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Potential for energy poverty reduction by error decomposition with machine learning

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ABSTRACT

Energy poverty remains a pressing global challenge, with approximately 685 million people lacking electricity access and 2.1 billion without clean cooking fuels. Traditional metrics often fail to capture the multidimensional nature of energy deprivation, prompting the adoption of frameworks like the World Bank's Multi-Tier Framework (MTF). However, existing approaches overlook the concept of potential to identify where and how energy poverty reduction efforts can be most effective. This study bridges this gap with an error decomposition framework that analyzes whether household-level or regional-level interventions should be prioritized. Using machine learning's (ML) XGBoost, we develop a predictive model of multidimensional energy poverty for Nepal, Myanmar, and Cambodia that helps avoid misspecification problems and outperforms traditional econometric methods, achieving test accuracies of up to 0.78 when incorporating spatial fixed effects. The error decomposition reveals systematic underperformance in certain regions and demographic groups, highlighting latent opportunities for policy intervention. Key findings indicate that energy poverty is shaped by both household-level characteristics and systemic regional factors, with urban-rural and ethnic disparities playing significant roles. In Nepal, marginalized ethnic groups exhibit persistent energy deprivation despite high socioeconomic status, while Myanmar's urban areas suffer from unreliable supply despite high connection rates. Cambodia's rural households remain underserved, emphasizing the need for decentralized energy solutions. By distinguishing between reducible and irreducible error components, our framework provides actionable insights for targeted policy interventions, advancing progress toward Sustainable Development Goal 7 (SDG 7).

Introduction

Energy poverty remains one of the most persistent global development challenges despite significant advances in recent years. According to the Tracking SDG 7: The Energy Progress Report 2025, almost 92 percent of the global population now has access to electricity (IEA, IRENA, UNSD, The World Bank, 2025). However, more than 666 million people still lack basic access, an indication that the current rate of progress remains inadequate to achieve universal access by 2030. Between 2010 and 2023, Central and Southern Asia saw remarkable improvements, reducing the population without electricity from 414 million to just 27 million. Yet, many developing Asian economies continue to struggle with poor reliability, unaffordable tariffs, and limited service quality,

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highlighting the multidimensional nature of energy deprivation. The figures show that despite substantial progress in energy access, persistent, multidimensional energy poverty hinders the achievement of SDG 7 (IEA, IRENA, UNSD, The World Bank, 2025).

Accurately measuring energy poverty is central to addressing it, yet defining it remains an ongoing challenge. The measurement of energy poverty depends critically on how it is conceptualized (Mendoza et al., 2019), and there is still no universally accepted framework for its quantification (Nathan & Hari, 2020; Wang et al., 2023). The diversity of proposed metrics reflects not only the heterogeneity of socio-economic and cultural contexts but also differences in data and service availability (Sy & Mokaddem, 2022). Early efforts, such as Boardman (1991) "10 percent rule," defined energy-poor households as those spending more than one-tenth of their income on energy, while subsequent models like the Low-Income High-Cost (LIHC) framework (Awaworyi Churchill & Smyth, 2021; Hills, 2012) introduced affordability dimensions by combining income thresholds with expenditure burdens. Paudel (2022) employed the expenditure–income approach to reveal consumption disparities and affordability barriers. Beyond these objective measures, subjective indicators such as households' reported ability to heat or power their homes capture lived experiences and social vulnerability (Thomson et al., 2017), though they often suffer from cross-country comparability issues. In response, multidimensional indices such as the Multidimensional Energy Poverty Index (MEPI) (Nussbaumer et al., 2012) were developed to integrate access, affordability, reliability, and quality. However, their reliance on static thresholds and equal weighting can obscure local variations and the complexity of deprivation across spatial scales.

The World Bank's Multi-Tier Framework (MTF) (Bhatia and Angelou, 2015) represents a major step forward by defining progressive tiers of access across multiple attributes, such as capacity, reliability, quality, affordability, and legality rather than relying on binary "connected/unconnected" indicators. This granularity allows for a more nuanced understanding of energy deprivation, revealing not only whether households are connected but also the adequacy and usability of that access. Recent studies demonstrate the MTF's expanding analytical relevance. For example, Chandrasekaran et al. (2023) used cross-country MTF data to explore the link between women's empowerment and household energy access, finding a positive correlation across most countries. Similarly, the World Bank and ESMAP report (Rahman & Koo, 2024) have utilized the MTF to map multidimensional access gaps and highlight systemic reliability and affordability issues. More recently, Kersey (2025) observed that while the MTF remains a valuable diagnostic tool, it may inadequately represent the conditions of fast-growing urban or informal settlements, where access fluctuates with time and informal supply arrangements.

Despite these advances, MTF-based analyses remain descriptive, focusing on classification rather than exploring the potential for improvement. In this context, potential refers to the difference between a household's observed score and its expected performance given its socioeconomic and contextual conditions. This distinction is critical for identifying where interventions could have the greatest marginal impact. Moreover, existing frameworks do not sufficiently identify intervention pathways for realizing this potential, nor do they specify the appropriate level (household, community, regional, or national) at which interventions should be targeted.

Energy Poverty (EP) results from a complex interplay of multi-level factors involving not only household-level circumstances but also the actions and capacities of local authorities, energy suppliers, and national institutions. In other words, EP emerges from the interaction between micro-level (individual and household) and macro-level (institutional and systemic) factors. In regions where large shares of the population are affected by EP, the influence of institutional actors may outweigh the impact of individual socio-economic conditions in determining EP outcomes. The severity of EP often reflects systemic deficiencies that lie beyond the control of individual households. Although EP is closely associated with socio-economic deprivation at the individual level, interventions targeting households alone may not always be the most effective strategies for alleviation. In particular, dimensions of EP captured by the Multi-Tier Framework (MTF) such as daily hours of electricity availability (duration), voltage quality, and reliability (frequency of outages) are largely determined by the energy supply side and are exogenous to households. Despite this, existing research tends to either focus narrowly on household characteristics or treat supply-side factors separately, without integrating them and assessing their relative importance.

This paper addresses these gaps through an integrated analytical framework that combines MTF indicators with machine learning (ML) decomposition analysis. By leveraging ML's ability to model complex, non-linear relationships (González Garibay et al., 2023; Mukelabai et al., 2023) the study quantifies how much of the variation in energy poverty can be systematically explained by socio-economic (micro-level) and spatial (macro-level) factors and how much remains unexplained. This decomposition distinguishes between policy-relevant factors, that is, factors that can be addressed through targeted policy interventions, such as improving grid reliability or connection affordability and structural components that capture more persistent geographic, institutional, or social constraints. Through this approach, the study moves beyond descriptive diagnostics to reveal where and how energy poverty can be most effectively targeted. It is important to emphasize that this study does not propose a new measurement framework. Instead, it utilizes existing MTF indicators and applies a predictive decomposition approach to derive the improvement potential of energy-poor households.

This paper contributes to the energy poverty literature in three ways. First, it advances the methodological frontier by introducing a predictive decomposition framework that links multidimensional EP measurement with actionable policy insights. Second, it empirically applies this framework across three diverse Asian contexts (Nepal, Myanmar, and Cambodia) demonstrating its adaptability across countries with distinct electrification trajectories. Third, it conceptualizes and operationalizes the notion of potential, offering policymakers a tool to identify where the largest gains in EP interventions can be achieved given existing conditions.

The analysis of Nepal, Myanmar, and Cambodia as case studies is motivated by the availability of harmonized MTF household data released by the World Bank, ensuring methodological comparability across contexts. Besides, these countries represent distinct stages of electrification: from near-universal access in Nepal with reliability gaps to widespread deficits in capacity and affordability in Myanmar and Cambodia. This diversity allows us to confirm the model's robustness under varying structural, socioeconomic, and institutional environments. Unlike previous cross-country comparisons (Rao et al., 2022), our analysis estimates each country separately to capture within-country heterogeneity. Moreover, while Price et al. (2021) analyzed MTF data for cooking transitions in Myanmar and Cambodia, our work extends this by decomposing household- versus regional-level contributions to energy poverty. Integrating Nepal, a South Asian case previously examined in relation to ethnic and socio-economic disparities in energy access (Paudel, 2021) further enhances the generalizability of our findings.

Empirical results reveal distinct, country specific dynamics. In Nepal, household-level socioeconomic characteristics largely explain variations in energy access, yet persistent disparities among marginalized ethnic groups point to institutional and cultural constraints beyond socioeconomic determinants. Myanmar exhibits strong regional heterogeneity, where urban areas despite higher connection rates experience substantial reliability deficits, underscoring systemic infrastructure weaknesses. In Cambodia, energy poverty is most pronounced in rural areas, where affordability and reliability gaps persist even after controlling for provincial factors, suggesting that centralized grid expansion alone cannot close the access divide. Across all three contexts, the error decomposition highlights that a significant share of energy poverty is reducible, driven by factors that are targetable through policy intervention such as supply reliability and affordability. These findings collectively emphasize that targeted, region-specific interventions can unlock the considerable potential for reducing energy poverty and advancing progress toward Sustainable Development Goal 7.

The remainder of the paper is structured as follows: Section 2 provides the background and literature review; Section 3 presents the conceptual framework; Section 4 details the empirical strategy; Section 5 reports results; Section 6 discusses implications; and Section 7 limitations and Section 8 concludes.

2. Background

Energy poverty is broadly defined as the inability to secure adequate, reliable, and clean energy for basic needs, often manifested through over-reliance on traditional biomass and limited access to commercial energy sources (Faiella & Lavecchia, 2021). This condition is especially prevalent in developing contexts, where a defining characteristic is the heavy dependence on traditional biomass such as firewood, charcoal, and animal dung for cooking and heating. This reliance not only perpetuates energy poverty but also exacerbates health risks, environmental degradation, and gender inequalities, as women and children bear a disproportionate burden of fuel collection and exposure to indoor air pollution (Kowsari & Zerriffi, 2011).

Understanding energy poverty is crucial because it intersects with multiple dimensions of human development, from health and gender to environmental sustainability and economic well-being. The transition from traditional to modern energy sources such as electricity, liquefied petroleum gas (LPG), or natural gas is therefore essential for achieving equitable and sustainable development. However, this transition is often constrained by a range of socioeconomic and structural barriers.

Historically, the conceptualization and measurement of energy poverty have evolved significantly. Early approaches relied on simplistic binary indicators such as grid connection status or the "10% rule," which defined energy poverty as a condition in which households spend more than 10% of their income on energy (Boardman, 1991). This method, however, was criticized for its lack of nuance and contextual relevance (Thomson et al., 2017). In response, the Low-Income High Cost (LIHC) index was introduced (Hills, 2011), incorporating both income and energy expenditure. While this represented progress, the reliance on subjective metrics and arbitrary thresholds continued to raise concerns about accuracy and practical utility (Churchill et al., 2022).

A significant shift occurred with the development of multidimensional indices like the Multidimensional Energy Poverty Index (MEPI) and the Multi-Tier Framework (MTF). These tools recognized energy poverty as a complex, multi-faceted phenomenon shaped by availability, reliability, quality, and safety of energy access (Bhatia and Angelou, 2015; Nussbaumer et al., 2012). Among them, the MTF stands out for its tiered structure, which distinguishes between basic access and high-quality service. This level of granularity allows policymakers to identify hidden inequalities for example, between a household with legal electricity access but frequent outages and one enjoying consistent supply (Bhatia and Angelou, 2015). Nevertheless, the MTF falls short of explicitly identifying the root causes of energy poverty, particularly whether they stem from household-level vulnerabilities or systemic regional constraints.

To address this gap, researchers have increasingly examined the determinants of energy usage across both micro (household) and macro (regional) levels factors that are respectively endogenous and exogenous, and can or cannot be controlled at the individual level.

At the household level, energy consumption patterns and fuel choices are shaped by various characteristics. In China, for instance, factors such as the age and physical health of the household head, educational levels of the head and spouse, off-farm employment, household size, wealth, dwelling conditions, and geographic location significantly influence energy use, while the gender of the household head has no statistical significance (Zou & Luo, 2019). Similar findings emerge from India (Pachauri, 2004) and Bangladesh (Miah et al., 2010), where land ownership also plays a crucial role. Higher income households tend to consume more commercial energy compared to lower-income ones, a pattern observed in both China and India (Ekholm et al., 2010; Zheng et al., 2024). The relative costs of energy sources further influence household decisions (Ekholm et al., 2010). Cultural preferences and behavioral aspects, such as awareness and feedback mechanisms, may influence energy-saving behavior but are less relevant as core determinants of energy poverty (Lutzenhiser, 1992).

On the macro or supply side, household energy choices are shaped by external factors like geography, infrastructure, market availability, and policy environments. Households in remote or harsh climates often rely on traditional fuels due to limited access to modern energy infrastructure. Even when cleaner fuels are available, poor road connectivity and unreliable supply chains reduce their practicality. Government policies such as subsidies, fuel rationing, or infrastructure expansion have had mixed success in improving energy access, often failing to reach the poorest households. Furthermore, high upfront costs for devices and bulk purchase requirements for fuels like LPG create affordability barriers. Inconsistent or unreliable energy supply can also discourage transitions, as households fall back on traditional biomass to ensure daily needs are met. These structural constraints highlight the need for energy interventions that go beyond affordability, addressing accessibility, reliability, and suitability of both fuels and technologies.

The affordability, availability, and reliability of energy supply are all influenced by regional, climatic, and policy conditions and shape household energy access and usage patterns. Globally, affordability remains a significant burden on low-income households (Hartono et al., 2020; Brown et al., 2020), shaped in part by regionally variable energy prices. Reliable electricity supply, in turn, has been shown to increase household income and asset accumulation, as evidenced in the United States (Shakouri et al., 2023) and Vietnam (Dang & La, 2019). Climate also acts as a long-term determinant of energy needs (Auffhammer & Mansur, 2014), while physical geography affects infrastructure deployment feasibility and cost (Sun et al., 2012). Furthermore, policy instruments such as energy subsidies can significantly influence fuel choice, either promoting or hindering a shift toward renewable sources (Liu & Li, 2011; Ouyang & Lin, 2014).

Regional studies emphasize the role of systemic structures. In Europe, economic indicators such as long-term unemployment, disposable income, and poverty display distinct regional patterns (Borozan, 2018). In China, urban and rural responses to GDP and infrastructure differ significantly (Wang et al., 2021), while in Spain, regional income, energy prices, and climate collectively shape electricity demand (Blázquez et al., 2013). These studies suggest that macroeconomic and policy environments must be factored into any meaningful analysis of energy poverty. The inclusion of GDP is especially relevant as it correlates with energy demand for productive use, though the direction of causality remains debated (Ozturk et al., 2010). Despite this evidence, discussions of energy poverty often overlook these macro dimensions, focusing narrowly on household-level factors.

This macro-micro interaction is particularly evident in the context of Nepal, Myanmar, and Cambodia, the selected countries for this study. In Nepal, energy poverty is strongly associated with geographic and ethnic disparities. Rural, mountainous communities and ethnic minorities face heightened deprivation due to poor infrastructure and marginalization, despite overall national progress in electrification (Paudel, 2021). In Myanmar, a stark urban-rural electrification gap persists (82% vs. 23%), with urban areas plagued by unreliable supply and rural regions largely excluded (Aung et al., 2022). Cambodia has achieved near-universal grid access, yet energy poverty endures due to unaffordable tariffs and unreliable rural service, sustaining a dependence on biomass.

These country-specific cases underscore that energy poverty cannot be fully understood or addressed by examining income alone. Instead, it is the complex interplay between household characteristics and systemic factors at the micro and macro level, both endogenous and exogenous that shape EP, as reflected in Table 1. Effective policy responses must therefore be locally tailored, multidimensional, and sensitive to both individual and structural determinants of energy poverty.

3. Conceptual framework

3.1. Index of potential

This study examines energy poverty and aims to identify where does potential for improvement in household energy access lies. Energy poverty is influenced by various factors, and we define it using the function:

$$y_i = X_i + u_i$$

where y_i is the multiclass energy poverty level of household i, measured with the multi-tier framework; X_i is a vector of factors that influence the consumption of energy by the household; u_i is the model error.

The potential is defined as the gap between a household's score and the expected score for a household with the same set of predefined conditions. A negative difference between actual score and the expected score given the same conditions indicates the feasibility for this household to achieve better energy access independently of its conditions, for example socio-economic or geographic conditions. Therefore, the potential of an individual household for better scores in energy poverty can be assessed by comparing its predicted score, conditional on X_i, with the realized score of EP, similar to the approach followed by Benedictis and Vicarelli (2005).

Table 1
Stylized facts from existing literature, clarifying the multilevel factors shaping energy poverty.

Determinant Category	Key Variables / Barriers	Supporting Evidence (from your sources)
Household Socioeconomic Characteristics	Income, education of household head and spouse, employment, household size, wealth	(Pachauri, 2004); (Ekholm et al., 2010); (Miah et al., 2010);(Zou & Luo, 2019); (Zheng et al., 2024)
Dwelling and Land Ownership	Housing quality, tenure, land possession	(Ekholm et al., 2010); (Miah et al., 2010);(Zou & Luo, 2019);
Energy Prices & Affordability	Tariffs, upfront cost of devices, bulk purchase requirements	(Hartono et al., 2020); (Brown et al., 2020); (Ekholm et al., 2010);
Access & Infrastructure Constraints	Grid extension, market availability, rural remoteness, weak supply chains	(Sun et al., 2012); (Aung et al., 2022) (Paudel, 2021)
Reliability & Quality of Supply	Outages, voltage drops, unstable distribution	(Bhatia and Angelou, 2015.); (Shakouri et al. 2023); (Aung et al., 2022)
Geography & Climate	Mountainous terrain, extreme weather, environmental barriers	(Sun et al., 2012); (Auffhammer & Mansur, 2014)
Policy and Institutional Environment	Subsidies, rationing, investment in infrastructure	(Liu & Li, 2011); (Ouyang & Lin, 2014)
Cultural & Behavioral Preferences	Cooking practices, awareness	(Lutzenhiser, 1992)
Structural Inequality and Demographics	Ethnic marginalization, rural disadvantage	(Paudel, 2021); (Aung et al., 2022)

The index of potential s_i is thus computed as:

$$s_i = -\frac{y_i - \widehat{y}_i}{Max\ (y)}\ OR\ s_i = -\frac{u_i}{Max\ (y)}$$

Where $\widehat{y}_i$ is the predicted value for y_i, and the index is standardized to take values between -1 and +1. A value $s_i < 0$ indicates over-performing households, whereas $s_i > 0$ indicates that the energy poverty score is lower than predicted, suggesting the household has a potential for improvement based on its characteristics X_i and is underperforming.

Socio-economic or geographic conditions, such as income and remoteness, are often strongly associated with EP but are, at least on the short-run, difficult to change. This computation helps determining how much of the EP score is explained by various sets of fixed conditions X_i. The variations in EP score left unexplained by these conditions indicate a potential for EP improvement independently of socioeconomic or institutional factors that are assessed in the model. Therefore, this potential is attributed to characteristics that are unobserved in the model and/or individual idiosyncrasies that could be leveraged for improvement of EP.

In the empirical approach, by adjusting the set of conditions gradually, we identify the groups of variables that help explain most variation in EP score, and therefore should be targeted for long-term structural changes, from conditions that leave a potential for EP improvement, indicating that unobserved characteristics, for example heterogeneity in households' preferences and habits within groups, could be leveraged for improvement in EP scores.

This approach complements existing studies that, importantly, explain the association between specific socio-economic, demographic and location factors with EP scores. However, they do not tell how much of total EP is and is not collectively tackled by these factors. This study builds upon existing studies to show the relative contribution of various sets of observed and unobserved factors to explain EP and help identify the existence of potential EP improvement beyond pre-determined factors.

3.2. Energy poverty with MTF

This study adopts the multidimensional energy poverty framework proposed by Nussbaumer et al. (2012) and is grounded in the Multi-Tier Framework (MTF) developed by the World Bank and the Energy Sector Management Assistance Program (ESMAP) (Bhatia and Angelou, 2015), and further adapted by the Council on Energy, Environment and Water (CEEW) (Jain et al., 2018).

Access to electricity is evaluated across six core dimensions: capacity, duration, reliability, quality, affordability and legal access. Households are assigned a tier score ranging from 0 (worst) to 2 (best) for each dimension. In line with a conservative interpretation of multidimensional deprivation, the overall electricity access tier is determined by the household's lowest-performing dimension. A household is therefore considered to be energy poor if it experiences severe deprivation in any one of the six dimensions, reflecting the principle that deficiency in a single essential aspect can undermine overall access (Wang et al., 2021).

Table 2 below outlines the cutoffs for classifying households in tiers, which are used to identify severe electricity poverty.

The overall electricity access level is constructed as the minimum tier achieved by a household across six critical dimensions: capacity, duration, reliability, quality, affordability, and legal access. More detailed results per dimension can be found in Appendix (Electricity access: proportion of households in each tier, per dimension). This study aims to identify the potential for improvement in EP, as measured by the overall electricity access level, accounting for a set of important drivers responsible for EP, using a range of household characteristics and regional effects.

3.3. Systematizing energy poverty drivers

Based on an extensive review of existing studies, Kowsari and Zerriffi (2011) propose a new integrated conceptual framework to analyse factors of influence of energy poverty profiles. By extension, deprivation in electricity access is also influenced by these factors. Adapting the framework to the drivers of EP helps categorize factors that influence EP according to characteristics that are relevant for policy analysis and intervention. Kowsari and Zerriffi (2011) distinguish between endogenous drivers that are linked to household characteristics and exogenous factors, such as external conditions that shape energy consumption and choice of the household. Household level factors include income, educational level, as well as preferences or ethnicity, and are thus household/individual specific. On the other hand, exogenous determinants can be attributed to geographical location of the household, policies, subsidies, the price and availability of different energy sources as well as characteristics of electricity-powered devices, and are generally shared

Table 2
Cutoffs for the different dimensions for electricity access measurement (adapted from the World Bank's Multi-Tier Framework (Beyond Connections: Energy Access Redefined, 2015) to classify households into Tiers 0–2, to fit data availability).

Dimension	Tier 0	Tier 1	Tier 2
Capacity	Households with no access to grid, mini-grid, or solar power.	Households that obtain power through solar power.	Households with access to the main grid.
Duration	0–12 hours of power per day	12–23 hours of power per day	24 hours of power per day
Reliability	More than 20 outages in a week	Less than 20 outages in a week	No outages in a week
Quality	N/A	Experience voltage fluctuations	No voltage fluctuations
Affordability	N/A	Unaffordable electricity: Households spend more than 6% of monthly income on electricity.	Affordable electricity: Households spend less than 6% of monthly income on electricity.
Legal	N/A	Households without a legal electric meter	Households with a legal electric meter

characteristics across households of a given region. All factors can be further distinguished between those pertaining to contextual or to personal domains. Contextual factors are those over which the household has no or little control and can occur both at the shared level (e.g., physical environment) or at the individual level (e.g., education). Factors relating to personal domain indicate choices of the households, or factors over which households have control. These are preferences and habits (household level) or may refer to cultural pre-disposition (shared level) for a certain energy behaviour. This new framework, adapted for EP, is summarized in Fig. 1.

The framework helps make a crucial distinction for EP between shared and individual factors. While energy poverty is measured and typically analysed at the household level, many contributing dimensions are beyond individual control. For instance, duration, reliability, and quality of energy supply are determined by the broader infrastructure and affect all households of a locality equally, regardless of income or demographics. Conversely, dimensions such as capacity, affordability, and to some extent legality are shaped by a mix of shared and individual factors such as grid availability, electricity prices, and access to legal metering on the one hand, and household income, education, or preferences on the other.

Among the individual-level factors, it is also important to distinguish between contextual constraints, which households cannot easily change in the short term, and personal choices shaped by preferences, habits, and cultural norms. For example, achievements in capacity and legality dimensions result from both contextual factors (physical availability of solar power, grid connection, and electric meters) and personal preferences. Recognizing this complexity allows for a more precise understanding of energy poverty.

Further, some factors that have often been linked to EP span several dimensions highlighted above. There are known disparities in energy poverty outcomes across gender, urban-rural residence, and ethnicity. Gender (e.g., male- vs. female-headed households) reflects an individual-level endogenous factor, where differences may arise from intra-household dynamics, decision-making power, or access to resources. Urban-rural distinctions represent shared exogenous conditions, often shaped by variations in infrastructure, market access, and public service provision. Ethnicity spans both factor (shared and individual): while cultural norms may influence individual behavior, historically rooted systemic marginalization contributes to group-level disadvantages in energy access. Disentangling these layers of heterogeneity helps identify whether energy poverty is primarily driven by household-level attributes, broader contextual constraints, or an interaction of both.

Thus, this adaptation of the framework proposed by Kowsari and Zerriffi (2011) proves valuable to broaden the conceptualization of energy poverty drivers beyond household-level insights only. It enables the identification of collective, structural conditions and individual behaviours, offering a more holistic perspective to inform effective and equitable policy responses.

4. Empirical strategy

To estimate and understand the determinants of EP potential across Cambodia, Myanmar, and Nepal, we adopt a machine learning (ML)-based empirical strategy designed to minimize prediction error. Our core aim is to predict EP with high accuracy while reducing model misspecification and allowing for nuanced decomposition of potential into individual-level and shared (regional) components.

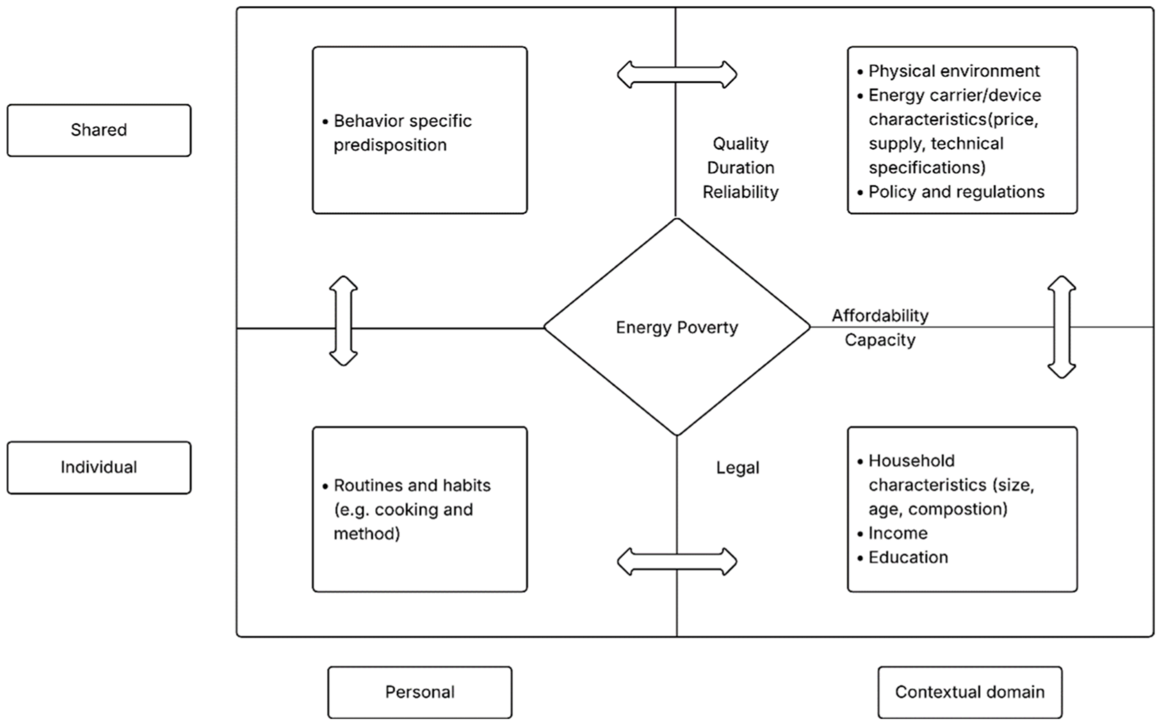


Fig. 1. Factors influencing energy poverty (Source: Authors' own elaboration based on Kowsari and Zerriffi (2011)).

4.1. Decomposition of model error

As shown above, the potential index depends on the error term of the model. As Benedictis and Vicarelli (2005) mention, determining the potential is affected by problems of model misspecification. Careful model specification is therefore needed to provide proper assessment of potential. The aim is to remove components that may be correlated with the outcome from the error term, such as omitted variables that create a bias in the predicted values, with consequences for the estimation of the potential.

Model error originates from multiple sources and can be decomposed in 3 parts (Harville, 1985; James & Hastie, 1997; Robeson & Willmott, 2023). First, an unsystematic part consists in idiosyncratic variations among the observed population, whereby the observed values y_i for a given set of inputs X_i differ from each other and from the average observed response $\overline{y_i}$. The unsystematic part is irreducible and can never be captured by the model, while the systematic part can be reduced through modelling choices, in particular, using machine learning. Second, a systematic part of the error represents the gap between expected observed response $\overline{y_i}$ and prediction $\widehat{y_i}$. This part is due to model specification and data issues, common to all observations and thus reducible. The reduction of the systematic part allows to estimate values of potential that reflect as true potential as possible, while preventing that the potential identified is due to model choices. Formally, the error is expressed as:

$$u_i = (y_i - \overline{y_i}) + (\overline{y_i} - \widehat{y_i})$$

The systematic part can further be decomposed into bias and variance of the predicted values (Harville, 1985).

4.2. Machine learning to tackle model misspecification

Traditional econometric models often have difficulty capturing complex, non-linear relationships and interactions inherent in socio-economic data. To address this, we apply the machine learning technique XGBoost, a scalable, tree-based ensemble learning method known for its ability to reduce both bias and variance through ensemble learning. The model also addresses model misspecification by constructing successive decision trees on feature subsets, capturing non-linearities and interactions that are common in energy poverty data but often missed by linear models.

XGBoost has been successfully applied in recent studies on energy poverty. Cadoret et al. (2024) used the algorithm to predict French households that cannot meet their heating needs while Grzybowska et al. (2024) applied it to Visegrad countries (Czech Republic, Hungary, Poland, and Slovakia), alongside other classifiers to analyze energy poverty, finding it to be one of the most effective tools for modeling imbalanced socio-economic datasets. These studies confirm its suitability for modeling complex socio-economic phenomena.

To test the ability of the XGBoost model to lower model misspecification problems, we compare the results to two simpler models, gradually building model complexity. First, we benchmark the XGBoost model against a logistic regression baseline, which represents a naive and conventional parametric approach widely used in empirical energy poverty studies, where we include all determinants in levels. Then, we expand this logistic regression by adding polynomial terms of degree 3 for all socio-economic and demographic variables, which would capture complex relationships. This model provides a middle point between the naïve model with levels and the nonlinear modelling approach of XGBoost. For consistency, we also compare model fit of XGBoost with and without the polynomial terms. This comparison allows to show the improvements machine learning can offer in modeling complex, non-linear relationships in energy poverty classification.

4.3. Modeling framework and fixed effects

We build 3 models: i) with household characteristics only, ii) with household characteristics and district level fixed effects, and iii) with household characteristics, district and regional level fixed effects, and evaluate the potential of EP reduction across models. The gradual inclusion of location fixed effects accounts for the role of exogenous factors present at district and regional level on EP outcomes. The fixed effects thus reflect all the factors that are common to all households of a district and region and are thus (mostly) outside the control of households (see section 3.3). They act as proxy for economic development, remoteness, infrastructure quality, but also factors of the energy supply (duration, reliability, quality and the price component of affordability), recognizing the challenge of controlling for all village and regional factors due to inconsistent and unavailable data across the three countries (Cambodia, Myanmar, and Nepal). By incorporating fixed effects at regional levels, the framework accounts for geographical and administrative disparities that might otherwise affect the estimation of the potential for energy poverty improvement.

By comparing performance across individual model specifications, we evaluate how much of the variation in energy poverty can be attributed to individual-level characteristics versus broader structural conditions. The gradual inclusion of fixed effects reveals the role of exogenous regional factors that are outside households' control in shaping EP outcomes. The study includes a heterogeneity analysis to evaluate how the potentials differ across demographic and geographic groups, such as male vs. female-headed households, urban vs. rural areas, and ethnic communities.

This layered modeling approach thus not only enhances prediction but also informs policy by identifying whether interventions should be targeted at the household or regional level to tackle structural disparities . The results section presents model performance metrics and compares predicted outcomes to actual EP labels to further explore these dynamics. Summary statistics of the data are specified hereafter.

4.4. Data

This study is based on data collected for Cambodia, Myanmar, and Nepal by the Energy Sector Management Assistance Program (ESMAP) in the World Bank (World Bank Group, 2023). The socio-economic and demographic conditions used in this analysis were informed by previous studies, including Sinha et al. (2022), which explored similar household level factors related to energy poverty. Table 3 summarizes key household characteristics

The dataset reveals notable regional differences across Cambodia, Myanmar, and Nepal in terms of household characteristics and energy poverty. With respect to the age distribution, Nepal has a significantly younger population compared to Cambodia and Myanmar, with a larger proportion of individuals aged 18–40. This demographic difference may have implications for energy usage patterns and access to energy services. Regarding education levels, Myanmar shows a relatively higher percentage of households without secondary education, while Cambodia and Nepal have more balanced distributions across different educational levels. Similarly, differences in education are expected to affect energy usage patterns.

Energy poverty, as measured by the Multi-Tier Framework, varies across the three countries. Cambodia has the highest percentage of households in Tier 0 (27.9%), indicating that a significant portion of its population experiences severe energy poverty. In contrast, Nepal exhibits the lowest percentage in Tier 0 (21.8%) and a higher proportion of households in Tier 1 (73%), suggesting relatively better energy poverty. Myanmar falls in between, with 34.4% of households in Tier 0 and 59.5% in Tier 1.

It is important to note that for Cambodia and Nepal, regional differences are analyzed at the provincial level, whereas for Myanmar, due to the lack of provincial-level data, state-level categorization is used instead. Utilizing the regional breakdown by provinces for Cambodia and Nepal, and states for Myanmar allows for a more detailed understanding of geographical disparities in energy access and energy poverty across the three countries.

The dataset was carefully preprocessed to ensure its suitability for model training and evaluation. Initially, the data was split into an 80:20 ratio for training and testing, ensuring a proper validation framework. Numerical features were standardized in the training dataset to bring all variables onto a common scale, which is essential for algorithms like XGBoost. Categorical variables were retained without transformation, as XGBoost inherently supports categorical data. To address the issue of class imbalance, particularly the underrepresentation of Tier 0 observations, we employed the Synthetic Minority Oversampling Technique (SMOTE). SMOTE helps mitigate bias in model training by generating synthetic examples for the minority class, thus improving the model's ability to generalize and perform well on unseen data (Chawla et al., 2002).

While the dataset offers valuable insights into multidimensional energy poverty, the analysis is based on cross-sectional data, which limits the causal interpretation of the results. The analysis identifies associations between household and regional characteristics with

Table 3

Summary statistics of Dataset

Total households' annual expenditures is considered and recorded in Cambodian Riel (KHR), Myanmar Kyat (MMK), and Nepalese Rupee (NPR).
Note: Dwelling type definitions vary by country. In Nepal, Type 1 is a multi-storied building with a single household; Type 2 houses refer to multiple households. In Myanmar, Type 1 refers to buildings with three or more flats/apartments, and Type 2 to multi-family houses. Cambodia lacks standardized definitions; so dwelling types are reported as classified in the original dataset without further distinction.

Variable	**Cambodia** (n=3771)	**Myanmar** (n=3446)	**Nepal** (n=6000)
Age			
18–40	29.8%	25.1%	66.6%
41–60	41.0%	48.1%	22.4%
Above 60	17.0%	26.8%	9.8%
Missing (NaN)	12.2%	0.0%	1.2%
Education Level			
No Schooling	2.9%	11.0%	—
Primary	32.9%	32.9%	34.7%
Secondary	24.4%	0.0%	39.4%
Vocational School	0.0%	8.3%	0.5%
Higher Secondary	10.1%	13.9%	13.8%
Graduate	2.7%	1.4%	4.7%
Post-Graduate	0.4%	1.2%	1.1%
Missing (NaN)	26.6%	31.3%	5.9%
Family Size	Mean = 4.46	Mean = 4.55	Mean = 4.61
Dwelling Type			
Type 1	92.1%	93.4%	89.1%
Type 2	6.6%	3.2%	6.6%
Others	1.3%	3.4%	4.2%
Energy Poverty Tier			
Tier 0	27.9%	34.4%	21.8%
Tier 1	60.2%	59.5%	73.0%
Tier 2	11.9%	6.0%	5.1%
Total Expenditures			
Mean	1,575,932 KHR	259,326 MMK	19,540 NPR
Std. dev	1,913,552 KHR	457,459 MMK	34,897 NPR
Min	20,296 KHR	0 MMK	767 NPR
Max	41,562,500 KHR	14,281,000 MMK	876,295 NPR

energy poverty outcomes but cannot capture temporal dynamics or establish causality. Nevertheless, cross-sectional data provides valuable insights into underlying household and regional factors, particularly with respect to structural characteristics that are static over time. Although the inclusion of spatial fixed effects and machine-learning-based modeling helps mitigate endogeneity and omitted-variable bias, potential issues such as reverse causality and selection bias cannot be fully ruled out. Therefore, the results should be interpreted as indicative rather than causal.

5. Results

This section presents the empirical findings in a structured sequence, beginning with the results of data preprocessing step to address class imbalance using SMOTE. We then evaluate the performance of alternative predictive models, comparing results from logistic regression and XGBoost, followed by a refined analysis incorporating spatial fixed effects. Based on model accuracy and consistency, the best-performing specification is selected for the in-depth interpretation of the results. Subsequent sections assess model error distributions across countries using a normalized index of predictive deviation, followed by heterogeneity analyses by gender, urban-rural residence, and ethnicity, where available. Together, these results provide a comprehensive understanding of the drivers and disparities in multidimensional energy poverty as well as the potential of improvements across Cambodia, Myanmar, and Nepal.

5.1. SMOTE-adjusted class distribution

Class imbalance mitigation via SMOTE ensures robust representation of all energy poverty tiers, which is particularly relevant for Tier 0 (severe deprivation) and Tier 2 as shown in Table 4. Post-SMOTE, the synthetic balancing of tiers (e.g., Nepal's Tier 0 increasing from 1,048 to 3,506 samples), addresses initial skews that could bias predictions toward the dominant Tier 1 class. This adjustment is pivotal for policy relevance, as accurate identification of severely deprived households (Tier 0) is a primary objective of the multi-dimensional framework. Table 4 shows the SMOTE Adjusted Class Distribution.

5.2. Model choice

The evaluation of model performance across Cambodia, Myanmar, and Nepal reveals distinct patterns in predictive accuracy, highlighting the effectiveness of XGBoost in capturing multidimensional energy poverty. Initial comparisons between the logistic regression and XGBoost demonstrate a clear advantage for the latter, with XGBoost achieving test accuracies of 0.65, 0.59, and 0.50 in Nepal, Cambodia, and Myanmar, respectively as shown in Table 5. In contrast, logistic regression models, including polynomial variants, consistently underperform, with accuracies ranging from 0.37 to 0.56. This disparity underscores XGBoost's superior ability to model complex interactions inherent in socio-economic energy poverty data, and thus to reduce the part of the error caused by model misspecification, as hypothesized in the methodology. The marginal improvement from polynomial logistic regression (e.g., 0.43 vs. 0.41 in Nepal) suggests limited gains from explicit non-linear feature engineering, whereas XGBoost's inherent tree-based structure accommodates such relationships without overfitting or previous specification.

Second, we compare models with and without spatial fixed effects, for the purpose of highlighting the role of shared regional characteristics on EP potential. The incorporation of spatial fixed effects as shown in Table 6 further refines the model accuracy, as evidenced by the progressive improvements from baseline (M) to district (M+D) and province/state-level (M+D+P/S) adjustments. For instance, Nepal's test accuracy rises from 0.65 to 0.78 with province-level fixed effects, while Myanmar exhibits the most pronounced gain (0.50 to 0.72), corroborating the hypothesis that unobserved regional heterogeneity significantly influences energy poverty. The convergence between training and testing accuracies evident in Cambodia's M+D+P/S model (0.86 train vs. 0.68 test) suggests effective regularization and reduced overfitting.

The results collectively affirm the methodological choices: XGBoost non-linear capabilities, spatial fixed effects for unobserved heterogeneity, and SMOTE for class balance are indispensable for reliable energy poverty measurement as they contribute to minimize the structural part of the error due to model specification.

To ensure the stability and generalizability of our results, we performed both internal validation of the algorithms predictive validity as well as model comparison, to confirm the correct specification of the relationship. Internal validation is obtained with an

Table 4
SMOTE adjusted class distribution.

Country	Tier	Original (Whole Data)	Pre-SMOTE (Training)	Post-SMOTE (Training)
Cambodia	0	1,051	841	1,815
	1	2,270	1,815	1,815
	2	450	360	1,815
Myanmar	0	1,187	949	1,641
	1	2,052	1,641	1,641
	2	207	166	1,641
Nepal	0	1,310	1,048	3,506
	1	4,383	3,506	3,506
	2	307	246	3,506

Table 5
Model accuracy comparison.

Model	Nepal	Cambodia	Myanmar
Logistic Regression	0.41	0.56	0.37
Logistic (Poly)	0.43	0.56	0.38
XGBoost	**0.65**	**0.59**	**0.50**
XGBoost (Poly)	0.63	0.57	0.48

Table 6
Model accuracy with fixed effects.

Model	Cambodia (Test/Train)	Nepal (Test/Train)	Myanmar (Test/Train)
Model (M)	0.59 / 0.79	0.65 / 0.80	0.50 / 0.77
Model + District FE (M+D)	0.60 / 0.80	0.75 / 0.82	0.65 / 0.79
Model + District FE +Province/State FE (M+D+P/S)	**0.68 / 0.86**	**0.78 / 0.85**	**0.72 / 0.84**

out-of-sample cross-validation procedure, training the machine learning model on a random subset of the data and testing it on unseen observations. To ensure robustness to model selection, the model used in this study is XGBoost, an ensemble algorithm that combines multiple decision trees to minimize overfitting. This ensemble structure contributes to the robustness of our estimates by aggregating many different trees (models). This approach lowers the risk of estimation bias. Additionally, we assessed robustness across countries, confirming that the decomposition patterns remain qualitatively similar despite contextual differences in Nepal, Cambodia, and Myanmar. This cross-country consistency strengthens the reliability of the proposed measure. This means that our methodological approach can capture patterns of energy poverty and reveal the potential for alleviation, regardless of the specific country context. This allows the approach to be adopted in different contexts and countries, making it a powerful tool for future policy measures. We also verify robustness with a within-country sensitivity analysis considering various ethnicities, sectors (urban/rural), and genders.

5.3. *Index of potential*

The error is calculated as (actual tier − predicted tier)/3, providing a normalized measure of deviation between observed and model predicted energy poverty outcomes. This metric allows us to identify households that systematically perform above or below expectations based on the socioeconomic and structural characteristics included in the model. Positive values indicate overachieving households those with higher actual energy Tier than predicted, suggesting that they have exceeded expectations given their underlying conditions. Conversely, negative values denote underachieving households, where actual energy Tier falls short of model predictions, implying unrealized potential. A value of zero reflects a perfect match between predicted and actual outcomes.

In Nepal, the error distribution shows minimal mean shifts across models (hovering near zero). The stable near-zero mean errors

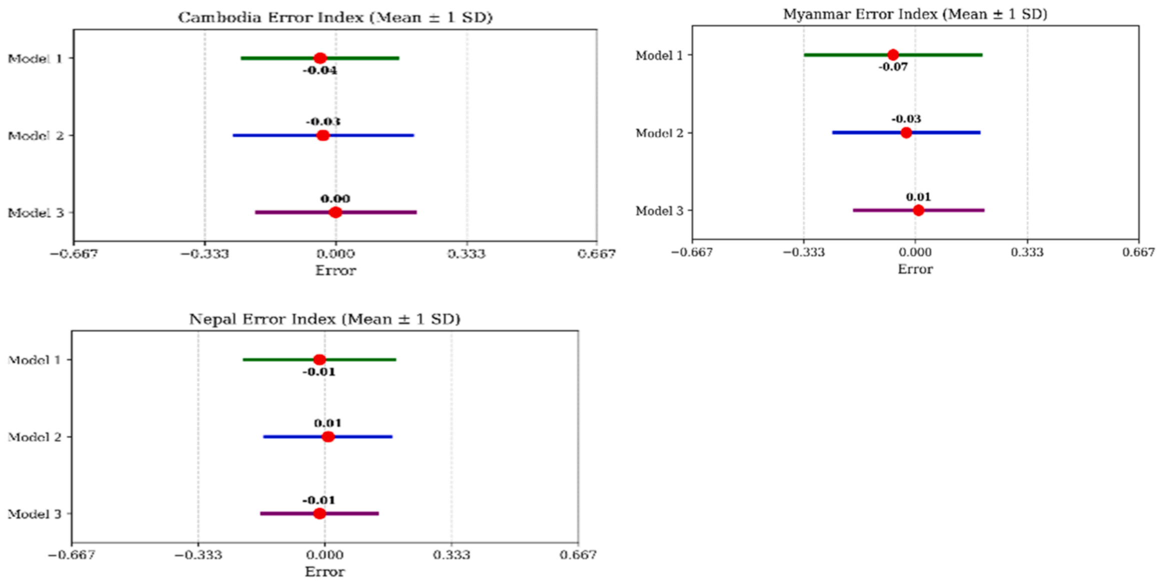


Fig. 2. Overall Error Index Across Models and Countries.
Model 1 (Demand), Model 2 (District Fixed Effects), and Model 3 (District + Province Fixed Effects).

suggest limited potential for improvement through spatial controls, although the standard deviation (SD) decreases with added fixed effects. This implies that socioeconomic characteristics (Model 1) already explain much of the variation in energy poverty, while district and province-level controls (Models 2&3) primarily reduce noise, as reflected by the decreasing standard deviation. The stable mean error near zero suggests that, on average, households' energy poverty tiers align with expectations given their socioeconomic and spatial attributes Fig. 2.

Cambodia's results show a gradual correction from Model 1's mean error of -0.04 to perfect alignment in Model 3 (0.00). The initial negative mean error reveals households are underachievers, and indicates that the model based on socioeconomic variables alone tends to overestimate energy poverty levels relative to the observed data. This suggests the presence of unobserved factors influencing energy poverty that are not captured by the baseline socioeconomic variables. The inclusion of provincial fixed effects in Model 3 accounts for these unobserved influences, eliminating the bias and improving the model's predictive accuracy at the provincial level.

Myanmar presents a more nuanced case. Here, the error index mean shifts marginally toward zero with district and state fixed effects (Models 2&3), while the SD contracts sharply. Model 1's large negative mean error (-0.07) reveals underachievers, indicating widespread potential for improvement. This alone fails to fully capture energy poverty dynamics, but spatial controls particularly at the state level correct for systematic biases. The improvement suggests that unobserved state-level disparities (e.g., uneven grid reliability, conflict-affected infrastructure) significantly influence energy access.

5.4. Heterogeneity analysis

5.4.1. Male and female

Fig. 3's comparison reveals distinct patterns in how gender and spatial hierarchies interact to shape energy poverty prediction accuracy. Cambodia's households show the most pronounced underachievement in base models (Model 2: -0.04 males, -0.03 females)

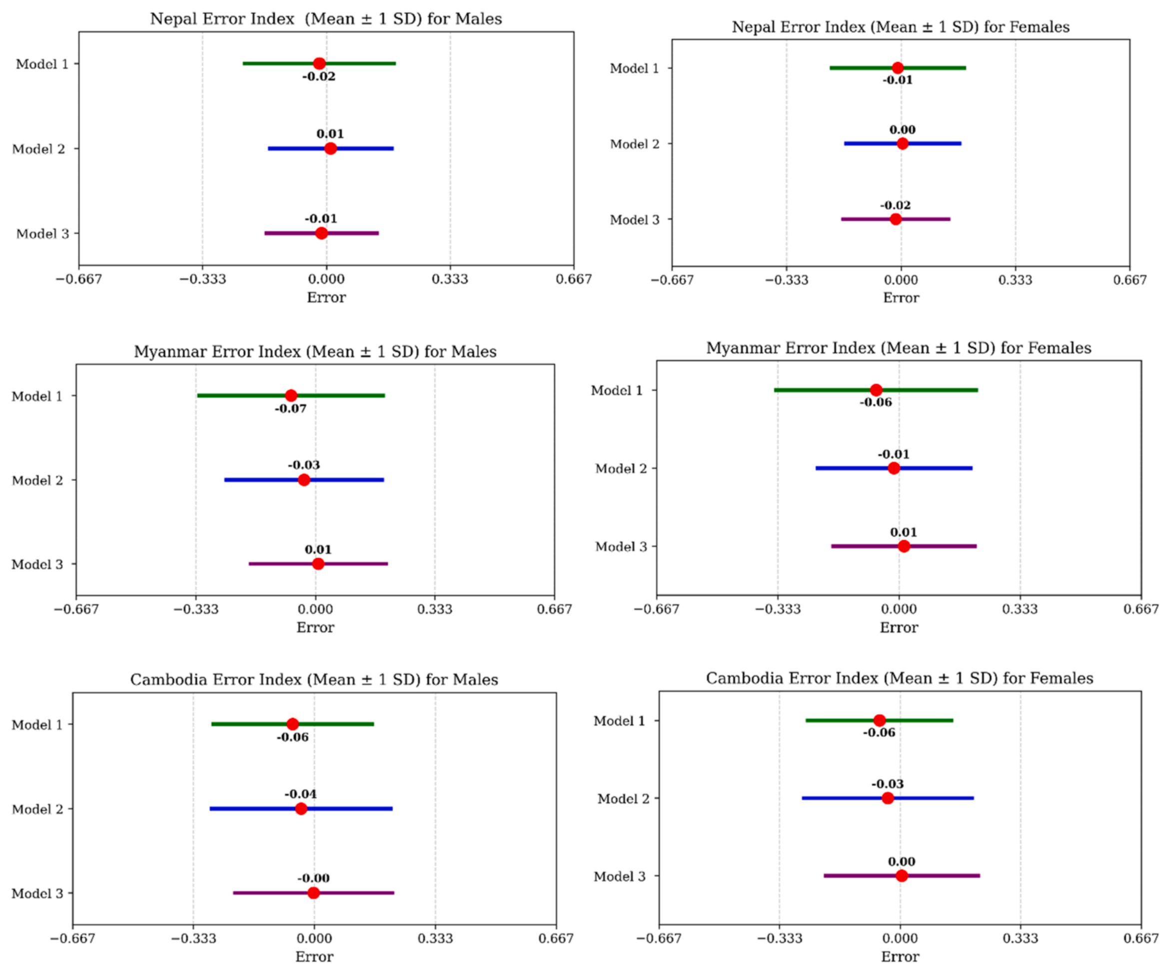


Fig. 3. Male vs. Female Error Index across Nepal, Myanmar, and Cambodia (Models 1–3).
Note: Model 1 is with only demand variable, Model 2 is with Demand variables + District Fixed effects and Model 3 with Demand variable + District FE + Province Fixed Effect.

that only fully resolves with provincial controls (Model 3), suggesting its energy access advantages are tightly clustered at the provincial level. This contrasts sharply with Nepal, where both genders maintain near-perfect alignment across all models (male errors: -0.02 to -0.01; female: -0.01 to 0.00), demonstrating consistency regardless of spatial scale. Myanmar occupies an intermediate position, with larger initial underachievement (Model 1: -0.07 males, -0.06 females) that requires state-level controls (Model 3) to resolve, indicating macro-regional disparities dominate its energy poverty landscape.

Gender disparities manifest differently across countries. While Cambodia's female-headed households show stronger initial underachievement than males (-0.06 vs -0.06), both genders converge to perfect prediction in Model 3. This implies that gender disparities are influenced by regional dynamics. Myanmar displays parallel but unequal correction patterns, where females' initial gap (-0.06) is slightly smaller than males' (-0.07), yet both reach similar final alignment (0.01). Nepal stands apart with minimal gender differences, as both sexes maintain errors within ±0.02 magnitudes throughout all models. The results point toward consistent energy poverty dynamics across male and female households in Nepal.

5.4.2. Urban vs rural

Fig. 4 shows urban-rural comparisons and reveals fundamental disparities in energy poverty prediction patterns across all three countries. Myanmar's urban areas demonstrate the most severe initial underachievement (Model 1: -0.08) that substantially corrects through spatial controls (Model 3: 0.02). Rural areas show more moderate but persistent gaps (Model 1: -0.05 to Model 3: 0). This urban-rural divide suggests Myanmar's cities contain concentrated advantages that models initially miss but can partially capture through state-level controls, likely reflecting complex regional factors such as infrastructure quality, governance, and localized service delivery that vary within urban areas, whereas rural energy poverty follows more predictable patterns.

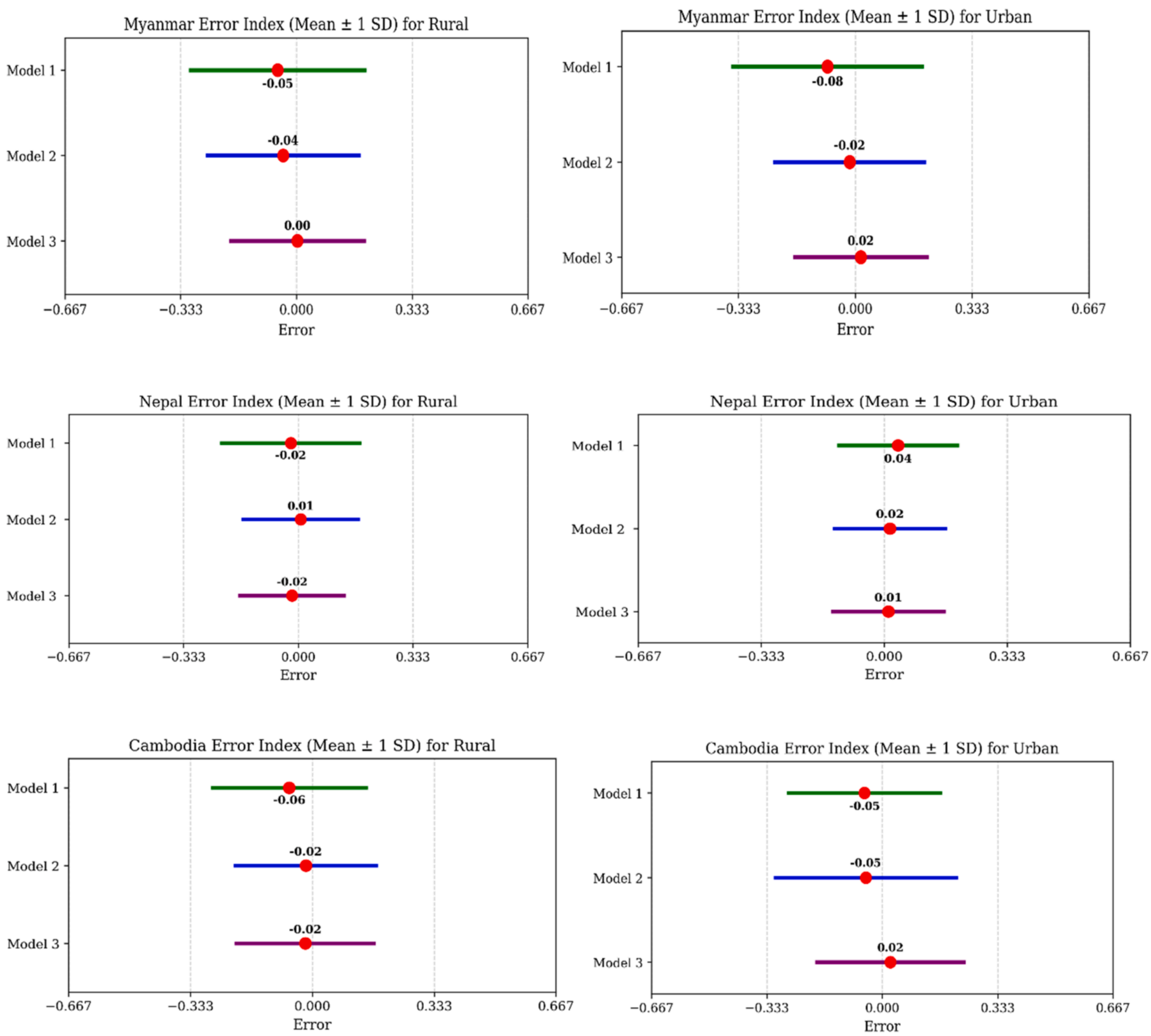


Fig. 4. Urban vs. Rural Error Index across Nepal, Myanmar, and Cambodia (Models 1–3).
Note: Model 1 is with only demand variable, Model 2 is with Demand variables + District Fixed effects and Model 3 with Demand variable + District FE + Province Fixed Effect.

Cambodia presents an inverse relationship, with rural households showing deeper initial underachievement (Model 1: -0.06) than urban areas (-0.05). While urban predictions fully normalize by Model 3 (0.02), rural errors remain slightly negative (-0.02), indicating provincial characteristics better explain urban energy poverty advantages. This urban bias contrasts sharply with Nepal's results, where urban areas show consistent overachievement (positive errors: 0.04 to 0.01 across models) against rural near-equilibrium predictions (errors within ±0.02). Nepal's exceptional rural-urban parity confirms its energy poverty determinants operate similarly across socioeconomic and spatial factors controlled for in the model.

First, urban areas universally show larger prediction gaps than rural areas in base models (Model 1), suggesting cities generate more unobserved energy poverty reduction. Second, spatial controls prove most valuable for urban predictions across all countries, with Myanmar's urban areas benefiting most from state-level controls (0.10 error reduction). Third, only Cambodia maintains residual rural underachievement in Model 3 (-0.02), revealing unique provincial-level barriers to rural energy access not present in other countries.

5.4.3. Ethnicity

The ethnic group analysis as shown in Fig. 5, only possible with data for Nepal, reveals distinct patterns in how Nepal's energy poverty predictions vary across communities. Sherpa, Magar, Madesi, and Muslim communities show the most significant initial underachievement in Model 1 (errors: -0.13 to -0.08), indicating these groups have potential to improve on energy poverty outcomes. These potentials partially persist even in Model 3 (errors: -0.05 to 0.01), suggesting their disadvantages in energy poverty outcomes aren't fully captured by standard spatial controls. The Dashnami Sanyasi present a unique case where underachievement worsens from Model 1 (-0.05) to Model 3 (-0.08), revealing increasing prediction gaps with added controls.

In contrast, Brahmin, Chetri, and general Janajati groups demonstrate remarkable prediction stability across all models (errors within ±0.02). Their near-perfect alignment suggests their energy poverty status follows expected patterns based on standard household and spatial characteristics. The Dalit and Tharu communities show inverse trajectories - while Dalits move from slight overachievement in Model 1 (0.02) to underachievement in Model 3 (-0.04), Tharus maintain consistent overachievement (0.04 to 0.03), indicating systemic advantages not reflected in the model inputs.

Newars occupy a middle ground, transitioning from Model 1 overachievement (0.03) to near-perfect alignment in later models. This pattern resembles the general Janajati trajectory but with greater initial variance. The ethnic comparisons collectively demonstrate how standard energy poverty models work well for Nepal's dominant groups (Brahmin, Chetri) but require special consideration for marginalized communities (Sherpa, Madesi) and advantaged groups (Tharu), whose energy poverty patterns defy conventional predictors.

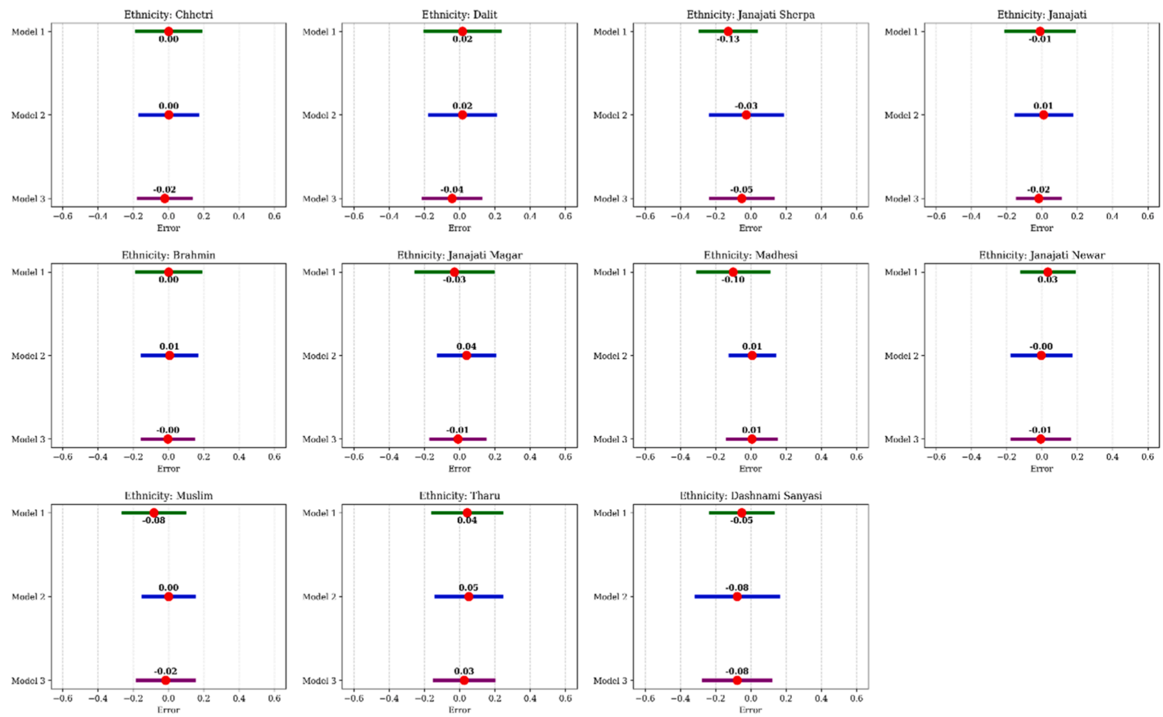


Fig. 5. Ethnicity-Based Performance in Nepal (Models 1–3).
Note: Model 1 is with only demand variable, Model 2 is with Demand variables + District Fixed effects and Model 3 with Demand variable + District FE + Province Fixed Effect.

6. Discussion

The findings of this study provide new insights into the complexity of energy poverty in Nepal, Myanmar, and Cambodia, while also corroborating key patterns identified in existing literature. In Nepal, our analysis confirms the strong link between ethnicity and energy poverty outcomes found by Paudel (2021) and Nepal et al. (2023), with marginalized ethnic groups consistently showing greater energy deprivation than predicted by standard socioeconomic models. However, our spatial analysis reveals that these ethnic disparities persist even after accounting for geographic factors, suggesting that cultural and institutional barriers beyond simple geographic factors, such as remoteness as highlighted by Bharadwaj et al. (2022), continue to hinder reductions in energy poverty for certain communities. The relative parity between urban and rural predictions in our models may indicate some success in Nepal's rural electrification efforts, though Malla (2013)'s findings on regional disparities remind us that significant gaps likely remain at more localized levels. These findings illustrate and reinforce the core principles of our conceptual framework, which emphasizes that energy poverty is driven by both endogenous household characteristics and exogenous structural and spatial factors (shared factors). The persistence of disparities, especially among marginalized groups and regions, highlights the importance of distinguishing between these drivers and understanding the potential for improvement that lies beyond socioeconomic variables alone.

For Myanmar, our results both confirm and complicate the conventional understanding of its energy poverty landscape. While we observe the expected urban-rural divide (Shyu, 2022), with urban areas showing higher connection rates, our models reveal a counterintuitive pattern where urban households systematically underperform. The findings align with observations from Aung et al. (2022) about unreliable urban electricity supply. This suggests that Myanmar's impressive electrification gains (Sovacool, 2013) may mask significant differences in the quality of access, particularly for low-income urban households. The strong performance of spatial fixed effects in our models underscores the importance of regional factors, likely including the ethnic conflict dynamics noted in studies of Rohingya energy deprivation (Rafa et al., 2022,Nazifa Rafa et al., 2024), though our data did not specifically examine refugee populations.

Cambodia's energy poverty profile emerges as particularly shaped by geographic factors, with rural households consistently lagging behind predictions despite the nation's remarkable electrification progress noted by Siciliano et al. (2025). The persistent rural underachievement in our models, even after controlling for provincial characteristics, supports Mika et al. (2021)'s findings about the challenges of remote energy access and reinforces the need for geographically targeted solutions as proposed by Bharadwaj et al. (2022). Interestingly, our results suggest that Cambodia's urban energy advantages are largely explained by provincial-level factors, pointing to concentrated infrastructure benefits in certain regions rather than uniformly distributed urban prosperity.

These findings carry important policy implications for each national context. In Nepal, energy poverty interventions must move beyond generic rural-focused programs to address the specific barriers facing marginalized ethnic groups, potentially through targeted subsidies and culturally appropriate energy solutions. Myanmar's policymakers should look beyond connection rates to address the quality and reliability of urban electricity supply, while continuing rural expansion efforts and developing special programs for conflict-affected regions. For Cambodia, the priority should be on bridging the persistent rural energy gap through decentralized solutions and provincial infrastructure investments, with particular attention to remote areas where grid extension remains challenging.

Across all three countries, the results demonstrate the value of spatially disaggregated energy poverty assessments and the need for policies that recognize the complex interplay of geographic, ethnic, gender, and socioeconomic factors in shaping energy poverty outcomes.

7. Limitations

The absence of longitudinal observations constrains our ability to control for time-varying unobserved determinants and household-specific fixed characteristics that persist over time. Accordingly, our results should be interpreted as associational rather than causal, reflecting patterns in multidimensional energy poverty rather than temporal changes.

The objective of our study differs from traditional causal-inference approaches. Our primary aim is to disentangle household-level (policy-reducible) and regional-level (structural) components of variation in energy poverty, rather than to estimate dynamic responses to specific variables. The machine learning based decomposition framework quantifies how much of the observed variation can be systematically explained by socioeconomic and spatial covariates and how much remains unexplained interpreted as structural heterogeneity arising from geographic, infrastructural, or institutional factors.

We recognize that the lack of time-varying and time-invariant fixed effects means potential endogeneity such as reverse causality and selection bias cannot be entirely ruled out. As noted in prior studies, certain household predictors (e.g., housing type, total expenditure) may simultaneously act as causes and consequences of energy access: households with better access often experience higher incomes and improved housing conditions, yet these same variables also influence the likelihood of energy adoption (Ekholm et al., 2010; Xiao et al., 2024). In contrast, variables such as education, geographic location, and regional infrastructure are more plausibly exogenous determinants, shaping energy poverty outcomes independently of short-term household behavior.

However, because our model is predictive rather than causal, we do not interpret individual coefficients in isolation. Instead, we focus on the aggregate explanatory contribution of household and regional factors, emphasizing how much of the observed energy poverty is attributable to observable socioeconomic conditions. This allows us to gain insights into the underlying dynamics that shape EP outcomes, although we only capture a snapshot moment.

If longitudinal MTF data become available, our framework could be extended to a panel-based design to assess dynamic effects, following methods such as Yang et al. (2024), who integrate spatial and temporal heterogeneity within machine-learning-based panel models.

8. Conclusion

Energy poverty remains a critical global challenge, with significant disparities observed across different regions and socioeconomic groups. This study has developed a novel framework integrating machine learning and error decomposition to assess the potential for improvements in energy poverty outcomes in Cambodia, Myanmar, and Nepal. By distinguishing between household-level and regional-level factors, our approach provides a more nuanced understanding of where interventions can be most effective.

The study broadens our conceptual understanding of the factors influencing energy poverty by contrasting shared and individual drivers, as well as endogenous and exogenous ones. Applying an error decomposition approach helps isolate among them the factors with the most potential for EP reduction and provide policymakers with actionable insights on where improvements can be made. Specifically, the incorporation of spatial fixed effects further refines predictions, emphasizing the importance of localized policy interventions. Methodologically, the study demonstrates the superiority of machine learning techniques, particularly XGBoost, which consistently outperforms traditional models. While logistic regression models generally achieve accuracies in the 0.37 to 0.56 range, XGBoost models reach 0.48 to 0.65, showing a clear improvement in predictive performance. This gain reflects XGBoost's capacity to reduce model misspecification and more effectively identify the true potential. The consistency of findings across alternative model specifications including logistic, polynomial, and XGBoost models with spatial fixed effects demonstrates the robustness of the predictive decomposition and its reliability in capturing energy poverty.

The findings reveal that energy poverty is not merely a function of individual household characteristics but is deeply influenced by broader structural and geographic factors. In Nepal, while socioeconomic variables explain much of the observed energy deprivation, persistent gaps among marginalized ethnic groups indicate unexploited potential for improvement that may be constrained by cultural and institutional barriers. In Myanmar, regional disparities in areas where infrastructure reliability is limited highlight spatially uneven potential for reducing energy poverty, emphasizing the need for targeted interventions to unlock this potential. Cambodia's rural-urban divide underscores that centralized grid expansion alone may not fully realize households' potential for energy access, pointing to decentralized and locally tailored energy solutions as key pathways to bridge this gap. Overall, these results suggest that addressing both observable and unobserved factors at multiple levels is critical to realizing the latent potential for improvement in energy poverty across these countries.

These insights carry important implications for energy policy. Rather than relying on uniform electrification strategies, governments and development agencies should adopt targeted approaches that account for country and regional contexts, infrastructure deficits, affordability constraints, and sociocultural barriers. Future research should expand this framework to other regions, incorporating longitudinal data and qualitative assessments to refine predictive models further.

The framework is intentionally designed to be replicable across countries where the Multi-Tier Framework (MTF) or comparable household energy survey data are available. This approach is particularly relevant in countries where regional and structural factors substantially influence energy access outcomes, especially those with pronounced geographic, political, or ethnic diversity. For instance, the SDG7 Energy Progress Report 2025 (IEA, IRENA, UNSD, The World Bank, 2025) identifies India and Indonesia to show persistent subnational inequality despite near-universal grid coverage, driven by infrastructural and geographic disparities. Ethiopia and the Philippines face similar challenges linked to ethnic and political fragmentation. This illustrates persistent within-country heterogeneity in EP and reveals further opportunities for our methodological approach to be applied. Most of these countries already have data available under the MTF survey framework, which makes our approach suitable to be extended to additional countries with similar challenges as well as for cross-country comparisons. Several cross-country studies such as Rao et al. (2022), who compare eleven nations using a unified multidimensional index, and Lan et al. (2022), who apply a composite indicator across Asian economies demonstrate that data-driven, indicator-based approaches can be consistently estimated across heterogeneous contexts. Building on this evidence, our model's data-driven structure and reliance on standardized MTF tiers make it readily extendable to additional countries, subject to data availability. Moreover, as Pelz et al. (2018) emphasize, complex indicators can be simplified through aggregation and weighting to facilitate international comparison while preserving contextual depth. Our framework aligns with that principle.

Ultimately, this study contributes to both academic and policy discussions by offering a data-driven, multidimensional approach to energy poverty reduction. By identifying whether the most impactful levers for intervention are at the household, district, or national level this research supports efforts to achieve Sustainable Development Goal 7: ensuring universal access to affordable, reliable, and modern energy for all. The path forward requires not only technological and infrastructural investments but also a commitment to equity, ensuring that the most vulnerable populations are not left behind in the global energy transition.

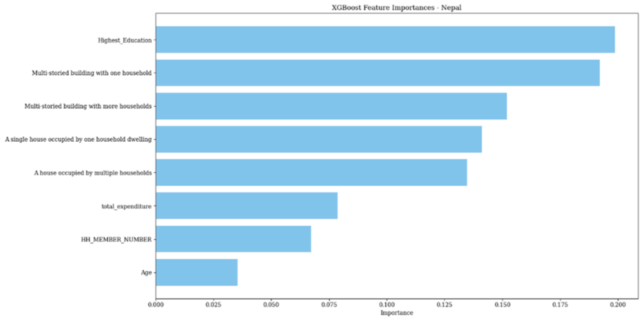
CRediT authorship contribution statement

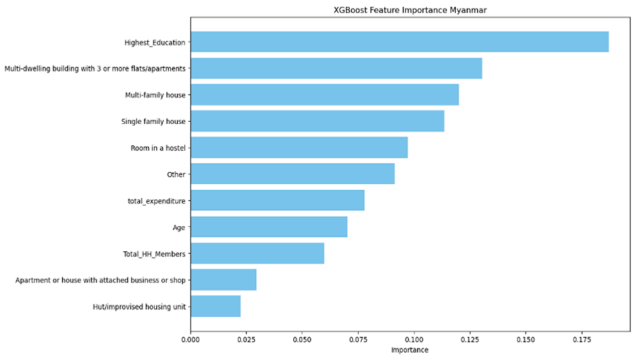
Sarath Chandra Koppolu: Writing – original draft, Validation, Methodology, Formal analysis, Data curation. **Lisa Hoeschle:** Writing – review & editing, Validation. **Lucie Maruejols:** Writing – review & editing, Supervision, Conceptualization.

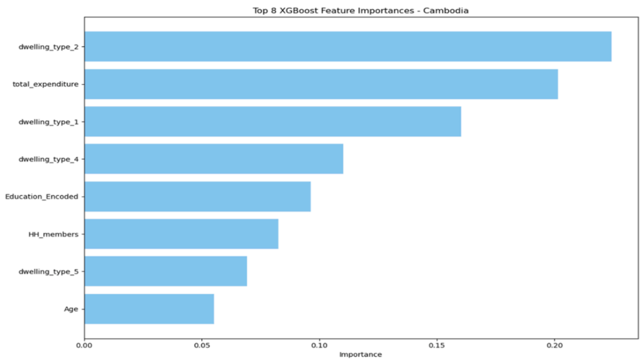
Appendix

Electricity access: proportion of households in each tier, per dimension

The three graphs illustrate the distribution of electricity access tiers across key energy dimensions for Cambodia, Myanmar, and Nepal. In Cambodia, most households are classified within Tiers 1–2, indicating moderate levels of access; however, low capacity and reliability in rural areas highlight persistent energy deprivation. Myanmar shows a concentration of households in Tiers 0–1, reflecting widespread energy poverty primarily driven by poor reliability and infrastructural limitations. Nepal performs comparatively better, with most households in Tiers 1–2, though disparities among marginalized groups reveal ongoing challenges in achieving equitable access. Overall, the graphs demonstrate that while all three countries have made progress in expanding electricity access, deficiencies in specific dimensions particularly reliability, capacity, and affordability continue to constrain the overall quality and consistency of energy access.







Interpretation of Feature Importance

The importance scores reported here are derived from the default feature importance metric in XGBoost, which calculates the relative importance of each feature based on its contribution to model performance, specifically through measures such as gain, coverage, and frequency of use within the model's decision trees.

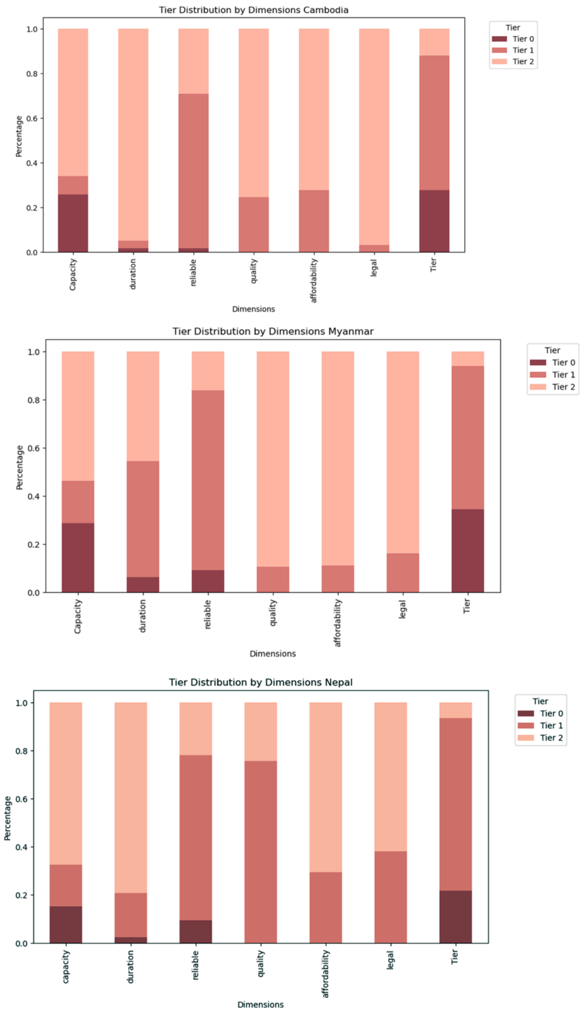


Fig. 6. XGBoost feature importance across models.

This study highlights the important methodological insights, confirming that country-specific variations in feature importance validate the flexibility of a multidimensional framework for capturing contextual energy poverty realities. As shown in Fig. 6, dwelling types dominate as key predictors in Cambodia with importance scores ranging from 0.15 to 0.20 highlighting infrastructure-based stratification. Myanmar shows more balanced importance scores, peaking at 0.15, indicating that energy poverty stems from multiple, diffuse factors likely including unmeasured regional disparities in grid development. Nepal reveals a sharp urban-rural divide, with multi-storied (urban) and single-household (rural) dwellings showing contrasting importance scores between 0.15 and 0.175, reflecting the country's known electrification gap. Across all three countries, expenditure and age emerge as consistent contributors to energy poverty. These patterns emphasize the need for tailored policies: infrastructure-focused interventions in Cambodia, urban-rural bridging in Nepal, and regionally comprehensive planning in Myanmar. This granular understanding enables more effective, context-specific electrification strategies.

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