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Research paper

Efficient energy usage typologies: Adoption and determinants of energy-saving appliances among Ugandan households

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ABSTRACT

This study investigates household adoption of energy-efficient technologies in Uganda using nationally representative data from the Uganda National Household Survey 2020/21. We develop an integrated econometric framework that combines Latent Class Analysis (LCA), Multinomial Logit (MNL) models, and Logistic and Poisson regressions to capture adoption heterogeneity, identify structural determinants, and differentiate between adoption incidence and intensity. LCA probabilistically classifies households into four adoption typologies: nonadopters, lighting-only adopters, heating-only adopters, and broad adopters. MNL models quantify the demographic, geographic, and infrastructural factors that shape class membership, whereas logistic and Poisson specifications reveal who adopts at least one technology and how deeply it extends across multiple domains. The results showed that over 90 % of the households remained non-adopters, with efficient lighting as the primary entry point, minimal cooking, and virtually no heating. Adoption is consistently constrained by electricity access, affordability, and household asset levels, whereas urban residences, education, and younger household heads significantly increase the likelihood of adoption. By integrating latent adoption typologies with incidence–intensity modeling using nationally representative household data, this study advances beyond conventional binary adoption analyses and provides robust, policy-relevant evidence on the structural constraints shaping Uganda's household energy transition.

1. Introduction

Access to modern, efficient, and sustainable energy services is the cornerstone of socio-economic transformation and environmental sustainability (Bruce and Vinuales, 2021; Mirzabaev and Chen, 2024). Globally, Sustainable Development Goal 7 (SDG 7) calls for ensuring access to affordable, reliable, sustainable, and modern energy, highlighting the pivotal role of energy systems in improving livelihoods, fostering inclusive economic growth, and mitigating climate change (Timilsina and Shah, 2020). Among the practical measures aligned with these aspirations, the adoption of energy-saving appliances such as improved cookstoves, efficient lighting systems, and modern heating solutions has gained increased attention (Bonan et al., 2014; Modi and Figueroa, 2013). These appliances promise a substantial reduction in household energy consumption, thereby reducing energy expenditure, improving indoor air quality, and reducing greenhouse gas emissions (Fuso Nerini et al., 2018). Consequently, energy-saving appliances are considered key instruments for accelerating energy transitions, enhancing household welfare, and supporting climate change mitigation efforts in both developed and developing economies (Burke and Melgar, 2022; Minas et al., 2024).

Despite significant progress in expanding energy access in sub-Saharan Africa, including Uganda, energy poverty remains widespread, and modern energy technology adoption remains far from optimal (Ssennono et al., 2021). Uganda's household energy landscape continues to be characterized by a heavy reliance on traditional biomass fuels, such as firewood and charcoal, alongside intermittent and often unreliable electricity access (Bonan et al., 2017; Nabukalu and Gieré, 2020). Even households with grid connectivity frequently lack the financial resources, market access, and awareness necessary for

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adopting modern energy-saving technologies (Alinaitwe, 2023). The implications of this gap are multidimensional: households incur higher energy costs, experience heightened vulnerability to energy price fluctuations and supply interruptions, and are exposed to environmental and health hazards associated with inefficient energy use (Nabukalu and Gieré, 2020). Against this backdrop, understanding how households adopt energy-saving appliances and identifying the factors that drive or constrain adoption have significant implications for both policy and practice (Mukisa et al., 2022; Namirembe et al., 2024).

The existing literature on energy access and technology adoption in sub-Saharan Africa has advanced our understanding of the transition from traditional to modern energy sources (Guta et al., 2022; Kizilcec et al., 2022). However, most studies tend to focus narrowly on single technologies, such as improved cookstoves or efficient lighting, thereby limiting the scope of understanding adoption patterns across multiple energy-saving appliances (Bonan et al., 2017; Mperejekumana et al., 2024). Moreover, studies on adoption determinants often rely on simplified binary outcomes that classify households as adopters or nonadopters (Bonan et al., 2017; Kayima et al., 2023). Such approaches fail to capture the heterogeneity of adoption behavior and neglect the interplay between multiple socioeconomic, demographic, and housing characteristics in shaping adoption outcomes (Kayima et al., 2023). This leaves an important knowledge gap; there is still limited empirical evidence on how diverse household characteristics jointly influence the breadth and patterns of energy-saving appliance adoption in Uganda.

This study addresses this knowledge gap by presenting a comprehensive household-level analysis of energy-saving appliance usage in Uganda. This is done by introducing a novel methodological approach that combines latent class analysis (LCA) and multinomial logit (MNL) modeling (Tuyiragize and Bassi, 2024). The latent class approach allows for the identification of distinct household typologies based on their adoption profiles, offering a nuanced understanding of the heterogeneity in adoption behavior that binary classifications cannot achieve (Tuyiragize and Bassi, 2024). A multinomial logit model was then applied to examine how socioeconomic and housing factors influenced the likelihood of belonging to these adoption classes. Together, these methods enable the development of evidence-based insights into both the extent of adoption and the underlying determinants, moving beyond the conventional one-size-fits-all understanding of household energy technology adoption (Peiffer and MacCarty, 2020).

The significance of this study is twofold. First, it generates comprehensive evidence on the adoption of energy-saving appliances at the household level, covering multiple technologies rather than focusing on a single appliance (Brown and Chapman, 2023; Hassen et al., 2023). Second, it advances the methodological frontier by applying a joint LCA–MNL framework that captures heterogeneity in adoption behavior, while linking it to observable household characteristics (Schulte et al., 2022; Wang et al., 2024). The findings are expected to inform energy policy and program design by highlighting which household segments lag behind in adoption and why, thus providing an empirical basis for targeted interventions such as financing mechanisms, market development strategies, and awareness campaigns (Namirembe et al., 2024). These insights have broader implications for sustainable energy transitions, climate change mitigation, and household welfare improvement in sub-Saharan Africa (Liao et al., 2021). Guided by the identified motivations and research gaps, this study pursues the overarching objective of evaluating household adoption of energy-efficient technologies in Uganda and identifying the socioeconomic and structural factors that shape adoption pathways (Han and Wei, 2021; Sotnyk et al., 2023).

This study addresses three core research questions. First, what distinct typologies of energy-efficient appliance adoption exist among Ugandan households across lighting, cooking, and heating domains? Second, which socioeconomic, demographic, and infrastructural factors determine household membership in these adoption typologies? Third, how do these factors shape both the incidence of adoption and the intensity of adoption once households begin transitioning toward energy-efficient technologies?

The remainder of the paper is organized as follows: Section 2 reviews the theoretical and empirical literature; Section 3 presents the research methodology; Section 4 reports the results; Section 5 discusses the results in relation to the existing literature; and Section 6 concludes and presents policy implications.

2. Literature review

While access to modern energy has long been recognized as a cornerstone of development, scholarly literature on household energy transitions in sub-Saharan Africa remains uneven in both focus and scope (Bonan et al., 2017; Prasad, 2011). A considerable body of research has investigated individual technologies that provide valuable insights into specific adoption challenges (Guta et al., 2022; Mperejekumana et al., 2024). However, this single-technology orientation has left significant gaps in our understanding of the broader configuration of household energy choice (Sterl et al., 2024). Adoption rarely occurs in isolation. Households make decisions across multiple domains of lighting, cooking, and heating; however, most existing studies have fragmented these processes into narrow silos (Hafner et al., 2018; Kelechi et al., 2023). As a result, the cumulative picture of how households engage with energy efficiency remains partial (Hancock, 2015; Tucho and Kumsa, 2020).

In methodological terms, prior studies have often relied on the binary treatment of adoption, classifying households simply as adopters or non-adopters (Schulte et al., 2022; van der Kam et al., 2024). Although tractable, this approach masks the heterogeneity of adoption pathways and structural factors that differentiate incremental from comprehensive transitions (Johanning et al., 2024; Robinson and Rai, 2015). The lack of frameworks capable of capturing both the diversity of adoption profiles and their socioeconomic underpinnings has limited the explanatory power of empirical literature (Bansal et al., 2024). Moreover, even when determinants are examined, they are often restricted to income or basic demographic characteristics, leaving aside the interplay between housing conditions, energy reliability, and regional disparities, which critically shapes adoption opportunities in resource-constrained settings (Min and Ko, 2023).

2.1. Theoretical review

The adoption of energy-saving appliances and their subsequent effects on electricity consumption are underpinned by robust theoretical frameworks that offer valuable insights into household decision making and energy use patterns. Theories, such as the diffusion of innovation theory and rational choice theory, provide complementary perspectives for analyzing these phenomena. While the Diffusion of Innovations Theory examines the processes influencing the adoption of energy-efficient technologies, including sociocultural and economic factors (Priest et al., 2015), Rational Choice Theory delves into the cost-benefit analyses that households perform to optimize utility and manage constraints (Cowan and Daim, 2013; Hesselink and Chappin, 2019). Together, these theoretical frameworks illuminate the drivers and barriers to adoption, and the mechanisms through which energy-efficient technologies impact electricity demand, offering a nuanced understanding of their role in promoting sustainable energy transitions in Uganda (Abrahamse and Schuitema, 2020; Kastner and Bobeth, 2018).

The Diffusion of Innovations Theory, developed by Everett Rogers, provides a robust framework for understanding how energy-saving appliances are adopted within Ugandan households (Staniszewska, 2015). This theory posits that the diffusion of new technologies follows a process influenced by five primary attributes: relative advantage, compatibility, complexity, trialability, and observability (Kapoor et al., 2011; Yu, 2022). Each attribute interacts with the socioeconomic and cultural realities of Ugandan households, thereby shaping their pace and extent (Yu, 2022).

At the core of the Diffusion of Innovations Theory lies the concept of relative advantage, which refers to the perceived benefits of a new technology compared to existing alternatives (Yu, 2022). In Uganda, energy-saving appliances offer several advantages including reduced electricity bills, improved energy efficiency, and environmental benefits (Hirmer and Guthrie, 2017). However, the perception of these benefits often depends on individual and community experience with appliances (Ball et al., 1999).

Compatibility, another key attribute, examines how well a new technology aligns with the values, practices, and needs of its potential adopters (Karahanna et al., 2006). In Uganda, the adoption of energy-saving appliances must align with household energy-consumption patterns and sociocultural norms (Mabey et al., 2023). Ensuring that appliances are seamlessly integrated into daily routines and that they meet the needs of Ugandan households is critical for enhancing compatibility and promoting adoption (Bunker et al., 2007; Holm-Nielsen et al., 2022).

The complexity of a technology, or the degree to which it is perceived as difficult to understand or use, significantly affects its adoption (Fürst et al., 2024; Oyetade et al., 2020). Energy-saving appliances that are simple to operate such as plug-and-play LED bulbs tend to achieve higher adoption rates. By contrast, more complex technologies, such as energy-efficient refrigerators, may require additional education or technical support to encourage their adoption (Iskin and Daim, 2013; Murto et al., 2019). In Uganda, where educational attainment varies widely, addressing complexity through user-friendly designs and community training programs is essential for overcoming this barrier (Greenhalgh et al., 2018; Iskin, 2011).

This theory also highlights the importance of trialability, which refers to the opportunity for potential adopters to experiment with a technology on a limited basis before committing its full use (Strömberg et al., 2016). In Uganda, where financial resources are constrained, the ability to trial energy-saving appliances significantly reduced the perceived risk of adoption (Levine et al., 2018).

Observability, or the extent to which the results of using a new technology are visible to others, plays a critical role in influencing its adoption (Iqbal and Zahidie, 2022). In Uganda, social dynamics often drive technology diffusion with early adopters serving as influential community leaders (Miller and Mobarak, 2015). When the benefits of energy-saving appliances, such as cost savings or improved functionality, are highly visible, they create a ripple effect that encourages others to adopt similar technologies (Zhang et al., 2002). Community-based demonstration projects and public awareness campaigns can further enhance observability by showcasing tangible advantages of these appliances (Graf-Vlachy and Buhtz, 2017).

Diffusion of innovation theory underscores the role of adopter categories in the diffusion process. In any community, individuals can be categorized as innovators, early adopters, early majority, late majority, or laggards, based on their propensity to adopt new technologies (Bianchi et al., 2017). In Uganda, early adopters often play a pivotal role in bridging the gap between innovators and the broader community (Nypan, 1970). These individuals, typically characterized by a higher socioeconomic status or greater access to information, act as conduits for disseminating knowledge about energy-saving appliances and demonstrating their benefits (Seebauer, 2015). By targeting early adopters with tailored interventions, policymakers and practitioners can accelerate the diffusion process and extend the reach of energy-efficient technologies to the early and late majorities (Bianchi et al., 2017).

The theory also emphasizes the role of contextual factors in shaping the adoption process. In Uganda, economic constraints, limited access to credit, and an unreliable electricity supply influence the rate and extent of adoption (Ebong et al., 2020; Namirembe et al., 2024). Addressing these contextual barriers through subsidies, financing options, and infrastructure improvements is essential to enable the wider diffusion of energy-efficient technologies (Conroy and Mancl, 2022; Namirembe et al., 2024).

The diffusion of innovation theory provides a comprehensive and nuanced framework for analyzing the extent of energy-saving appliance adoption in Ugandan households. By focusing on attributes, such as relative advantage, compatibility, complexity, trialability, and observability, this theory offers valuable insights into the factors driving adoption and the barriers that hinder it (Call and Herber, 2022; Yu, 2022). Additionally, its emphasis on social dynamics and contextual factors underscores the importance of community-based approaches and supportive policy interventions to promote energy-saving technologies (Eder et al., 2015; Priest et al., 2015). Applying this theoretical lens enables a deeper understanding of how energy efficiency can be achieved in resource-constrained settings, thereby contributing to sustainable energy transition in Uganda and elsewhere (Eder et al., 2015; Staniszewska, 2015).

2.2. Empirical review

The adoption of energy-saving appliances represents a pivotal strategy for addressing the energy efficiency and sustainability challenges in Uganda (Alinaitwe, 2023). However, understanding its impact requires a thorough examination of two critical dimensions: the extent of adoption, and its effects on household electricity consumption (Kayima et al., 2023). These themes encapsulate the socioeconomic and technological dynamics that influence energy efficiency, highlighting both opportunities and barriers within Ugandan households (Chadwick et al., 2022; Fashina et al., 2018). While the extent of adoption reflects the penetration of energy-saving technologies and the factors driving or hindering their uptake (Kizilcec et al., 2022; Levine et al., 2018), the effects on electricity consumption reveal tangible outcomes, in terms of reduced energy demand and enhanced household welfare (Marchi et al., 2024). Together, these dimensions provide a comprehensive lens for analyzing how energy-saving appliances contribute to sustainable energy transitions in Uganda (Iskin, 2011; Kasangana and Masekameni, 2019).

Empirical studies have highlighted significant variations in energy-saving appliance adoption rates across socioeconomic groups and geographic regions in Uganda. Urban households with greater access to formal electricity grids and higher disposable incomes exhibit higher adoption rates than their rural counterparts do (Tuyiragize and Bassi, 2024). This disparity underscores the critical role of access to reliable electricity as a precondition for the uptake of energy-efficient technologies (Almeshqab and Ustun, 2019). In rural areas, limited electrification and the dominance of traditional energy sources, such as kerosene lamps and biomass for cooking, present substantial barriers to adoption (Mukhadi et al., 2021). These findings suggest that the extent of adoption is closely tied to the degree of integration with formal energy systems, revealing an inequitable distribution of benefits associated with energy-saving appliances (Levine et al., 2018; MacDonald et al., 2020).

Income and affordability have emerged as the dominant determinants in empirical analyses of adoption (Azimi et al., 2024; Haq et al., 2024). Energy-saving appliances, such as LED bulbs and efficient refrigerators, often require higher upfront investments than their less efficient counterparts (Aggarwal et al., 2022; Hinestroza-Olascuaga et al., 2022). This cost barrier disproportionately affects low-income households, which prioritize immediate subsistence needs over long-term investments in energy efficiency (Azimi et al., 2024, 2023). As a result, adoption among these households remains low even when the long-term financial benefits of reduced electricity bills are evident (Hassen et al., 2023; Muloo et al., 2023). Empirical findings also point to the limited availability of affordable financing mechanisms, such as microcredit or pay-as-you-go systems, which could bridge the affordability gap and facilitate broader access to energy-efficient technologies (Aggarwal et al., 2022; Hassen et al., 2023).

Awareness and information dissemination are equally critical in shaping adoption patterns. Empirical studies have consistently shown that households with greater awareness of the economic and

environmental benefits of energy-saving appliances are more likely to adopt them (Yilmaz et al., 2023). However, knowledge gaps regarding the functionality and advantages of energy-efficient technologies are widespread in Uganda, particularly in rural areas (Tornel-Vázquez et al., 2024). These informational barriers limit the perceived value of energy-saving appliances, reducing the likelihood of adoption even among households with financial means to invest in such technologies (Ball et al., 1999).

The role of social dynamics in influencing adoption is a key focus of the empirical research (Du et al., 2024; Sibtain et al., 2024). Adoption patterns often follow a diffusion process in which early adopters within a community serve as role models, demonstrating the benefits of energy-saving appliances to their peers (Li et al., 2025). In Uganda, the influence of social networks is particularly pronounced in rural areas, where collective norms and communal decision making play a central role in shaping household behaviors (Dello Russo et al., 2024). Studies have found that households are more likely to adopt energy-saving appliances when they observe neighbors or community leaders benefiting from such technologies (Miranda et al., 2024). This social spillover effect underscores the importance of leveraging community-based approaches to accelerate the diffusion of energy-efficient technologies (Abdul Mumin and Goetz, 2024; Cioc et al., 2023).

Market dynamics, including the availability and quality of energy-saving appliances, also significantly impact the adoption rates. In Uganda, the penetration of high-quality energy-efficient products remains limited because of weak supply chains, high import costs, and prevalence of counterfeit or substandard goods (Alinaitwe, 2023). Households that invest in low-quality appliances often experience reduced performance and shorter lifespans, eroding trust in energy-saving technologies and deterring further adoption (Aggarwal et al., 2022). Empirical studies emphasize the need for stronger regulatory frameworks and quality assurance mechanisms to ensure that households have access to reliable and durable products that deliver promised energy savings.

Gender dynamics also play a nuanced role in the adoption of energy-saving appliances, particularly in rural Uganda where women are often the primary users and managers of household energy resources (Elasu et al., 2024, 2023). Empirical evidence suggests that empowering women through targeted awareness programs and financial inclusion initiatives can significantly enhance the adoption of energy-efficient technologies (Chandrasekaran et al., 2023; Tornel-Vázquez et al., 2024). Women's involvement in decision-making processes has been shown to increase the prioritization of appliances that reduce labor and improve household energy efficiency, highlighting the need for gender-sensitive approaches in energy policy and program design (Mpiira et al., 2024; Niemann et al., 2024).

Despite these challenges, success stories from pilot programs and localized initiatives provide valuable insights into strategies for enhancing adoption (Blackburn et al., 2020). Programs that combine subsidies with awareness campaigns and community demonstrations have achieved notable success in increasing the adoption rates (Weber and Guérin, 2014). These programmes also highlight the importance of tailored interventions that address the specific needs and constraints of different demographic and geographic segments (Corbett et al., 2023; Kumar et al., 2020).

The empirical literature on the extent of energy-saving appliance adoption among Ugandan households reveals a complex interplay of factors that influence uptake. Despite progress has been made, significant barriers related to affordability, awareness, and access persist, thereby limiting the widespread adoption of these technologies (Aggarwal et al., 2022). Addressing these challenges requires an integrated approach that combines financial incentives, robust supply chains, targeted awareness campaigns, and community-based interventions (Eze et al., 2023). By synthesizing empirical insights, this review provides a foundation for designing policies and programs that not only enhance the adoption of energy-saving appliances, but also contribute to Uganda's broader energy sustainability goals (Alinaitwe, 2023; Kayima et al., 2023; Tuyiragize and Bassi, 2024).

The reviewed literature provides valuable insights into household energy access and the adoption of energy-efficient technologies, particularly in low- and middle-income country contexts. However, three limitations remain evident. First, most studies examine adoption decisions for single technologies in isolation, which obscures the interrelated nature of household choices across lighting, cooking, and heating domains. Second, adoption is commonly modeled as a binary outcome, limiting the ability to distinguish between initial uptake and deeper, multi-technology transitions. Third, existing studies rarely integrate the identification of adoption typologies with econometric analysis of both adoption incidence and adoption intensity using nationally representative data. This study addresses these gaps by combining latent class analysis with incidence–intensity regression models, thereby advancing the literature beyond conventional binary and single-technology frameworks.

3. Research methodology

This study employed an integrated econometric framework to capture the heterogeneity of household adoption behavior and structural determinants of Uganda's energy transition (Alinaitwe, 2023). Adoption was conceptualized as a layered process, not as a discrete event, unfolding across the domains of lighting, cooking, and heating and varying in both incidence and intensity (Namirembe et al., 2024). To model this complexity, the analysis combines Latent Class Analysis (LCA), Multinomial Logit (MNL) models, and Logistic and Poisson regressions (Aggarwal et al., 2025). LCA, estimated through a Generalized Structural Equation Modeling (GSEM) framework, probabilistically identified the following household typologies: non-adopters, lighting-only adopters, rare adopters of efficient cooking or heating, and broad adopters (Bernards et al., 2018). This approach accounted for unobserved heterogeneity while incorporating structural covariates such as household head age, electricity costs, power availability, and asset holdings (Chekol et al., 2023). Building on this classification, the MNL specification formalized the determinants of adoption classes relative to the non-adopter baseline, with coefficients expressed as relative risk ratios, to quantify how sociodemographic and infrastructural factors differentiated rare adopters from the majority (Khurshid et al., 2024).

To complement typology-based analysis, logistic regression models adoption incidence, whereas Poisson regression captures adoption intensity or the number of technologies adopted once the transition begins (Bernards et al., 2018; Ebnou Abdem et al., 2023). Together, these models distinguish between initiation and depth of adoption, extending the explanatory power beyond latent typologies (Min and Ko, 2023). Robustness was ensured through diagnostics, including entropy measures for class separation, Pearson and deviance goodness-of-fit tests, link tests for model specification, ROC analysis, and predictive accuracy metrics, such as sensitivity, specificity, and F1 scores (Dong et al., 2023; Hu et al., 2020). This layered framework provides a comprehensive and rigorous means of mapping Uganda's household energy adoption landscape, while clarifying the structural conditions under which transitions occur.

This study used microdata from the Uganda National Household Survey (UNHS) 2020/21 conducted by the Uganda Bureau of Statistics (UBOS). UNHS is a nationally representative household-based survey that targets the non-institutional household population. The sampling frame was derived from the Uganda Population and Housing Census (UPHC) 2014 Enumeration Area (EA) frame, which provides a complete national listing of households by residence and region. Consistent with standard UNHS implementation, the survey applies a stratified two-stage sampling design in which Enumeration Areas are selected at the first stage using probability proportional to size (PPS), followed by systematic selection of households within sampled EAs based on

updated household listings. Household listing and interviewing are conducted using computer-assisted personal interviewing (CAPI) on tablet devices, with geographic coordinates recorded during field operations.

Given the stratified and clustered sampling design, survey weights were required to restore population representativeness. Following UBOS methodology, household weights were computed as the inverse of the overall probability of selection, defined as the product of the EA-level selection probability and the household-level selection probability, with adjustment for non-response. All descriptive statistics and econometric estimations in this study applied the UNHS survey weights to ensure nationally representative inference. Limitations related to the cross-sectional nature of the UNHS data, potential reporting error, and implications for inference are discussed in Section 6.3.

The analytic sample comprised 197,343 households, and the survey weights supplied by the UBOS were applied to preserve representativeness across the national and regional levels (Aggarwal et al., 2025). Energy adoption was operationalized across three domains: efficient lighting, efficient cooking, and efficient heating (Terfa et al., 2022). Binary adoption indicators were constructed for each domain, with additional derived outcomes: a categorical latent variable distinguishing adopter typologies, a binary "any adoption" indicator, and a count variable capturing adoption intensity (Emmanuel and Japhet, 2020). These outcomes provide the dependent variables for the GSEM–LCA, MNL, logistic, and Poisson specifications, thereby ensuring consistency across a layered analytical framework (Namirembe et al., 2024).

3.1. Latent class analysis via GSEM approach

The first step in the empirical strategy was to identify unobserved household typologies of energy adoption using Latent Class Analysis (LCA) (Brown et al., 2014). LCA assumes that the population is composed of mutually exclusive and exhaustive latent groups, or "classes," which explains the observed heterogeneity in household adoption patterns (Brown et al., 2014). In this context, the observed binary indicators of efficient lighting, cooking, and heating were treated as manifest variables, driven by an unobserved categorical latent variable representing the adoption class (Sen and Qiu, 2020; Tuyiragize and Bassi, 2024).

Formally, let y_{ij} denotes the observed adoption outcome for household i for technology j, where $y_{ij} \in \{0, 1\}$. Suppose that there exist C latent classes indexed by $c \in \{1, \ldots, C\}$. The probability of observing a particular adoption pattern for household i is expressed as

$$P(y_i) = \sum_{c=1}^{C} \pi_c \prod_{j=1}^{J} P\left(y_{ij} \middle| c\right) \tag{1}$$

where π_c is the prior probability of belonging to class c (class prevalence) and $P\left(y_{ij} \middle| c\right)$ is the class-conditional probability of adopting technology j given class membership.

Estimation proceeds by maximizing the likelihood across all households:

$$\mathscr{L}(\pi, \theta) = \prod_{i=1}^{N} \sum_{c=1}^{C} \pi_c \prod_{j=1}^{J} P\left(y_{ij} \middle| \theta_c\right) \tag{2}$$

where θ_c represents the set of parameters associated with the class c. The model was estimated using a generalized structural equation modeling (GSEM) framework that accommodated the incorporation of covariates to explain the class membership (Bakk et al., 2022; Lanza et al., 2007). Specifically, the probability of belonging to class c for household i is modeled as

$$\pi_{ic} = \frac{\exp(X_i \beta_c)}{\sum_{c'=1}^{C} \exp(X_i \beta_{c'})} \tag{3}$$

Where X_i is the vector of household covariates, and β_c is the associated coefficient vector. Class C was normalized to zero for identification. A four-class solution was selected, corresponding to broad adopters, lighting-only adopters, heating-only adopters, and non-adopters.

3.2. Multinomial logit model

3.2.1. Model specification

Following latent class identification, the second stage employed a multinomial logit (MNL) model to estimate the determinants of household membership in each adoption class (Greene and Hensher, 2003; Nibbering, 2024). This specification is particularly suitable because the dependent variable, class membership, is categorical with more than two unordered outcomes (Caudill, 2000; Deneke et al., 2024). The four outcomes in this study were Class 1 (Broad Adopters), Class 2 (Lighting-only Adopters), Class 3 (Heating-only Adopters), and Class 4 (Non-adopters, serving as the base category) (Greene and Hensher, 2013).

Let Y_i denote the adoption class of household i. The probability that household i belongs to class c relative to the base outcome is expressed as:

$$P(Y_i = c \quad | \quad X_i) = \frac{\exp(X_i \beta_c)}{\sum_{k=1}^{C} \exp(X_i \beta_k)} \tag{4}$$

Where X_i is a vector of covariates, including household demographics, socioeconomic indicators, and structural factors, and β_c is the parameter vector associated with class c. For identification, $\beta_4 = 0$.

3.2.2. Log-likelihood function

The MNL model is estimated by maximizing the log-likelihood of observing the actual class outcomes across all N households (Paolino, 2021; Wu and Daziano, 2023). If d_{ic} is a binary indicator equal to 1 if household i belongs to class c, and 0 otherwise, the log-likelihood function is

$$\mathscr{L}(\beta) = \sum_{i=1}^{N} \sum_{c=1}^{C} d_{ic} \mathrm{In} \quad P(Y_i = c \quad | \quad X_i) \tag{5}$$

This function aggregates the log-probabilities of the realized class assignments weighted by the observed outcomes. The consistency and efficiency of the maximum likelihood estimates rely on the standard assumptions of independence across households and correct model specifications.

3.2.3. Relative risk ratios

The coefficients estimated from the multinomial logit are usually reported as relative risk ratios (RRRs), obtained by exponentiating the raw coefficients (Abdulhafedh, 2017; Fitzhugh et al., 2023):

$$RRR_C = \exp(\beta_c) \tag{6}$$

An $RRR_C > 1$ indicates that an increase in the covariate increases the probability of being in class c relative to the base class (non-adopters), whereas an $RRR_C < 1$ implies a reduction in the probability. These ratios provide an intuitive measure of effect size, allowing for the interpretation of how demographic, socioeconomic, and infrastructural variables shift household adoption pathways.

3.3. Logistic and poisson specifications for incidence and intensity

Although the multinomial logit model identifies the determinants of

class membership, it does not distinguish whether households initiate adoption or how many technologies they have adopted (Lasway et al., 2020; Zegeye et al., 2022). To address this, binary logistic regression modeled adoption incidence (Martin et al., 2008), and Poisson regression modeled adoption intensity (Zegeye et al., 2022).

3.3.1. Logistic model: adoption incidence

Logistic regression was applied to assess the probability of household i adopting at least one type of energy-efficient technology. Let $Y_i = 1$ if household i adopts at least one efficient technology and $Y_i = 0$ otherwise. The conditional probability of adoption, given the covariates X_i, is modeled as

$$P(Y_i = 1 \quad | \quad X_i) = \frac{\exp(X_i\beta)}{1 + \exp(X_i\beta)} \tag{7}$$

Equivalently, the log-odds of adoption are expressed as:

$$\mathrm{In}\left(\frac{P(Y_i = 1 \quad | \quad X_i)}{1 - P(Y_i = 1 \quad | \quad X_i)}\right) = X_i\beta \tag{8}$$

where β is the parameter vector to be estimated. The log-likelihood function for the logistic model across N households is:

$$\ell(\beta) = \sum_{i=1}^{N} [Y_i \mathrm{In}P(Y_i = 1 \quad | \quad X_i) + (1 - Y_i)\mathrm{In}P(Y_i = 1 \quad | \quad X_i)] \tag{9}$$

The maximization of this function yields consistent estimates of β, and the coefficients can be exponentiated to obtain odds ratios (ORs), which measure how changes in each covariate shift the odds of adoption.

3.3.2. Poisson model: adoption intensity

While the logistic model captures incidence (whether adoption occurs), it cannot reflect how many technologies are adopted once a household transitions (Ramirez and Shultz, 2000). For this reason, a Poisson regression was employed to model the adoption intensity (Awuni et al., 2018; Paxton et al., 2011), defined as the count of efficient technologies adopted by household i. Let $Y_i \in \{0, 1, 2, 3\}$ denote the number of technologies adopted.

The Poisson probability mass function is:

$$P(Y_i = y \quad | \quad X_i) = \frac{\exp(-\lambda_i)\lambda_{ii}^{y}}{y!}, \quad y = 0, \quad 1, \quad 2, \quad . \quad . \quad . \tag{10}$$

where the conditional mean λ_i is modeled as: $\lambda_i = \exp(X_i\beta)$

The log-likelihood function for the Poisson specification is:

$$\ell(\beta) = \sum_{i=1}^{N} [Y_i(X_i\beta) - \exp(X_i\beta)\mathrm{In}(Y_i!)] \tag{11}$$

The coefficients in the Poisson model are interpreted as incidence rate ratios (IRRs), derived as follows:

$$IRR = \exp(\beta) \tag{12}$$

An $IRR > 1$ indicates that an increase in the covariate increases the expected number of efficient technologies adopted, whereas an $IRR < 1$ indicates a reduction.

3.3.3. Complementarity of the two models

The logistic and Poisson specifications are complementary, rather than substitutive. Logistic regression identifies the structural and demographic factors that determine whether a household takes the first step in adoption (incidence) (Ebnou Abdem et al., 2023; Rana and Rahman, 2024), whereas Poisson regression quantifies the extent to which adoption deepens across multiple domains (intensity) (Zhang et al., 2016). Together, these models allow the analysis to distinguish entry into adoption from progression within adoption, thereby offering a fuller characterization of household energy transition pathways (Bhatta et al., 2018).

3.4. Model diagnostics and validation

A robust econometric framework requires not only carefully specified models but also rigorous validation of their adequacy, stability, and predictive performance. Multiple diagnostic tests were employed including spanning goodness-of-fit assessments, specification checks, influence measures, class separation indices, and predictive accuracy metrics (Karl, 2024; Sasaki and Wang, 2023). This subsection provides the formal statistical underpinnings of each test and clarifies their role in verifying whether the estimated models are valid internally and reliable externally.

3.4.1. Model fit

The Log-Likelihood Ratio Test for global significance of the model compares the full model to the null model.

$$\chi^2 = -2\left(\log L_{\mathrm{null}} - \log L_{\mathrm{full}}\right) \tag{13}$$

which follows a chi-square distribution, with degrees of freedom equal to the number of predictors $\times$ (K −1). McFadden's pseudo – R^2 is calculated as:

$$R^2_{\mathrm{McF}} = 1 - \frac{\log L_{\mathrm{full}}}{\log L_{\mathrm{null}}} \tag{14}$$

Values between 0.2 and 0.4 represent good fit in discrete choice models.

3.4.2. Influence and outlier diagnostics

The Standardized Pearson Residual is a diagnostic statistic used to assess how well a multinomial logistic regression model fits individual observations. For households i and category k, it is computed as:

$$r_{ik} = \frac{y_{ik} - \widehat{p}_{ik}}{\sqrt{\widehat{p}_{ik}(1 - \widehat{p}_{ik})}} \tag{15}$$

where y_{ik} is the observed response (equal to 1 if the individual chooses category k, and 0 otherwise), and $\widehat{p}_{ik}$ is the predicted probability for that category derived from the model. Residuals with large absolute values (typically greater than two or three) may indicate observations that are poorly predicted by the model, suggesting the presence of outliers or model misspecification.

Cook's distance is a measure of the overall influence of individual observations on estimated model parameters. It captures the extent to which the fitted values, and consequently the parameter estimates, would change if that observation is excluded from the estimation process. Cook's distance for observation i is given by:

$$D_i = \sum_{k=1}^{K} \frac{\left(\widehat{p}_{ik}^{-i} - \widehat{p}_{ik}\right)^2}{(K-1) \bullet \widehat{p}_{ik}} \tag{16}$$

where $\widehat{p}_{ik}$ is the predicted probability of class k with observation i included and $\widehat{p}_{ik}^{-i}$ is the predicted probability of class k when observation i is omitted. A high value of D_i value indicates that the observation has a notable impact on the model's estimated probabilities, and may be considered an influential data point.

4. Results

The results of this study reveal a stark portrait of household energy transitions in Uganda, where modern and efficient energy technologies remain an exception rather than the norm. The analysis demonstrates that energy choices are neither uniform nor random but are patterned by socioeconomic realities, settlement locations, and technological accessibility. Rural households, which constitute the majority of the

population, continue to rely heavily on traditional and inefficient energy sources, whereas urban households, although constrained, show a comparatively greater penetration of efficient options. The scarcity of adoption across domains such as lighting, cooking, and heating underscores both the persistence of structural barriers and the uneven distribution of opportunities to transition. This chapter presents these findings in a structured manner, beginning with descriptive evidence on adoption prevalence and settlement composition, before progressing to formal modelling that identifies the socioeconomic and locational drivers shaping adoption outcomes. The discussion establishes an empirical backdrop against which subsequent econometric estimates can be interpreted, linking descriptive insights with latent class, multinomial logit, logistic, and Poisson models to provide a holistic understanding of household energy behavior in Uganda.

4.1. Prevalence and Urban–rural composition of efficient energy use

The prevalence of adoption was low at only 5.96 % of households, and the overwhelming majority (94.04 %) still relied on inefficient lighting sources. This highlights that, even for lighting, the domain is often considered the first step in modern energy-efficient uptake, which remains a minor phenomenon.

In terms of composition, non-adopters mirror the baseline: 76 % rural and 24 % urban adopters., among adopters, the split shifts to 67 % rural and 33 % urban, indicating that urban households are disproportionately represented. Converting these composition shifts into implied adoption rates, urban uptake was approximately 8.2 % versus 5.3 % in rural areas. This indicates that the early diffusion of efficient lighting is modestly tilted towards urban households, which is consistent with their easier access to infrastructure and markets.

Adoption is exceedingly rare, with only 0.20 % of households reporting efficient cooking uptake compared with 99.80 % of non-adopters. This indicates a near-universal reliance on traditional cooking systems at the time of the survey, underlining the structural barriers to cooking energy transitions.

Here, the urban–rural composition diverges more starkly. Non-adopters comprised 76 % rural and 24 % urban; however, among adopters, the balance shifted to 51 % rural and 49 % urban. This represents an enrichment of + 25 %age points for urban households, relative to their baseline share. In terms of rates, adoption reached approximately 0.41 % in urban areas versus 0.13 % in rural areas, which was slightly more than three times higher in towns and cities. Although adoption is virtually negligible in absolute terms, the relative pattern is unmistakable; efficient cooking at this stage is an overwhelming urban practice.

The scarcest domain, efficient heating adoption, was 0.03 %, with 99.97 % of households reporting non-use. This near-zero prevalence underscores the marginal efficiency of heating technologies in the Ugandan household energy landscape.

Among adopters, the imbalance is extreme: 94 % are urban versus 6 % rural. The implied adoption rate in urban areas is approximately 0.118 % compared to 0.002 % in rural households, indicating that uptake is nearly 50 times higher in urban areas. Although the absolute numbers were vanishingly small, the directional signal was unambiguous and efficient heating was almost exclusively urban.

Three systematic patterns were observed across the panels. First, adoption scarcity increased as we shifted from lighting to cooking to heating. Even at its "highest," efficient lighting adoption was below 6 %, whereas cooking and heating remained almost entirely absent. Second, urban overrepresentation among adopters strengthens as technology becomes rarer: 33 % for lighting, 49 % for cooking, and 94 % for heating, although urban households constitute only 24 % of the sample. Third, rural non-adoption dominates the landscape. The majority of the rural composition of the sample, coupled with low adoption rates, means that every non-adopter bar is overwhelmingly rural, accentuating the relative over-representation of urban households in adopter bars.

4.2. Latent class assignment and classification

4.2.1. Latent classes assignment

Table 1 presents the results of the latent class assignment model estimated using the generalized structural equation modeling (GSEM) approach. The model differentiates households into four latent classes, based on their likelihood of adopting efficient lighting, cooking, and heating technologies. The coefficients reflected the influence of each covariate on the probability of membership in each class. Statistical significance was indicated by the reported p-values, where the results at the 1 %, 5 %, and 10 % levels provided strong, moderate, and weak evidence of association, respectively.

The results for household head age suggest nuanced effects across the latent classes. For Class 2, which was associated with efficient cooking, the coefficient was 0.0149 with a p-value of 0.000, indicating a highly significant and positive effect. This means that as household heads age, the likelihood of belonging to an efficient cooking class increases, albeit marginally. For Class 3, which represents efficient heating, age again emerged as significant, with a coefficient of 0.0084 and p-value of 0.075, suggesting a weaker but still positive effect. In contrast, the coefficients for classes 1 and 4 were not statistically significant, highlighting that age was not a determining factor in the membership of efficient lighting adopters or non-adopters.

The availability of electricity, measured in terms of power hours, played a decisive role in certain classes. For Class 2 (efficient cooking), the coefficient was 0.0141 with a p-value of 0.027, indicating that longer hours of electricity supply significantly increased the probability of belonging to this class. The effect is even more pronounced with the second entry under Class 2, with a coefficient of 0.1708 and a p-value of 0.005. Conversely, for Class 4 (non-adopters), power hours are also significant, with a coefficient of 0.0021 and a p-value of 0.000, suggesting that reliable electricity access reduces the likelihood of remaining a non-adopter. These results highlight that electricity availability is a key enabling factor in transitioning away from non-adoption, particularly toward efficient cooking.

Electricity costs have emerged as a critical factor across all classes, although their influence is asymmetric. For Class 1 (efficient lighting), the coefficient is –0.0001, with a p-value of 0.000, indicating that higher costs reduce the probability of adopting efficient lighting. Similarly, for Class 3 (efficient heating), the coefficients are negative and significant, with values of –0.0000 ($p = 0.005$) and 0.0000 ($p = 0.019$), showing that higher electricity costs deter heating adoption. In contrast, for Class 2 (efficient cooking), the coefficients are positive and significant (0.0001 and 0.0000, respectively, both with $p = 0.000$), suggesting that adopters of efficient cooking may be more resilient to electricity costs, possibly because of their higher willingness or capacity to pay. For Class 4 (non-adopters), the negative coefficient of –0.0003, with $p = 0.000$, reinforces that overall electricity costs are a deterrent to adoption.

The household wealth proxied by the asset index shows different effects. For Class 2 (efficient cooking), the coefficient is –0.2355 with a p-value of 0.002, implying that households with higher asset scores are paradoxically less likely to adopt efficient cooking. By contrast, for Class 3 (efficient heating), the coefficient is 0.1967, with a p-value of 0.005, indicating that greater asset holdings increase the likelihood of belonging to this class. In Class 4 (non-adopters), the coefficient was 0.1720 ($p = 0.020$), suggesting that wealthier households were more likely to remain non-adopters. This pattern underscores the complexity of asset ownership, where wealth may enable the adoption of certain technologies but does not universally translate into greater energy efficiency adoption.

The constant terms vary widely across classes and are often highly significant, reflecting the baseline probability of class membership before accounting for the covariates. For Class 2 (efficient cooking), constants of –2.6453 ($p = 0.000$) and –8.3811 ($p = 0.000$) indicated very low baseline probabilities, which is consistent with the rarity of adoption observed in the descriptive analysis. For Class 3 (efficient

Table 1
Latent classes assignment.

Class assignment (LCA) GSEM, 4-Class	Type 1: Efficient lighting		Type 2: Efficient cooking		Type 3: Efficient heating	
Covariates	Coef.	p-value	Coef.	p-value	Coef.	p-value
Age head						
Class 1	0.0030	0.730	0.0004	0.999	0.0031	1.000
Class 2	0.0149***	0.000	0.0021	0.703	-0.0357	0.697
Class 3	0.0084*	0.075	0.0283***	0.000	0.0031	1.000
Class 4	0.0084	0.473	0.0052	0.981	-0.0358	0.562
Power hours						
Class 1	0.0023	0.937	0.0815	0.842	0.0021	1.000
Class 2	0.0141**	0.027	0.1708***	0.005	10.8485	0.991
Class 3	0.0198	0.287	0.0291	0.209	0.0021	0.664
Class 4	-0.0044	0.902	0.0913	0.825	0.0021***	0.000
Electricity cost						
Class 1	-0.0001***	0.000	-0.0111	0.869	0.0000	1.000
Class 2	0.0001***	0.000	0.0000***	0.000	-0.0002	0.531
Class 3	-0.0000***	0.005	0.0000**	0.019	0.0000	1.000
Class 4	-0.0003***	0.000	-0.0044	0.288	-0.0002	0.447
Asset index						
Class 1	-0.0184	0.889	-0.0744	0.976	0.0502	1.000
Class 2	-0.0024	0.920	-0.2355***	0.002	-0.6252	0.614
Class 3	0.0377	0.499	0.1967***	0.005	0.0502	0.695
Class 4	0.1720**	0.020	-0.1538	0.949	-0.6233	0.471
Constant						
Class 1	-2.5685	0.640	-6.9495	0.582	-19.0159	1.000
Class 2	-2.6453***	0.000	-8.3811***	0.000	-264.7157	0.991
Class 3	-3.0353	0.217	-6.9123***	0.000	-19.0159	0.787
Class 4	-2.6902	0.349	-6.9740	0.591	-19.0159	0.370

Notes: ***, ** and * represent 1 %, 5 % and 10 % significance levels.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

heating), similarly large negative constants of − 6.9123 (p = 0.000) highlight the near absence of adoption in the sample. In contrast, the constants for Class 1 (efficient lighting) and Class 4 (non-adopters) are less precise but still suggest that adoption is rare without favorable covariates.

Table 1 highlights the critical role of the household head age, electricity access (measured by power hours), and electricity cost in shaping latent class membership. Age increases the likelihood of adopting efficient cooking and heating, while a reliable electricity supply shifts households away from non-adoption, especially toward efficient cooking. High electricity costs are consistently a barrier, except in the case of efficient cooking adopters who appear to be absorbed by resilient or wealthier households. Asset ownership presents a complex picture, supporting heating adoption but not necessarily cooking adoption, and in some cases, reinforcing non-adoption.

4.2.2. *Latent class classification*

Table 2 presents the distribution of households across the four latent classes identified in the LCA–GSEM framework. This table is fundamental because it translates the model's statistical architecture into concrete empirical prevalence, showing how widespread each adoption typology is in the national sample.

The results reveal a striking imbalance across the four classes. Of the 197,343 households, an overwhelming majority of 185,334 (equivalent to 93.91 % of the sample) were classified as non-adopters. This finding confirms the descriptive patterns shown in Fig. 1 and underscores the fact that efficient energy use remains extremely rare in Uganda. It also illustrates that the baseline for all subsequent analyses is entrenched non-adoption, in which households overwhelmingly depend on traditional and inefficient energy technologies.

Table 2
Latent class classification.

Latent class	Freq.	Percent	Cum
Broad adopters	222	0.1125	0.1125
Lighting only	11542	5.8487	5.9612
Heating only	245	0.1241	6.0853
Non-adopters	185334	93.9147	100
Total	197343	100	

Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

Only 222 households (0.11 % of the sample) fell into the broad adopter category, indicating that they combined efficient lighting, cooking, and heating. This near-negligible prevalence demonstrates the extraordinary rarity of adopting a comprehensive energy efficiency. The vanishingly small size of this class signals severe barriers to simultaneous uptake across domains, whether due to affordability constraints, supply side availability, or behavioral factors.

The largest minority group, 11,542 households (5.85 %), consisted of households that adopted efficient lighting alone. This pattern is consistent with descriptive evidence that lighting is typically the first and often only entry point in modern energy adoption. Although still a small fraction of the population, this group demonstrates that limited modernization is feasible for some households, likely because of the relative affordability and availability of efficient lighting technologies compared to cooking and heating.

In total, 245 households were classified as heating-only adopters (0.12 % of the sample). This is an exceptionally small group, emphasizing that efficient heating technologies remain almost entirely absent from household energy portfolios. The rarity of this category suggests not only economic and infrastructural barriers, but also the marginal importance of heating in Uganda's climatic context, where the demand for space heating is intrinsically lower than in colder environments.

The dominant class, comprising 185,334 households (93.91 %), was non-adopters. The cumulative prevalence of non-adoption leaves only 6.09 % of the households with any form of efficient energy uptake. This numerical dominance implies that the latent class structure is heavily skewed, thereby introducing methodological and policy significance. Methodologically, this raises the challenge of class imbalance, which motivated this study to use weighting and cross-validation strategies. From a policy perspective, the overwhelming size of this group illustrates the scale of the challenge of moving households toward efficient

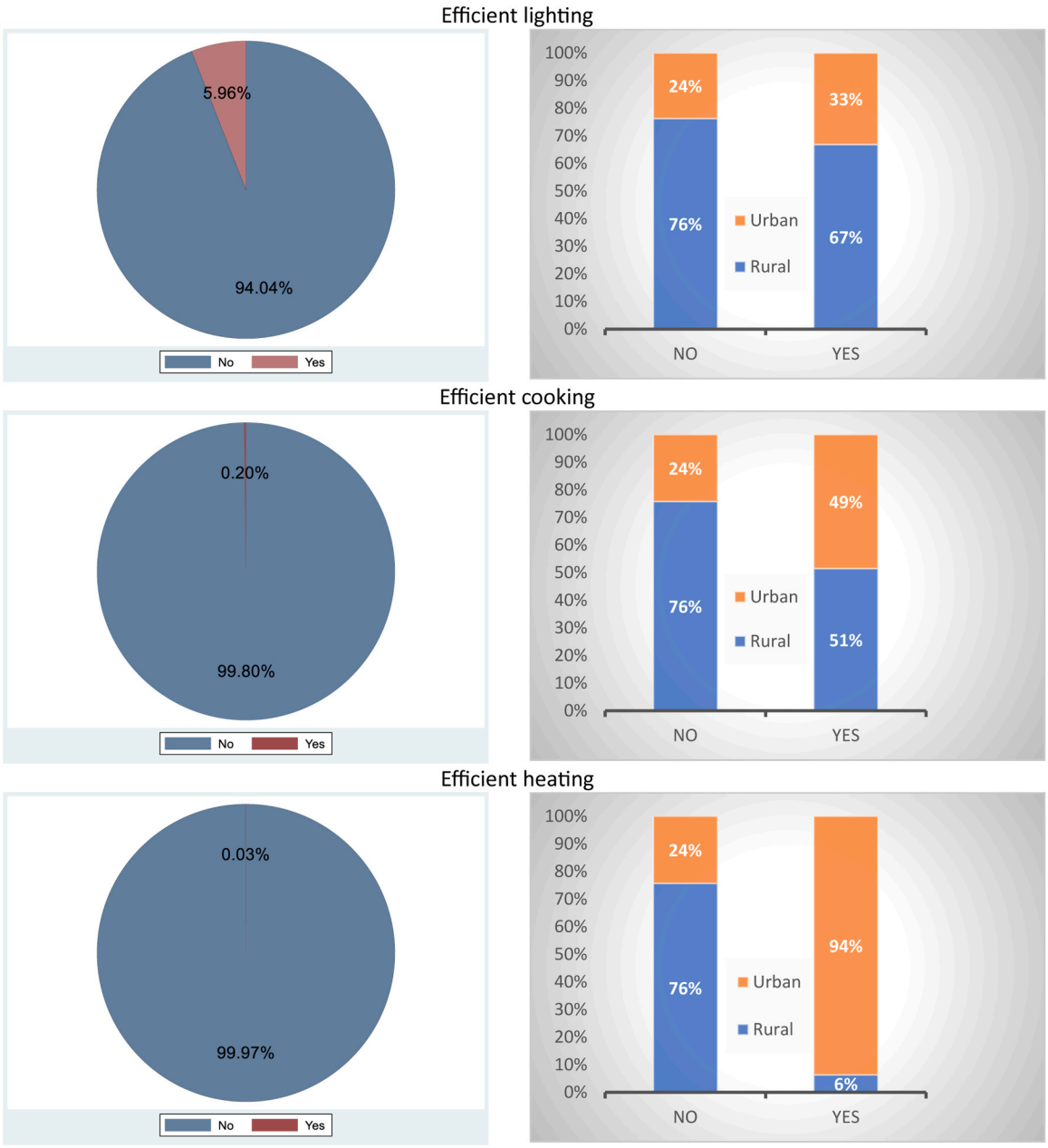


Fig. 1. Efficient energy use typologies among Ugandan households. Notes: Each row corresponds to an efficient energy domain: lighting (top), cooking (middle), or heating (bottom). The pie chart on the left shows the overall prevalence of adoption ("Yes") versus non-adoption ("No"). The right panel shows the urban–rural composition of these two groups: the stacked bar on the left for non-adopters and that on the right for adopters.

energy technologies.

The class size distribution provides a foundation for interpreting the coefficients reported in Table 1. Specifically, the dominance of non-adopters explains why certain covariates show strong statistical significance because even small shifts in probabilities translate into marked relative differences against the massive baseline of non-adopters. The small but non-trivial size of the lighting-only group also justifies the emphasis on electricity access variables in the modeling, whereas the near absence of broad and heating-only adopters highlights structural barriers to deeper adoption.

4.3. Drivers of household adoption of energy-efficient technologies

Table 3 builds directly on the latent class typologies described in Tables 1 and 2 by examining the determinants of class membership, using a multinomial logit specification. Here, Class 4 (non-adopters) serves as the base outcome, against which is the likelihood of belonging to road adopters (Class 1), Lighting-Only Adopters (Class 2), and Heating-Only Adopters (Class 3). The coefficients are expressed as relative risk ratios (RRRs), providing an interpretable measure of how household and contextual covariates shift the probability of belonging to each adoption class relative to the remaining non-adopters.

Regional heterogeneity was among the strongest determinants of class membership. Belonging to the Eastern, Northern, or Western regions dramatically reduces the probability of being in the Broad Adopter class compared to non-adopters, with relative risk ratios effectively tending toward zero. This indicates that adoption across all domains was concentrated almost exclusively in the central region. However, when considering lighting-only adopters, location in Eastern Uganda increases the likelihood of adoption, with a relative risk ratio of 2.74 ($p < 0.10$). A similar, although slightly weaker, pattern was observed for northern households, whereas the western location showed no significant

Table 3
Multinomial logit model for the drivers of household adoption of energy-efficient technologies.

	Comparison group (Base outcome = Class 4: Non-adopters)					
	Class 1: Broad Adopters		Class 2: Lighting only		Class 3: Heating only	
Covariates	RRR	p- value	RRR	p-value	RRR	p-value
Region						
Eastern	0.0000***	0.000	2.7392*	0.065	0.0000***	0.000
Northern	0.0000***	0.000	2.5922	0.105	0.3292	0.524
Western	0.0000***	0.000	1.1900	0.643	0.0000***	0.000
Age household head	0.9646***	0.002	1.0270***	0.000	0.9077*	0.050
Region#Age head						
Eastern	0.8264***	0.000	0.9566***	0.003	0.9750	0.779
Northern	1.0459**	0.037	0.9536***	0.000	1.1181**	0.045
Western	1.3066***	0.000	0.9952	0.587	1.3050***	0.001
Urban/Rural						
Urban	0.0259***	0.000	1.3165	0.198	0.0001***	0.006
Sex of Household head						
Female	0.0103***	0.000	1.9028***	0.000	0.7659	0.831
Highest grade	1.1728***	0.000	1.0010	0.823	0.9600	0.318
Mobile money saving						
No	0.5349	0.590	1.9311***	0.001	2.0508***	0.000
Asset value	1.0000	0.529	1.0000	0.194	1.0000	0.163
Power hours	1.4487***	0.000	0.9865	0.274	0.7276	0.286
Electricity cost	1.0001***	0.000	1.0000	0.513	1.0000	0.927
Asset index	0.9581	0.804	0.9905	0.784	32.2614***	0.000
Constant	1.0000***	0.000	0.2916***	0.005	0.0000***	0.000

Notes: ***, ** and * indicate significance at 1 %, 5 % and 10 % level, respectively.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

difference. These results suggest that while broad adoption is highly centralized, incremental adoption of lighting is geographically more dispersed.

Importantly, region–age interactions have nuanced effects. For Broad Adopters, being older in Eastern and Western regions sharply reduces the probability of adoption (RRR = 0.83 and 1.31, respectively, both highly significant), whereas in Northern Uganda, older household heads are marginally more likely to adopt (RRR = 1.05, $p < 0.05$). These interactive terms highlight that age influences adoption differently depending on the regional context, reflecting both the demographic structure and the uneven penetration of efficient technologies across the country.

Independent of region, age plays a consistent role across classes. Broad Adopters were significantly less likely to have older household heads (RRR = 0.96, $p < 0.01$), suggesting that younger households were vanguards for comprehensive adoption. By contrast, lighting-only adopters exhibited the opposite pattern: the probability of adoption increased with age (RRR = 1.03, $p < 0.01$). For Heating-Only adopters, older age significantly reduced their likelihood of adoption (RRR = 0.91, $p < 0.10$). This divergence illustrates the dual nature of age: younger households are more flexible and willing to embrace full modernization, whereas older households are somewhat more likely to adopt incremental, low-barrier options, such as efficient lighting, but highly unlikely to transition to heating technologies.

The urban–rural contrast reinforces earlier descriptive findings. Urban households are substantially more likely to be road adopters than are non-adopters (RRR = 0.03, $p < 0.01$), although the interpretation is extremely small. For Heating-Only adopters, urban residence was an even stronger determinant (RRR = 0.0001, $p < 0.01$), indicating that efficient heating was absent in rural settings. However, lighting-only adoption showed no statistically significant difference between urban and rural households, suggesting that efficient lighting penetrated rural areas more evenly than cooking and heating technologies.

Household gender also shapes the adoption trajectories. Female-headed households were far less likely to be road adopters (RRR = 0.01, $p < 0.01$), indicating that the few households that achieved comprehensive adoption were overwhelmingly male headed. However, for lighting-only adoption, female-headed households were nearly twice as likely to adopt than male-headed households (RRR = 1.90, $p < 0.01$). This pattern suggests that incremental improvements in energy efficiency, such as lighting, may resonate more with female-headed households that directly manage domestic energy use, but broader transitions remain heavily gender skewed toward men.

Education, proxied by the highest grade attained, strongly predicts adoption. Broad Adopters were significantly more likely to have higher educational levels (RRR = 1.17, $p < 0.01$), aligning with the expectation that education would enhance awareness and the ability to invest in efficient technologies. However, education does not significantly influence Lighting-Only or Heating-Only adoption, indicating that these domains are less dependent on educational attainment.

Savings' behavior introduces further nuances. Households without mobile money savings were nearly twice as likely to adopt lighting only (RRR = 1.93, $p < 0.01$) and heating only (RRR = 2.05, $p < 0.01$), although this was not significantly different for road adoption. This counterintuitive result may reflect a substitution effect in which households without formal or semi-formal saving channels invest small amounts in energy upgrades rather than financial accounts.

The electricity supply variables yielded the strongest results. For road adopters, greater power availability sharply increases the likelihood of adoption (RRR = 1.45, $p < 0.01$). This confirms that a reliable electricity supply is necessary for cross-domain modernization. In contrast, power availability does not significantly influence Lighting-Only or Heating-Only adoption, reflecting that even a limited supply is sufficient for incremental adoption.

Electricity cost has a positive and significant effect on road adopters (RRR = 1.0001, $p < 0.01$), but no effect on the other classes. While counterintuitive at first glance, this likely reflects reverse causality: households consuming more efficient electricity-intensive technologies incur higher costs than the cost itself driving adoption.

The asset-related variables have mixed effects. For Heating-Only adopters, higher asset indices strongly predicted adoption (RRR = 32.26, $p < 0.01$); however, this was not true for Broad- or Lighting-Only adopters. This highlights the extreme resource intensity associated with efficient heating. However, the asset value does not significantly differentiate any of the classes, suggesting that relative wealth matters more than absolute wealth in energy adoption decisions.

Taken together, the progression from Table 1 (GSEM coefficients), Table 2 (class sizes), and Table 3 (MNL drivers) show a consistent story.

Table 2 demonstrates that nearly 94 % of households are non-adopters, with lighting being the dominant entry point in modernization. Table 1 shows that age, power availability, and asset holdings already exerted a significant influence on class assignment at the latent level. Table 3 then translates these patterns into relative risks against the massive baseline of non-adoption, clarifying that education, urban residence, regional disparities, and electricity reliability are the most powerful differentiators of the adoption trajectories.

4.4. Model predictive performance

Table 4 summarizes the predictive performance of the multinomial logit model using three core metrics: overall classification accuracy, micro-averaged F1 score, and macro-averaged F1 score. Each was computed across five stratified folds of cross-validation, ensuring robustness against sample imbalance and providing insights into how well the model generalizes beyond the estimated sample.

The mean classification accuracy across folds was 0.9270 (92.7 %) with only minimal variation (standard deviation 0.0024, minimum 92.3 %, maximum 93.0 %). This high level of accuracy indicates that the model correctly assigned households to their latent classes in more than nine out of ten cases, reflecting strong internal validity. Importantly, the closeness of the minimum and maximum values suggests that the predictive performance is stable across different validation subsets and not driven by the peculiarities of a single fold.

The micro-averaged F1 score mirrors the accuracy, also averaging 0.9270 (92.7 %), with an identical spread across folds (standard deviation 0.0024, range 92.3 %–93.0 %). The micro-F1 aggregates true positives, false positives, and false negatives across all classes before computing precision and recall. Its equivalence to accuracy in this context confirms that misclassification rates are balanced across the sample as a whole, and that no one class dominates model performance when treated collectively. Given the highly imbalanced class structure documented in Table 2, this finding underscores that the model maintains overall reliability despite a large "Non-adopter" majority.

In contrast, the macro-averaged F1 score was markedly lower at 0.2566 (25.7 %), with modest variation across folds (standard deviation 0.0088, range 24.4 %–26.8 %). Unlike micro-F1, macro-F1 calculates F1 scores separately for each class and then averages them, assigning equal weights, regardless of the class size. The pronounced gap between micro-F1 and macro-F1 highlights the difficulty in correctly identifying smaller adopter classes, particularly for efficient cooking and heating. Although the model performs well for dominant "non-adopters," it struggles to achieve high precision and recall for minority groups. This divergence reflects an inherent imbalance in the underlying data, where the adoption rates remain very low.

Collectively, these metrics illustrate the dual concept. The model achieved exceptionally high predictive performance in aggregate terms, as evidenced by its accuracy and micro-F1 scores, which exceeded 92 %. However, a depressed macro-F1 underscores the structural challenge posed by rare adoption events that the model does not capture with equal fidelity. From a methodological standpoint, this validates the need for class-balancing weights and robust cross-validation, whereas, from a substantive perspective, it reinforces the rarity and concentration of the energy-efficient adoption patterns documented in Fig. 1 and Tables 1–3.

Table 4
Model predictive performance.

Variable	Obs	Mean	Std. dev.	Min	Max
Classification Accuracy (acc)	5	0.9270	0.0024	0.9233	0.9298
Micro-averaged F1 Score (microF1)	5	0.9270	0.0024	0.9233	0.9298
Macro-averaged F1 Score (macroF1)	5	0.2566	0.0088	0.2437	0.2680

Source: Author's computation using Uganda's 2020/2021 national household survey data.

4.5. Adoption intensity and incidence

The results of the logistic regression in Table 5 confirm that the household adoption of at least one efficient energy technology is systematically influenced by demographic, locational, and housing characteristics. This region emerged as a particularly strong determinant. Compared with households in the central region (reference), those in the Northern and Western regions are significantly more likely to adopt, with coefficients of 0.5001 ($p < 0.01$) and 0.1507 ($p < 0.01$), respectively. By contrast, eastern households display no statistically significant difference from the reference, suggesting regional disparities in adoption that cut across socioeconomic and infrastructural gradients. These findings resonate with descriptive evidence where location effects play a central role in shaping adoption patterns.

Settlement type also matters. Urban households are less likely to adopt any efficient energy option, with a negative and highly significant coefficient of − 0.1871 ($p < 0.01$). This result underscores that, despite better access to markets and infrastructure, urban households face structural or affordability barriers that dampen adoption. Female-headed households show a positive and significant association with adoption, with a coefficient of 0.1134 ($p < 0.01$). This suggests that female decision makers may be more inclined to prioritize efficient energy use, perhaps because of the direct health and time-saving benefits that these technologies bring to household management.

Housing material is a critical predictor. Households with tiled roofs have a strong positive coefficient of 0.5145 ($p < 0.01$), suggesting that roof quality is a proxy for broader wealth and investment in durable structures, which correlates with efficient energy adoption. Households with burnt or stabilized brick walls were significantly more likely to adopt wall materials, with a coefficient of 0.4931 ($p < 0.05$), whereas those with unburnt bricks (with either mud or cement binding) were much less likely, with coefficients of − 1.9149 ($p < 0.01$) and − 1.6461 ($p < 0.01$), respectively. Similar patterns were observed for floor materials: brick flooring was strongly negatively associated with adoption (− 1.8743, $p < 0.01$), whereas stone flooring was positively and strongly associated (2.1124, $p < 0.01$). These material effects emphasize that dwelling quality is both a proxy for wealth and an enabling factor for integrating modern energy technologies.

Turning to household characteristics, the age of the household head was positively, albeit modestly, associated with adoption, with a coefficient of 0.0060 ($p < 0.01$). This indicates that older household heads are slightly more likely to adopt efficient technologies, perhaps reflecting their greater experience or stability in household investment decisions. Despite being small, electricity costs show a highly significant positive effect, consistent with the idea that exposure to energy pricing motivates efficiency gain. The asset index is positively associated with adoption with a coefficient of 0.0283 ($p < 0.01$), confirming the central role of household wealth in enabling the transition to modern energy use.

The Poisson regression results in Table 5 provide complementary insights by modelling adoption intensity, measured as the count of efficient technologies adopted. Again, regional differences were prominent. Eastern households adopt about 1.38 times as many technologies as those in the central region, northern households adopt 1.22 times more, and Western households 1.12 times more, all significant at conventional levels. This indicates that, when adoption occurs outside the central region, it tends to be deeper and involves more than one technology. Urban households adopt a slightly higher intensity than rural households, with an incidence rate ratio (IRR) of 1.12, which is marginally significant at the 10 % level. By contrast, female-headed households adopt a slightly lower intensity (IRR = 0.91, $p < 0.10$), which, in conjunction with the logistic results, suggests that while female heads are more likely to adopt at least one technology, they are less likely to diversify across multiple domains.

Table 5
Adoption intensity and incidence.

	Logistic: any adopt			Poisson: adopt count		
Covariates	Coefficient	Std. err.	p-value	IRR	Std. err.	p-value
Region						
Eastern	0.0400	(0.0674)	0.552	1.3809***	(0.1147)	0.000
Northern	0.5001***	(0.0828)	0.000	1.2227**	(0.1163)	0.035
Western	0.1507***	(0.0531)	0.005	1.1225**	(0.0599)	0.030
Urban/Rural						
Urban	-0.1871***	(0.0521)	0.000	1.1169*	(0.0658)	0.061
Sex Household head						
Female	0.1134***	(0.0417)	0.007	0.9144*	(0.0439)	0.063
Roof material						
Tiles	0.5145***	(0.1521)	0.001	0.7286	(0.1483)	0.120
Thatch	0.5591	(0.9281)	0.547	1.0051	(0.9351)	0.996
Wall material						
Burnt / stabilized bricks	0.4931**	(0.1987)	0.013	3.1669***	(1.0776)	0.001
Unburnt bricks with cement	-1.9149***	(0.6134)	0.002	0.3152	(0.2401)	0.130
Unburnt bricks with mud	-1.6461***	(0.6182)	0.008	0.4661	(0.3372)	0.291
Wood	-1.1210	(1.0365)	0.279	0.7441	(0.7895)	0.781
Mud and pole	0.8302***	(0.2184)	0.000	2.9469***	(1.0656)	0.003
Tin / iron	2.4669***	(0.2483)	0.000	6.6702***	(2.3031)	0.000
Floor material						
Bricks	-1.8743***	(0.5257)	0.000	0.2689**	(0.1433)	0.014
Stone	2.1124***	(0.3056)	0.000	11.2052***	(2.6599)	0.000
Cement screed	-0.1910	(0.1349)	0.157	0.7366**	(0.1126)	0.045
Rammed earth	0.1532	(0.1615)	0.343	2.7312***	(0.4706)	0.000
Tiles	0.0085	(0.1435)	0.952	0.9867	(0.1580)	0.934
Age household head	0.0060***	(0.0010)	0.000	1.0137***	(0.0011)	0.000
Power hours	-0.0015	(0.0032)	0.646	0.9918**	(0.0038)	0.031
Electricity cost	0.0000***	(0.0000)	0.000	1.0000***	(0.0000)	0.000
Asset index	0.0283***	(0.0104)	0.006	1.0388***	(0.0128)	0.002
Constant	-3.0780***	(0.2569)	0.000	0.0149***	(0.0058)	0.000

Notes: ***, ** and * indicate significance at 1 %, 5 % and 10 % level, respectively.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

Housing material effects were even more pronounced in the Poisson model. Burnt or stabilized brick walls were associated with households adopting more than three times more technologies (IRR = 3.17, $p < 0.01$). Households with mud and pole walls adopted almost three times more (IRR = 2.95, $p < 0.01$), whereas households with tin or iron walls adopted almost seven times more (IRR = 6.67, $p < 0.01$). The floor material showed a similar stark gradient: stone flooring was associated with adoption intensities that were more than 11 times higher (IRR = 11.21, $p < 0.01$), whereas cement-screed floors reduced adoption intensity (IRR = 0.74, $p < 0.05$). Rammed earth floors were associated with nearly three-fold higher adoption counts (IRR = 2.73, $p < 0.01$). These results indicate that the physical environment and building infrastructure are critical enablers of efficient energy technology integration.

The household head's age remains a significant positive predictor of adoption intensity, with each additional year being associated with a 1.4 % increase in the number of technologies adopted. Power reliability, measured in average supply hours, was negatively associated with adoption intensity (IRR = 0.99, $p < 0.05$), suggesting that households with fewer supply constraints diversify more aggressively into efficient technologies. Electricity costs remain positively associated with intensity, reinforcing the interpretation that households adjust toward efficiency as energy expenses increase. The asset index continued to display a robust positive effect, with wealthier households adopting more efficient options across domains.

Taken together, the logistic and Poisson results complement the latent class and multinomial logit analyses by confirming that adoption is both unevenly distributed and highly dependent on the structural household characteristics. The logistic results clarify who adopts at least one efficient technology, whereas the Poisson results reveal how deeply households adopt across multiple domains. Both reinforced the narrative of strong regional disparities, importance of housing infrastructure, and central role of wealth and affordability in shaping Uganda's energy transition landscape.

4.6. Model diagnostics, predictive performance and robustness analysis

The link test provides a diagnostic for model specification by checking whether the predicted values (_hat) and their squared term (_hatsq) contribute significantly to the outcome. In a correctly specified model, the predicted values should be strong and significant predictors of the dependent variable, whereas the squared term should not add to the explanatory power.

In Table 6, the coefficient of the predicted values is 1.0971 and highly significant ($p < 0.01$), confirming that the model's predictions are systematically related to the observed outcome of adoption. By contrast, the squared term has a coefficient of 0.0288 with a p-value of 0.310, which is not statistically significant. The absence of significance indicates that there is no evidence of major nonlinearity or omitted higher order terms. Collectively, these results suggest that the logistic model is well-specified, capturing the essential structure of the data without critical misspecification errors.

4.6.1. Logistic ROC analysis

The ROC-based discrimination Table 7 evaluates the model's ability to correctly classify adopters versus nonadopters. The model achieved an overall classification accuracy of 90.27 %, indicating that nine out of ten households were correctly identified relative to their actual adoption status. Specificity is exceptionally high at 99.82 %, showing that the model almost perfectly identifies non-adopters, reflecting the class imbalance in which a vast majority of households fall into this category.

However, the sensitivity was very low (2.41 %), indicating that the model struggled to detect relatively few adopters. This asymmetry highlights the inherent challenge of modeling rare events in highly imbalanced datasets. The positive predictive value is 59.82 %, suggesting that when the model predicts adoption, it is correct in approximately three-fifths of cases. The negative predictive value was 90.39 %, indicating strong reliability in ruling out adoption for predicted non-adopters.

Table 6
Logistic model specification.

any_adopt	Coefficient	Std. err.	z	p-value	[95 % conf.	interval]
_hat	1.0971***	0.1036	10.5900	0.0000	0.8941	1.3001
_hatsq	0.0288	0.0284	1.0100	0.3100	-0.0269	0.0845
_cons	0.0676	0.1077	0.6300	0.5310	-0.1436	0.2787

Notes: ***, ** and * indicate significance at 1 %, 5 % and 10 % level, respectively.
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

Table 7
Model discrimination assessment using logistic ROC analysis.

	True		
Classified	D	~D	Total
+	67	45	112
-	2716	25538	28254
Sensitivity		Pr(+| D)	2.41 %
Specificity		Pr(–|~D)	99.82 %
Positive predictive value		Pr(D| +)	59.82 %
Negative predictive value		Pr(~D| –)	90.39 %
False + rate for true ~D		Pr(+|~D)	0.18 %
False - rate for true ~D		Pr(–| D)	97.59 %
False + rate for classified +		Pr(~D| +)	40.18 %
False - rate for classified –		Pr(D| –)	9.61 %
Correctly classified			90.27 %

Notes: Classified + if predicted Pr(D) $\geq$ 0.5; True D defined as any_adopt ! = 0
Source: Author's computation using Uganda's 2020/2021 National Household Survey data.

The false-positive rate was minimal (0.18 %), but the false-negative rate was very high (97.59 %), again underscoring the difficulty in correctly identifying adopters. From a methodological standpoint, these diagnostics demonstrate that the model is extremely effective at capturing the overwhelming pattern of non-adoption but less successful at distinguishing a small minority of adopters. This imbalance explains why subsequent analyses relied on class weighting and complementary model structures to handle adoption scarcity better.

The distribution of Pearson residuals for the Poisson specification in Fig. 2 is tightly centered around zero, with only a very light tail, confirming that the predicted counts align closely with the observed adoption outcomes for the vast majority of households. This alignment strongly indicates that the Poisson assumption provides an adequate approximation of extremely low adoption rates. Similarly, Cook's distance plot for the Poisson model demonstrates that virtually all observations exert a negligible influence on parameter estimates, with no single case unduly driving the results. This is precisely the pattern expected from a stable and well fitted model.

The leverage residual plots for both logistic and Poisson regressions reinforce this stability. In each case, the data cloud was compact with residuals distributed symmetrically around zero, and the leverage scores were concentrated at low values. Only a handful of cases appear with slightly elevated residuals or leverage, but none reaches thresholds that would raise concerns in a sample of this size. The absence of high-leverage outliers confirms that the models' estimated coefficients are well-supported by the underlying data and are not overly sensitive to individual observations.

The combined Cook's distance and leverage panels indicated that the fitted models were robust. The entire distribution sits comfortably within the low-influence, low-leverage region, providing confidence that both the incidence (logit) and intensity (Poisson) specifications are correctly specified and not prone to instability. Taken together, these diagnostics affirm that the modelling strategy is not only statistically sound but also empirically appropriate for capturing adoption behavior in a context where efficient energy uptake is scarce. Therefore, the reported results can be interpreted with a high degree of confidence, and robustness checks confirm the reliability of the model.

5. Discussion of results

5.1. Household adoption patterns

The descriptive patterns of efficient energy use revealed a landscape characterized by scarcity, uneven distribution, and clear spatial divides (Jeuland et al., 2021). Modern and efficient technologies, even in the basic lighting domain, are far from universal, whereas efficient cooking and heating technologies are virtually absent (Munro and Bartlett, 2019; Pachauri et al., 2013). This establishes an important baseline: despite global narratives around energy transition, the reality for low-income countries such as Uganda is that modern energy uptake is still in its infancy. This backdrop demands careful consideration of the socioeconomic and infrastructural constraints that underpin household choices (Gadgil et al., 2011; Saligari, 2023). Scarcity at this scale also provides insight into why subsequent latent-class modelling yields a dominant "non-adopter" group, with only a marginal representation of more advanced energy users (Falchetta et al., 2020; Moksnes et al., 2024).

The second critical dimension is the pronounced urban bias embedded in adoption. The over-representation of urban households among adopters across all domains suggests that location operates not only as a correlating factor, but also as a structural determinant of access (Haq et al., 2024; Sun and Tong, 2024). Urban households benefit from denser infrastructure networks, greater market penetration of efficient devices, and higher purchasing power, all of which converge to lower barriers to uptake (Broto et al., 2017). By contrast, rural households remain entrenched in traditional energy practices, a pattern that aligns with longstanding observations in the literature that rural energy poverty is particularly resistant to change (Kapfudzaruwa et al., 2017; Tornel-Vázquez et al., 2024). The direction of imbalance highlights how infrastructural and affordability barriers compound as the technology in question becomes less common and more capital intensive (Bharadwaj et al., 2022).

These patterns underscore the layered nature of energy transition in low-income countries. Adoption does not proceed uniformly across domains, but follows a hierarchy, with households most likely to modernize lighting before cooking and cooking long before heating (Tuyiragize and Bassi, 2024). This sequencing reflects not only affordability and availability but also cultural practices and the immediacy of household needs (Guta et al., 2022; Tornel-Vázquez et al., 2024). In this sense, descriptive evidence provides an essential backdrop for latent class analysis and multinomial logit modelling: the heavy dominance of non-adoption, the selective emergence of lighting-only adopters, and the near invisibility of heating adopters are not statistical artifacts, but grounded reflections of structural realities in the Ugandan energy landscape (Lanza et al., 2024; Tuyiragize and Bassi, 2024).

5.2. Latent class structures and determinants

The latent class analysis underscores how deeply entrenched energy non-adoption remains in Uganda, but it also reveals meaningful heterogeneity in the small minority of households that have begun to modernize (Tuyiragize and Bassi, 2024). The class assignment model, estimated through the generalized structural equation modeling framework, highlights that adoption is not random, but systematically shaped by household characteristics and structural conditions

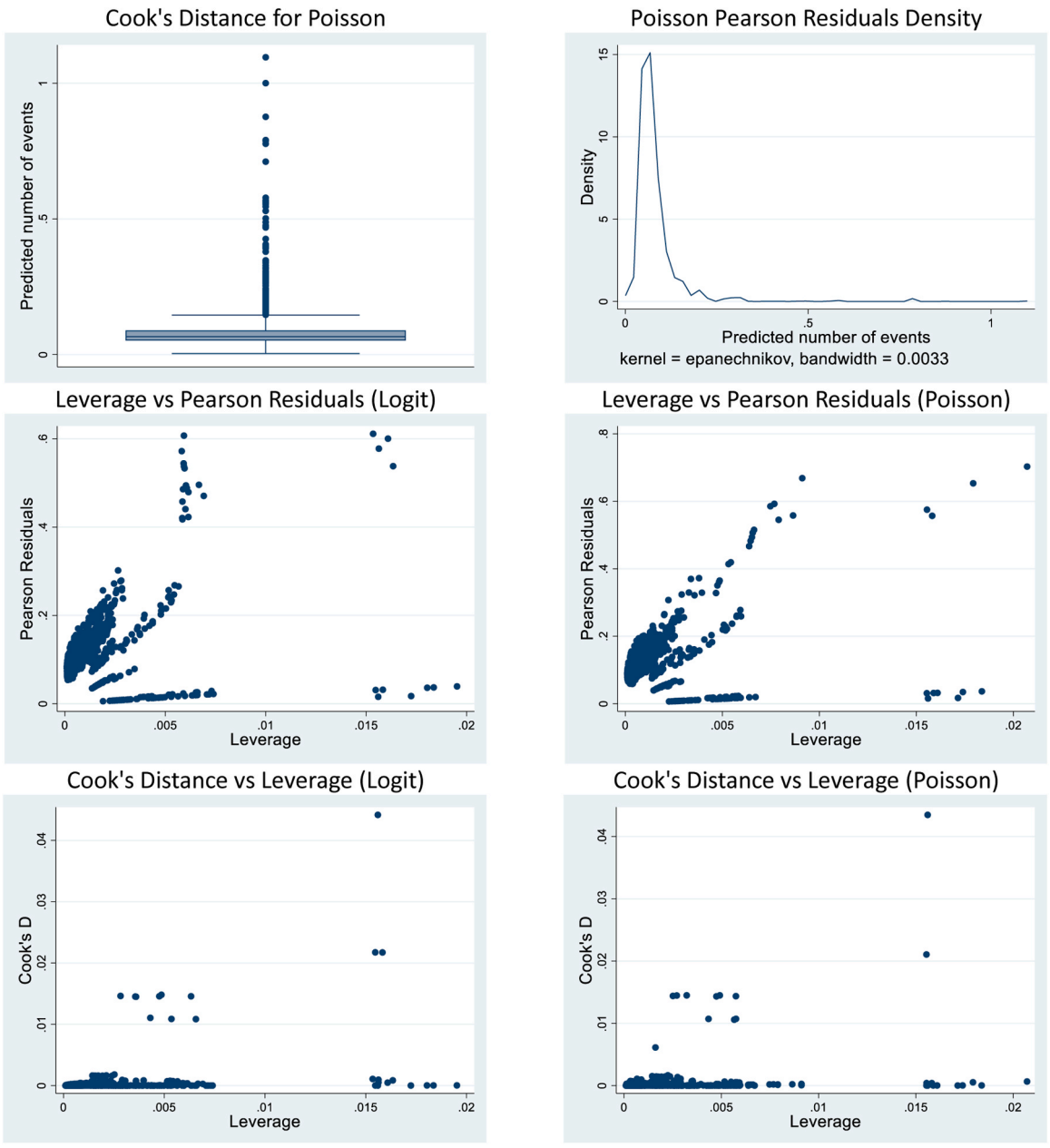


Fig. 2. Model diagnostics, predictive performance and robustness analysis.

(Tuyiragize and Bassi, 2024). The age of the household head, reliability of the electricity supply, and cost of power emerged as consistent drivers across classes, whereas asset ownership showed divergent roles depending on the specific energy domain. Taken together, these results point to a nuanced picture: energy transitions are highly constrained; however, within these constraints, discernible pathways and the logic of adoption exist (Namirembe et al., 2024).

Class size distribution provides an empirical foundation for these insights (Antonopoulos et al., 2024). Nearly 94 % of households remain in the non-adopter class, reflecting the overwhelming persistence of traditional energy practices (Herington et al., 2017). The dominance of non-adoption has two implications. Methodologically, this justifies the study's weighting and cross-validation strategies to ensure that the small adopter groups are not overwhelmed in the estimation (Müller-Hansen et al., 2020). Substantively, it emphasizes the scale of the challenge; any policy or program aimed at scaling up efficient energy use works against an entrenched baseline. The near absence of broad adopters and the marginal presence of heating adopters indicate that comprehensive modernization remains aspirational for almost all households (Streimikiene et al., 2024).

However, within this structure, the emergence of a sizable minority of lighting-only adopters indicates where the first cracks appear in the traditional energy regime. Efficient lighting is a natural entry point; it is relatively affordable, more widely available, and less culturally embedded than efficient cooking or heating (Harrington et al., 2020). The significance of the electricity access variables in shaping the latent class membership reinforces this point (Beath et al., 2023). When electricity is more reliable, households are more likely to shift out of non-adoption, and at least partial adoption, particularly for lighting (Hou and Urpelainen, 2020). Conversely, high electricity costs consistently dampen adoption probabilities, underscoring affordability as a binding constraint (Scott et al., 2024). The counterintuitive patterns around asset ownership speak to the complexity of how wealth interacts with energy transition (Grabher et al., 2023). Wealthier households may invest in certain modern technologies while continuing to rely on traditional practices in others, reflecting not only economic, but also

cultural and practical considerations (Lay et al., 2013).

In summary, the latent class framework categorizes households. This reveals the structural fault lines of Uganda's energy landscape: a vast majority is still locked into non-adoption, a small minority has taken the first step through lighting, and vanishingly rare groups have ventured into cooking or heating efficiency (Tuyiragize and Bassi, 2024). The determinants of class membership, particularly electricity access, costs, and household characteristics, explain why these distributions look at the way they do, and why they are unlikely to shift without substantial structural change. Thus, the latent class results serve as both a mirror of the present realities and a precursor to multinomial logit analysis, further exploring the drivers of class membership in relative terms (Tuyiragize and Bassi, 2024).

5.3. Drivers of household adoption of energy-efficient technologies

Multinomial logit analysis deepens the understanding of adoption pathways by quantifying how household and contextual characteristics shift the likelihood of belonging to the three adoption classes relative to the dominant baseline of non-adoption. The results align with, but also extend, the insights derived from the latent class models (Min and Ko, 2023). They revealed that location, household head demographics, education, and electricity reliability are the most decisive forces shaping adoption trajectories (Haq et al., 2024; Min et al., 2024), whereas wealth and financial inclusion play more complex and uneven roles (Kaur and Sharma, 2024; Tibebu et al., 2024).

Regional and demographic heterogeneity. Regional disparities emerged and were particularly pronounced. Belonging to the Eastern, Northern, or Western regions drastically reduces the likelihood of comprehensive adoption, confirming that broad adoption is almost exclusively a phenomenon in the central region (Su and Tan, 2023). However, when adoption is partial and concentrated in lighting, regional differences shift: households in Eastern Uganda are more than twice as likely to adopt efficient lighting compared to non-adopters, with northern households displaying a similar, though less precise, pattern (Namirembe et al., 2024). These results underscore that while comprehensive adoption is centralized, incremental adoption has diffused more widely across the country (Peiffer and MacCarty, 2020). Importantly, the interaction effects between region and age reveal that these geographical patterns are not uniform: older household heads in North are modestly more likely to adopt, whereas in Eastern and Western Uganda, aging reduces adoption probability (Wang et al., 2022). This reflects the interplay between demographic composition and uneven technological penetration (Gunawan et al., 2024).

Age and settlement type. Age played a dual role. Younger household heads are the vanguard for broad adoption, which is consistent with the idea that they are more flexible and future-oriented (Kaur and Sharma, 2024; Meyer, 2008). In contrast, older heads are more likely to adopt incremental, lower-barrier technologies such as efficient lighting (Hassen et al., 2023), but are markedly less likely to transition to efficient heating (Chai et al., 2024). The settlement type further reinforces the urban advantage: the probability of heating adoption is almost entirely concentrated in urban areas (Hassen et al., 2023), whereas lighting adoption displays no significant urban–rural differences, indicating that efficient lighting technologies have diffused more broadly, even in rural settings (Figueroa, 2016).

Gender and education. The gender composition of the households reveals another axis of differentiation. Broad adoption is an overwhelmingly male-headed phenomenon, whereas female-headed households are disproportionately represented by efficient lighting-only adoption. This suggests that, while women may prioritize incremental efficiency improvements, larger systemic transitions remain male-dominated (Adjakloe et al., 2021; Chen et al., 2024). Education further amplifies adoption disparities: higher levels of schooling significantly increase the likelihood of broad adoption but play no meaningful role in lighting- or heating-only adoption. This confirms the interpretation that education matters most for a more resource-intensive and comprehensive transition (Tornel-Vázquez et al., 2024; Vogel et al., 2024).

Financial and energy supply factors. Savings patterns introduce a counterintuitive result: households without mobile money savings are significantly more likely to adopt lighting and heating, although not so broadly. This may reflect substitution in which households are unable or unwilling to use financial savings channels instead of allocating small surpluses toward energy improvements (Walwyn and Hanlin, 2022). However, the strongest predictors remained electricity-related variables. Greater power availability sharply increases the probability of broad adoption, underscoring that reliable supply is a prerequisite for cross-domain modernization. Electricity costs appear to be positively associated with broad adoption, reflecting that households with a higher consumption of efficient energy technologies are also those paying more, and not that higher costs encourage adoption (Twumasi et al., 2024). Asset indices matter only in the heating category, where they strongly predict adoption, which is consistent with the resource-intensive nature of efficient heating technologies.

Synthesis across tables. When viewed alongside the latent class assignment (Table 1) and class size distribution (Table 2), the multinomial logit results (Table 3) confirmed a consistent narrative. Comprehensive adoption is scarce, strongly urban-centered, and driven by younger, better-educated, and male-headed households with reliable electricity access (Awan et al., 2023; Tuyiragize and Bassi, 2024). Incremental lighting adoption is widespread, particularly among female-headed households and regions outside the central region, which reflects its affordability and accessibility (Kamuzora, 2024). The adoption of heating remains rare, but where it occurs, it is associated with wealth and an overwhelming urban bias (Awan et al., 2023). Therefore, the multinomial logit results sharpen the latent class picture by quantifying relative risks, showing precisely how sociodemographic and structural characteristics differentiate rare adopters from non-adopters (Kamuzora, 2024).

5.4. Adoption intensity and incidence

Regression analyses deepen our understanding of how sociodemographic, infrastructural, and housing characteristics shape both the incidence and intensity of adopting efficient energy technologies (Antonopoulos et al., 2024; Noonan et al., 2015). The logistic specification focuses on the probability of a household adopting at least one efficient technology, whereas the Poisson model examines the extent of adoption across multiple domains (Sen and Qiu, 2020; Wang and Hewitt, 2019). Taken together, these results demonstrate that household adoption decisions are both selective and structured, reflecting a combination of regional disparities, settlement types, household composition, and dwelling qualities (Chekol et al., 2023; Noonan et al., 2015).

Regional patterns have emerged as particularly decisive. The logistic model indicates that households in the Northern and Western regions are significantly more likely to adopt compared to the central baseline, whereas eastern households are not statistically different (Smith and Song, 2004). The Poisson model extends this finding by showing that, conditional on adoption, households in all three non-Central regions adopt at a higher intensity, with incidence rate ratios of 1.38 Eastern, 1.22 Northern, and 1.12 for the Western region. This finding reinforces the idea that, when adoption occurs outside the central region, it tends to be deeper, potentially because households overcome more structural barriers to do so (Schreinemachers et al., 2009).

Settlement type and gender also differentiated adoption. Urban households are less likely to adopt the logistic model despite their superior access to infrastructure, suggesting that affordability and cost barriers are more binding in urban settings (Bensch et al., 2015). However, once adoption occurs, urban households exhibit a marginally higher intensity, underscoring a dual reality: adoption is harder to initiate in towns and cities, but once it begins, it tends to extend across

multiple technologies (Bensch et al., 2015). Conversely, female-headed households are more likely to adopt at least one efficient technology, but are less likely to diversify across domains, indicating differentiated adoption strategies driven by gendered household management roles (Gebre et al., 2019; Neway and Zegeye, 2022).

Dwelling materials consistently act as structural proxies for wealth and readiness to efficiently integrate energy (Colston et al., 2024). The roofs of tiles and walls of stabilized bricks are positively associated with adoption probability, whereas unburnt or mud-based structures sharply reduce it (Colston et al., 2024). Poisson estimates magnify these gradients; tin or iron walls are associated with adoption intensities nearly seven times greater than the baseline, whereas stone floors correspond to adoption counts more than 11 times greater (Min and Ko, 2023). These results highlight the physical built environment as both a marker and enabler of the transition toward efficiency (Alassaf, 2024; Nair, 2015).

Household characteristics further refine this picture. Older household heads are slightly more likely to adopt and diversify, which suggests that age contributes to stability and investment capacity (Alinaitwe, 2023; Hassen et al., 2023). Electricity costs, although marginal in magnitude, consistently display positive associations with adoption, implying that households facing higher expenses are also the most incentivized to seek efficiency (Awan et al., 2023; Usman et al., 2024). Wealth, proxied by the asset index, has emerged as a robust predictor of both incidence and intensity, reaffirming that resource availability is central to Uganda's household energy transition (Alinaitwe, 2023; Best et al., 2024).

Taken together, the logistic and Poisson results complement the latent class and multinomial logit findings, and extend them by demonstrating how specific household and structural attributes jointly shape both the likelihood and depth of efficient energy adoption (Mothala et al., 2022; Namirembe et al., 2024). These results confirm that Uganda's energy transition is patterned not simply by choice, but by a matrix of demographic, economic, and infrastructural constraints that determine whether households adopt, and if so, how far they advance across domains (Elasu et al., 2024).

6. Conclusions and policy implications

6.1. Conclusions

This study provides a comprehensive account of household energy adoption patterns in Uganda by integrating latent class analysis with multinomial logit, logistic, and Poisson models. Across all specifications, the results reveal a highly stratified and constrained energy landscape in which modern and efficient technologies remain marginal and unevenly distributed.

Efficient energy adoption is rare across all domains. Fewer than six percent of households adopt efficient lighting, while adoption of efficient cooking and heating is negligible. Latent class analysis confirms this scarcity, showing that the overwhelming majority of households remain non-adopters, with only a small minority transitioning into lighting adoption and very few adopting heating or combining multiple efficient technologies. These findings indicate that Uganda's household energy transition is at an early stage and unfolds hierarchically, with lighting serving as the primary entry point.

Multinomial logit estimates highlight strong structural and demographic differentiation between adopters and non-adopters. Regional location emerges as the most decisive factor, with comprehensive adoption concentrated in the central region and incremental lighting adoption more widely distributed in the East and North. Age, gender, and education further stratify adoption trajectories, while reliable electricity supply is critical for adoption beyond lighting and affordability constraints continue to suppress uptake.

Logistic and Poisson analyses further distinguish adoption incidence from adoption intensity. Female-headed households are more likely to adopt at least one efficient technology, whereas urban households face affordability barriers that limit initial uptake despite infrastructural advantages. Among adopters, however, adoption intensity increases with urban residence, durable housing, and asset ownership, underscoring the importance of household investment capacity and dwelling characteristics in shaping deeper adoption.

6.2. Policy implications

Beyond their immediate empirical relevance, the findings indicate that household energy transitions in low-income contexts are heterogeneous and sequential rather than uniform. The identification of distinct adoption typologies and the clear separation between adoption incidence and adoption intensity show that initial uptake and deeper multi-technology adoption are governed by different constraints and cannot be inferred from binary adoption models alone. These results highlight the importance of analytical frameworks that explicitly account for heterogeneity and sequencing when examining household energy transitions in settings characterized by uneven access to modern energy services.

The empirical dominance of non-adoption, confirmed by latent class analysis showing that the vast majority of households remain non-adopters, implies that policy efforts must first address entry barriers. Targeted subsidies, bulk procurement, or distribution programs for efficient lighting can reduce initial costs and leverage lighting as the empirically observed first step into efficient energy use.

Strong spatial heterogeneity identified in the multinomial logit results suggests that national energy strategies should be regionally differentiated. Comprehensive adoption remains concentrated in the central region, while Eastern and Northern regions exhibit primarily incremental lighting adoption. In these regions, policies should prioritize infrastructure expansion and demand-side incentives that facilitate initial uptake, recognizing that adoption intensity increases once households overcome entry constraints.

Demographic differentiation further implies the need for targeted interventions. Younger and more educated household heads are more likely to engage in broad adoption, whereas women and older household heads are more strongly represented among incremental adopters. Policies should therefore combine lighting-focused interventions that support incremental adoption with complementary financing, technical support, or information programs that enable progression into cooking and heating technologies.

The logistic and Poisson results demonstrate that housing quality and asset ownership are critical enablers of both adoption probability and adoption intensity. This suggests that energy policy should be coordinated with housing improvement and affordable financing mechanisms. Linking efficient energy technologies to pay-as-you-go schemes, microfinance products, or incremental housing upgrades can support deeper and more sustained adoption across multiple energy domains.

6.3. Study limitations

This study had some limitations. The reliance on self-reported household survey data introduces the possibility of minor recall or reporting inaccuracies, whereas the extreme imbalance between adopters and non-adopters constrains the sample size available for some categories, particularly for cooking and heating. In addition, although the models incorporate a wide range of demographic, economic, and infrastructural covariates, certain cultural and behavioral dimensions remain outside the scope of this analysis. However, these limitations are inherent to large-scale household surveys in low-income contexts, and were carefully mitigated through the use of appropriate estimation techniques, weighting, and robustness checks, ensuring that the results remain rigorous and informative.

6.4. Further research

Future research should explore how adoption pathways evolve as Uganda's energy landscape changes, particularly with the expansion of off-grid and renewable energy solutions that were not yet widespread at the time of this analysis. Examining how household-level adoption interacts with community initiatives such as shared systems, neighborhood-level distribution, and cooperative financing could offer valuable insights into scaling efficiency gains. Comparative work across other low-income countries would also help clarify whether the stratified adoption observed in Uganda reflects a broader regional pattern or country-specific dynamic. These avenues would not replicate what has been done here but would enrich the evidence base for understanding how incremental adoption can accumulate into deeper and more transformative transitions.

Ethical approval

This study never involved human subjects and got ethical clearance from relevant authorities.

Funding statement

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Consent to publish

This work has not been presented to a publishing house before and upon acceptance by this journal and will relinquish the consent to publish.

Consent to participate

Since no human subjects were involved, there was no need for consent from participants.

CRediT authorship contribution statement

Muyiwa S. Adaramola: Writing – review & editing, Validation, Supervision, Resources, Conceptualization. **Twaha Kigongo Kaawaase:** Writing – review & editing, Validation, Supervision, Conceptualization. **Francis Wasswa:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization. **Geoffrey Mubiinzi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Livingstone Senyonga:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Maria Nantongo:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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