function.

Table 7
Dumitrescu-Hurlin panel causality analysis.

H_0	EU dose not Granger cause LE		LE dose not Granger cause EU	
Lag	Z-bar	Prob.	Z-bar	Prob.
1	55.502	0.000	23.312	0.000
2	44.636	0.000	26.280	0.000
3	13.021	0.000	33.549	0.000
s	16.663	0.000	91.651	0.000
H_0	AYS dose not Granger cause LE		LE dose not Granger cause AYS	
1	120.595	0.000	20.236	0.000
2	62.998	0.000	23.092	0.000
3	20.905	0.000	26.370	0.000
4	15.845	0.000	38.189	0.000
H_0	EU dose not Granger cause AYS		AYS dose not Granger cause EU	
1	8.736	0.000	12.181	0.000
2	5.673	0.000	11.340	0.000
3	7.390	0.000	10.768	0.000
4	15.456	0.000	250.881	0.000

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

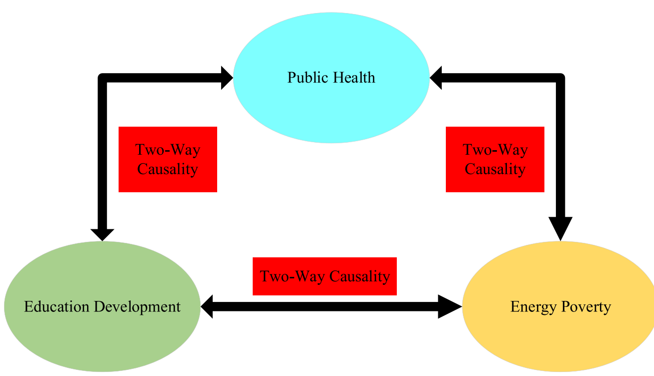

Fig. 5. Granger-causality.

subsample. Similarly, we created four subsamples based on the *EU* and *AYS* medians. We then examined the second-generation unit root test for these six subsamples. The results indicated that the *LE*, *EU*, and *AYS*levels were not stationary, while the first differences among the three selected variables were stationary. As these selected variables demonstrated progression in I (1) in six subsamples, we also conducted the Westerlund and Edgerton (2007) cointegration estimation to examine the relationship between the cointegration links. As shown in Table 8, the results of the six subsamples indicated that energy poverty, educational development, and public health were correlated, which is in line with the earlier results.

Furthermore, we employed PMG estimation to evaluate the long- and short-term influences of energy poverty and educational development on public health using four subsamples. As shown in Table 9, for the High-EU subsample, the *EU* coefficient was 3.139, passing the 1% significance test, which indicated that energy use had a positive effect on public health. The *AYS* coefficient was −2.793, which was significant at the 1% level, suggesting that educational development harmed public health in the High-EU subsample. From the results for the Low-EU subsample, we found that energy use also had a positive impact on public health. Educational development exerted a significant and favourable influence on public health in the long term. For the subsample with High-AYS, energy poverty did not affect public health effectively, while educational development significantly favoured public health. For the subsample with Low-AYS, the results showed that energy use significantly and positively impacted public health, while educational development positively affected public health in the long term. Table 9 presents the short-term PMG estimates for the four subsamples.

Table 8
Panel cointegration test for sub-samples.

	Model	G_τ- value	G_α- value	P_τ- value	P_α- value
High-LE	LE V.S. EU	−2.000	−3.954	−9.819***	−4.744
		(-1.238)	(2.928)	(-2.596)	(-0.579)
	LE V.S. AYS	−4.827***	−5.423	−19.171***	−7.203***
		(-16.971)	(1.579)	(-12.002)	(-3.348)
	LE V.S. EU& AYS	−2.497***	−3.390	−11.790***	−2.186
		(-2.509)	(4.572)	(-3.123)	(3.290)
Low-LE	LE V.S. EU	−7.336***	−5.135***	−31.121	−8.333***
		(-30.938)	(1.843)	(-24.021)	(-4.621)
	LE V.S. AYS	−6.886***	−11.743***	−24.635***	−14.747***
		(-28.432)	(-4.226)	(-17.498)	(-11.845)
	LE V.S. EU& AYS	−5.730***	−5.162	−28.431***	−10.482***
		(-20.061)	(3.159)	(-19.238)	(-4.128)
High-EU	LE V.S. EU	−4.190***	−7.892	−32.654***	−8.265***
		(-13.429)	(-0.689)	(-25.563)	(-4.545)
	LE V.S. AYS	−6.236***	−9.634**	−28.376***	−13.495***
		(-24.815)	(-2.289)	(-21.260)	(-10.434)
	LE V.S. EU& AYS	−4.521***	−4.999	−38.750***	−10.661***
		(-13.500)	(3.289)	(-29.231)	(-4.289)
Low-EU	LE V.S. EU	−5.146***	−1.197	−23.767***	−7.878***
		(-18.747)	(5.460)	(-16.625)	(-4.109)
	LE V.S. AYS	−5.477***	−7.532	−17.007***	−11.897***
		(-20.588)	(-0.358)	(-9.826)	(-8.634)
	LE V.S. EU& AYS	−3.705***	−3.552	−7.480	−3.561
		(-9.070)	(4.442)	(1.051)	(2.060)
High-AYS	LE V.S. EU	−3.283***	−6.867	−26.661***	−7.327***
		(-8.542)	(0.257)	(-19.392)	(-3.556)
	LE V.S. AYS	−3.614***	−7.158	−19.354***	−10.057***
		(-10.420)	(-0.014)	(-12.042)	(-6.692)
	LE V.S. EU& AYS	−3.240***	−4.150	−16.311***	−3.720
		(-6.675)	(4.044)	(-7.337)	(1.956)
Low-AYS	LE V.S. EU	−6.169***	−2.028	−29.241***	−8.599***
		(-23.949)	(4.602)	(-22.277)	(-4.821)
	LE V.S. AYS	−8.286***	−10.127***	−27.620***	−16.430***
		(-35.494)	(-2.686)	(-20.647)	(-13.462)
	LE V.S. EU& AYS	−5.059***	−4.412	−31.622***	−13.282***
		(-16.088)	(3.681)	(-22.496)	(-6.498)

Note: t statistics in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9
PMG estimating result for sub-samples.

	LE	LE	LE	LE
	High-EU	Low-EU	High-AYS	Low-AYS
Long-run				
EU	3.139***	1.000***	0.057	2.217***
	(6.677)	(10.587)	(1.578)	(5.734)
AYS	−2.793***	0.093***	2.018***	1.796***
	(-5.218)	(2.946)	(19.848)	(9.018)
CONS	−0.024	0.020	−0.008	0.060
	(-0.308)	(0.867)	(-0.995)	(1.008)
Short-run				
ECM	−0.003	0.006	−0.018	0.004
	(-0.407)	(0.597)	(-1.427)	(0.937)
ΔEU	−0.001	0.002	0.004	0.002
	(-0.076)	(0.190)	(0.706)	(0.114)
ΔAYS	0.004	−0.006	−0.007	−0.009
	(0.403)	(-0.862)	(-0.738)	(-0.796)

Note: t statistics in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The *ECM* coefficients were all insignificant at the 10% level, suggesting that *LE*, *EU*, and *AYS* do not move together. Similarly, the coefficients of ΔEU and ΔAYSwere also insignificant at the 10% level, providing strong evidence that energy poverty and educational development do not significantly impact public health in the short term.

4.6.2. Changing the variables

Following Banerjee et al. (2021), we constructed an EDI to measure energy poverty for our robustness test. For this, we changed the way we measured educational development by replacing the original *AYS* with *PR*, and reported the new PMG results of the emerging and non-emerging samples in Table 10. We find that the main empirical results of the subsamples are similar to those in Table 6, thereby supporting the reliability of our previous findings.

5. Conclusions, policy recommendations, and research prospects

5.1. Conclusions

This study contributes to a growing body of literature on the effects of energy poverty. Several studies have investigated the influence of energy poverty on important socioeconomic variables or dimensions such as education, well-being, and gender. However, little attention has been paid to the impacts of energy poverty and educational development on public health. Thus far, the focus has been on the impact of energy poverty on the health and well-being in European countries, with few studies conducted in developing countries or countries outside Europe, especially after distinguishing between emerging and non-emerging economies. Our research explores the cointegration link and two-way causality relationship among energy poverty, educational development, and public health; investigates the impacts of energy poverty and educational development on public health; and identifies short- and long-term differences in these relationships.

Using panel data covering 50 developing countries across Asia, Latin America, and Africa from 2000 to 2017, we conducted empirical research by employing estimations such as the CADF unit root test, Westerlund and Edgerton's (2007) cointegration test, and the PMG estimation, all of which can account for potential CSD. The long-term cointegration association and two-way causal relationship among energy poverty, public health, and educational development have been proven. Additionally, long-term PMG estimates indicate that in emerging economies and nations with high energy poverty rates, public health is positively influenced by educational development. However, in non-emerging economies and countries with lower energy poverty rates, educational development negatively affects public health.

Table 10
Result of the PMG estimations-changing the energy poverty variable and education variable.

Dependent variable: LE		
Independent variable: EDI & PR		
	Emerging	Non-emerging
Long-run		
EDI	0.430***	0.306***
	(34.946)	(22.059)
PR	0.188***	−0.001
	(11.108)	(-0.138)
CONS	0.096	−3.885
	(1.418)	(-0.940)
Short-run		
ECM	−0.028	−0.026**
	(-1.305)	(-1.987)
ΔEDI	−0.014	0.004
	(-0.720)	(0.339)
ΔPR	0.023	313.680
	(0.570)	(0.919)

Note: t statistics in parentheses, $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

5.2. Policy recommendations

As this study focuses on the cointegration link and two-way causality among energy poverty, public health, and educational development, our findings have significant implications for policymakers.

First, policymakers in developing countries should consider the level of educational development and energy poverty when formulating policies to improve public health. Additionally, when assessing the impact of energy poverty and educational development, governments should focus on their long-term impact rather than their short-term effect because the expression of a policy's effect requires sufficient time to develop. Moreover, it is recommended that individuals be directed towards the adoption of practices such as the utilisation of environmentally friendly energy sources, implementation of uncomplicated packaging methods, promotion of eco-friendly modes of transportation, and other measures aimed at promoting sustainability (Hao et al., 2023).

Second, regional energy policies must be formulated based on local conditions. For instance, women and children are primarily tasked with collecting traditional fuel resources such as branches and dead leaves. However, they spend too much time collecting these resources, which has a negative impact on the children's education. International experience has demonstrated this relationship between energy supply and literacy. Therefore, governments must start projects that provide people experiencing energy poverty access to high-quality energy, allowing them to devote more time to childcare, education, and income generation. At the macro level, it is necessary to comprehensively quantify the economic performance of each province, municipality, and region; combine local resources and actual economic levels; formulate differentiated and coordinated renewable energy policies; and optimise the overall renewable energy structure (Wang, 2022).

Third, given the significantly different economic development levels, trends, and international statuses of emerging and non-emerging countries, specific suggestions should be provided, particularly from the perspective of natural resource policy optimization. In the process of formulating natural resource policies for emerging economies, more focus should be placed on the geographical distribution of natural resources in the country rather than simply pursuing rapid economic growth and exporting a large number of natural resources, resulting in an uneven distribution of natural resources and aggravating the problem of energy poverty (Adedoyin et al., 2021; Cang et al., 2021). Given the slow economic development, lack of resources, and low international status of non-emerging economies, more attention should be paid to cooperation with other countries in the formulation of natural resource policies, such as formulating policies that are beneficial to other countries, introducing foreign investment, and learning from the experiences of emerging countries to optimise the allocation of natural resources.

Overall, our findings draw from a wealth of data from multiple countries and underscore the importance of improving access to modern energy sources such as oil. In turn, our findings have helped promote a broader view of energy poverty as a global challenge, rather than perceived as being confined to specific geographical challenges. Future policies should include integrated efforts, the development of management processes and practices, and capacity building by community-based organisations and local authorities to promote better access to modern energy sources, especially in areas where households use traditional energy sources, which increase public health risks. Therefore, we hope that people working in this field will consider new alternative energy sources, such as solar and wind energy, which can improve the health of the population and provide society with a more comprehensive and context-specific energy source.

5.3. Research prospects

Given that this study has primarily focused on analysing the relationships among energy poverty, public health, and educational development across 50 developing nations, its significant findings will aid future research and policymaking. However, some limitations should be highlighted to indicate the way forward. For instance, with the exception of energy poverty, health, and education, many other related factors were not included in the analysis because of difficulties in data collection. Further studies should be conducted when additional indicators are available. In addition to the methods mentioned in this study, further econometric models such as ordinary least squares, generalised method of moments, instrumental variables, and machine learning may be considered to expand the scale and depth of this topic. Furthermore, although the investigation period of the data used in this study is from before 2019, the results still provide essential reference value for balancing the relationship between energy poverty, educational development, and public health in the post COVID-19 pandemic era. However, as there has been no focus on the three years after the novel COVID-19 outbreak, some limitations are inevitable. In the future, if daily data on the number of COVID-19-infected people at the international level become available, we will continue to expand on the research topics of this article. Finally, the phenomenon of spillover effects stemming from volatility in oil and other commodities, in the aftermath of the global financial crisis, has garnered scholars' attention (Riaz et al., 2023). More attention should be paid to the protection and rational use of natural resources in their own countries and the elimination of the possibility of natural resource waste under the precondition of safety.

Author statement

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Yidong Chen & Ruiwen Zhang: Validation, Formal analysis, Investigation, Resources, Writing-original draft.
Renfu Luo: Review&editing, Visualization, Supervision.
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Declaration of competing interest

No conflict of interest exits in the submission of this manuscript, and the manuscript is approved by all authors for publication.

Data availability

Data will be made available on request.

Appendix 1. List of countries

Africa	Asia	Latin America
Angola	Azerbaijan	Argentina
Benin	Bangladesh	Bolivia
Botswana	India	Brazil
Cameroon	Indonesia	Chile
Cote D'Ivoire	Iran	Colombia
Egypt	Iraq	Ecuador
Ethiopia	Jordan	Paraguay
Gabon	Kyrgyz Republic	Peru
Ghana	Malaysia	Uruguay
Kenya	Nepal	Venezuela
Morocco	Pakistan	
Mozambique	Philippines	
Namibia	Sri Lanka	
Niger	Syria	
Nigeria	Thailand	
Senegal	Vietnam	
South Africa	Yemen	
Sudan		
Tanzania		
Togo		
Tunisia		
Zambia		
Zimbabwe		

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