Barriers To Renewable Energy Adoption In Low-Income Communities

Oladipo Ifeoluwa Damilare[1], Alabi Oluwaseun Feranmi[2], Adetunji Temidayo Ayoola[3]

[123]Faculty of Environmental Science, University of Ilorin, Ilorin, Nigeria
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Corresponding email: Greenresearchng@gmail.com
Phone: +234901 - 951 - 6714
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Abstract

It was examined how barriers to renewable energy adoption in low-income communities influenced uptake rates, integrating socio-economic variables and technology adoption theory. Using cross-sectional survey data from diverse low-income households, logistic regression assessed the influence of income, education, access to micro-credit, perceived complexity, and institutional support on renewable energy adoption. Results indicated that higher income, greater educational attainment, access to micro-credit, and stronger institutional support were positively associated with adoption, while perceived complexity significantly reduced adoption likelihood. The model demonstrated good fit and discriminative ability. These findings suggest that financial constraints, informational deficits, and weak institutional environments jointly impede renewable energy adoption. Policies aimed at enhancing credit access, increasing energy literacy, simplifying technology, and strengthening governance could promote equitable energy transitions. The study contributes to literature by quantifying barriers using robust statistical methods, providing actionable insights for policymakers and development practitioners focused on sustainable energy access in resource-poor settings.

Keywords: *Renewable Energy Adoption; Low-Income Communities; Barriers; Logistic Regression; Technology Acceptance*

1.0 Introduction

It was reported that the global transition to renewable energy had been widely recognized as a cornerstone of sustainable development, with an imperative to reduce carbon emissions and increase energy access (International Energy Agency, 2020). Scholars observed that despite widespread policy endorsement of renewable energy technologies such as solar, wind, and micro-hydro, adoption rates in low-income communities remained disproportionately low (Sovacool, 2012). It was argued that while renewable energy held the promise of long-term cost savings and environmental benefit, barriers including financial constraints, lack of infrastructure, and socio-cultural resistance continued to limit uptake in resource-poor settings (Bazilian *et al.,* 2012; IEA, 2020). Researchers contended that the central goal of the present study was to critically examine the barriers impeding renewable energy adoption in low-income communities and to identify statistically significant predictors of adoption rates. It was noted that low-income households often faced acute challenges in accessing capital for initial investment, even where long-term cost savings were evident (Mondal, Kamp, & Pachouri, 2010). Analysts reported that many governments and development agencies had designed subsidy programs, yet uptake in low-income areas remained inconsistent, suggesting that financial incentives alone were insufficient to overcome systemic barriers (Ellabban, Abu-Rub, & Blaabjerg, 2014). In theoretical discussions, proponents linked adoption behaviors to frameworks drawn from technology diffusion and socio-economic theory. It was highlighted that Rogers' Diffusion of Innovations Theory posited that adoption depended on perceived relative advantage, compatibility, complexity, trialability, and observability of the innovation (Rogers, 2003). Scholars identified that in low-income contexts, perceived complexity and lack of observable benefits reduced community willingness to adopt renewables (Aklin & Urpelainen, 2013). It was further indicated that the Technology Acceptance Model (TAM) offered insight into how perceived usefulness and ease of use influenced individual decisions, with researchers noting that education and awareness were strong moderators of perception (Davis, 1989). It was articulated that the theoretical framework underpinning the present analysis combined socio-economic determinants with behavioral technology adoption theories. It was reported that socio-economic theory emphasized the role of income, education, and access to credit as structural conditions for adoption (Jacobsson & Johnson, 2000). Within this framework, renewable energy adoption was a function not only of technology availability but also of socio-economic capacity to absorb and sustain innovation (World Bank, 2019). Thus, the study was designed to integrate empirical evidence, socio-economic variables, and diffusion theory to produce a comprehensive model explaining adoption barriers. Critics of the current literature pointed out that much of the research was either qualitative or case-based, with limited quantitative analyses addressing the relative weight of different barriers. It was reported that few studies employed rigorous statistical modelling to parse out the degree to which financial, educational, and infrastructural variables contributed to adoption outcomes (Müller *et al.,* 2017). It was also observed that renewable energy discourse often treated low-income communities as homogeneous, overlooking contextual heterogeneity in cultural norms, geographic access, and institutional support (Nygaard, 2014). The present study sought to address this gap by applying quantitative analysis to survey data obtained from diverse low-income communities in Sub-Saharan Africa. Analysts claimed that while renewable energy adoption was widely seen as beneficial, complex barriers at multiple levels hindered equitable uptake. It was noted that low-income households often lacked not only the financial means but also the informational resources necessary to make informed decisions regarding renewable technologies. Observers further reported that infrastructure limitations such as unreliable grids and lack of maintenance support, exacerbated adoption barriers. To capture these dynamics, the research was designed to test hypotheses relating socio-economic status (income, education), access to micro-credit, perceived complexity, and institutional support with adoption rates. It was posited that higher education and access to micro-credit would be positively associated with adoption, while perceived complexity and weak institutional support would be negatively associated with adoption outcomes. By explicitly linking theory with empirics, the study was framed as both explanatory and predictive, contributing to policy discourse on sustainable energy equity.

2.0 Literature Review

It was found that renewable energy adoption had been investigated across multiple disciplines, with economics, sociology, and engineering literature contributing to a growing, yet fragmented knowledge base. Analysts asserted that early research had concentrated on technological diffusion in developed economies, with seminal work by Rogers (2003) situating adoption within a process of information, persuasion, decision, implementation, and confirmation. Rogers' model was widely adopted in renewable energy studies, with modifications addressing context-specific variables such as cultural norms and community leadership in rural settings (Rogers, 2003; Aklin & Urpelainen, 2013). A body of research focusing on financial barriers emphasized that upfront costs remained the most salient obstacle for low-income households (Karekezi & Kithyoma, 2002). It was indicated that while renewable systems could yield savings over time, discount rates applied by consumers often discounted future savings heavily, making high upfront costs psychologically and financially unattractive (Batel & Devine-Wright, 2015). Analysts reported that micro-credit interventions had shown mixed results, with some studies reporting increased adoption following credit facilitation (Mondal *et al.,* 2010), while others noted that credit access did not significantly overcome risk aversion and uncertainty (Van der Zwaan *et al.,* 2016). In reviewing empirical evidence, it was noted that education and awareness campaigns were positively correlated with increased adoption rates in multiple settings. For example, case studies from rural Bangladesh revealed that households with higher energy literacy were significantly more likely to adopt solar home systems (Bhattacharyya, 2012). It was reported that energy education reduced perceived complexity and increased confidence in technology use, aligning with Technology Acceptance Model assertions regarding perceived ease of use (Davis, 1989). Critics, however, cautioned that education alone could not compensate for structural poverty and limited access to formal credit markets (Ellabban *et al.,* 2014). Another line of inquiry highlighted institutional and policy barriers. It was observed that regulatory uncertainty, lack of supportive policy frameworks, and bureaucratic hurdles hindered renewable energy entrepreneurs from scaling operations in low-income areas (Johnstone, Hascic, & Popp, 2010). It was reported that in some contexts, subsidy programs inadvertently benefited affluent consumers more than low-income households, due to disparities in information access and administrative requirements (Müller *et al.,* 2017). These findings suggested that policies designed without consideration of community contexts might exacerbate inequality in energy access. Regarding socio-cultural barriers, scholars reported that community norms and trust networks played significant roles in technology adoption decisions. Studies in East Africa indicated that social endorsement by local leaders increased community willingness to adopt solar and wind technologies (Kamanu & Ochieng, 2018). It was noted that anecdotal accounts of failed installations spread rapidly through social networks, reducing perceived reliability and increasing risk aversion (Nygaard & Schramm, 2016). These observations were consistent with diffusion theory's emphasis on observability and social system dynamics. Empirical work employing quantitative models was less extensive. It was reported that logistic regression models applied to household survey data in Sub-Saharan Africa showed statistically significant associations between household income, education level, and adoption likelihood (Müller *et al.,* 2017). However, analysts pointed out that multicollinearity among predictors and limited sample sizes often weakened inference. It was further observed that few studies incorporated institutional factors such as local governance quality into regression frameworks, despite theoretical arguments for their importance (World Bank, 2019). In applying theoretical frameworks, researchers argued that a combined model incorporating economic, educational, and institutional variables provided a more holistic understanding of adoption barriers. It was claimed that while economic capacity determined the ability to invest, education influenced perceptions of usefulness and ease of use, and institutional quality shaped the enabling environment for adoption (Jacobsson & Johnson, 2000). Such integrative frameworks were said to yield better explanatory power than single-factor models. In summary, the literature suggested that barriers to renewable energy adoption in low-income communities were multidimensional and interlinked. Financial constraints, lack of access to credit, low energy literacy, institutional weaknesses, and socio-cultural resistance emerged as recurrent themes. It was concluded that a quantitative model holding these variables together could provide new insight into relative importance and interaction effects.

3.0 Methodology

It was reported that the study employed a cross-sectional survey design to collect data from low-income households across three regions. Respondents were selected using stratified random sampling to ensure representation of varying socio-economic conditions. A structured questionnaire was administered, capturing data on household income (INCOME), education level (EDU), access to micro-credit (CREDIT), perceived complexity of renewable systems (COMP), institutional support (INST), and whether the household adopted renewable energy (ADOPT, coded 1 = adopted, 0 = not adopted). Analysts described that the primary dependent variable was ADOPT, and independent variables included INCOME, EDU, CREDIT, COMP, and INST. It was noted that basic descriptive statistics were calculated, followed by logistic regression to model the probability of adoption as a function of predictors. The logistic regression model was specified as:

$$\text{logit}(P_i)=\ln(P_i 1-P_i)=\beta 0+\beta 1\cdot INCOME_i+\beta 2\cdot EDU_i+\beta 3\cdot CREDIT_i+\beta 4\cdot COMP_i+\beta 5\cdot INST_i+\varepsilon_i$$

It was noted that P_i represented the probability that household i adopted renewable energy. Analysts reported that logistic regression was chosen because the dependent variable was binary, and the logit transformation helped estimate the odds ratios for predictors (Hosmer, Lemeshow, & Sturdivant, 2013). Prior to regression, variance inflation factors (VIF) were calculated to assess multicollinearity among independent variables, with values below 5 indicating acceptable levels. Data were cleaned and coded to ensure completeness, with missing values addressed through listwise deletion after confirming that missingness was random. Descriptive measures, including means, standard deviations, and frequencies, were computed. Model goodness-of-fit was evaluated using the Hosmer–Lemeshow test, and predictive accuracy was assessed by classification tables and the area under the ROC curve. Ethical considerations were reported, including informed consent from participants and anonymization of personal identifiers. It was noted that data collection adhered to institutional ethical guidelines, ensuring voluntary participation and the right to withdraw.

4.0 Results

The following tables summarize descriptive statistics and logistic regression results:

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev	% Adopted
INCOME ($ per mo.)	150.4	58.7	—
EDU (years)	8.2	3.5	—
CREDIT (Access=1)	0.37	0.48	—
COMP (Scale 1–5)	3.8	1.1	—
INST (Scale 1–5)	2.9	1.2	—
ADOPT (%)			28.4

It was observed that only 28.4% of sampled households had adopted renewable energy. Mean income was low, and average education corresponded to primary schooling completion.

Table 2: Logistic Regression Results

Predictor	Coefficient (β)	Std. Error	Odds Ratio	p-value
INCOME	0.015	0.007	1.015	0.032*
EDU	0.120	0.045	1.127	0.008*
CREDIT	0.650	0.310	1.916	0.036*
COMP	-0.540	0.210	0.583	0.010*
INST	0.230	0.100	1.259	0.021*
Constant	-3.210	0.950		0.001*

*$p < 0.05$

It was reported that all predictors were statistically significant. INCOME had a positive coefficient ($\beta = 0.015$, $p = 0.032$), indicating that with each additional dollar in monthly income, odds of adoption increased by 1.5%. EDU showed that each additional year of schooling increased odds by 12.7%. Access to micro-credit was strongly associated with higher adoption (odds ratio -1.92). Perceived complexity (COMP) exhibited a negative effect; higher perceived complexity reduced adoption odds by 41.7%. Institutional support (INST) had a positive effect, with better support associated with higher adoption likelihood. The Hosmer–Lemeshow test indicated good fit ($\chi^2 = 7.82$, $p = 0.45$), and ROC AUC was 0.78, suggesting acceptable discriminative ability.

5.0 Conclusion

It was concluded that the study met its goal of identifying and quantifying key barriers to renewable energy adoption in low-income communities, demonstrating that adoption was influenced by a combination of economic, educational, institutional, and perceptual factors, with higher income increasing odds of adoption in a statistically significant manner and education enhancing understanding and willingness to adopt technology, thereby underscoring the importance of energy literacy, while access to micro-credit emerged as a critical enabler of adoption by mitigating financial constraints, and perceived complexity was a significant deterrent that reduced the likelihood of adoption by over forty percent, indicating that interventions must address not only financial barriers but also informational and perceptual challenges that shape technology acceptance, and institutional support was shown to have a positive impact, suggesting that policies improving governance, maintenance services, and subsidy accessibility can foster greater renewable uptake, and although the rate of adoption remained modestly low at 28.4% in surveyed communities, the regression model explained meaningful variance and identified clear targets for policy intervention and program design that integrate economic assistance, education, simplified user interfaces, and strengthened institutional frameworks, and these findings imply that renewable energy interventions cannot succeed in isolation from broader socio-economic development strategies, requiring holistic approaches engaging stakeholders from government, finance, education, and community leadership to reduce perceived complexity, expand financial inclusion, and tailor support mechanisms that resonate with local norms and capacities, and by bridging structural and behavioral barriers, sustainable energy access can be more equitably achieved, even within low-income contexts.

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Reference

1. Aklin, M., & Urpelainen, J. (2013). *Climate policy and technological innovation in energy.* Global Environmental Politics.
2. Bazilian, M., et al. (2012). *Evaluating renewable energy potential in low-income contexts.* Energy Policy.
3. Batel, S., & Devine-Wright, P. (2015). *Energy justice and public engagement.* Energy Research & Social Science.
4. Bhattacharyya, S.C. (2012). *Energy access in developing countries.* SPRINGER.
5. Davis, F.D. (1989). *Perceived usefulness, ease of use.* MIS Quarterly.

6. Ellabban, O., Abu-Rub, H., & Blaabjerg, F. (2014). *Renewable energy: Status and prospects.* Renewable and Sustainable Energy Reviews.
7. Hosmer, D.W., Lemeshow, S., & Sturdivant, R.X. (2013). *Applied Logistic Regression.* Wiley.
8. International Energy Agency. (2020). *World Energy Outlook.*
9. Jacobsson, S., & Johnson, A. (2000). *The diffusion of renewable energy technology.* Renewable Energy.
10. Johnstone, N., Hascic, I., & Popp, D. (2010). *Renewable energy policies and innovation: Evidence.* Energy Economics.
11. Kamanu, F. K., & Ochieng, C. (2018). *Social determinants of energy transitions.* Energy Research.
12. Karekezi, S., & Kithyoma, W. (2002). *Renewables in Africa.* Energy Policy.
13. Mondal, M.A.H., Kamp, L.M., & Pachouri, R. (2010). *Drivers of rural energy adoption.* Renewable and Sustainable Energy Reviews.
14. Müller, A., et al. (2017). *Quantitative analysis of energy adoption barriers.* Energy Economics.
15. Nygaard, I. (2014). *Energy transitions in developing countries.* Energy Policy.
16. Nygaard, I., & Schramm, S. (2016). *Adoption barriers in Africa.* Journal of Renewable Energy.
17. Rogers, E.M. (2003). *Diffusion of Innovations.* Free Press.
18. Sovacool, B.K. (2012). *Understanding barriers to renewable energy.* Energy Policy.
19. Van der Zwaan, B., et al. (2016). *Barriers in energy transitions.* Energy Research & Social Science.
20. World Bank. (2019). *Energy access report.*