

An exploratory study of perceived financial and housing barriers to electricity access in rural Kitui County Kenya

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Research Article

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Abstract

Household finance and housing readiness may constrain electrification, yet perceptions of these mechanisms require separate examination from observed access. This exploratory study examines perceived electricity-access barriers among 380 respondents in rural Kitui County, Kenya. Four ten-item scores summarized agreement with statements about socioeconomic barriers, credit, expenditure and housing. Measurement assessment included internal consistency, principal components, permutation parallel analysis and heterotrait–monotrait correlation ratios. Ordinary least-squares regression used HC3 standard errors, categorical demographic adjustment and influence sensitivity analysis. Composite means ranged from 4.322 to 4.333; 5.3–6.6% of respondents attained the scale maximum. Parallel analysis retained one component within each score block and five across the combined 40-item instrument, indicating uncertainty about its joint measurement structure. The baseline model explained 37.0% of outcome-score variation. Credit-related agreement was positively associated with broad socioeconomic barrier agreement ($B = .546$; 95% CI [.259, .833]). The expenditure association was less conclusive after demographic adjustment, and the housing association was imprecise. Influence screening flagged 44 records, all retained in the primary analysis. These findings describe relationships among perceptions rather than causal effects on household electricity access. They suggest shared recognition of financial barriers while highlighting the need for independently measured access outcomes, stronger construct validation and careful assessment of influential observations in household energy research.

1.0 Introduction

Electricity can support sustainable development when households obtain useful, reliable and affordable services. Infrastructure coverage, household connection and effective use are distinct stages: proximity to a network does not ensure uptake, and a connection does not guarantee improvements in livelihoods (Blimpo & Cosgrove-Davies, 2019; Blimpo et al., 2020; Lee et al., 2020a; Onyeji et al., 2012). This distinction motivates an examination of financial and physical constraints alongside the availability of supply.

Sustainable Development Goal 7 (SDG 7) places equitable access to affordable, dependable and sustainable energy at the centre of the 2030 Agenda. Target 7.1 seeks universal access to modern energy services by 2030, while indicator 7.1.1 tracks the share of the population with electricity access (United Nations, n.d.). This study addresses perceived financial and housing barriers relevant to that access agenda. Its agreement scores do not measure indicator 7.1.1 or establish progress towards the target.

Recent research strengthens the case for examining the conditions under which access becomes useful. A review in Energy for Sustainable Development documents variation in the relationship between electricity access and human development (MacGinley et al., 2025). Reviews of African energy poverty and transitions in developing countries likewise identify interrelated financial, infrastructural and

institutional challenges (Leal Filho et al., 2024; Mustapha et al., 2025). These findings support a service-oriented interpretation of access rather than treating the presence of a connection as a complete development outcome.

The meaning of energy poverty also depends on what is measured. Domestic energy deprivation encompasses the ability to secure services that meet household needs, while a capabilities perspective asks what people can accomplish with those services (Bouzarovski & Petrova, 2015; Day et al., 2016). Measurement research distinguishes indicators of deprivation from explanations of its causes and emphasizes the consequences of indicator selection (Al Kez et al., 2024; Pachauri & Spreng, 2011). Agreement with a statement about an access barrier is therefore conceptually different from an observation that the household experiences that barrier.

Connection charges, internal wiring and appliance purchases impose upfront costs, while electricity use creates recurring expenditure. Borrowing may spread those costs, but loan suitability depends on repayment capacity. In an experiment involving an energy-efficient cookstove in Nairobi, credit increased willingness to pay (Berkouwer & Dean, 2022). This provides evidence of a financing mechanism in a related technology setting; it does not demonstrate an effect on electricity connections in Kitui.

For electricity, research in Rwanda has examined willingness to pay for off-grid solar, while experimental work on microsolar adoption has evaluated vouchers, cash transfers and microfinance (Grimm et al., 2020; Wong et al., 2022). More recent Kenyan evidence examines willingness to pay for grid connections and solar home systems (Zuch, 2025). Together these studies motivate separating upfront affordability, preferences and financing arrangements rather than interpreting an agreement score as a direct measure of any one of them.

Financial inclusion is similarly broader than a single credit product. Research in sub-Saharan Africa examines its relationship with electricity and clean-cooking access, and a recent household study finds that the role of financial services differs by gender and rural–urban setting (Richardson et al., 2025; Said & Acheampong, 2023). Work on remittances adds another potential source of household resources (Agradi, 2023). The present survey does not observe these financial flows or products, so their relevance remains a theoretical motivation rather than an estimated channel.

Kenyan solar research and payment-record analysis from Rwanda and Kenya show why the form and timing of payments deserve attention (Adwek et al., 2020; Mergulhão et al., 2023). Critical studies of East African solar markets also examine exclusion, consumer debt and the commercial relationships embedded in access (Baker, 2023; Cross & Neumark, 2021). Interviews in Tanzania and Malawi identify trade-offs between waiting to save, borrowing and reliance on social networks (Ojong et al., 2025). Consequently, greater availability of credit should not automatically be equated with sustained affordability.

Housing readiness combines physical and social conditions. Studies of tenure and energy choices in Ghana and Rwanda, and of electricity networks in urban Kenya, motivate attention to ownership,

landlord–tenant relations and control over installations (Klege et al., 2022; Martey, 2019; Smith, 2019). Recent work links housing policy with energy security in Kenya and the Democratic Republic of Congo, while other studies examine housing loans and household–community infrastructure (Choda et al., 2023; Sadiki, 2025; Shon & Lee, 2026). These studies concern different populations and measures; they justify examining housing mechanisms without establishing their magnitude in rural Kitui.

The study examines perceptions of electricity-access barriers among respondents in rural Kitui County. Its questionnaire asks whether credit, poverty, expenditure, income and housing shape access. Related item blocks address credit mechanisms, competing expenditures and housing readiness. The scores therefore represent agreement with propositions about access barriers. Connection status, loan eligibility, monetary expenditure, dwelling quality, supply availability and electricity consumption were not directly measured.

Research among refugees in Zambia, Malawi and Uganda examines electricity access and willingness to pay for reliable supply, highlighting variation across settlements and the relevance of income and service awareness (Casati et al., 2024). This evidence comes from a distinct humanitarian context. Its relevance here is to motivate careful definition of the population, access outcome and affordability measure before drawing policy conclusions.

The research question is whether agreement about credit, expenditure and housing barriers is associated with agreement about broader socioeconomic barriers to electricity access. The study contributes exploratory evidence on how respondents endorse these interconnected explanations, alongside an assessment of measurement structure and statistical sensitivity. Its contribution is a transparent examination of perceptions in this respondent sample. It does not estimate the effects of financial or housing interventions on connection status.

2.0 Integrated framework and exploratory expectations

The framework treats financial and physical resources as potentially complementary conditions for obtaining useful electricity services. Credit-related mechanisms concern upfront liquidity; expenditure-related mechanisms concern competing demands on income; housing mechanisms concern physical readiness and control over installations. These mechanisms are consistent with an emphasis on service capabilities (Day et al., 2016). The energy ladder supplies a broad affordability rationale, but critiques of linear fuel switching show why changing resources need not produce a uniform progression through technologies (Masera et al., 2000). The present instrument does not directly test asset accumulation, fuel switching or development trajectories.

An energy-justice perspective adds attention to whose needs are recognized and how access opportunities and burdens are distributed (Jenkins et al., 2016). Quantitative work on women’s energy justice in Benin, Senegal and Togo and research on women’s experiences of electrification in Zambia illustrate the importance of examining differentiated experiences (Jodoin et al., 2024; Kannan et al.,

2024). Gender, age and education enter the present analysis as observed demographic characteristics; they do not provide a comprehensive test of distributional or procedural justice.

The livelihood rationale for electricity also requires complementary opportunities. Studies have examined employment effects in South Africa, the welfare implications of Rwanda's grid expansion and the outcomes of basic off-grid provision in India (Aklin et al., 2017; Dinkelman, 2011; Lenz et al., 2017). These settings and interventions cannot be assumed to generate identical outcomes. A systematic review of productive electricity use in African agriculture identifies financing, skills, reliable supply and market access as relevant constraints (Raji et al., 2024). These mechanisms explain why household perceptions may concern more than connection charges alone.

The integrated conceptual sequence is that infrastructure and service quality create opportunities, household resources affect feasibility, and safe installations enable use. Feedback is possible: electricity can itself affect income, assets and creditworthiness. Wealth, tenure, network distance, tariffs, household size and provider reliability may jointly influence access and household resources. A cross-sectional perception survey cannot identify those causal pathways or eliminate omitted causes by adding demographic controls.

Infrastructure and service conditions remain important omitted dimensions. Research on renewable-energy investment in Kenya and Ghana examines constraints beyond household resources (Pueyo, 2018). Evidence from Kenya considers the role of blackouts in connection status and appliance acquisition, while the recent Last Mile evaluation examines a large-scale connectivity intervention (Bajo-Buenestado, 2021; Kassem et al., 2026). An experimental study of rural grid electrification also illustrates the value of designs that directly measure uptake and welfare outcomes (Lee et al., 2020b). None of these conditions or outcomes can be recovered from the agreement scores analyzed here.

Use after connection is another distinct stage. A Kenyan mini-grid study traces appliance adoption over time, and demand modelling links electricity use with appliance ownership and household resources (Poblete-Cazenave & Pachauri, 2021; Tomas Fillol et al., 2025). Recent panel research in Malawi examines solar devices of different capacities and their uses (McCord et al., 2026). These studies motivate measuring service needs and equipment separately from whether respondents agree that socioeconomic barriers exist.

The exploratory expectations are that the credit, expenditure and housing agreement scores will each be associated with the broader barrier-agreement score. A positive coefficient is interpreted as stronger co-endorsement of propositions, not evidence that higher real-world spending pressure improves access. The expenditure items primarily describe spending constraints; naming that score expenditure capacity would reverse its meaning. Likewise, agreement that better housing facilitates access is not a direct observation of better housing.

Figure 1 presents the proposed associations between credit-, expenditure- and housing-related agreement and perceived socioeconomic barriers to electricity access (EA), measured as an agreement

score. Gender, age and education are included as demographic controls. The arrows indicate the model specification and do not establish causal direction.

2.1 Framework explanation and exploratory hypotheses

The framework links three agreement scores to broad socioeconomic barrier agreement (EA). The credit pathway concerns respondents' recognition of financing constraints; the expenditure pathway concerns competing demands on household budgets; and the housing pathway concerns perceived installation and physical-readiness barriers. A positive association means that stronger endorsement of a specific barrier accompanies stronger endorsement of broader socioeconomic barriers. It does not mean that the respondent has greater credit access, higher expenditure or better housing.

The solid arrows represent the explanatory relationships examined in the regression. The dashed arrow represents demographic adjustment for gender, age and education, allowing the associations to be examined conditional on these observed characteristics. Because the data are cross-sectional and the item content overlaps, the arrows do not identify causal direction. The following hypotheses are exploratory statements of the associations examined, rather than preregistered confirmatory predictions:

H1: Credit-related agreement (HAC) is positively associated with broad socioeconomic barrier agreement (EA).

H2: Expenditure-related agreement (HE) is positively associated with broad socioeconomic barrier agreement (EA).

H3: Housing-related agreement (HLC) is positively associated with broad socioeconomic barrier agreement (EA).

3.0 Materials and methods

3.1 Data and preparation

A cross-sectional questionnaire survey provided 380 respondent records from rural Kitui County. The instrument included gender, age, education and 60 five-point agreement items. The analysis focuses on 40 items representing the four score blocks specified below. All included items and demographic variables were complete. Administrative timestamps were excluded from statistical models and the deidentified diagnostic record. The analysis does not use sampling weights or cluster adjustments because selection probabilities and cluster identifiers were unavailable; findings are interpreted at the respondent-sample level.

Responses were coded 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree and 5 = strongly agree. Text labels were standardized by trimming whitespace, including duplicate primary-education labels. No response was imputed, and every respondent was retained in the primary analysis. Gender, age and

education were represented categorically in the adjusted model. Reference categories were female, age 20–30 years and primary education.

3.2 Score construction and interpretation

Four arithmetic-mean scores were calculated from ten items each: EA, broad socioeconomic barrier agreement; HAC, credit-related agreement; HE, expenditure-related agreement; and HLC, housing-related agreement. The analysis concerns agreement with proposed mechanisms, not resource levels or physical access. The income and poverty item blocks were outside the specified three-predictor scope. Item membership followed the questionnaire blocks, without selection by statistical significance.

All included items retained their original agreement direction. Both enabling statements, such as credit facilitating a connection, and constraint statements, such as poverty limiting borrowing, endorse the relevance of a barrier mechanism when respondents agree. The composite definitions therefore reflect endorsement rather than a bipolar resource scale. No items were removed to improve internal consistency or regression significance.

Transparent score definitions are important because a numerical association is interpretable only in relation to the content of the items. Measurement guidance emphasizes making item selection, scoring and validity claims explicit (Flake & Fried, 2020). Here, consistency of coding does not establish that the four blocks represent independent household resources or realized access. The conceptual overlap between the outcome and predictor wording is retained as a limitation rather than resolved by relabelling the scores.

Table 3.1 Analysis variables and interpretation

Code	Items	Interpretation
EA	EA1–EA10	Agreement that socioeconomic conditions and poverty shape electricity access.
HAC	HAC1–HAC10	Agreement with credit-related mechanisms and constraints.
HE	HE1–HE10	Agreement with expenditure-related constraints and remedies.
HLC	HLC1–HLC10	Agreement with housing and physical-readiness mechanisms.

Each score is the arithmetic mean of ten items coded from 1 to 5. The same definitions are used in descriptive, measurement and regression analyses. EA denotes broad socioeconomic barrier agreement; HAC, HE and HLC denote credit-, expenditure- and housing-related agreement, respectively.

3.3 Measurement assessment

Internal consistency was assessed with Cronbach's alpha. Within-block principal component analyses used Pearson item-correlation matrices. Component retention was assessed using permutation parallel analysis with 1,000 independently column-permuted datasets and the 95th-percentile reference eigenvalues (Horn, 1965). Components were retained sequentially from the largest eigenvalue. Permutation preserved the marginal response distributions, and random seed 20261021 was used for reproducibility. Principal components summarize observed covariance rather than confirm a latent measurement model. Alpha is reported as an internal-consistency summary, not proof of unidimensionality or validity; alternative reliability approaches require an appropriate measurement model (McNeish, 2018).

A corresponding parallel analysis examined all 40 items together. Heterotrait–monotrait correlation ratios were calculated as the mean absolute between-block item correlation divided by the geometric mean of the two within-block correlation means (Henseler et al., 2015). These are descriptive checks, not evidence that the item wording measures actual access or resources. Maximum-score percentages and distribution plots quantify upper-end concentration; high means alone are not treated as proof of a severe ceiling effect. Guidance on exploratory factor analysis supports evaluating retention and interpretability together rather than treating a single numerical rule as sufficient (Goretzko et al., 2021). Because these are ordinal and unevenly distributed responses, the use of Pearson correlations is an exploratory approximation; research on categorical measurement supports assessing estimator suitability in relation to category distributions and model conditions (Rhemtulla et al., 2012).

3.4 Regression and diagnostic strategy

The baseline model is $EA_i = \alpha + b_1HAC_i + b_2HE_i + b_3HLC_i + \epsilon_i$. A second model adds categorical gender, age and education indicators. Both use all 380 responses. HC3 heteroscedasticity-consistent standard errors and t-based 95% confidence intervals are reported, with residual degrees of freedom 376 and 368, respectively (MacKinnon & White, 1985). Model fit and unstandardized coefficients are obtained from ordinary least squares. The reported conventional model F statistic is distinguished from HC3 coefficient inference.

Diagnostics include VIFs, residual-versus-fitted and normal Q–Q plots, externally studentized residuals, leverage and Cook's distances (Cook, 1977). Screening thresholds are Cook's $D > 4/380$, leverage $> 2(4)/380$ and absolute externally studentized residual > 3 . They identify cases for investigation, not invalid observations. The Breusch–Pagan auxiliary regression assesses heteroscedasticity; an HC3 test of an added squared fitted-value term provides a limited functional-form check. No test is interpreted as proving all model assumptions. VIFs are interpreted in relation to the specification and precision of the estimates rather than as a mechanical pass–fail rule (O'Brien, 2007).

The primary analysis retains every record. A sensitivity model removes the union of screened cases solely to show how results depend on influential observations; its selected-sample p values are descriptive and do not replace full-sample inference. A Huber M-estimation sensitivity, implemented by

iteratively reweighted least squares with tuning constant 1.345, is reported for coefficient direction and magnitude only. It limits large-residual influence and does not necessarily protect against high-leverage cases. The data offer no verified cluster identifiers, so cluster-robust or spatial inference is not claimed.

Demographic adjustment is descriptive. It does not make each regression coefficient a causal effect or ensure that all confounding has been controlled (Rohrer, 2018; Westreich & Greenland, 2013). Shared wording and a common questionnaire method can also affect covariance between scores (Podsakoff et al., 2003; Podsakoff et al., 2012). No statistical diagnostic used here identifies the share of an association attributable to those sources.

4.0 Results

4.1 Respondent characteristics and score distributions

Table 4.1 Respondent characteristics

Characteristic	Category	n	Percent
Gender	Female	253	66.58
Gender	Male	127	33.42
Age	41- 50 years	171	45.00
Age	31- 40 years	127	33.42
Age	20- 30 years	47	12.37
Age	Above 50 years	35	9.21
Education	Certificate/ Diploma	130	34.21
Education	Secondary education	118	31.05
Education	Bachelor’s Degree	62	16.32
Education	Primary	45	11.84
Education	Post-graduate education	25	6.58

N = 380. Percentages use the full sample as the denominator. Education categories were standardized before tabulation.

Table 4.2 Composite score distributions

Score	Mean	SD	Range	At 5 (%)	≥ 4.5 (%)
EA	4.3334	0.46317	1.2–5.0	5.79	36.32
HAC	4.3232	0.42076	1.9–5.0	5.26	32.63
HE	4.3221	0.40607	2.0–5.0	6.32	30.53
HLC	4.3279	0.38461	2.0–5.0	6.58	30.53

N = 380 for each score. At 5 indicates an exact composite maximum; ≥ 4.5 indicates a mean agreement score of at least 4.5.

The score distributions were concentrated toward high agreement, with skewness ranging from –2.776 for EA to –1.309 for HLC. Exact composite maxima occurred in 5.26–6.58% of responses, while 30.53–36.32% scored at least 4.5. These results quantify upper-end concentration without establishing a severe ceiling effect from high means alone.

4.3 Measurement structure

Table 4.3 Reliability and parallel analysis

Scale	Alpha	KMO	Second eigenvalue	Null 95th second	Retained
EA	0.876	0.905	0.977	1.233	1
HAC	0.861	0.894	0.933	1.230	1
HE	0.862	0.905	1.047	1.231	1
HLC	0.842	0.882	1.055	1.233	1

Ten items and N = 380 per scale. All Bartlett tests have df = 45 and p < .001. Parallel analysis uses 1,000 permutations. The second eigenvalue is below its permutation reference for every scale.

The second eigenvalues for HE and HLC were 1.047 and 1.055, below their corresponding parallel-analysis reference values of 1.231 and 1.233. Parallel analysis therefore retained one component within each block. The within-block results support exploratory agreement summaries, but do not establish substantive content validity or confirm the four-construct measurement structure.

The combined 40-item analysis retains five components, with the first explaining 27.44% of total standardized item variance. The fifth observed eigenvalue is 1.750 against a 95th-percentile reference of 1.484; the sixth is 1.131 against 1.441. HTMT ratios range from .385 to .678. The ratios do not suggest near-identity of all blocks, but the joint dimensionality result does not confirm the intended four-construct structure. Further exploratory/confirmatory work and an independent validation sample are

warranted; assigning a substantive meaning to a fifth component from eigenvalues alone would be unsupported.

Content review remains decisive. For example, EA1 asserts that better credit makes electricity connections easier to afford, while HAC1 asserts that credit allows households to afford initial connection fees. The outcome and credit block therefore overlap in meaning. Other EA items explicitly mention expenditure, income and housing. Statistical separation of item blocks cannot transform these propositions into independent measurements of real household resources and realized access.

4.4 Regression results

The baseline ordinary least-squares model explained 37.0% of EA variation ($R^2 = .3703$; adjusted $R^2 = .3652$). The residual standard error was .3690 and the conventional model test was $F(3, 376) = 73.690$, $p < .001$. Table 4.4 presents the baseline and demographically adjusted estimates with HC3 uncertainty intervals.

Table 4.4 Full-sample regression with HC3 uncertainty

Term	Base B	Base 95% CI	Base p	Adjusted B	Adjusted 95% CI	Adjusted p
Intercept	1.060	[0.169, 1.952]	0.020	1.121	[0.206, 2.036]	0.016
HAC	0.546	[0.259, 0.833]	< .001	0.543	[0.254, 0.832]	< .001
HE	0.183	[0.004, 0.362]	0.045	0.179	[-0.006, 0.365]	0.058
HLC	0.028	[-0.166, 0.222]	0.777	0.025	[-0.169, 0.219]	0.800

N = 380 for both models. Adjusted model adds categorical gender, age and education indicators and has $R^2 = .3790$. Confidence intervals and coefficient p values use HC3 standard errors and residual-df t references. The adjusted intercept refers to female respondents aged 20–30 with primary education. All coefficients describe agreement-score associations.

Credit-related agreement was positively associated with EA in the baseline model ($B = .546$; HC3 SE = .146; 95% CI [.259, .833]). The expenditure coefficient was .183 (SE = .091; CI [.004, .362]), while the housing coefficient was .028 (SE = .099; CI [-.166, .222]). The standardized coefficients were .496, .161 and .023, respectively.

With categorical demographic adjustment, the credit coefficient was .543 (95% CI [.254, .832]). The expenditure coefficient was .179 (CI [-.006, .365]; $p = .058$), and the housing coefficient was .025 (CI [-.169, .219]; $p = .800$). Credit-related agreement was the most consistently positive conditional association. Overlapping item content nevertheless limits interpretation as a distinct household-resource relationship. The positive credit association is consistent with H1. Evidence for H2 is sensitive to demographic adjustment, while the housing estimate does not provide clear support for H3.

4.5 Multicollinearity influence and sensitivity

Table 4.5 Regression diagnostics

Check	Result	Implication
VIFs	HAC 1.508; HE 1.514; HLC 1.392	No pronounced predictor collinearity by these VIFs.
Breusch–Pagan	LM 40.369; $p < .001$	Residual variance is not constant; HC3 uncertainty is used.
Maximum Cook's D	.877; 29 above .01053	Influential records warrant inspection; all retained in the primary model.
Maximum leverage	.125; 37 above .02105	Several unusual predictor profiles are present.
Externally studentized residuals	–6.496 to 3.155; seven absolute values > 3	Residual outliers are present and included in sensitivity screening.
Union of screening flags	44 records	Sensitivity removal leaves 336; no records are labelled erroneous from these rules.
Fitted EA range	2.539–4.846	All primary fitted values lie within 1–5.
HC3 squared-fitted check	F 1.273; $p = .260$	No detected quadratic fitted-value term; this is a limited specification check.

Diagnostics apply to the baseline mean-score model. Screening thresholds identify observations for investigation and sensitivity analysis rather than automatic deletion.

Table 4.6 Coefficient sensitivity

Term	Full sample B	Flagged cases omitted B	Omitted sample 95% CI	Huber B
HAC	0.546	0.340	[0.204, 0.476]	0.473
HE	0.183	0.244	[0.112, 0.376]	0.144
HLC	0.028	0.123	[-0.004, 0.251]	0.112

Full sample and Huber sensitivities use $N = 380$. Flagged-case omission uses $N = 336$ with HC3 intervals; its $R^2 = .3486$. Omission is a diagnostic sensitivity only. Huber estimates are descriptive, without inferential intervals.

The credit coefficient falls from .546 to .340 after flagged-case omission, showing sensitivity of its magnitude even though its direction remains positive. The expenditure coefficient changes from .183 to .244; the housing coefficient changes from .028 to .123, with an interval still including zero. Huber coefficient estimates are .473, .144 and .112. These comparisons show that independent effect rankings and precise magnitudes should not be treated as stable policy quantities. Normal Q–Q and residual plots

also show departures relevant to conventional Gaussian-error inference; HC3 addresses variance estimation but cannot cure influential observations, measurement overlap or endogeneity.

5.0 Discussion

Respondents who more strongly endorsed credit-related barriers also tended to endorse broader socioeconomic explanations of electricity-access constraints. This pattern remained after the selected demographic controls. It may reflect shared recognition of liquidity constraints, overlapping wording, acquiescence or a general tendency to endorse socioeconomic explanations. The design does not distinguish among those mechanisms or establish that respondents with actual access to credit are more likely to be connected.

The financial interpretation is plausible in light of recent evidence on willingness to pay in Kenya and the heterogeneous role of financial services in African household energy transitions (Richardson et al., 2025; Zuch, 2025). However, plausibility is not identification. The positive HAC coefficient can arise when respondents endorse the same financing proposition in both the credit block and the outcome block. A stronger future test would record credit eligibility, borrowing terms and connection payments separately, alongside an independently observed access outcome.

Affordability should also be assessed after connection. Research on prepaid electricity among low-income Ghanaian households examines continuing energy poverty despite network access (Bloomer & Boateng, 2024). A 2026 assessment of residential tariffs across sub-Saharan Africa shows why affordability depends on income and the level of service demanded (Kou et al., 2026). These findings suggest collecting bills, consumption, interruptions and payment difficulties rather than inferring affordability from a high expenditure-agreement score.

The expenditure association was less conclusive under demographic adjustment, and the housing estimate remained imprecise. The findings therefore support a cautious interpretation of co-endorsed perceptions. They do not establish the effectiveness of lending, subsidies or wiring programs. Such interventions require evaluation against observed access, affordability, safety and welfare outcomes (Blimpo & Cosgrove-Davies, 2019; Lee et al., 2020a).

The uncertain housing association does not establish that dwellings or tenure are unimportant. The score captures beliefs about enabling housing conditions, while research on tenure and infrastructure examines observed or institutionally situated constraints (Klege et al., 2022; Shon & Lee, 2026; Smith, 2019). Housing and energy policy integration is therefore a relevant topic for future investigation, but the present coefficient cannot select a housing intervention or quantify its expected benefit (Sadiki, 2025).

The wider sustainable-development relevance also requires direct outcome evidence. Kenyan research has examined energy poverty and health, and recent international work proposes coordinated assessment of energy security, sustainability and affordability (Ang'u et al., 2023; Pittalis et al., 2026). Those outcomes extend beyond the current questionnaire. They provide a rationale for linking future

perception studies with health, service-quality and welfare measures rather than assuming that stronger agreement implies greater deprivation.

Within-block parallel analysis retained one component for each agreement scale, while the joint analysis retained five components. This combination supports exploratory summaries within item blocks but leaves uncertainty about their joint structure. Independent validation should examine dimensionality, wording effects and criterion validity. Future instruments should separate perceived explanations from observed access outcomes before testing relationships among them.

Future instrument development should use interviews or cognitive testing to establish what respondents understand by credit, spending pressure, dwelling readiness and access. Items assessing actual resources should be separated from items asking whether those resources matter. An independent sample could then assess the proposed structure and its relationship with observed access (Flake & Fried, 2020; Goretzko et al., 2021). A high reliability coefficient or a low between-block ratio would not by itself resolve semantic overlap.

The distinction matters for sustainable-development research. A useful access measure could record connection type, available hours, reliability, affordability and safety, while separate measures capture loan access, expenditure constraints and dwelling readiness. Demand and appliance ownership also depend on service requirements and household resources (Poblete-Cazenave & Pachauri, 2021). Asking respondents whether those relationships exist is informative about perceptions, but it cannot substitute for measuring the underlying conditions.

For SDG 7, the findings identify perceptions that can inform the design of subsequent access assessments, rather than establish which intervention will achieve universal electrification. The prominence of credit-related agreement motivates further investigation of connection costs and financing terms; expenditure and housing perceptions motivate separate assessment of recurring affordability and installation readiness. Future studies should pair these perceptions with observed connection status, supply reliability, electricity bills and dwelling conditions. This would connect locally reported concerns with target 7.1 while distinguishing the official electricity-access indicator from the broader quality and affordability of services (United Nations, n.d.; Kou et al., 2026).

6.0 Limitations and conclusion

This exploratory cross-sectional survey has several limitations. Sampling probabilities and cluster identifiers were unavailable, limiting population generalization and assessment of within-cluster dependence. The regressions cannot establish causal direction or eliminate confounding by unmeasured wealth, infrastructure or service quality. Pearson-based component and parallel analyses are exploratory for ordinal responses; an ordinal confirmatory model and external criterion validation were not undertaken. All score blocks share a response method and overlap in their item content.

Upper-end concentration, residual heteroscedasticity and influential records limit precision and stability. Screening-based omission changes the analyzed sample, so it is not a preferred corrected estimate. HC3 uncertainty and Huber coefficient sensitivity do not validate the constructs or account for unknown clustering. Findings apply to the submitted respondents and their agreement responses; population prevalence of electricity access, household financial capacity or housing quality cannot be inferred.

Perceived credit barriers were positively associated with broader socioeconomic barrier agreement among the 380 respondents. The baseline model explained 37.0% of score variation, while demographic adjustment and influence analyses qualified the expenditure and housing findings and the precision of coefficient magnitudes. The study provides exploratory evidence about perceptions of rural electrification constraints. Future research should validate the instrument and link perceptions to independently measured electricity access and household circumstances. Linking these measures would strengthen the evidence available for locally appropriate action towards SDG 7, particularly target 7.1.

Declarations

7.1 CRediT authorship contribution statement

Alex Kyalo Mwangangi: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. Simeon Nganai: Writing – review & editing, Supervision, Formal analysis, Conceptualization.

7.2 Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used AI to assist with language editing, manuscript organization, code development for data processing and visualization, and statistical reporting. The reported results were calculated from the questionnaire responses using the documented analysis procedures. No respondent observations were generated or imputed.

7.3 Funding

This research received no external funding.

7.4 Declaration of competing interest

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

7.5 Ethics and informed consent

Research approval was obtained from the relevant authorities in 2025. Participants provided informed consent before taking part in the study.

7.6 Data availability

The respondent-level data are not publicly available. Any sharing is subject to applicable participant-consent and privacy requirements.

References

1. Adwek, G., Boxiong, S., Ndolo, P. O., Siagi, Z. O., Chepsaigutt, C., Kemunto, C. M., Arowo, M., Shimmon, J., Simiyu, P., & Yabo, A. C. (2020). The solar energy access in Kenya: a review focusing on Pay-As-You-Go solar home system. *Environment, Development and Sustainability*, 22(5), 3897–3938. <https://doi.org/10.1007/s10668-019-00372-x>
2. Agradi, M. (2023). Does remittance inflow influence energy poverty?. *Applied Energy*, 335, Article 120668. <https://doi.org/10.1016/j.apenergy.2023.120668>
3. Aklin, M., Bayer, P., Harish, S. P., & Urpelainen, J. (2017). Does basic energy access generate socioeconomic benefits? A field experiment with off-grid solar power in India. *Science Advances*, 3(5), Article e1602153. <https://doi.org/10.1126/sciadv.1602153>
4. Al Kez, D., Foley, A., Lowans, C., & Del Rio, D. F. (2024). Energy poverty assessment: Indicators and implications for developing and developed countries. *Energy Conversion and Management*, 307, Article 118324. <https://doi.org/10.1016/j.enconman.2024.118324>
5. Ang'u, C., Muthama, N. J., Mutuku, M. A., & M'ikiugu, M. H. (2023). Analysis of energy poverty in Kenya and its implications for human health. *Energy Policy*, 176, Article 113506. <https://doi.org/10.1016/j.enpol.2023.113506>
6. Bajo-Buenestado, R. (2021). The effect of blackouts on household electrification status: Evidence from Kenya. *Energy Economics*, 94, Article 105067. <https://doi.org/10.1016/j.eneco.2020.105067>
7. Baker, L. (2023). New frontiers of electricity capital: energy access in sub-Saharan Africa. *New Political Economy*, 28(2), 206–222. <https://doi.org/10.1080/13563467.2022.2084524>
8. Berkouwer, S. B., & Dean, J. T. (2022). Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households. *American Economic Review*, 112(10), 3291–3330. <https://doi.org/10.1257/aer.20210766>
9. Blimpo, M. P., & Cosgrove-Davies, M. (2019). *Electricity access in sub-Saharan Africa: Uptake, reliability, and complementary factors for economic impact*. World Bank. <https://doi.org/10.1596/978-1-4648-1361-0>

10. Blimpo, M. P., Postepska, A., & Xu, Y. (2020). Why is household electricity uptake low in Sub-Saharan Africa?. *World Development*, 133, Article 105002. <https://doi.org/10.1016/j.worlddev.2020.105002>
11. Bloomer, J., & Boateng, D. (2024). Prepaid into poverty? Exploring energy poverty and access to alternative electricity sources among urban poor households in Ghana. *Energy Research & Social Science*, 112, Article 103510. <https://doi.org/10.1016/j.erss.2024.103510>
12. Bouzarovski, S., & Petrova, S. (2015). A global perspective on domestic energy deprivation: Overcoming the energy poverty–fuel poverty binary. *Energy Research & Social Science*, 10, 31–40. <https://doi.org/10.1016/j.erss.2015.06.007>
13. Casati, P., Fumagalli, E., Baldi, D., & Moner-Girona, M. (2024). Understanding the drivers of electricity access and willingness to pay for reliable electricity in African refugee settlements: Evidence from Zambia, Malawi, and Uganda. *Energy Research & Social Science*, 113, Article 103546. <https://doi.org/10.1016/j.erss.2024.103546>
14. Choda, A., Schoofs, A., & Verrinder, N. (2023). Improving housing conditions: labelled loans in Kenya and Uganda. *Journal of Development Effectiveness*, 15(4), 406–437. <https://doi.org/10.1080/19439342.2022.2116077>
15. Cook, R. D. (1977). Detection of influential observation in linear regression. *Technometrics*, 19(1), 15–18. <https://doi.org/10.1080/00401706.1977.10489493>
16. Cross, J., & Neumark, T. (2021). Solar power and its discontents: Critiquing off-grid infrastructures of inclusion in East Africa. *Development and Change*, 52(4), 902–926. <https://doi.org/10.1111/dech.12668>
17. Day, R., Walker, G., & Simcock, N. (2016). Conceptualising energy use and energy poverty using a capabilities framework. *Energy Policy*, 93, 255–264. <https://doi.org/10.1016/j.enpol.2016.03.019>
18. Dinkelman, T. (2011). The effects of rural electrification on employment: New evidence from south Africa. *American Economic Review*, 101(7), 3078–3108. <https://doi.org/10.1257/aer.101.7.3078>
19. Flake, J. K., & Fried, E. I. (2020). Measurement schmeasurement: Questionable measurement practices and how to avoid them. *Advances in Methods and Practices in Psychological Science*, 3(4), 456–465. <https://doi.org/10.1177/2515245920952393>
20. Goretzko, D., Pham, T. T. H., & Bühner, M. (2021). Exploratory factor analysis: Current use, methodological developments and recommendations for good practice. *Current Psychology*, 40(7), 3510–3521. <https://doi.org/10.1007/s12144-019-00300-2>
21. Grimm, M., Lenz, L., Peters, J., & Sievert, M. (2020). Demand for off-grid solar electricity: Experimental evidence from Rwanda. *Journal of the Association of Environmental and Resource Economists*, 7(3), 417–454. <https://doi.org/10.1086/707384>
22. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
23. Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, 30(2), 179–185. <https://doi.org/10.1007/bf02289447>

24. Jenkins, K., McCauley, D., Heffron, R., Stephan, H., & Rehner, R. (2016). Energy justice: A conceptual review. *Energy Research & Social Science*, 11, 174–182. <https://doi.org/10.1016/j.erss.2015.10.004>
25. Jodoin, L., Gafa, D. W., Egbendewe, A., Domegni, L. K., Gaye, I. D., Ague, V. J., Lo, K., Ouendo, E.-M., Fagbémi, L., & Diop, M. (2024). Making energy justice work for women in rural sub-Saharan Africa: A quantitative diagnostic from Benin, Senegal, and Togo. *Energy Research & Social Science*, 118, Article 103754. <https://doi.org/10.1016/j.erss.2024.103754>
26. Kannan, S., Bessette, D., & Makai, L. (2024). Electricity access empowers women through expansion of economic, physical, and mental spaces in Zambia. *Energy Research & Social Science*, 116, Article 103687. <https://doi.org/10.1016/j.erss.2024.103687>
27. Kassem, D., Zane, G., & Uzor, E. (2026). Revisiting the Last Mile: The development effects of a mass electrification program in Kenya. *Energy Economics*, 154, Article 109098. <https://doi.org/10.1016/j.eneco.2025.109098>
28. Klege, R. A., Amuakwa-Mensah, F., & Visser, M. (2022). Tenancy and energy choices in Rwanda. A replication and extension study. *World Development Perspectives*, 26, Article 100429. <https://doi.org/10.1016/j.wdp.2022.100429>
29. Kou, Y., Hirmer, S., Yang, P., Leonard, A., & Egli, F. (2026). Assessing grid affordability for universal electricity access in Sub-Saharan Africa. *Nature Communications*, 17(1), Article 8455. <https://doi.org/10.1038/s41467-026-75104-7>
30. Leal Filho, W., Gatto, A., Sharifi, A., Salvia, A. L., Guevara, Z., Awoniyi, S., Mang-Benza, C., Nwedu, C. N., Surroop, D., Teddy, K. O., Muhammad, U., Nalule, V. R., & da Silva, I. (2024). Energy poverty in African countries: An assessment of trends and policies. *Energy Research & Social Science*, 117, Article 103664. <https://doi.org/10.1016/j.erss.2024.103664>
31. Lee, K., Miguel, E., & Wolfram, C. (2020a). Does household electrification supercharge economic development?. *Journal of Economic Perspectives*, 34(1), 122–144. <https://doi.org/10.1257/jep.34.1.122>
32. Lee, K., Miguel, E., & Wolfram, C. (2020b). Experimental evidence on the economics of rural electrification. *Journal of Political Economy*, 128(4), 1523–1565. <https://doi.org/10.1086/705417>
33. Lenz, L., Munyehirwe, A., Peters, J., & Sievert, M. (2017). Does large-scale infrastructure investment alleviate poverty? Impacts of Rwanda's electricity access roll-out program. *World Development*, 89, 88–110. <https://doi.org/10.1016/j.worlddev.2016.08.003>
34. MacGinley, T. J., Heynen, A. P., Sharma, V., & Lant, P. A. (2025). Electricity access advances human development...but not always. *Energy for Sustainable Development*, 88, Article 101770. <https://doi.org/10.1016/j.esd.2025.101770>
35. MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics*, 29(3), 305–325. [https://doi.org/10.1016/0304-4076\(85\)90158-7](https://doi.org/10.1016/0304-4076(85)90158-7)
36. Martey, E. (2019). Tenancy and energy choice for lighting and cooking: Evidence from Ghana. *Energy Economics*, 80, 570–581. <https://doi.org/10.1016/j.eneco.2019.02.008>

37. Masera, O. R., Saatkamp, B. D., & Kammen, D. M. (2000). From linear fuel switching to multiple cooking strategies: A critique and alternative to the energy ladder model. *World Development*, 28(12), 2083–2103. [https://doi.org/10.1016/s0305-750x\(00\)00076-0](https://doi.org/10.1016/s0305-750x(00)00076-0)
38. McCord, R., Beach, K. E. B., Mahieu, A., Chilongo, T., Jumbe, C., & Jagger, P. (2026). Shining light on the scale, use, and impact of household solar for achieving energy access in rural Malawi. *Energy Research & Social Science*, 133, Article 104616. <https://doi.org/10.1016/j.erss.2026.104616>
39. McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological Methods*, 23(3), 412–433. <https://doi.org/10.1037/met0000144>
40. Mergulhão, V. P., Capra, L., Voglitsis, K., & Parikh, P. (2023). How do they pay as they go?: Learning payment patterns from solar home system users data in Rwanda and Kenya. *Energy for Sustainable Development*, 76, Article 101295. <https://doi.org/10.1016/j.esd.2023.101295>
41. Mustapha, R. A., Devidas, A. R., & Sharma, A. (2025). Navigating the energy transition: insights from a systematic scoping review of challenges and pathways in developing nations. *Energy Research & Social Science*, 125, Article 104098. <https://doi.org/10.1016/j.erss.2025.104098>
42. O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, 41(5), 673–690. <https://doi.org/10.1007/s11135-006-9018-6>
43. Ojong, N., Gill-Wiehl, A., & Agbe, E. (2025). Cash, credit, or kin? Financing pathways and the uneven sustainability of off-grid solar electrification in Tanzania and Malawi. *Sustainable Development*, 33(S1), 427–443. <https://doi.org/10.1002/sd.70009>
44. Onyeji, I., Bazilian, M., & Nussbaumer, P. (2012). Contextualizing electricity access in sub-Saharan Africa. *Energy for Sustainable Development*, 16(4), 520–527. <https://doi.org/10.1016/j.esd.2012.08.007>
45. Pachauri, S., & Spreng, D. (2011). Measuring and monitoring energy poverty. *Energy Policy*, 39(12), 7497–7504. <https://doi.org/10.1016/j.enpol.2011.07.008>
46. Pittalis, M., Palermo, V., Bezerra, P., Haems, P., Currás, T. A., Ortega Segundo, A., Sen, R., & Skoula, I. (2026). Progress on urban energy access and energy poverty in the Global Covenant of Mayors initiative. *Nature Energy*, 11(5), 767–779. <https://doi.org/10.1038/s41560-026-02019-4>
47. Poblete-Cazenave, M., & Pachauri, S. (2021). A model of energy poverty and access: Estimating household electricity demand and appliance ownership. *Energy Economics*, 98, Article 105266. <https://doi.org/10.1016/j.eneco.2021.105266>
48. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
49. Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63(1), 539–569. <https://doi.org/10.1146/annurev-psych-120710-100452>
50. Pueyo, A. (2018). What constrains renewable energy investment in Sub-Saharan Africa? A comparison of Kenya and Ghana. *World Development*, 109, 85–100.

<https://doi.org/10.1016/j.worlddev.2018.04.008>

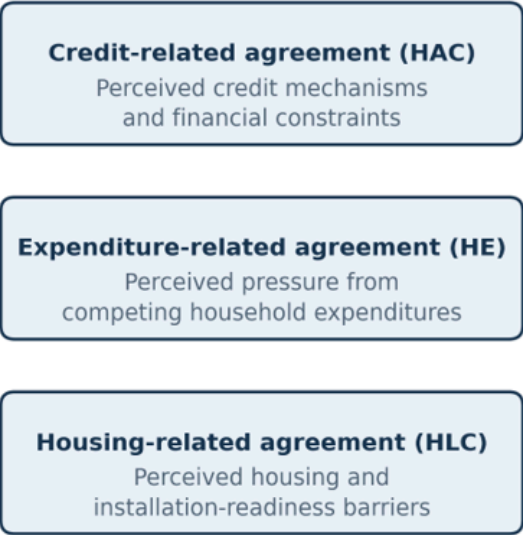
51. Raji, T., Allee, A., & Williams, N. J. (2024). Productive use of electricity in agriculture in sub-Saharan Africa: a systematic review. *Progress in Energy*, 6(4), 042003. <https://doi.org/10.1088/2516-1083/ad6c9e>
52. Rhemtulla, M., Brosseau-Liard, P. É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods*, 17(3), 354–373. <https://doi.org/10.1037/a0029315>
53. Richardson, L., Shrestha, P., Milliken, C., Sills, E. O., Lloyd, S., Nareau, L., Scott, S., & Jagger, P. (2025). Money matters: Does access to financial services foster household energy transitions in Africa?. *Energy Research & Social Science*, 127, Article 104215. <https://doi.org/10.1016/j.erss.2025.104215>
54. Rohrer, J. M. (2018). Thinking clearly about correlations and causation: Graphical causal models for observational data. *Advances in Methods and Practices in Psychological Science*, 1(1), 27–42. <https://doi.org/10.1177/2515245917745629>
55. Sadiki, J.-L.-R. A. (2025). Housing quality and energy security in urban sub-Saharan Africa: A qualitative policy analysis in the DR Congo and Kenya. *Sustainable Earth Reviews*, 8(1), Article 13. <https://doi.org/10.1186/s42055-025-00114-0>
56. Said, R., & Acheampong, A. O. (2023). Financial inclusion and energy poverty reduction in sub-Saharan Africa. *Utilities Policy*, 82, Article 101567. <https://doi.org/10.1016/j.jup.2023.101567>
57. Shon, H., & Lee, H. (2026). The role of household and community infrastructures in mitigating energy poverty in Africa: Between and within urban and rural areas. *Energy Economics*, 154, Article 109045. <https://doi.org/10.1016/j.eneco.2025.109045>
58. Smith, S. (2019). Hybrid networks, everyday life and social control: Electricity access in urban Kenya. *Urban Studies*, 56(6), 1250–1266. <https://doi.org/10.1177/0042098018760148>
59. Tomas Fillol, L., Pinomaa, A., Stevanato, N., Mereu, R., & Honkapuro, S. (2025). What happens after electrification? Exploring the evolution of appliance adoption in rural Kenya. *Energy Research & Social Science*, 122, Article 104015. <https://doi.org/10.1016/j.erss.2025.104015>
60. United Nations. (n.d.). Goal 7. Department of Economic and Social Affairs. Retrieved October 22, 2026, from <https://sdgs.un.org/goals/goal7>
61. Westreich, D., & Greenland, S. (2013). The table 2 fallacy: Presenting and interpreting confounder and modifier coefficients. *American Journal of Epidemiology*, 177(4), 292–298. <https://doi.org/10.1093/aje/kws412>
62. Wong, J. C. Y., Blankenship, B., Harish, S. P., & Urpelainen, J. (2022). Increasing microsolar technology adoption: Efficacy of vouchers, cash transfers, and microfinance schemes. *Energy Economics*, 110, Article 105952. <https://doi.org/10.1016/j.eneco.2022.105952>
63. Zuch, M. (2025). Rural electrification in sub-Saharan Africa: A willingness to pay analysis of electricity access in Kenya. *Energy Policy*, 206, Article 114720. <https://doi.org/10.1016/j.enpol.2025.114720>

Figures

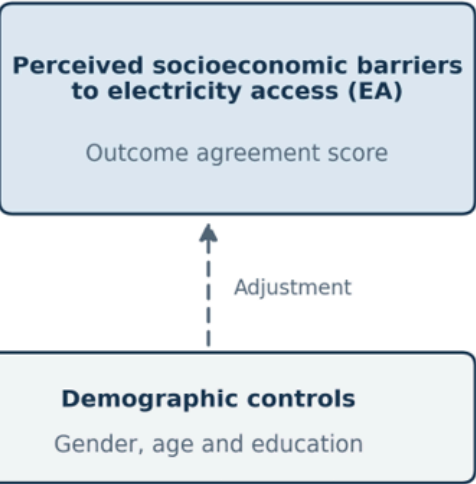
Conceptual framework

Perceived barriers to electricity access in rural Kitui County, Kenya

EXPLANATORY AGREEMENT SCORES



OUTCOME AGREEMENT SCORE



Arrows represent proposed statistical associations; they do not establish causal effects.

Figure 1

Conceptual framework for perceived barriers to electricity access.

Supplementary Files

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