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Spatial Dimensions of Energy Poverty Alleviation and Socioeconomic Sustainability in Sub-Saharan Africa

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ABSTRACT

Despite sub-Saharan Africa's vast endowment of energy resources, more than half of the region's population remains without access to electricity, positioning energy poverty as a persistent constraint on sustainable socioeconomic development. Consequently, a growing body of empirical literature has examined the socioeconomic consequences of energy poverty; however, its spatial transmission mechanisms remain insufficiently explored. Therefore, this study investigates the spatial spillover effects of energy poverty on key socioeconomic outcomes, with particular emphasis on health, education, and labor market performance. The analysis employs three spatial panel regressions: the spatial Durbin model, the spatial autoregressive model, and the spatial error model, using data from 25 sub-Saharan African countries over the period 2000–2021. The results reveal that the spillover effects of energy poverty are more pronounced than the direct effects. The spatial Durbin model results indicate that the total effect of a one-unit reduction in urban energy poverty is associated with an increase of 0.17 units in life expectancy and a decrease of 0.79 units in infant mortality rates. Furthermore, energy poverty is found to be a significant impediment to educational attainment and labor market development. These findings underscore the importance of accounting for geographical proximity and the equitable distribution of energy infrastructure when designing policies aimed at alleviating energy poverty in sub-Saharan Africa.

JEL Classification: P25, P28, R12

1 | Introduction

Energy poverty remains a critical challenge that undermines the global objective of poverty alleviation. Beyond depriving millions of people of basic energy services, it poses a serious threat to the achievement of the sustainable development agenda (Guevara et al. 2023). Despite sub-Saharan Africa's vast endowment of energy resources, which positions the region prominently within the global energy landscape, more than 600 million people—approximately 50.6% of the population—still lack access to electricity, and over 80% rely on inefficient, costly, and polluting fuels for cooking and heating (WDI 2024). The region's total electricity grid capacity is estimated at only about 90 GW, far below the global average. In countries such as South Sudan and Sierra Leone, many urban areas remain entirely unelectrified, while electrification rates in several other countries fall below 10% (Ouedraogo 2017). According to a report published by the United States Agency for International Development (USAID), the sub-Saharan African region needs to invest approximately 15–20 billion USD annually to achieve universal access to

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electricity by 2030. However, the region currently spends less than 1% of its Gross National Product on energy research and development (Wang et al. 2023).

The lack of access to efficient, affordable, and sustainable energy services remains a major impediment to socioeconomic development in sub-Saharan Africa. Frequent electricity outages impose substantial costs on businesses, reducing the turnover of large firms by approximately 6% and that of small enterprises by around 16% (Wang et al. 2023). Moreover, energy poverty is projected to slow Africa's economic growth by more than 2% annually (AFDB 2010). Service-oriented sectors are particularly constrained by limited access to reliable and sustainable energy sources, which hampers productivity and expansion (Ouedraogo and Schimanski 2018). Inadequate energy supply deprives millions of individuals of educational opportunities, significantly undermining learning outcomes, especially in rural areas, where access to dependable energy infrastructure is even more limited (Sule et al. 2022).

Conceptually, energy poverty refers to the inability of households to acquire ample, reliable, clean, safe, and sustainable energy to facilitate their daily needs (Rafi et al. 2021). Despite broad agreement on this general definition, considerable divergence persists in the literature regarding the theoretical foundations of energy poverty. Scholars have approached the concept from multiple perspectives, including the basic needs approach, the accessibility framework, and the energy justice paradigm (Banerjee et al. 2021; Guevara and Aldama 2022). Traditional fuel poverty theories frequently rely on Boardman's 10% rule, which classifies households as energy poor when they are required to spend more than 10% of their income to secure adequate energy services (Guevara and Aldama 2022). More recently, an expanding body of research has adopted an energy justice perspective by incorporating Sen's capability approach into energy poverty analysis, emphasizing the role of energy access in enabling essential human capabilities (Jenkins et al. 2016).

Theoretically, the relationship between energy poverty and socioeconomic development is primarily grounded in two frameworks: capability theory and human capital theory. Capability theory, originally developed by Sen (1993), provides a robust framework for understanding the complex linkage between energy poverty and socioeconomic development. The theory emphasizes the expansion of individuals' freedoms and opportunities to achieve valuable functioning and realize their full potential. From this perspective, energy poverty is conceptualized as a deprivation of capabilities that directly constrains access to essential services and limits individuals' ability to make meaningful life choices (Alkire 2013; Alnour et al. 2024). Accordingly, the framework underscores the importance of examining how energy deprivation restricts opportunities rather than focusing solely on energy availability. It further stresses that energy access should translate into substantive improvements in well-being and quality of life. Consistent with the principles of energy justice, capability theory advocates for policies that not only alleviate energy poverty but also promote equal opportunities and overall societal well-being.

Human capital theory posits that a nation's productivity increases in proportion to the share of its labor force that is well educated and in good health, as individuals with higher levels of education and better health are able to perform cognitively demanding tasks more efficiently and productively (Schultz 1960). Accordingly, investment in education and the accumulation of human capital are regarded as fundamental determinants of long-term economic prosperity. Improvements in health, education, and labor training enhance human capital formation and facilitate the transition toward cleaner and more efficient energy sources through better pricing mechanisms, technological adoption, and informed decision-making, thereby contributing to the reduction of energy poverty (Sadath and Acharya 2017). Individuals who are healthier and more educated are more likely to be conscious of their energy consumption patterns and to adopt more efficient and cleaner energy mixes. From a demand-side perspective, societies with a higher proportion of educated and healthy individuals are better positioned to regulate energy use effectively and shift away from traditional fuels such as biomass, kerosene, crop residues, and animal dung toward modern commercial energy sources, including electricity, natural gas, renewable energy, and petroleum products. Conversely, limited access to modern energy services can exacerbate health risks, including malnutrition and cardiovascular diseases, thereby constraining human development more broadly (Sharma et al. 2019).

Empirically, a substantial body of literature has examined the complex relationship between energy poverty and various socioeconomic outcomes (Lee and Yuan 2024; Ndubuisi et al. 2023). Despite the breadth of this literature and the diversity of outcomes explored, we report several gaps. First, the existing literature has largely relied on conventional analytical frameworks, often overlooking the spatial transmission of energy poverty. This is a significant limitation, especially in a region like sub-Saharan Africa, which comprises the most vulnerable and geographically interconnected countries, owing to factors such as labor mobility, transboundary resource corridors, shared ethnic ties, refugee flows, and regional political alliances. In this context, resource-induced issues in one country are often influenced by conditions in neighboring states (Buhaug and Gleditsch 2008; Wang et al. 2023). Recognizing these facts in policy implementation is essential. Therefore, harmonizing resource policies is not merely desirable for sub-Saharan Africa; it is crucial for achieving deeper regional integration. Such integration can facilitate the optimization of shared resources, enhance long-term prosperity, and smooth the transition to a sustainable future in a way that domestic institutions often fail to achieve. Thus, understanding the extent to which energy poverty in neighboring countries affects domestic socioeconomic indicators is vital for designing effective and coordinated actions for regional development. Therefore, given the above considerations, this study primarily aims to adopt spatial spillover panel regressions to assess the national and cross-national socioeconomic repercussions of energy poverty for 25 countries across sub-Saharan Africa during the time extending 2000–2021.

Second, the existing literature on the energy poverty-socioeconomic development nexus is primarily country-specific and based on household-level data. Evidence at the global or regional level remains limited. Despite the abundant energy resources in sub-Saharan Africa, energy continues to be a chronic obstacle to socioeconomic development.

Addressing this paradox requires comprehensive scientific modeling using regional-level data, which the current study seeks to provide. Third, prior studies have predominantly relied on relatively aggregate proxies for energy poverty. The current research adopts a disaggregated method, distinguishing energy poverty indicators across rural and urban areas to better reflect differences in energy infrastructure and accessibility. In practice, the geographic distribution of rural settlements in sub-Saharan Africa is highly fragmented and spatially dispersed. The long distances, challenging terrain, and low population density have increased the cost of electricity services for many single-family rural households to approximately USD 180/MWh. The annual cost of electricity transmission in Africa is estimated at about USD 5.9 billion. As a result, only about 2%–5% of rural households in the region have access to the electricity grid (Wang et al. 2023). These disparities in energy infrastructure, together with natural barriers and policy challenges, lead to unequal access to energy services, reflecting differences in the determinants of energy poverty between rural and urban areas. These differences, in turn, generate heterogeneous effects on socioeconomic outcomes. Therefore, to provide more policy-relevant evidence, it is important to understand the extent to which socioeconomic indicators in rural and urban areas respond separately to energy poverty.

The organization of subsequent sections is presented as follows: Section 2 reviews the literature and hypotheses development. Section 3 describes data and methodology. Section 4 yields the empirical findings and discussion. Section 5 delineates the conclusion.

2 | Literature Review and Hypotheses Development

This study is pertinent to three research spectra. The first spectrum discusses the nexus between energy poverty and health indicators. The second spectrum outlines the relationship between energy poverty and educational attainment. The last section delves into the nexus between energy poverty and labor force participation.

2.1 | Energy Poverty and Health Outcomes

Health is a vital human capital that reinforces individual learning outcomes through education, on-the-job, and off-the-job training. Empirical studies witnessed that human capital also boosts economic growth and development because the healthier worker has the potential to adopt and invent contemporary technologies that make them more productive (Dong et al. 2018; Gallardo-Albarrán 2018). Economic documents suggest that access to reliable, affordable, and clean energy sources has positive implications for public health. Energy consumption improves an individual's health by boosting the standard of living.

First, energy accessibility ensures the availability of clean and safe drinking water that is directly and positively associated with human health. Second, it provides individuals with an opportunity to have safe and proper cooking facilities that are fundamental to human survival. Third, it ensures adequate lighting, cooling, and heating in hard weather, ventilation, sanitation, and cleanliness, which are vital for human health. Fourth, it ensures quick access to hospitals and cardiac units, online medical services, and television and social media platforms that disseminate information regarding medical and healthcare. Finally, a reliable and sustainable energy supply to public and commercial hospitals and other healthcare units enhances life expectancy through state-of-the-art health services provision. It enables them to provide better care and treatment to mothers, newborn babies, children, cardiovascular patients, and other patients by enabling hospitals and laboratories to work 24/7 without any interruption (Banerjee et al. 2021). Lending support to the argument, Ahmad et al. (2014) revealed that adequate access to energy sources has significantly reduced diseases and boosted health outcomes in Indian households, particularly among children. Likewise, Pan et al. (2021) found that higher living standards with adequate access to energy have significantly improved health indicators among households in a panel of 175 countries. Whereas insufficient access to energy has severely affected public health.

On the contrary, energy poverty is detrimental to human health. The literature discloses that it deteriorates health indicators in various ways (Ballesteros-Arjona et al. 2022). Among children, lack of energy sources ignites respiratory diseases, general sickness due to improper ventilation, and hard weather as children are more vulnerable to cold and dehydration in extreme weather conditions (Liddell and Morris 2010; Rafi et al. 2021). Among adults and youth, energy poverty causes physical and mental diseases and subsequently reduces their cognitive and learning capabilities. The underlying reason is the persistent struggle and stress that arise due to the absence of cooling and heating systems necessary to cope with extreme temperatures (Ballesteros-Arjona et al. 2022). In line with the argument, Abbas et al. (2021) explored the negative implications of energy poverty on health indicators in South Asia. The author found that insufficient access to energy sources is associated with multiple diseases among individuals. Using PLFC methodology, Lee and Yuan (2024) discovered a negative linkage between the decline in energy access and public health in 185 countries. The study revealed that energy poverty aggravates health indicators in regions with urbanization below a certain threshold level. Likewise, several studies found an undesirable effect of decrease in energy access on both children's and adults' health across countries, including the Global South, European and other developed countries like Sweden and France (Bales et al. 2023; Bukari et al. 2021). Because this phenomenon is equally prevalent in many developed countries (Wilkinson et al. 2007). Given the above discussion, we derive the following hypothesis:

H1. *Energy poverty raises the infant mortality rate and reduces life expectancy in sub-Saharan Africa.*

2.2 | Energy Poverty and Educational Attainment

Education is an important factor for development in every sense. Being the most significant human capital, it enhances the production and creative capacities and capabilities of the workforce to raise the productivity levels in an economy. It also promotes workers' learning outcomes, knowledge stock, and competence to make efficient use of technology and other managerial and entrepreneurial skills that pay back financially to raise their standard of living and thus social status. Neoclassical growth models revealed that education yields a higher private rate of return, boosts earnings, and accelerates economic growth and development through increasing human capital, enhancing innovative capacity, and knowledge of contemporary technologies in an economy (de Meulemeester and Rochat 1995; Glewwe et al. 2014). Given the importance of education as a precursor of human capital, it is noteworthy that energy poverty is among the fundamental factors that have severe implications for education and subsequent economic development. It hinders children's access to education through various mechanisms. First, it hinders access to online learning platforms, as energy is necessary to access the internet and other online educational services. Second, it reduces study hours for a child as the unavailability of electricity for lighting at night. Third, in the absence of energy services for heating and cooling, it becomes impossible for pupils to concentrate and even carry on studies and other learning activities in the region where weather conditions are predominantly harsh.

On the contrary, energy access enables children and adults to perform better at schools and HEIs by providing them with an opportunity to study at night. It also allows female students and working adults to reallocate their time from domestic work and jobs to higher education (Rafi et al. 2021; Toman and Jemelkova 2003; Zajacova and Lawrence 2018). Economic literature witnessed that children from families living in extreme poverty spend ample time in search of firewood and traditional fuels to facilitate lighting and cooking; this consumes a significant portion of their time and even years to stay out of school. Empirics suggested that children of families having access to electricity have spent extra years at schools and HEIs and subsequently earned more income (Anil Cabraal et al. 2005). Besides, access to energy is inevitable for quality education, thus household welfare. Access to clean, safe, affordable, and reliable energy boosts enrollment at schools and educational quality by providing both students and teachers with various facilities. For instance, it ensures (i) proper lighting at homes and classrooms, (ii) sustainable heating and cooling facilities for students and educators, (iii) running of laboratory-related equipment for experiments, (iv) access to online study-related material and teaching, and (v) better working conditions in general (Banerjee et al. 2021). Empirically, several studies revealed a positive impact of access to energy sources on education. For instance, Toman and Jemelkova (2003) discovered a negative impact of energy poverty on education quality. The authors claimed that access to energy provides an opportunity to attain quality education and subsequently raises productivity levels. Acharya and Sadath (2019) reached the same conclusion for Indian households. Likewise, Banerjee et al. (2021) found the positive influence of energy development on educational attainment both at primary and secondary levels. Given the foregoing, we derive the following hypothesis:

H2. *Energy poverty reduces school enrollment and literacy rate in sub-Saharan Africa.*

2.3 | Energy Poverty, Labor Productivity, and Per Capita Income

Economic literature recorded that labor productivity is of vital importance to pursuing economic objectives. For that, human capital development is essential, particularly in the context of SDGs, and energy poverty is among the major obstacles to human capital development. It reduces human capital and subsequently labor productivity through education and health channels (Banerjee et al. 2021; Bonan et al. 2017). According to Banerjee et al. (2021), deteriorated health of the workforce, illiteracy, lower enrollment rates, and poor educational outcomes are among the major consequences of energy poverty and are fundamentally responsible for low productivity and subsequently lower per capita incomes. Economic literature maintained that the poor health of energy-poor workers stops them from working longer and more efficiently, as a healthy body is essential for a healthy brain and subsequently for learning and developing skills. Similarly, poor educational outcomes limit workers' efficiency by restricting the capabilities of the workers to understand and develop contemporary productive skills to make efficient use of modern technology and equipment. In short, the inability to work longer as a consequence of bad health and technology-relatedness due to poor educational outcomes limits workers' productivity and subsequently leads to lower levels of economic gains (Bonan et al. 2017; Zajacova and Lawrence 2018). Conversely, adequate access to affordable, clean, and reliable energy is a powerful tool to raise workers' efficiency, hence more income. It enhances human capital development by cultivating the fruits of better health and quality education (Banerjee et al. 2021; Toman and Jemelkova 2003). A significant portion of economic literature identified a positive nexus between sufficient access to energy and an individual's health and educational outcomes. Health permits workers to stay in their jobs over a longer period to gain adequate skills and experience to perform their duties with greater efficiency, which in turn raises productivity and income levels. Likewise, quality education allows workers to swiftly understand and adopt new modes of production that eventually boost their productive efficiency (Bukari et al. 2021).

Several empirical studies witnessed the negative implications of energy poverty on workers' productivity and per capita income. For instance, Garba and Bellingham (2021) and Raghutla and Chittedi (2022) highlighted that inadequate access to clean, safe, reliable, and affordable energy reduces workers' productivity and per capita incomes by deteriorating health and educational outcomes of workers. It further deteriorates the human capital accumulation by curtailing individuals' access to quality education and healthcare services. On a macro level, energy poverty adversely affects an economy's overall production capacity by hindering the efficient use of contemporary technologies. It also slows down the digitalization process and enhances production costs by disrupting the power supply, limiting the power plant's operational hours. Above all, energy poverty diminishes returns on investment by raising the cost of production due to excessive reliance on inefficient energy sources (Das and Drine 2020). Recently, Ndubuisi et al. (2023) found a negative influence of energy poverty on the production efficiency of workers while assessing the nexus between energy poverty and productive efficiency in 100 developing countries. In light of the above discussion, this study proposes the following hypothesis:

H3. *Energy poverty reduces labor force participation hence reduced per capita income in sub-Saharan Africa*.

3 | Data and Methodology

3.1 | Data

3.1.1 | Socioeconomic Measures

To estimate the spatial interlinkage between energy poverty and socioeconomic indicators for sub-Saharan Africa, this study considers health, education, and labor force participation and utilizes annual data extending the period 2000–2021 for 25 countries selected based on data availability. Table A6 reports on the list of countries included in the current study. Following Banerjee et al. (2021), life expectancy and infant mortality rates are widely used to measure the effect of energy access on healthcare conditions, especially in developing countries. Similarly, school enrollment is extensively used by the existing literature to measure the consequences of energy poverty for education (Ahmad et al. 2014). For the sake of a comprehensive view on the socioeconomic outcomes, this study further considers modeling the dynamics between energy poverty and labor force participation. The following equations reflect the main study objectives:

$$LEX_{jt} = \alpha_0 + \alpha_1 REP_{jt} + \alpha_2 UEP_{jt} + \alpha_3 SCH_{jt} + \alpha_4 GDP_{jt} + \varepsilon_{jt} \tag{1}$$

$$IMR_{jt} = \alpha_0 + \alpha_1 REP_{jt} + \alpha_2 UEP_{jt} + \alpha_3 SCH_{jt} + \alpha_4 GDP_{jt} + \varepsilon_{jt} \tag{2}$$

$$SCH_{jt} = \alpha_0 + \alpha_1 REP_{jt} + \alpha_2 UEP_{jt} + \alpha_3 LEX_{jt} + \alpha_4 GDP_{jt} + \varepsilon_{jt} \tag{3}$$

$$LFP_{jt} = \alpha_0 + \alpha_1 REP_{jt} + \alpha_2 UEP_{jt} + \alpha_3 IMR_{jt} + \alpha_4 SCH_{jt} + \varepsilon_{jt} \tag{4}$$

where the corresponding health, education, and labor force participation are represented by LEX_{jt}, IMR_{jt}, SCH_{jt}, and LFP_{jt} in country j at time t. α_1, α_2, α_3, and α_4 are the parameters to be estimated. ε_{jt} indicates the stochastic error term. To capture the possible heterogeneity, this study disaggregates rural energy poverty from urban energy poverty.

3.1.2 | Energy Poverty Measures

Evidently, the literature has not reached a consensus regarding energy poverty measures. Earlier research extensively used the well-known 10% rule introduced by Boardman (1991) to capture energy poverty. This rule terms an individual as energy-poor if an individual devotes over and above 10% of his/her income to energy (Imbert et al. 2016). However, it faced criticism due to various shortcomings, namely, (i) it ignores energy prices, (ii) over- and underestimates energy poverty, and (iii) arbitrarily determines households' income (Healy and Clinch 2004). Also, the double median method to capture energy poverty was introduced (Isherwood and Hancock 1979). This method considers national median expenses on energy sources to decide whether an individual is energy poor. Recently, Nussbaumer et al. (2012) introduced their famous multidimensional energy poverty index, which is often regarded as a comprehensive energy poverty measure. It takes into consideration six weighted indicators to estimate energy poverty, including electricity usage, clean energy use for cooking, state of home appliances, entertainment, municipal pollution, and education.

Besides, economic literature observed several other energy poverty measures developed by individual researchers following local conditions and other requirements. For instance, Moore (2012) devised an energy poverty measure known as the Minimum Income Standard (MIS) to link energy poverty with energy equity (Bradshaw et al. 2008). Accordingly, a household is considered energy-poor if he/she is unable to pay energy-related bills after paying utility bills. Other energy poverty approaches include After Fuel Cost Poverty (AFCP), Residual Income Approach (RIA), and Multidimensional Energy Poverty Index (MEPI) (Adzawla et al. 2020). The AFCP measure declares energy-poor if the leftover income is insufficient to cover the household's minimum possible expenses after covering energy-related expenditures (Castaño-Rosa et al. 2019). The same is true for the Residual Income Approach (RIA) energy poverty measure (Miniaci et al. 2014). However, it is difficult to rely on the approaches mentioned earlier to capture energy poverty because the minimum possible expenditures vary across countries due to dissimilarities in living standards and volatile energy prices (Rehmat and Mirza 2021).

While most of the above energy poverty measures have been utilized for country-level data analysis, there is a lack of specific energy poverty measures on the regional level. In this context, following Banerjee et al. (2021), energy poverty can be proxied by the percentage of the population having access to electricity. This measure is more comprehensive as it counts the overall population status. Therefore, this study considers using the percentage of the population having access to energy services as a proxy for energy poverty. Figure 1 illustrates the spatial ranking of the sampled countries based on energy access by population. The higher the number, the lower the energy poverty rate. Figure 2 outlines the technical roadmap of the study. A full description of the study variables, including symbols, definitions, units of measurement, and associated data sources, is provided in Table 1.

3.2 | Methodology

3.2.1 | Spatial Weight Matrix

Prior to employing spatial regressions, it is vital to construct the spatial weight matrix. It is an exogenous parameter that measures the degree of spatial dependency among the states i and j in the study samples. This study employs a Queen contiguity weight matrix, in which spatial units that share either a common boundary or vertex are assigned a weight of 1, while all other non-adjacent units receive a weight of 0. W is an $n \times n$

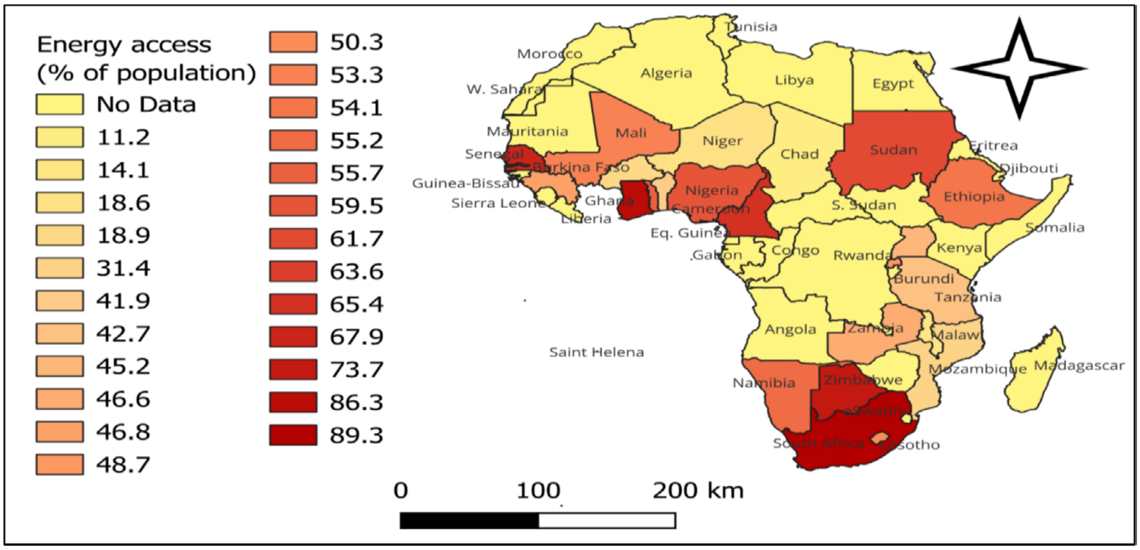
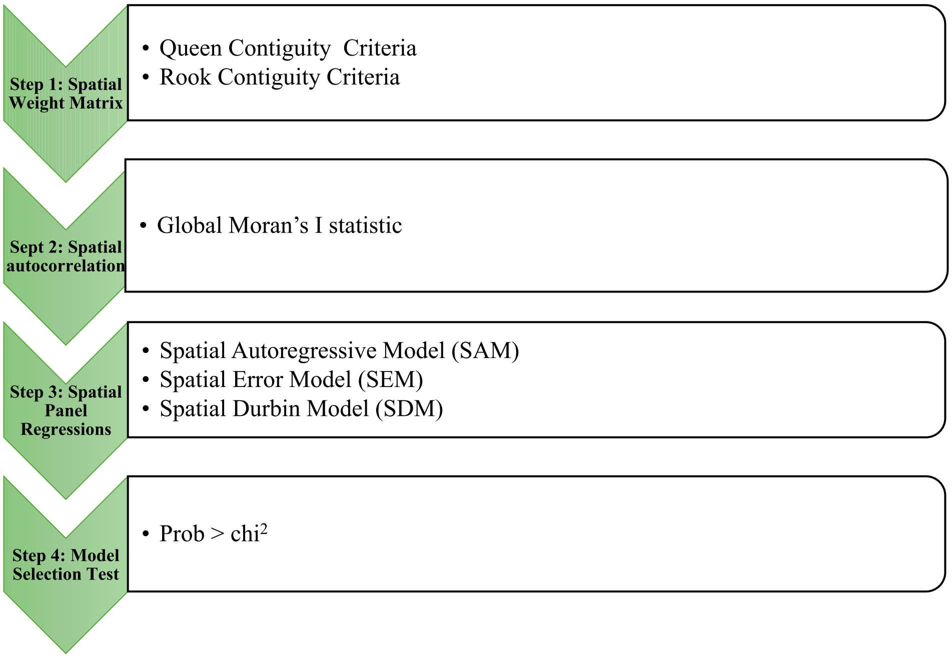


FIGURE 1 | A choropleth map illustrates the ranking of countries by the percentage of the population with access to electricity. The figure reveals substantial spatial disparities in electricity access across sub-Saharan Africa. Southern African countries generally exhibit relatively high electrification rates (89.3%), whereas Central Africa and parts of East and West Africa are characterized by low access levels (11.2%).



- Queen Contiguity Criteria
- Rook Contiguity Criteria

- Global Moran's I statistic

- Spatial Autoregressive Model (SAM)
- Spatial Error Model (SEM)
- Spatial Durbin Model (SDM)

- Prob > chi^2

FIGURE 2 | Technical roadmap of the study. The analysis is conducted using a combination of three software packages: QGIS for shapefiles extraction and data visualization, GeoDa for spatial weight matrix construction and Moran's *I* test of spatial autocorrelation, and Stata for estimating spatial panel regression models and model selection test.

spatial weights matrix representing the adjacency structure among spatial units.

$$W_{ij} = \begin{cases} 1, \text{countries } i \text{ and } j \text{ are neighboring countries} \\ 0, \text{countries } i \text{ and } j \text{ are not neighboring countries} \end{cases} \tag{5}$$

This approach has the potential to identify a larger number of neighboring units, thereby reflecting broader and more realistic spatial interactions. Figures A1 and A2 clearly demonstrate this by showing the number of neighbors based on Queen contiguity and Rook contiguity criteria. Consequently, the Queen contiguity matrix better captures the spillovers, reduces the likelihood of isolated regions, and produces more robust spatial models, particularly when underlying processes diffuse through both shared borders and points of contact (Anselin 1988). Recent empirical literature also widely employed the Queen contiguity matrix in spatial analysis due to its above-mentioned advantages (Guo et al. 2025; Hossain et al. 2025).

TABLE 1 | Data description.

Symbol	Variables	Definition and measurement	Source
REP	Rural energy poverty	It is measured by the percentage of rural population having access to electricity services.	World Bank (World Development Indicators)
UEP	Urban energy poverty	It is measured by the percentage of urban population having access to electricity services.	World Bank (World Development Indicators)
LEX	Life expectancy at birth	Proxied by the total years index. This index shows how many years a newborn baby would live if the death rate that was in place at the time of the baby's birth continued to be unchanged.	World Bank (World Development Indicators)
INM	Infant mortality rate	It is measured by the percentage of newborns that pass away before becoming 1 year old per 1000 live births.	World Bank (World Development Indicators)
SCH	School enrollment	Primary (% gross). It indicates the number of students enrolled in primary education, irrespective of age, divided by the number of people of the age group that formally represents primary education, which is multiplied by 100.	World Bank (World Development Indicators)
GDP	Gross domestic product	It refers to economic growth, measured in constant US Dollars of 2015.	World Bank (World Development Indicators), and Instituto Nacional de tatística
LFP	Labor force participations	Total (% population between 15 and 64 years of age) based on International Labor Organization estimates	World Bank (World Development Indicators)

3.2.2 | Spatial Autocorrelation

After specifying the spatial weight matrix, we assess the presence of spatial dependence using the Global Moran's *I* statistic, a widely used measure for detecting spatial autocorrelation among spatial units (Kuşkaya et al. 2025). Following Moran (1948), the global Moran's *I* index is calculated as:

$$\text{Moran's } I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}\left(u_i - \bar{u}\right)\left(u_j - \bar{u}\right)}{s^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}} \quad \forall i = 1, \dots, n \wedge \forall j = 1, \dots, n \tag{6}$$

where

$$\bar{u} = \frac{1}{N} \sum_{i=1}^{n} u_i, s^2 = \frac{1}{N} \sum_{i=1}^{n} \left(u_i - \bar{u}\right)^2 \tag{7}$$

where u_i and u_j correspondingly indicate the dependent variables (life expectancy, infant mortality, schooling enrollment, and labor force participation) in the spatial unit (countries) i and j. n indicates the number of spatial units. W_{ij} are the elements of spatial weights linking country i and j (Kuşkaya et al. 2025). Figures 3–7 present the results of the spatial autocorrelation tests for health, education, labor market participation, and per capita income.

3.2.3 | Spatial Panel Regressions

In this study, initially, three spatial panel regressions are employed, namely, the spatial autoregressive model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM) to study the socioeconomic repercussions of energy poverty in sub-Saharan Africa. Starting with the SAR model, the structure of the SAR is given by

$$z_{it} = \alpha + \lambda \Sigma_{j=1} W z_{jt} + \Sigma_k x_{it}^{(k)} \delta_k + \mu_i + \vartheta_t + \varepsilon_{it} \tag{8}$$

where z_{it} proxies the dependent variable for country $i = 1, 2, \dots N$. At time $t = 1, 2, \dots T$. x_{it} is a $k \times 1$ vector of regressors. W *is* a row-normalized weight matrix. The term $W z_{jt}$ captures the spillover effects of the dependent variable in neighboring countries on the dependent variable z_{it}, while λ indicates the magnitude and direction of spatial interaction between a given country and its geographically proximate counterparts. μ_i and ϑ_t indicate the spatial specific effects and time-period effect.

In the SEM, the stochastic term of country i is hypothesized to rely on the error terms of neighboring countries j according to the spatial weight matrix (W) and an idiosyncratic component (e_{it}). The specification of SEM can take the following form:

$$z_{it} = \alpha + \lambda \Sigma_{j=1} W z_{jt} + \Sigma_k x_{it}^{(k)} \delta_k + \mu_i + \vartheta_t + e_{it} \tag{9}$$

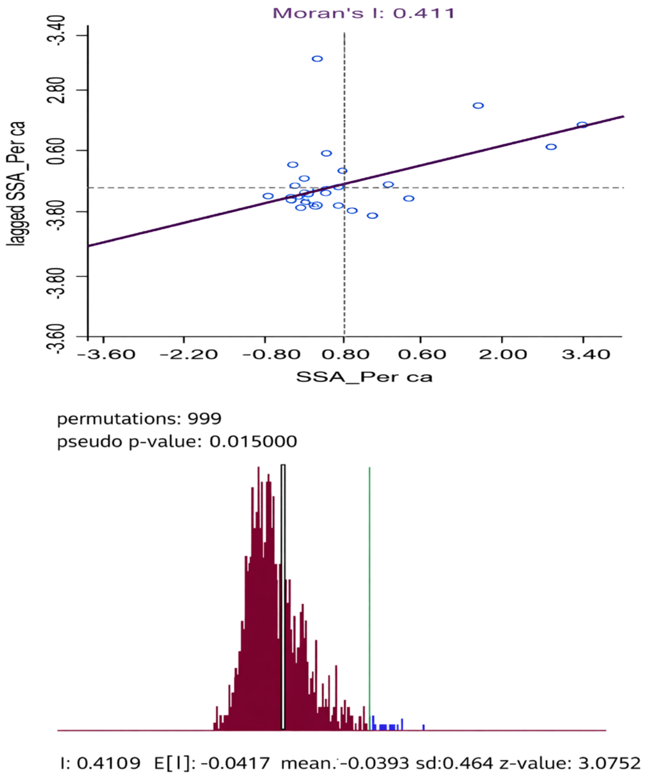


FIGURE 3 | The spatial autocorrelation test for per capita income. The Moran's I statistic is 0.411, indicating a moderate and significant positive spatial autocorrelation (pseudo p value of 0.015 and the z value of 3.075). This suggests that countries with similar income levels tend to cluster geographically in the SSA region. The upward-sloping Moran scatter plot confirms this spatial clustering pattern. The observed Moran's I (0.4109) is substantially higher than the expected value under spatial randomness (−0.0417).

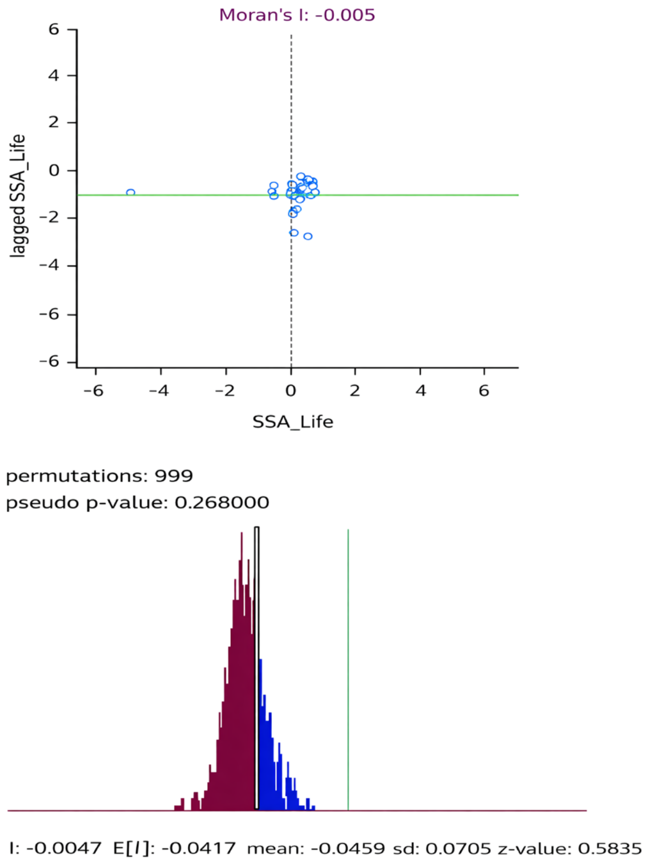


FIGURE 4 | The results of the spatial autocorrelation test for life expectancy at birth. The Moran's test yields a value close to 0 (−0.005) and is statistically insignificant ($p = 0.268$), indicating the absence of global spatial autocorrelation. This suggests that life expectancy across the region is spatially random, with no evidence of systematic geographic clustering at the regional level.

where $e_{it} = \phi\Sigma j = 1We_{jt} + \varepsilon_{it}$. In the above equation, geographical interconnectivity is represented in disturbance terms. We_{jt} indicates the geographical interlinkage among the disturbance terms of the different states under examination. To reflect the spatial interactions in both dependent and independent variables, the SDM was developed. It can be specified as follows:

$$z_{it} = \alpha + \lambda\Sigma_{j=1}Wz_{jt} + \Sigma_k x_{it}^{(k)}\delta_k + \Sigma_{j=1}Wx_{jt}^{(k)}\theta_k + \mu_i + \vartheta_t + \eta_{it} \tag{10}$$

where θ is a $k \times 1$ vector of parameters to be estimated. η_{it} is the disturbance term. To surpass the inconsistencies associated with fixed and random effects, the SDM uses the maximum likelihood estimation technique (Kuşkaya et al. 2025).

4 | Empirical Results and Discussion

The empirical analysis begins with an examination of key measures of central tendency and dispersion for the variables of interest. Table 2 reports the mean, standard deviation, minimum and maximum values, as well as the total number of observations. Although cross-sectional dependence tests are not a prerequisite for spatial econometric modeling, we nonetheless assess the stationarity properties of the variables with and without cross-sectional dependence by applying the Levin–Lin–Chu and Im–Pesaran–Shin panel unit root tests. Tables 3 and 4 present mixed results, indicating that some variables are stationary in levels, while others are integrated of order one. Subsequently, we conduct a cointegration analysis to examine the existence of a long-run relationship among the variables of interest. The results from the Kao cointegration test in Table 5 strongly reject the null hypothesis of no cointegration at the 1% level of significance, confirming the presence of a long-term equilibrium relationship among the variables.

Prior to estimating the spatial regression models, it is important to assess the presence of spatial dependence within the study sample. The spatial autocorrelation of the dependent variable was examined using Moran's I index for the most recent available cross-sectional data (2021). While the Global Moran's I statistics are widely used to test spatial autocorrelation, it only reflects a cross-sectional value at a specific point in time. Therefore, to capture the average spatial dependence, we also examined the spatial autoregressive coefficient (ρ). This parameter measures the average influence of neighboring units on a given spatial unit. A nonsignificant ρ value would indicate the absence of spatial dependence in the data. Tables 6–9 report the ρ test results, which indicate the rejection of the null hypothesis of no spatial dependence at the 1% and 10% levels of significance. To further

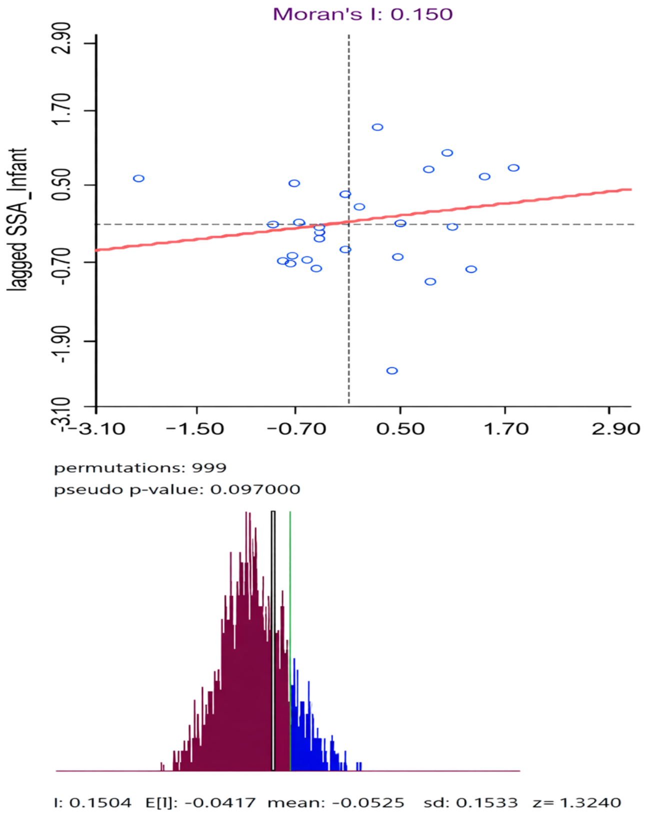


FIGURE 5 | The outcomes of the spatial autocorrelation test for infant mortality across sub-Saharan Africa. The Moran's statistic is 0.150, suggesting weak positive spatial autocorrelation (pseudo p value = 0.097). These results indicate that infant mortality exhibits only mild spatial grouping, with neighboring countries showing somewhat similar levels of infant mortality but with weak spatial autocorrelation.

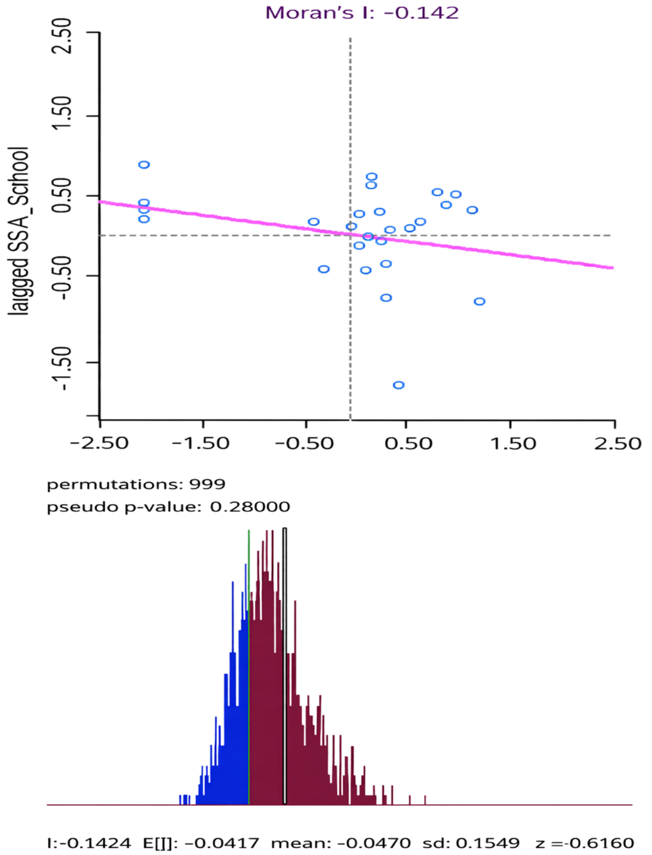


FIGURE 6 | The results of the spatial autocorrelation test for school enrollment. The Moran's I statistic is −0.142, indicating a weak negative spatial autocorrelation across the SSA region. The scatter plot, characterized by a downward-sloping regression line and widely dispersed observations, confirms the absence of strong spatial clustering in school enrollment levels.

examine the distributional patterns of the study variables, we use data for the year 2021 to analyze their spatial distribution characteristics. The spatial distributions of the variables are illustrated in Figures 8–14.

To select the appropriate spatial model after estimating the SDM, SAR, and SEM specifications, we conducted a chi-square test. When the Prob > X^2 = 0.000, we strongly reject the null hypothesis, as the p value is below 1%. In this case, the SDM is preferred. In this study, all model selection tests consistently support the SDM specification; X^2 p values are found to be lower than 1%. Therefore, we report and interpret only the SDM results as the baseline model for the analysis. Given the substantial disparities in socioeconomic development and energy infrastructure across countries in sub-Saharan Africa, the presence of heterogeneity is anticipated. The standard Pesaran–Yamagata slope heterogeneity test (Table A5) confirms the existence of cross-sectional heterogeneity. Nevertheless, we argue that a significant portion of the detected heterogeneity is attributable to spatial dependence, spillover effects, and spatially correlated differences in infrastructure capacity. As the SDM explicitly captures spatial interactions by incorporating both endogenous and exogenous spillovers, it constitutes an appropriate and robust framework for estimating average direct and indirect effects across countries. Moreover, the SDM is widely recognized as a flexible specification that helps reduce bias arising from omitted spatially correlated variables. By including spatial lags of the explanatory variables, the model captures unobserved factors that are spatially correlated with the regressors, thereby mitigating unobserved spatial heterogeneity (Beer and Riedl 2012; Kopczewska et al. 2017). Finally, the robustness of the results is assessed using an alternative spatial weight matrix based on the Rook contiguity criterion. The robustness checks yield almost similar results, with only minor differences in magnitude but consistent directions of the estimated effects. This consistency supports the choice of the Queen contiguity matrix for the main results (see Tables A1–A4).

To examine the potential spatial spillover effects of energy poverty on socioeconomic indicators across sub-Saharan Africa, it is necessary to estimate the direct and indirect effects. The direct effect captures how changes in energy poverty influence the socioeconomic indicators of a given country. In contrast, the indirect effect reflects the impact of changes in energy poverty in neighboring countries on socioeconomic outcomes. The total effect represents the combined influence of both the direct and indirect effects. For health indicators, this study utilizes life expectancy and infant mortality rate since they are widely used measures for human health status (Banerjee et al. 2021). Table 6 reports the SDM results for life expectancy model. Considering the total effects, the results reveal that both rural and urban

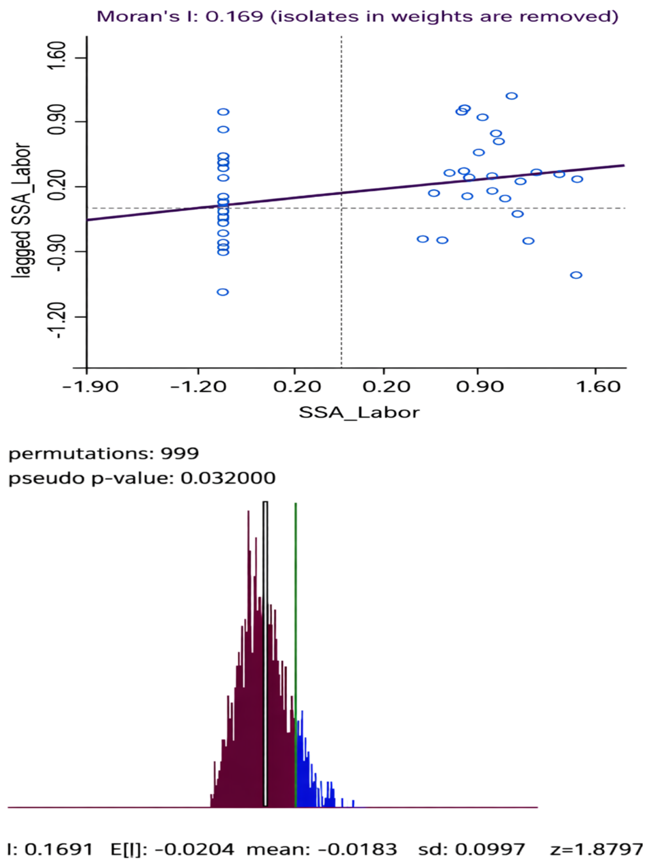


FIGURE 7 | The spatial autocorrelation test for labor force participation in sub-Saharan Africa. The Moran's test reveals a positive and statistically significant spatial autocorrelation (0.169; $p = 0.032$), indicating that countries with similar labor participation rates tend to cluster geographically across the region, suggesting the presence of regional spillovers or shared structural characteristics in labor market outcomes.

TABLE 2 | Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min	Max
LEX	550	57.261	5.3430	42.91	68.52
INM	550	60.021	19.189	26.4	112
REP	550	17.403	18.293	0.52	95.53
UEP	550	65.445	20.324	10.06	97.98
GDP	550	1478.0	1504.2	255.1	6485
SCH	550	95.203	25.192	31.84	150.4
LFP	550	67.085	9.6360	46.88	89.45

TABLE 3 | Panel unit root test (with cross-sectional dependence).

	Level		1st difference	
Variables	**Statistic**	***p***	**Statistic**	***p***
Lim–Pesaran–Shin unit root				
LEX	−1.9934	0.023**	1.7801	0.9625
INM	−9.9442	0.000*	0.2225	0.5881
REP	3.5321	0.9998	−16.284	0.000*
UEP	4.8810	1.0000	−19.211	0.000*
GDP	3.1697	0.9992	−7.5529	0.000*
SCH	−1.5483	0.060**	−10.300	0.000*
LFP	2.8014	0.9975	−8.4892	0.000*
Levin–Lin–Chu unit root				
LEX**	−7.8467	0.000*	9.5958	1.0000
INM	−9.1045	0.000*	−5.0953	0.0000
REP	1.0743	0.8587	−11.974	0.000*
UEP	−0.8757	0.1906	−13.597	0.000*
GDP	−1.5087	0.06***	−4.0372	0.000*
SCH	−1.7141	0.04**	5.8830	1.0000
LFP	−3.7933	0.000*	0.4616	0.6778

Note: *, ** and *** indicate the rejection of the null hypothesis of no stationarity at 1%, 5% and 10% levels of significance, respectively.

TABLE 4 | Panel unit root test (with no cross-sectional dependence).

	Level		1st difference	
Variables	**Statistic**	***p***	**Statistic**	***p***
Lim–Pesaran–Shin unit root				
LEX	−2.820	0.002*	−3.195	0.000*
INM	−6.663	0.000*	−0.891	0.1863
REP	−0.717	0.236	−14.09	0.000*
UEP	−1.233	0.108	−14.58	0.000*
GDP	3.169	0.999	−7.552	0.000*
SCH	−0.778	0.218	−11.78	0.000*
LFP	2.801	0.997	−8.489	0.000*
Levin–Lin–Chu unit root				
LEX	−5.136	0.000*	2.411	0.9921
INM	−8.588	0.000*	−5.586	0.000*
REP	2.173	0.9851	−11.93	0.000*
UEP	−2.35	0.009*	−13.19	0.000*
GDP	−2.724	0.003*	−4.770	0.000*
SCH	5.929	1.000	9.794	1.0000
LFP	−2.770	0.002*	−3.253	0.000*

Note: * indicates the rejection of null hypothesis of no stationarity at 1% level of significance.

energy poverty exert a significant negative influence on life expectancy. Specifically, a one-unit increase in the share of the rural population with access to electricity (reflecting a reduction in rural energy poverty) is associated with an increase of 0.172 units in life expectancy. Similarly, a one-unit increase in the proportion of the urban population with access to energy services is associated with a 0.173-unit increase in life expectancy. These results are consistent with those of Banerjee et al. (2021) and many others who concluded that adequate access to electricity improves health and life expectancy rate (Abbas et al. 2021;

TABLE 5 | Cointegration test.

Kao test	Statistic	*p*
Model 1		
Modified Dickey–Fuller	−4.2593	0.0000*
Dickey–Fuller	−4.0571	0.0000*
Augmented Dickey–Fuller	−2.6356	0.0042*
Unadjusted modified Dickey–Fuller	−2.3323	0.0098*
Unadjusted Dickey–Fuller	−3.3542	0.0004*
Model 2		
Modified Dickey–Fuller	−7.0566	0.0000*
Dickey–Fuller	−6.2657	0.0000*
Augmented Dickey–Fuller	−4.6523	0.0000*
Unadjusted modified Dickey–Fuller	−2.4922	0.0063*
Unadjusted Dickey–Fuller	−5.5071	0.0000*
Model 3		
Modified Dickey–Fuller	0.7256	0.2340
Dickey–Fuller	1.6395	0.05**
Augmented Dickey–Fuller	1.7128	0.04**
Unadjusted modified Dickey–Fuller	0.7617	0.2231
Unadjusted Dickey–Fuller	1.6709	0.04**
Model 4		
Modified Dickey–Fuller	2.3283	0.009*
Dickey–Fuller	1.6252	0.05**
Augmented Dickey–Fuller	2.1983	0.014*
Unadjusted modified Dickey–Fuller	2.1023	0.017*
Unadjusted Dickey–Fuller	1.3624	0.08

Note: * and ** indicate the rejection of the null hypothesis of no cointegration at 1% and 5% levels of significance, respectively.

Bukari et al. 2021; Rafi et al. 2021). When comparing the magnitudes, we found that the spillover effect of energy poverty on life expectancy is stronger (0.103) than the local effect (0.069), particularly in urban energy poverty. More notably, the indirect (spillover) effect of rural energy poverty on life expectancy is both stronger and statistically significant, in contrast to the insignificant or weaker domestic (direct) effect. These results underscore the critical role that neighboring countries' energy poverty plays in shaping local health outcomes. One plausible explanation is the cross-border or regional influx of patients from energy-poor neighboring countries into domestic healthcare systems, which may strain already limited healthcare capacity and reduce the quality of service provision, ultimately leading to preventable morbidity and mortality. This interpretation is particularly relevant in developing-country contexts, where healthcare systems are often underdeveloped, overburdened, and insufficiently equipped to meet even domestic demand, let alone additional external pressures.

Table 7 outlines the results of the infant mortality rate model. Based on the total effects estimated from the SDM, the results indicate that both rural and urban energy poverty have a significant impact on infant mortality in the SSA region. As expected, improvements in energy access are associated with lower infant mortality rates. Specifically, a one-unit increase in the share of the rural population with access to electricity is associated with a 0.493-unit reduction in the infant mortality rate. Similarly, a one-unit increase in the proportion of the urban population with access to energy services leads to a 0.7961-unit decline in infant mortality. These outcomes are consistent with the findings of Oliveras et al. (2020, 2021). The inability to afford efficient transportation services to convey mothers and infants to hospitals or maternity centers, often located at considerable distances, particularly in rural areas, can significantly increase infant mortality rates. Moreover, limited access to electricity and electronic communication devices, such as mobile phones, reduces awareness of infant health needs and timely medical responses, thereby exacerbating infant mortality. In addition, inadequate access to vaccinations due to difficulties in reaching healthcare facilities, coupled with poor quality of healthcare services resulting from frequent electricity interruptions during medical procedures and improper storage of vaccines caused by power outages, may further contribute to elevated infant mortality, especially in sub-Saharan African countries (Anil Cabraal et al. 2005; Banerjee et al. 2021).

Moreover, the persistence of maternal and infant undernourishment may constitute another important channel, as energy-poor households are more likely to experience underemployment, low productivity, and income poverty, thereby limiting their ability to secure adequate nutrition for mothers and children. When we compare the coefficients, we find that neighboring energy poverty has a stronger effect on infant mortalities than local energy poverty. For instance, a one-unit increase in the share of the population with access to energy services in neighboring countries is associated with a 0.622-unit reduction in the domestic infant mortality rate, reflecting the spillover effect. Meanwhile, a one-unit increase in the population with access to energy services within a country leads to a 0.173-unit decline in infant mortality, capturing the direct effect, holding other factors constant. One plausible explanation for these results relates to pressures on domestic healthcare systems arising from cross-border mobility. The inflow of infants, particularly premature babies requiring incubators and critical medical care from neighboring energy-poor countries, may place additional strain on already limited healthcare infrastructure. Furthermore, migration flows involving families, pregnant women, and infants seeking employment opportunities or refuge from conflict-affected areas within sub-Saharan Africa, combined with the outward migration of medical professionals in search of better employment prospects, may further exacerbate constraints on healthcare service delivery.

Consistent with prior expectations, educational attainment significantly reduces the infant mortality rate. A one-unit increase in educational attainment is associated with a 0.235-unit decline in infant mortality. Moreover, the indirect (spillover)

TABLE 6 | Spatial Durbin model (SDM) results—Model 1.

Life expectancy	Coef.	Std. Err.	*z*	*p* > *z*	[95% Conf. Interval]
Main					
REP	0.0114	0.0108	−1.05	0.294	−0.0327 to 0.0098
UEP	0.0576	0.0088	6.53	0.000*	0.0403–0.0750
SCH	−0.0032	0.0043	−0.75	0.454	−0.0117 to 0.0052
GDP	0.0015	0.0003	4.58	0.000*	0.0008–0.0022
_cons	16.934	1.6877	10.03	0.000*	13.626–20.242
W(*x*)					
*W**(REP)	0.0947	0.0188	5.03	0.000*	0.0578–0.1315
*W**(UEP)	0.0284	0.0122	2.32	0.02**	0.0044–0.0525
*W**(SCH)	0.0277	0.0080	3.45	0.001*	0.0119–0.0435
*W**(GDP)	0.0003	0.0005	−0.55	0.583	−0.0014 to 0.0008
Spatial ρ	0.5082	0.0378	13.44	0.000*	0.4341–0.5823
Variance					
lgt_theta	2.3720	0.1735	−13.67	0.000*	−2.7122 to −2.0319
sigma2_e	2.4755	0.1576	15.7	0.000*	2.1665–2.7846
X^2	144.86			0.000*	
Log-likelihood	−1118.0				
Direct effect					
REP	0.00884	0.0121	0.72	0.469	−0.015 to 0.0327
UEP	0.06975	0.0095	7.32	0.000*	0.0510–0.0884
SCH	0.00292	0.0046	0.63	0.531	−0.0062 to 0.0120
GDP	0.00165	0.0003	4.5	0.000*	0.0009–0.0023
Indirect effect					
REP	0.16391	0.0341	4.8	0.000*	0.0969–0.2308
UEP	0.10349	0.0205	5.03	0.000*	0.0632–0.1437
SCH	0.04745	0.0148	3.2	0.001*	0.0183–0.0765
GDP	0.00090	0.0009	0.91	0.365	−0.001 to 0.0028
Total effect					
REP	0.17275	0.0408	4.23	0.000*	0.0926–0.2528
UEP	0.17325	0.0269	6.43	0.000*	0.1204–0.2260
SCH	0.05037	0.0175	2.87	0.004*	0.0159–0.0848
GDP	0.00255	0.0011	2.14	0.033*	0.0002–0.0048

Note: * indicates a 1% level of significance.

effect of educational attainment in neighboring countries is more pronounced, resulting in a 0.148-unit reduction in infant mortality, compared with the direct (local) effect, which accounts for a 0.086-unit decline. Our analysis further indicates that educational attainment and per capita income play a significant and positive role in improving life expectancy in sub-Saharan Africa. A one-unit increase in school enrollment is associated with a 0.05037-unit increase in life expectancy. Similarly, a one-unit increase in per capita income leads to a 0.00255-unit rise in life expectancy, holding other factors constant. While these findings are consistent with expectations, the effect of educational attainment in neighboring countries is notably stronger. Specifically, a one-unit increase in neighbors' education levels is associated with a 0.0474-unit increase in domestic life expectancy, whereas the local education effect is not statistically significant.

TABLE 7 | Spatial Durbin model (SDM) results—Model 2.

Infant mortality rate	Coef.	Std. Err.	z	p>z	[95% Conf. Interval]
Main					
REP	−0.0007	0.0339	−0.02	0.984	−0.0672 to 0.0658
UEP	−0.1059	0.0292	−3.62	0.000*	−0.1632 to −0.0485
SCH	−0.0717	0.0135	−5.27	0.000*	−0.0983 to −0.0450
GDP	0.0014	0.0011	1.19	0.234	−0.0009 to 0.0037
_cons	78.457	7.1186	11.02	0.000*	64.50–92.409
W(*x*)					
*W**(REP)	−0.2873	0.0588	−4.88	0.000*	−0.4027 to −0.1718
*W**(UEP)	−0.3507	0.0396	−8.84	0.000*	−0.4285 to −0.2730
*W**(SCH)	−0.0646	0.0272	−2.38	0.017*	−0.1180 to −0.0113
*W**(GDP)	0.0007	0.0018	0.37	0.709	−0.0029 to 0.0043
Spatial ρ	0.4227	0.0397	10.64	0.000*	0.3448–0.5005
Variance					
lgt_theta	−2.5909	0.1775	−14.59	0.000*	−2.9389 to −2.2429
sigma2_e	23.981	1.5332	15.64	0.000*	20.976–26.986
X^2	239.23			0.000*	
Log-likelihood	−1738.4				
Direct effect					
REP	−0.0473	0.0367	−1.29	0.197	−0.1193 to 0.0246
UEP	−0.1739	0.0288	−6.03	0.000*	−0.2304 to −0.1174
SCH	−0.0862	0.0137	−6.27	0.000*	−0.1131 to −0.0593
GDP	0.0016	0.0012	1.35	0.177	−0.0007 to 0.0039
Indirect effect					
REP	−0.4462	0.0897	−4.97	0.000*	−0.622 to −0.2703
UEP	−0.6221	0.0552	−11.25	0.000*	−0.730 to −0.5138
SCH	−0.1489	0.0385	−3.87	0.000*	−0.224 to −0.0734
GDP	0.0021	0.0027	0.79	0.43	−0.003 to 0.0075
Total effect					
REP	−0.4935	0.1070	−4.61	0.000*	−0.7033 to −0.2837
UEP	−0.7961	0.0717	−11.1	0.000*	−0.9367 to −0.6555
SCH	−0.2351	0.0450	−5.22	0.000*	−0.3234 to −0.1468
GDP	0.0037	0.0032	1.18	0.239	−0.0025 to 0.0100

Note: * indicates a 1% level of significance.

Table 8 reveals spatial regression analysis for education. The results indicate that urban energy poverty has a significant total effect on educational attainment. Focusing on the indirect (spillover) effect, a one-unit reduction in rural energy poverty is associated with a 0.3153-unit increase in educational attainment in neighboring areas. The outcome is in line with the empirical findings of Banerjee et al. (2021) and Khandker et al. (2014). Inadequate access to energy can adversely affect educational attainment through several channels. First, energy poverty is closely associated with school absenteeism and early dropout, particularly in rural areas (Ahmad et al. 2014). Second, access to electricity has been shown to improve educational performance and extend children's schooling duration by up to 2 years compared with children from energy-poor households (Anil Cabraal et al. 2005). In electricity-deprived households, especially in rural settings, substantial time is

TABLE 8 | Spatial Durbin model (SDM) results—Model 3.

School enrollment	Coef.	Std. Err.	z	$p>z$	[95% Conf. Interval]
Main					
REP	−0.5753	0.10338	−5.57	0.000*	−0.778 to −0.3727
UEP	−0.2132	0.08759	−2.43	0.015*	−0.3848 to −0.0415
LEX	−0.4965	0.42006	−1.18	0.237	−1.3199 to 0.3267
GDP	0.0096	0.00251	3.82	0.000*	0.0046–0.0145
_cons	13.440	18.3795	0.73	0.465	−22.583 to 49.463
W(*x*)					
*W**(REP)	0.3432	0.18569	1.85	0.065**	−0.0206 to 0.70723
*W**(UEP)	−0.1399	0.13015	−1.08	0.282	−0.3950 to 0.11510
*W**(LEX)	2.0398	0.56624	3.6	0.000*	0.9300–3.14964
*W**(GDP)	−0.0020	0.00424	−0.49	0.623	−0.0104 to 0.00623
Spatial ρ	0.0971	0.05401	1.8	0.072***	−0.0086 to 0.20302
Variance					
lgt_theta	−1.6177	0.17927	−9.02	0.000*	−1.9691 to −1.2663
sigma2_e	245.09	15.1827	16.14	0.000*	215.33–274.85
X^2	22.15			0.0002*	
Log-likelihood	−2339.1				
Direct effect					
REP	−0.5622	0.1056	−5.32	0.000*	−0.7693 to −0.3551
UEP	−0.2229	0.0864	−2.58	0.01*	−0.3923 to −0.0535
LEX	−0.3885	0.3912	−0.99	0.321	−1.1553 to 0.3783
GDP	0.0094	0.0024	3.87	0.000*	0.0046–0.0142
Indirect effect					
REP	0.3153	0.1858	1.7	0.09***	−0.0488 to 0.67965
UEP	−0.1768	0.1504	−1.18	0.24	−0.4718 to 0.11810
LEX	2.1038	0.6000	3.51	0.000*	0.9277–3.27981
GDP	−0.0008	0.0043	−0.2	0.838	−0.0094 to 0.00761
Total effect					
REP	−0.2468	0.2087	−1.18	0.237	−0.656 to 0.1623
UEP	−0.3998	0.1912	−2.09	0.037**	−0.7747 to −0.0249
LEX	1.7153	0.5077	3.38	0.001*	0.720 to 2.7104
GDP	0.0086	0.0045	1.88	0.061***	−0.0003 to 0.0175

Note: *, **, *** indicate 1%, 5% and 10% level of significance, respectively.

devoted to collecting firewood and other traditional biomass fuels for cooking and heating. During prolonged periods of extreme weather, such as heavy rainfall or snowfall, households are unable to collect fuel on a daily basis and must instead maintain fuel stocks for weeks or months. This labor-intensive task cannot be fully undertaken by working adults, who must allocate time to income-generating activities. Consequently, non-earning household members, particularly boys and girls, are often compelled to assume responsibility for fuel collection at the expense of their schooling. Similar conclusions were reached by Khandker et al. (2014) in their analysis of rural electrification and education outcomes in India. Likewise, Anil Cabraal et al. (2005) report that children in extremely poor households devote substantial time to gathering firewood and traditional fuels for lighting and cooking, which significantly reduces school attendance and increases

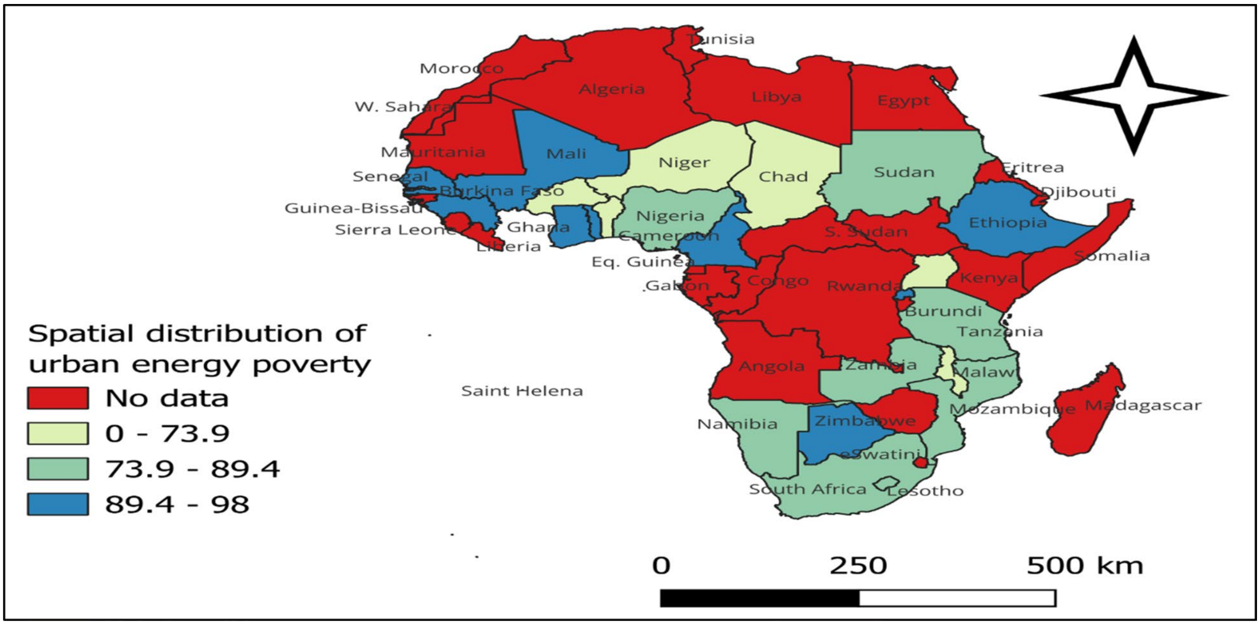


FIGURE 8 | Spatial distribution of urban energy poverty in sub-Saharan Africa, proxied by the percentage of the urban population with access to electricity. A data-driven classification is used to distinguish countries with lower levels of urban energy poverty (in blue) from those with higher levels of energy poverty (in light green).

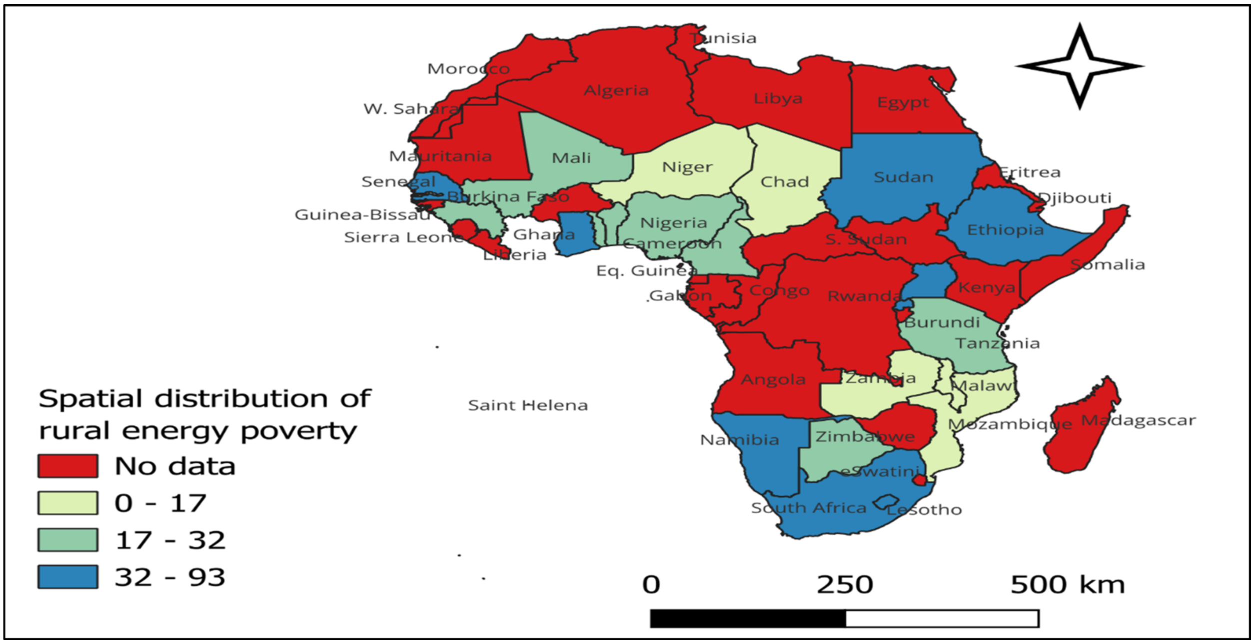


FIGURE 9 | Spatial distribution of rural energy poverty in the SSA region represented by the percentage of the rural population with access to electricity. It depicts the countries with lower (in blue) and higher (in light green) levels of rural energy poverty.

the likelihood of prolonged educational exclusion. Moreover, the growing impact of energy poverty on educational attainment may reflect increased awareness of the fundamental role of education in breaking cycles of poverty and underemployment. In this context, urban households may have become more sensitive to investing in their children's education after observing the socioeconomic consequences of poverty and energy deprivation in neighboring regions. Educational outcomes may also have improved due to the expansion of free primary education and financial support programs provided by government institutions. Finally, our analysis indicates that health is a critical determinant of educational attainment in sub-Saharan Africa; improvements in healthcare services that enhance life expectancy are found to have a positive effect on educational outcomes. The results reveal that improvements in life expectancy significantly enhance learning outcomes. Specifically, a one-unit increase in life expectancy is associated with a 1.7153-unit improvement in learning outcomes. In addition, economic growth plays a significant role in enhancing educational attainment, as a one-unit increase

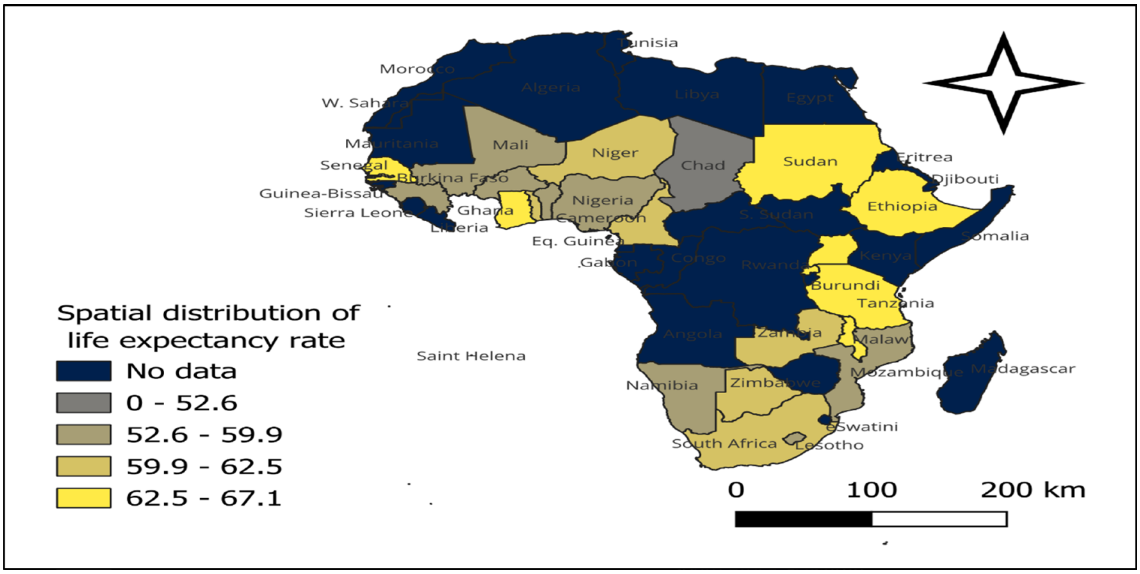


FIGURE 10 | Spatial distribution of life expectancy at birth in the SSA region. The figure illustrates countries with higher life expectancy (in yellow) and those with lower life expectancy (in gray).

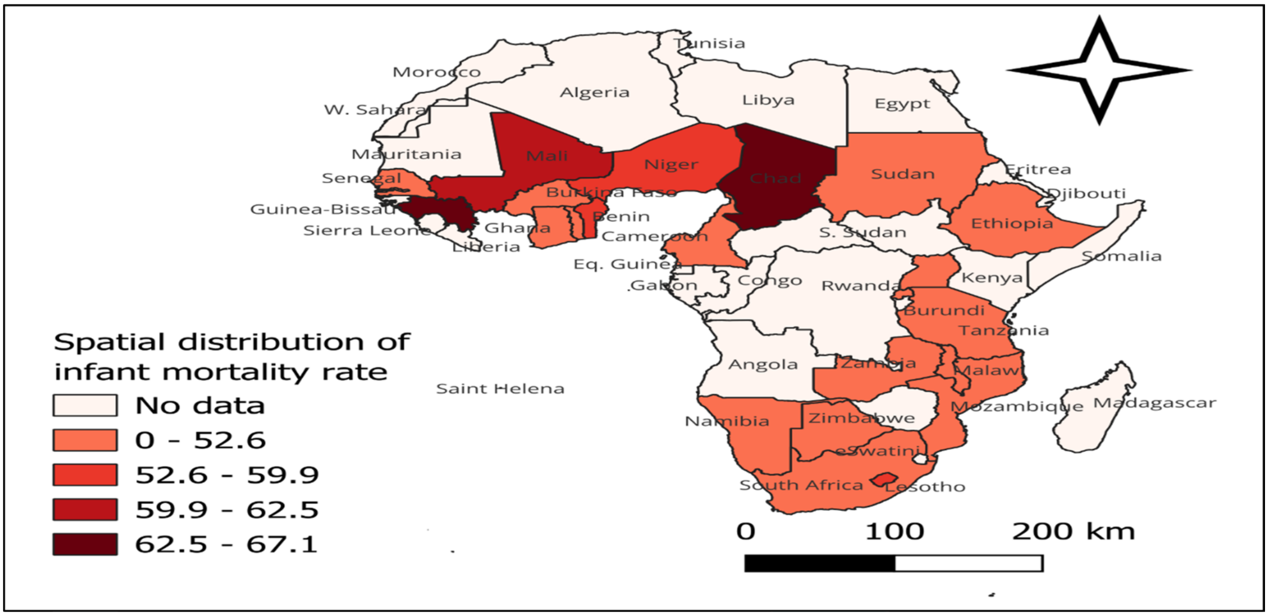


FIGURE 11 | Spatial distribution of the infant mortality rate in sub-Saharan Africa, measured as the number of deaths of infants under 1 year of age per 1000 live births. The figure distinguishes countries with lower infant mortality rates (in dark red) from those with higher infant mortality rates (in light red).

in per capita income leads to a 0.0086-unit increase in learning outcomes, holding other factors constant.

Table 9 sheds light on the labor force participation model. The results indicate that rural energy poverty negatively affects labor force participation. Considering the total effects estimated from the SDM, a one-unit increase in the share of the rural population with access to energy is associated with a 0.0795-unit increase in labor force participation. Further analysis indicates that rural energy poverty in neighboring countries exerts a stronger influence on labor market outcomes. Specifically, a one-unit increase in rural energy poverty in neighboring countries is associated with a 0.0540-unit reduction in domestic labor force participation, whereas the local (direct) effect of rural energy poverty leads to a smaller 0.0255-unit decline, holding other factors constant. These findings are consistent with expectations and with existing empirical evidence. For instance, Bakehe (2022) concluded that energy poverty has a detrimental impact on participation in the labor market in Cameroon, particularly for women. Similar evidence was reported by Stabridis and van Gameren (2018) in Mexico, where energy poverty causes respiratory problems and reduces labor force participation. Bakehe (2021) further emphasized that using clean fuels minimizes the risk

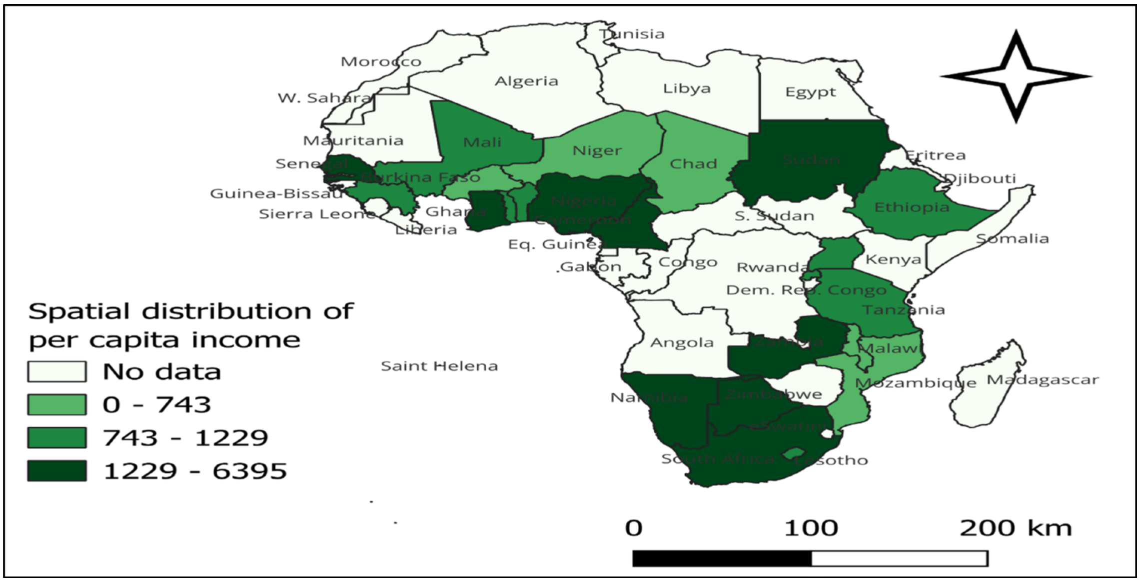


FIGURE 12 | Spatial distribution of per capita income in sub-Saharan Africa, measured in constant 2015 US dollars. A data-driven classification is used to distinguish countries with higher (in dark green) and lower (in light green) income levels.

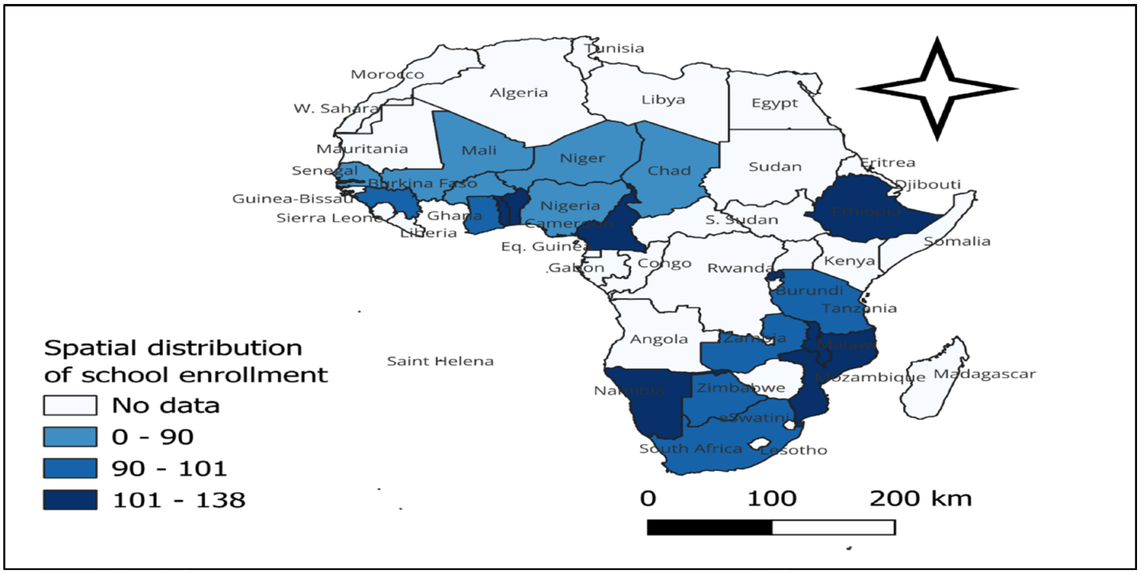


FIGURE 13 | Spatial distribution of school enrollment in sub-Saharan Africa, represented by the number of students enrolled in primary education. The figure shows the countries with higher (in dark blue) and lower (in light blue) educational attainment.

of respiratory infection and increases the likelihood of labor market participation.

Moreover, the results reveal that educational attainment is an important determinant that positively influences labor force participation. Specifically, a one-unit improvement in learning outcomes is associated with a 0.0343-unit increase in labor force participation, holding other factors constant. Infant mortality does not exhibit a statistically significant direct effect on labor market participation. However, the health conditions of neighboring countries captured through spatial spillovers are found to exert a significant adverse effect on domestic labor market outcomes. More unexpectedly, higher infant mortality rates within a country are associated with increased labor force participation. One possible interpretation is that elevated mortality and adverse health conditions may compel surviving household members to enter the labor market earlier or more intensively as a coping strategy to offset income losses and rising healthcare-related expenses. The critical role of adequate energy access in fostering economic growth and development has been widely emphasized in the literature (Amin et al. 2020; Raghutla and Chittedi 2022). In contrast, inadequate or unreliable electricity supply leads to production inefficiencies and reduced labor productivity. Several studies argue that the adverse health and educational outcomes associated with energy poverty limit individuals' ability to work longer hours and perform efficiently. Poor health, inadequate skills, and limited access to energy-related technologies ultimately reduce labor productivity and constrain effective labor market participation (Ndubuisi et al. 2023). Finally, cross-border inflows of energy-poor skilled

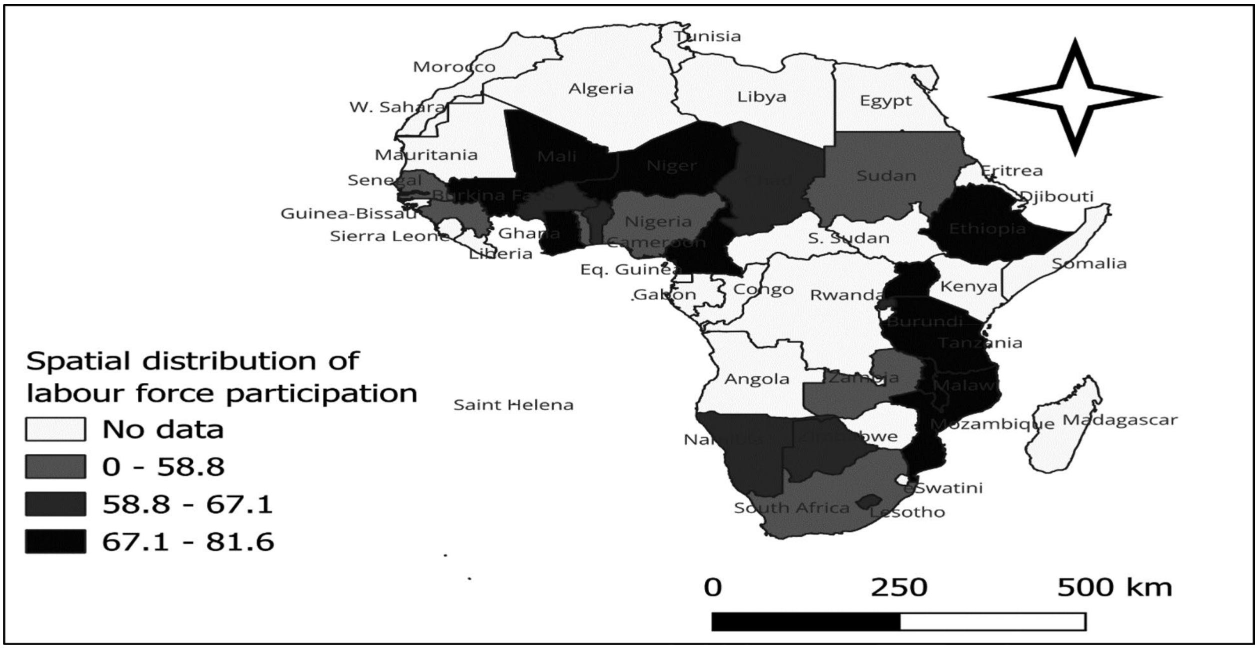


FIGURE 14 | Spatial distribution of labor force participation in sub-Saharan Africa. A data-driven classification is used to highlight countries with higher labor force participation rates (shown in black) and those with lower participation rates (shown in dark gray).

TABLE 9 | Spatial Durbin model (SDM) results—Model 4.

Labor force participation	Coef.	Std. Err.	z	$p > z$	[95% Conf. Interval]
Main					
REP	0.0206	0.01277	1.61	0.106	−0.00442 to 0.0456
UEP	−0.0172	0.01215	−1.42	0.155	−0.04109 to 0.0065
IMR	0.0770	0.01707	4.51	0.000*	0.04359–0.1105
SCH	−0.0189	0.00535	−3.53	0.000*	−0.02942 to −0.0084
_cons	54.034	4.90658	11.01	0.000*	44.4181–63.651
$W(x)$					
W*(REP)	0.0332	0.02202	1.51	0.132	−0.0099 to 0.0763
W*(UEP)	−0.1252	0.01684	−7.44	0.000*	−0.1582 to −0.0922
W*(IMR)	−0.0851	0.02334	−3.65	0.000*	−0.1308 to −0.0393
W*(SCH)	0.0425	0.01096	3.88	0.000*	0.0210–0.0640
Spatial ρ	0.2934	0.04499	6.52	0.000*	0.2053–0.3816
Variance					
lgt_theta	−3.1356	0.15220	−20.6	0.000*	−3.4339 to −2.8373
sigma2_e	3.5711	0.22393	15.95	0.000*	3.1322–4.0100
X^2	87.81			0.000*	
Log-likelihood	−1218.0				
Direct effect					
REP	0.0255	0.01329	1.92	0.055**	−0.0005 to 0.0515
UEP	−0.0317	0.01249	−2.54	0.011*	−0.05625 to −0.0072

(Continues)

TABLE 9 | (Continued)

Labor force participation	Coef.	Std. Err.	z	p>z	[95% Conf. Interval]
IMR	0.0719	0.01592	4.52	0.000*	0.0407–0.1031
SCH	−0.0148	0.00529	−2.81	0.005*	−0.0252 to −0.0045
Indirect effect					
REP	0.0540	0.02917	1.85	0.064***	−0.0031 to 0.111
UEP	−0.1720	0.02668	−6.45	0.000*	−0.2243 to −0.119
IMR	−0.0836	0.02867	−2.92	0.004*	−0.1398 to −0.027
SCH	0.0492	0.01433	3.44	0.001*	0.0211–0.077
Total effect					
REP	0.0795	0.03390	2.35	0.019*	0.0131–0.146
UEP	−0.2038	0.03478	−5.86	0.000*	−0.272 to −0.135
IMR	−0.0117	0.03102	−0.38	0.706	−0.0725 to 0.0491
SCH	0.0343	0.01626	2.11	0.035*	0.0024–0.0662

Note: *, **, and *** indicate 1%, 5%, and 10% level of significance, respectively.

and unskilled workers into countries with relatively better energy access in search of employment may also influence domestic labor markets. While such inflows can increase labor supply and potentially support economic activity by lowering labor costs, they may simultaneously exert downward pressure on wages and strain employment opportunities, thereby shaping labor market dynamics (Doğanalp et al. 2021).

5 | Conclusion and Policy Recommendations

This study has illuminated the implications of energy poverty on sustainable socioeconomic development in sub-Saharan Africa, with a particular emphasis on its spatial dimensions. The study utilizes a novel approach based on a spatial spillover framework to examine the broader effects of energy poverty on health outcomes, educational attainment, and labor force participation across 25 sub-Saharan African countries over the period 2000–2021. Existing literature suggests that countries are geographically interconnected, which can potentially influence their neighboring counterparts. Our empirical results strongly highlight the presence of regional spillover effects, indicating that a reduction in energy poverty is associated with greater socioeconomic progress not only within a country but also in adjacent states.

In short, the outcomes of the present study are a stark reflection of the inefficiencies on the part of national and regional institutions of sub-Saharan Africa to cope with the colossal challenge of energy poverty and its consequent ramifications. In connection with the persistence of a more pronounced spillover impact of energy poverty on all socioeconomic indicators as compared to the direct impact, the present study calls for a coordinated local and regional action and subsequent alignment of local and regional institutions for combating energy poverty and its consequent ramifications. To this end, the very first step is to form a dedicated institution for energy development at the level of sub-Saharan Africa (e.g., the Sub-Saharan African Commission for Energy Development) under the umbrella of existing institutions of NEPAD (New Partnership for Africa's Development) and UNECA (United Nations Economic Commission for Africa). The proposed institutions should be comprised of high-powered representatives of energy-related national institutions from member countries, experts, and delegates from the aforementioned institutions, with the core agenda of developing energy generation and distribution infrastructure. This sort of formation will allow it to expand its cooperation with the relevant economic, financial, and social institutions working under and in collaboration with the UN and the African Union for generating funds and acquiring necessary information, data, and expertise. Secondly, the domain of this institution (with consent after consultation) should be over the member states/countries regarding: (i) the collection of relevant data on energy poverty, (ii) identification of potential and available mega energy resources across regions and states, and (iii) deployment of multi-national and region-specific grid stations, transmission lines, solar parks, and water reservoirs. Furthermore, the aforementioned institution should form working groups at various subregional levels to align local and regional energy-related units and institutions for eradicating energy poverty with a well-planned and properly thought-out concerted line of action. Not to mention, this cooperation and alignment among national, subregional, and regional energy-related institutions is not realizable without legal backing. Therefore, member states should introduce legislation and enact legal frameworks for ensuring regional cooperation, homogeneity of energy policies, and a uniform line of action for combating energy poverty.

Besides, policymakers and local stakeholders should focus on non-discriminatory power distribution by prioritizing the worst-hit energy-poor populations, rural areas, and low-income groups, for successfully realizing the SDG goal 7 of providing affordable and clean energy services in the SSA region. It will allow the rural areas to absorb the mounting pressure on the cities with severe consequent ramifications, originating from unplanned migration to seek better life amenities. The results further indicate that energy poverty has adverse effects on health indicators. Considering the total effect, the results indicate that a one-unit reduction in energy poverty leads to an increase of 0.1727 units in life expectancy and a decrease of 0.7961 units in the infant mortality rate. Accordingly, governments in SSA countries should implement policies that expand energy access for childbirth services, ensure a reliable and uninterrupted power supply during critical medical procedures, enhance vaccine storage capacity, and support the effective operation of medical equipment in healthcare facilities.

In addition, the results indicate that energy poverty constitutes a critical barrier to educational attainment and labor force participation in the SSA region. Notably, the spillover effects of energy poverty on educational outcomes and labor force participation are stronger than the corresponding local effects. These findings underscore the need for coordinated policies and collective actions aimed at improving educational outcomes and fostering more efficient labor markets across the SSA region. To enhance the enrollment ratio, the government should focus on two main fronts. First, the government should provide free education, transport (wherever required), books, and school uniforms, despite monthly direct cash transfers to enrolled students to compensate (in monetary terms) for their efforts to find wood fuels for cooking and heating purposes. Second, the governments should legislate to ensure mandatory enrollment for a certain time (a given number of years) and devise local institutions at the district and sub-district level for oversight, with a mandate to provide the aforementioned incentives and to penalize in case of non-compliance. Third, the regional governments should agree upon allocating a certain percentage of the annual budget for educational purposes to avoid free riding and mounting pressures on educational infrastructure, originating from migration. Finally, the female working-age population has to choose between staying out of school and working at home to collect firewood and biofuels. Therefore, an increase in the female labor force population is not realizable without the provision of adequate access to affordable and clean energy resources. Besides, the governments should: (i) establish free rural and local vocational education and training centers, (ii) provide a stipend during training to compensate for their household services, (iii) establish smart factories and handicrafts at the town and village level, (iv) grant paid maternity leave, and (v) legislate to ensure their security at the workplace to raise the female labor force participation.

Finally, despite the significant contribution of this study to advancing the understanding of the spatial spillover dynamics of energy poverty and its socioeconomic consequences, several limitations warrant acknowledgment. First, the analysis covers only 25 sub-Saharan African countries and relies on data spanning the period 2000–2021. Second, the study employs aggregate proxies for energy poverty, such as the percentage of the population with access to electricity. Future research could address these limitations by incorporating more recent data and adopting more comprehensive measures of energy poverty, such as the Multidimensional Energy Poverty Index (MEPI). In addition, subnational analyses using provincial- or district-level data on energy poverty would provide deeper insights and help better address potential endogeneity concerns.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Appendix A

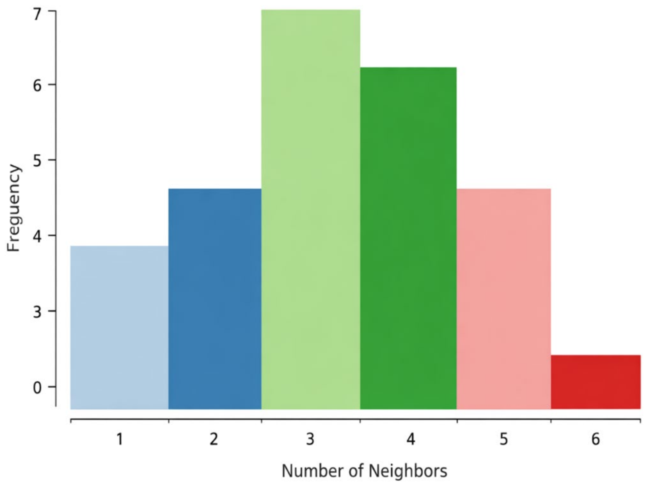

FIGURE A1 | Number of neighbors based on Queen contiguity criteria.

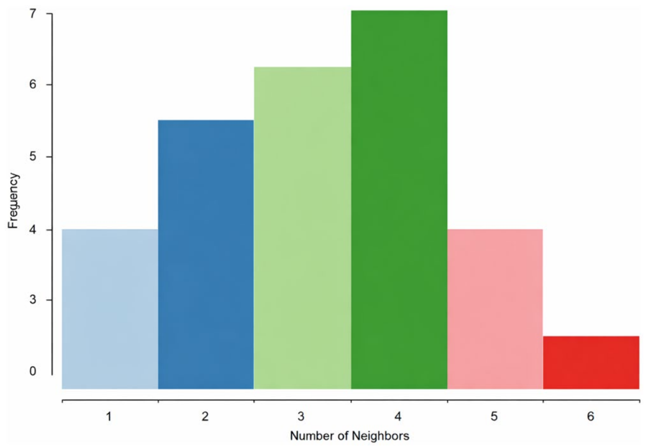

FIGURE A2 | Number of neighbors based on Rook contiguity criteria.

TABLE A1 | Spatial Durbin model (SDM) results based on Rook contiguity criteria—Model 1.

Life expectancy	Coef.	Std. Err.	z	$p > z$	[95% Conf. Interval]
Main					
REP	−0.008	0.0111	−0.78	0.438	−0.030 to 0.0132
UEP	0.061	0.0090	6.78	0.000*	0.043–0.0792
SCH	−0.003	0.0044	−0.77	0.442	−0.012 to 0.0053
GDP	0.001	0.0003	4.56	0.000*	0.0009–0.0022
_cons	18.265	1.7126	10.66	0.000*	14.908–21.622
$W(x)$					
REP	0.087	0.0191	4.57	0.000*	0.0501–0.1252
UEP	0.035	0.0126	2.8	0.005*	0.0106–0.0603
SCH	0.029	0.0081	3.64	0.000*	0.0137–0.0458
GDP	−0.0002	0.0005	−0.33	0.742	−0.0013 to 0.0009
Spatial ρ	0.465	0.0384	12.1	0.000*	0.3900–0.5407
Variance					
lgt_theta	−2.352	0.1777	−13.23	0.000*	−2.7014 to −2.0044
sigma2_e	2.624	0.1662	15.79	0.000*	2.2988–2.9505
X^2	150.5			0.000*	
Log-likelihood	−1129.2				
LR_Direct					
REP	0.0084	0.0122	0.69	0.492	−0.0156 to 0.032
UEP	0.0734	0.0095	7.7	0.000*	0.0547–0.092
SCH	0.0025	0.0046	0.54	0.588	−0.0066 to 0.011
GDP	0.0017	0.0003	4.55	0.000*	0.0009–0.002
LR_Indirect					
REP	0.1424	0.0316	4.5	0.000*	0.0803–0.204
UEP	0.1061	0.0193	5.49	0.000*	0.0683–0.144
SCH	0.0472	0.0139	3.39	0.001*	0.0199–0.074
GDP	0.0009	0.0009	1.03	0.305	−0.0008 to 0.002
LR_Total					
REP	0.1508	0.0380	3.96	0.000*	0.0762–0.225
UEP	0.1796	0.0254	7.07	0.000*	0.1298–0.229
SCH	0.0497	0.0165	3.01	0.003*	0.0173–0.082
GDP	0.0026	0.0011	2.34	0.019*	0.0004–0.004

Note: * indicates a 1% level of significance.

TABLE A2 | Spatial Durbin model (SDM) results based on Rook contiguity criteria—Model 2.

Infant mortality rate	Coef.	Std. Err.	z	$p>z$	[95% Conf. Interval]
Main					
REP	−0.002	0.0340	−0.09	0.931	−0.069 to 0.063
UEP	−0.109	0.0293	−3.73	0.000*	−0.166 to −0.051
SCH	−0.070	0.0136	−5.18	0.000*	−0.097 to −0.044
GDP	0.001	0.0011	1.09	0.277	−0.001 to 0.003
_cons	80.38	7.0624	11.38	0.000*	66.54–94.22
$W(x)$					
REP	−0.284	0.0585	−4.87	0.000*	−0.399 to −0.170
UEP	−0.355	0.0398	−8.92	0.000*	−0.433 to −0.277
SCH	−0.068	0.0267	−2.54	0.011*	−0.120 to −0.015
GDP	0.0007	0.0018	0.4	0.687	−0.002 to 0.004
Spatial ρ	0.4107	0.0393	10.45	0.000*	0.333–0.487
Variance					
lgt_theta	−2.5820	0.1777	−14.52	0.000*	−2.930 to −2.233
sigma2_e	24.252	1.5488	15.66	0.000*	21.21–27.28
X^2	248.80			0.000*	
Log-likelihood	−1740.63				
LR_Direct					
REP	−0.0484	0.0367	−1.32	0.187	−0.120 to 0.023
UEP	−0.1768	0.0287	−6.14	0.000*	−0.233 to −0.120
SCH	−0.0854	0.0138	−6.19	0.000*	−0.112 to −0.058
GDP	0.0014	0.0012	1.24	0.214	−0.000 to 0.003
LR_Indirect					
REP	−0.4346	0.0873	−4.98	0.000*	−0.605 to −0.263
UEP	−0.6164	0.0543	−11.34	0.000*	−0.723 to −0.509
SCH	−0.1490	0.0373	−3.99	0.000*	−0.222 to −0.075
GDP	0.0020	0.0026	0.78	0.433	−0.003 to 0.007
LR_Total					
REP	−0.4831	0.1046	−4.62	0.000*	−0.688 to −0.278
UEP	−0.7933	0.0705	−11.24	0.000*	−0.931 to −0.655
SCH	−0.2345	0.043	−5.33	0.000*	−0.320 to −0.148
GDP	0.0035	0.0031	1.15	0.252	−0.002 to 0.009

Note: * indicates a 1% level of significance.

TABLE A3 | Spatial Durbin model (SDM) results based on Rook contiguity criteria—Model 3.

School enrollment	Coef.	Std. Err.	z	$p>z$	[95% Conf. Interval]
Main					
REP	−0.5741	0.1027	−5.59	0.000*	−0.775 to −0.372
UEP	−0.2156	0.0873	−2.47	0.013*	−0.386 to −0.044
LEX	−0.5055	0.4044	−1.25	0.211	−1.298 to 0.287
GDP	0.0096	0.0024	3.88	0.000*	0.004–0.014
_cons	11.869	18.029	0.66	0.51	−23.46 to 47.20
$W(x)$					
REP	0.3277	0.1831	1.79	0.073***	−0.031 to 0.686
UEP	−0.1500	0.1293	−1.16	0.246	−0.403 to 0.103
LEX	2.1138	0.5307	3.98	0.000*	1.073–3.154
GDP	−0.0024	0.0041	−0.58	0.565	−0.010 to 0.005
Spatial ρ	0.0863	0.0534	1.62	0.106	−0.018 to 0.191
Variance					
lgt_theta	−1.6085	0.1793	−8.97	0.000*	−1.959 to −1.257
sigma2_e	244.24	15.122	16.15	0.000*	214.6–273.8
X^2	25.18			0.000*	
Log-likelihood	−2337.8				
LR_Direct					
REP	−0.5621	0.1050	−5.35	0.000*	−0.768 to −0.356
UEP	−0.2251	0.0860	−2.62	0.009*	−0.393 to −0.056
LEX	−0.4028	0.3779	−1.07	0.287	−1.143 to 0.338
GDP	0.0095	0.0024	3.93	0.000*	0.004–0.014
LR_Indirect					
REP	0.3028	0.1818	1.67	0.096***	−0.053 to 0.6591
UEP	−0.1842	0.1478	−1.25	0.213	−0.474 to 0.1056
LEX	2.1718	0.5615	3.87	0.000*	1.071–3.2725
GDP	−0.0013	0.0042	−0.31	0.753	−0.009 to 0.0069
LR_Total					
REP	−0.2593	0.2048	−1.27	0.205	−0.660 to 0.1420
UEP	−0.4094	0.1878	−2.18	0.029**	−0.777 to −0.0412
LEX	1.7689	0.4899	3.61	0.000*	0.808–2.7293
GDP	0.0082	0.0044	1.85	0.065***	−0.0005 to 0.0169

Note: *, **, and *** indicate 1%, 5%, and 10% level of significance, respectively.

TABLE A4 | Spatial Durbin model (SDM) results based on Rook contiguity criteria—Model 4.

Labor force participation	**Coef.**	**Std. Err.**	z	$p>z$	**[95% Conf. Interval]**
Main					
REP	0.0227	0.0127	1.78	0.076***	−0.0023 to 0.047
UEP	−0.0160	0.0121	−1.33	0.185	−0.0398 to 0.007
IMR	0.0740	0.0170	4.35	0.000*	0.0407–0.107
SCH	−0.0185	0.005	−3.44	0.001*	−0.0290 to −0.007
_cons	54.800	4.891	11.2	0.000*	45.213–64.38
$W(x)$					
REP	0.0178	0.0218	0.82	0.415	−0.0250 to 0.060
UEP	−0.1218	0.0168	−7.24	0.000*	−0.1547 to −0.088
IMR	−0.0826	0.0227	−3.63	0.000*	−0.1272 to −0.038
SCH	0.0422	0.0107	3.94	0.000*	0.0212–0.063
Spatial ρ	0.2807	0.0451	6.22	0.000*	0.1922–0.369
Variance					
lgt_theta	−3.129	0.1523	−20.54	0.000*	−3.4275 to −2.830
sigma2_e	3.595	0.2253	15.96	0.000*	3.1537–4.036
X^2	86.74			0.000*	
Log-likelihood	−1219.14				
LR_Direct					
REP	0.0259	0.0132	1.95	0.051**	−0.0001 to 0.051
UEP	−0.0297	0.0124	−2.39	0.017*	−0.0540 to −0.005
IMR	0.0692	0.0158	4.36	0.000*	0.0380–0.100
SCH	−0.0146	0.0053	−2.75	0.006*	−0.0250 to −0.004
LR_Indirect					
REP	0.0337	0.0284	1.19	0.236	−0.022 to 0.089
UEP	−0.1639	0.0258	−6.33	0.000*	−0.214 to −0.113
IMR	−0.0813	0.0275	−2.95	0.003*	−0.135 to −0.027
SCH	0.0485	0.0137	3.52	0.000*	0.021–0.075
LR_Total					
REP	0.0596	0.0331	1.8	0.072***	−0.005 to 0.124
UEP	−0.1936	0.0338	−5.72	0.000*	−0.260 to −0.127
IMR	−0.0121	0.0300	−0.4	0.686	−0.070 to 0.046
SCH	0.0339	0.0157	2.15	0.031**	0.003–0.064

Note: *, **, and *** indicate 1%, 5%, and 10% level of significance, respectively.

TABLE A5 | Pesaran–Yamagata slope heterogeneity test.

	Delta (*Δ*)	*p*
Model 1	19.686	0.000*
	23.499 (adj.)	0.000*
Model 2	23.247	0.000*
	27.259 (adj.)	0.000*
Model 3	13.546	0.000*
	15.884 (adj.)	0.000*
Model 4	20.067	0.000*
	23.530 (adj.)	0.000*

Note: H0: slope coefficients are homogenous (Pesaran and Yamagata 2008). * indicates a 1% level of significance.

TABLE A6 | List of sample countries.

1	**Benin**
2	Botswana
3	Burkina Faso
4	Cameroon
5	Chad
6	Cote d'Ivoire
7	Ethiopia
8	Gambia
9	Ghana
10	Guinea
11	Lesotho
12	Malawi
13	Mali
14	Mozambique
15	Namibia
16	Niger
17	Nigeria
18	Rwanda
19	Senegal
20	South Africa
21	Sudan
22	Tanzania
23	Togo
24	Uganda
25	Zambia